Surveillance & Society

Pred-Pol-Pov: Visibility, Data Flows, and the Predictive Policing of Poverty

Elle Pearson, Rikke Bjerg Jensen and Peter Adey

Volume 22, Number 2, 2024

Open Issue

URI: https://id.erudit.org/iderudit/1112223ar
DOI: https://doi.org/10.24908/ss.v22i2.15826

See table of contents

Publisher(s)

Surveillance Studies Network

ISSN

1477-7487 (digital)

Cite this article

Pearson, E., Bjerg Jensen, R. & Adey, P. (2024). Pred-Pol-Pov: Visibility, Data Flows, and the Predictive Policing of Poverty. *Surveillance & Society*, *22*(2), 120–137. https://doi.org/10.24908/ss.v22i2.15826

Article abstract

Predictive and data-driven policing systems continue to proliferate around the world, enticing police forces with promises of improvements in efficiency and the ability to offer various ways of addressing the future to pre-empt, predict, or prevent crime. As more of these systems become operationalised in England and Wales, this paper takes up Duarte's (2021) observation that there is a lack of description as to what such systems actually are. This paper adapts a social network methodology to explore what is a data-driven policing system. Using a police force in England, UK, as a case study, we provide a visualisation of a data-driven policing system based on the data flows it requires to operate. The paper shows how a disparate network of affiliate organisations act as collators of specific data types that are then used in a range of policing applications. We make visible how data travels from its source through various nodes and the various potential points of translation that occur. We show, as others have argued before us, the data points used are proxies for poverty, making certain groups and sections of society highly visible to the digital system whilst other groups and crimes become less visible—and sometimes even hidden.

Surveillance & Society

Article

Pred-Pol-Pov: Visibility, Data Flows, and the Predictive Policing of Poverty[1]

Elle Pearson

Royal Holloway, University of London, UK
elle.pearson.2020@live.rhul.ac.uk

Rikke Bjerg Jensen

Royal Holloway, University of London, UK
rikke.jensen@rhul.ac.uk

Peter Adey

Royal Holloway, University of London, UK
peter.adey@rhul.ac.uk

Abstract

Predictive and data-driven policing systems continue to proliferate around the world, enticing police forces with promises of improvements in efficiency and the ability to offer various ways of addressing the future to pre-empt, predict, or prevent crime. As more of these systems become operationalised in England and Wales, this paper takes up Duarte's (2021) observation that there is a lack of description as to what such systems actually *are*. This paper adapts a social network methodology to explore what *is* a data-driven policing system. Using a police force in England, UK, as a case study, we provide a visualisation of a data-driven policing system based on the data flows it requires to operate. The paper shows how a disparate network of affiliate organisations act as collators of specific data types that are then used in a range of policing applications. We make visible how data travels from its source through various nodes and the various potential points of translation that occur. We show, as others have argued before us, the data points used are proxies for poverty, making certain groups and sections of society highly visible to the digital system whilst other groups and crimes become less visible—and sometimes even hidden.

Introduction

Data-driven policing, assisted by predictive analytics and big data, is currently expanding in the United Kingdom (UK). Qlik Sense is a predictive analytics platform that merges and visualises multiple data sets, whilst utilising statistical data analysis tools such as R and SPSS, to perform management and operational functions. This includes predictive risk scoring and crime mapping for Avon and Somerset Constabulary[2] in England with two hundred and fifty thousand people filtered and processed by the system daily and scored based on their predicted risk of committing, or becoming a victim of, a crime (Dencik et al. 2018). The system absorbs approximately ten million pieces of data per day (Marsh and Price 2020), including data

[1] The data gathering and writing of this article, along with the creation of the data sharing network, took place during 2021–2022 and relied solely on information and documentation publicly available during that time.

[2] Police forces in the UK are organised into regional police divisions and Avon and Somerset Constabulary is one of these divisions.

Pearson, Elle, Rikke Bjerg Jensen, and Peter Adey. 2024. Pred-Pol-Pov: Visibility, Data Flows, and the Predictive Policing of Poverty. *Surveillance & Society* 22(2): 120-137.
https://ojs.library.queensu.ca/index.php/surveillance-and-society/index | ISSN: 1477-7487

from several different policing systems, historic crime data, as well as a wide range of health and social data from external organisations (Dencik et al. 2018; Eaton and Bertoncin 2018). Through Qlik Sense, a large selection of individually tailored applications[3] have been created, ranging from applications that monitor staff performance or calculate the risk of child sexual abuse, for example, to applications that predict pleas, suicides, or crimes and victimisation (Couchman 2019; Eaton and Bertoncin 2018).

Such data-driven systems, often referred to as "predictive policing," or "precision policing" as noted by Wilson (2019), continue to be developed, refined, and implemented, following a longer lineage of policing systems and practices elsewhere, especially in the United States (US), such as PredPol and Chicago's Strategic Subject List.[4] Couchman's (2019) research on the use of predictive analytics by different police forces in England and Wales illustrates how large amounts of sensitive data, some of which the police have no legal right to hold, are aggregated into predictive policing systems whilst merging databases from external, non-police organisations. The research, conducted on behalf of Liberty, raises concerns about data sharing and how such systems could replace suspicious behaviour with suspicious data. Couchman (2019) and Dencik et al. (2018, 2019) reveal that Qlik Sense is more expansive in its scope in comparison to anything else that currently exists in the UK; reaching beyond one or two applications—as is the case with other systems—to have a variety of different, interlinked applications with the aim of predicting a diversity of events.

Qlik Sense is more comprehensive than other systems currently deployed by police forces in the UK. It is fully operational with multiple applications that use predictive analytics covering both geographic and individualised types of predictive policing (Couchman 2019; Dencik et al. 2018; Dencik et al. 2019). Further, Dencik et al. (2018, 2019) point to an increase in the use of predictive risk scoring, not only in predictive policing systems but also by local authorities for social care, health, and safeguarding purposes, raising concerns about the level of data sharing occurring to facilitate such scores. Dencik et al. (2019: 11) problematise how those tasked with operating such systems often view data collection and risk scoring as providing a reliable and factual "golden view" of individuals.

This paper focuses on the data sharing that permits Avon and Somerset Constabulary to operate their various Qlik Sense applications by identifying what data are being used to facilitate its day-to-day operations, from where that data(set) originates to the potential implications of its use. We build on the foundations of Couchman (2019) and Dencik et al. (2018, 2019) and are motivated by Duarte's (2021) observation that new research on predictive policing is needed to provide detailed and descriptive accounts of predictive systems. Duarte points to a lack of in-depth research in this area and calls for new research to record and describe in detail "the symbiotic relationships between data, algorithms, and humans…before an understanding of how (in)security practices are produced in the everyday" (Duarte 2021: 212). Our project here is not to uncover the practices that enable and shape Qlik Sense. Instead, we take the first step in exploring it as an information infrastructure (Bowker et al. 2010) of social control by reconstructing it as a network. In so doing, we also recognise that this form of information sharing, surveillance, and control benefits the institutions that implement such systems.

We explore and make visible the data flows that underpin the network using a social network methodology to illustrate the network that is bound together through Qlik Sense. We do this by consolidating publicly available, but highly fragmented, information and sources to reveal key parts of the network. This paper thus contributes to existing scholarly work on predictive policing and surveillance by providing an example

[3] The applications are pieces of software tailored for specific purposes and are displayed in a grid-like formation on the user interface, much like applications on a mobile device that users then click to access.

[4] Predictive analytics are used for a range of law enforcement purposes, with many systems operational within the US Criminal Justice System such as Palantir's Gotham platform and PredPol. There is a range of literature covering such systems, for example Brayne (2017, 2021), Brayne and Christin (2020), Ferguson (2012, 2017b), Linder (2019), Mantello (2016), Richardson, Schultz, and Crawford (2019), and Wilson (2018, 2019, 2020); yet the present paper focuses on the UK operationalisation of such systems, exemplified by Qlik Sense.

of how data-sharing results in the enhanced network visibility of certain groups to data-driven policing systems. It makes visible the different data-sharing relationships that make up the network, revealing what types of data are being considered and key areas and institutions where data flows through, is collated, and shared. In some instances, this occurs on a daily basis using predictive risk scoring to putatively prevent crimes by, as the company behind Qlik Sense asserts, "pre-empt[ing] certain events from happening" (QlikTech International AB 2017). This substantively extends our understanding of the relationship between policing approaches and knowledges with other government organisations and service providers, including local government, NGOs, and private companies. It is suggestive of different kinds of possible skews and reinforcements or feedback loops that become possible through systems like Qlik Sense, which directs police resources and intelligence—within new and wider networks of data sharing—towards a focus on the poorest. This occurs via the relationship between specific datapoints and poverty, a point recognised in work by Dencik et al. (2019) on systems in England and Wales and Eubanks (2018) in the US.

The paper is structured into five sections. Following this introduction, the first section outlines and discusses related scholarly work on predictive and data-driven policing to situate our work in the broader literature. The next section establishes the context within which Qlik Sense exists and describes the underpinning research methodology and the steps taken to reconstruct the network that makes up Qlik Sense. The following section provides an overview of the Qlik Sense network, the nodes that make up the network, and their links, while examining the data sharing and feedback loops that are constituted by the Qlik Sense network. We conclude in the final section.

Approaching Predictive Policing

Tracing Predictive Policing

Policing has almost always relied upon police intuition and degrees of anticipation—often using racial tropes and categorisations such as so-called shifty behaviour. Fictional narratives of policing, such as *Minority Report* (2002), have also imagined perfect systems where crimes can be anticipated and prevented before they take place. These have been widely compared to broader sets of security and policing approaches that have been understood as pre-emptive, especially in the context of borders (Weber 2007; Wilson and Weber 2008). During the 1990s, police strategy in the UK, led by Kent Police, began to focus on intelligence-led policing that placed importance on data collection, an ethos that grew alongside US security-driven initiatives after 9/11, and provided justification for the hoarding of data "just in case" (Ericson and Shearing, 1997; Wilson 2020: 150). This strategy expanded in light of claims that the collation and analysis of disparate data could have prevented the 9/11 attacks (Wilson 2020). Predictive policing systems are thus an evolution of previous policing approaches that have shifted and adapted alongside the technology of the time, often as a means to improve efficiency (Egbert and Krasmann 2020). The novel component of such systems is their ability to incorporate data on a scale not previously possible, while making inferential judgements based on disparate associations and statistical tests to reach risk scores. The scale at which recent systems operate has grown significantly when compared to systems like COMPSTAT (short for computer statistics) in the 1990s.

COMPSTAT was used to improve efficiency through crime mapping techniques, statistics, and performance indicators to manage patrols in the face of budget cuts by the New York Police Department (Egbert and Leese 2021). In 2011, PredPol,[5] a predictive policing collaboration between the Los Angeles Police Department and the University of California, was launched; it merged criminological theory and police data with the aim of predicting geographic locations of crimes. More recent systems include the Chicago Police Department Strategic Subject List (SSL), known as the Heat List, which uses a range of different data to assign a risk score to an individual indicating their probability of being either a victim or perpetrator of a shooting incident using crime-based data as indicators (City of Chicago 2016). The SSL was shut down in 2020 after various legal challenges. Other systems include Rio de Janeiro's CrimeRadar (Duarte 2021) and

[5] PredPol rebranded to Geolitica and provides the rationale for doing so here: https://blog.predpol.com/geolitica-a-new-name-a-new-focus.

a range of other software that forms part of these systems such as HunchLab, IBM SPSS, Hitachi, and Motorola. Avon and Somerset Constabulary's system incorporates aspects of PredPol and the SSL as it is both a place-based and person-based system whilst also utilising IBM SPSS.

Conceptualising Predictive Policing

There are various approaches, conceptual lenses, and debates surrounding definitions of the type of digital policing systems we discuss in this paper. Many describe them as predictive policing (Ferguson 2012; Meijer and Wessels 2019; Uchida 2009), others as pre-emptive policing (Andrejevic, Dencik, and Treré 2020; Egbert and Krasmann 2020; McCulloch and Wilson 2016), platform policing (Hälterlein 2021; Linder 2019; Wilson 2020), and precision policing (Wilson 2019), and the terms are often used interchangeably. We use the umbrella term "data-driven policing" (Jansen 2018) to highlight Qlik Sense as a data-driven system with predictive applications, and to underline that the object of our research is the data components of the system, we draw on broader definitional discourses.

The term predictive policing lacks definitional clarity (Ferguson 2012; Meijer and Wessels 2019; Wilson 2020) but generally refers to a variety of different methods, tools, and processes that police forces utilise in the form of digital technologies such as algorithms, big data, and software in an attempt to control, and/or modify, the future (Egbert and Leese 2021). These digital technologies parallel changes within policing as it moves away from "a focus on moral transgression and reactive crime control towards governing problems in terms of their probabilistic nature and potential harms" (O'Malley 2015: 427). The different digital tools and techniques that form predictive policing systems claim to be able to predict and therefore enable the prevention of a crime before it might occur, or at least make it less likely (Egbert and Leese 2021), with probabilistic risk scores guiding justifications for action. Aradau and Blanke (2017) note how the epistemic credibility of prediction changes through epochs, from ancient divination to machine learning that is romanticised as providing a true ability to predict the future.

Often the technology is analysed through a lens of shifting police paradigms such as the shift in policing from prevention to pre-emption (Andrejevic 2017; Mantello 2016), sometimes also referred to as precrime (McCulloch and Wilson 2016; Zedner 2007). Zedner (2007: 265) describes the shift from a post-crime to pre-crime society based on a logic of security that, instead of reacting to a past crime, addresses "the conditions precedent to it." This temporal shift uses the rationale of risk to classify and categorise risky populations so early interventions can be enacted upon them to prevent their forecasted future crimes from ever occurring. Predictive policing employs similar logics to those in pre-emptive war and targeted assassinations through so-called pattern of life recognition (Amoore and Raley 2016; Egbert and Krasmann 2020) and even forms of counter-terrorism (McCulloch and Wilson 2016). Day (2014: 133) shows how the documentation and then indexing of an individual "provides the codes for the subject's social positioning and expressions by others and by itself." The individual is portrayed via an index of documents, and if this index is shared in a network, then that documentary index of the person is how the individual is characterised and viewed by others.

Such a process renders individuals visible through data rather than through a physical gaze, and this visibility allows the maintenance of order. This reduction is discussed by Deleuze (1992) with reference to the '*dividual*, a reduction of a person to a set of data. More recently, Amoore (2011) describes the data derivative, a process whereby an individual is deconstructed into a set of attributes upon which inferences and predictions can be made about them. Such processes can erase what makes individuals individual, whilst the data held about them renders them in a way that may not be accurate because the "small data" (boyd and Crawford 2012: 670) is missing. Mantello (2016) discusses this as a paradigm shift from post-crime to the pre-crime assemblage, building on Haggerty and Ericson's (2000) surveillant assemblage. Moreover, Mantello (2016: 1) describes the use of data visualisation as an "aesthetic and prescient turn in the surveillant assemblage," the result of which is that people are judged not on what they have done but on what others in the same category as them have done in the past. Such a shift, Mantello (2016: 10) continues, is facilitating "an emergent modality of power" delegated to software systems to enact social control.

Data is required for predictive analytics to operate. The increasing datafication of society and social life (Mayer-Schönberger and Cukier 2013), and the subsequent surveillance that collects the data trails (Lyon 2014), has allowed for the quantification of human behaviour that is converted into an analysable form (Mayer-Schönberger and Cukier 2013). Brayne (2017) describes how the merging of separated systems is facilitating the spread of surveillance through a range of institutions and how big data surveillance is amplifying existing (smaller scale) surveillance practices. Data-driven policing systems are tapping into this information, using predictive analytics, and predictive crime mapping, to assist decision-making and allocate police resources. Egbert (2019) notes how the drive for more data will lead to increased datafication of police work and, as a consequence, expansive surveillance and data collection. Egbert (2019) further argues that the merging of crime data with external data sets increases the potential for function creep via the "collect it all" ethos of data collection being inbuilt in such systems. This point is also recognised by Wilson (2018) who further points to an obfuscation of data sources; as predictive policing systems expand, the datasets they use often rely on external providers to supply the data, creating a risk of surveillance creep.

Critiques of Predictive Policing

The advent of predictive policing systems has been accompanied by significant critiques. The large-scale data collection driving such systems facilitates the use of algorithms that perform predictive risk scores. This has raised concerns about profiling (Harcourt 2007; Lammerant and de Hert 2016; Mann and Matzner 2019) and the disproportionate monitoring of particular groups based on ethnicity and socio-economic status (Dencik et al. 2018; Dencik et al. 2019; Eubanks 2018), as such groups are constructed as a threat due to their non-conformity to social norms (Schinkel 2011). Privacy concerns (Crawford 2021; Eubanks 2018; Zuboff 2019), bias and discrimination (Barocas and Selbst 2016; O'Neil 2017; Pasquale 2015), racist outputs of algorithms (Chander 2017), influence on human decision-making (Eubanks 2018; Holmqvist 2013; Magalhães 2018; Oswald et al. 2018), human rights implications (Bennett Moses and Chan 2014; Ferguson 2012) and the dehumanising nature of the data-derivative (Amoore 2011) have been raised as significant issues.

Of particular salience in our work is the reliance on crime data and the longstanding concerns regarding its (in)accuracy (Coleman and Moynihan 2010; Maguire 2012; Nelken 2012; Richardson et al. 2019; Završnik 2019), its lack of social and contextual grounding, and the under-representation of certain crimes (Maguire 2012; Nelken 2012). Richardson et al. (2019), in their research on US predictive policing systems, emphasise issues with "dirty data" stemming from historical problems within policing such as institutional racism and a focus on street-level crimes. Crime data are also affected by under-reporting leading to incomplete data, the so-called "dark figure" of crime (Završnik 2019).

These systems can take the deterministic view that without intervention those observed as risks will become larger problems later on and so preventative and pre-emptive action is required to avoid this (Schinkel 2011). Schinkel (2011: 373, 376) calls this type of prevention "prepression," a "pro-active repression that attempts the timely suppression of certain forms of life" that "criminalizes 'risks' and incriminates 'risky populations.'" Those identified with "risky causal chains," meeting multiple risky indicators, are those that are targeted for prepression (Schinkel 2011: 373). This highlights how actuarial systems are enabling specific types of governance to be enacted on specific populations. When such systems are employed by the police, they make visible those that are deemed to require further observation, triggering interventions to prevent this over-determined future from occurring. Others suggest algorithmic risk assessment operates an omnivorous data-collection process using any and all data available (Mehozay and Fisher 2019).

A 2020 report by the defence and security think tank, the Royal United Services Institute (RUSI) (2020), acknowledges, on one hand, existing and legitimate concerns over the use of police-recorded data due to discriminatory disparities embedded within them, which are reported to be caused by racial bias in the Criminal Justice System. However, on the other hand, the report notes how there is insufficient evidence to confirm the existence of bias caused by algorithms used in policing in England and Wales. Yet, others show the detrimental effects the technology could have on suspicion and discretion (Ferguson 2012, 2015, 2017a; Joh 2015), along with modes of translation (Duarte 2021) and feedback loops (Ferguson 2017a; Richardson, Schultz, and Crawford 2019; Završnik 2019). Dencik et al. (2019) show specifically how Bristol's Integrated Analytics Hub, which works with Qlik Sense, does not include any positive contextual information that could insulate people from the risks for which they are being risk scored. This has the potential to create feedback loops, as it may compound the skewed and disproportionate treatment of already marginalised groups (Ferguson 2017a; Eubanks 2018). Moreover, historical police data and likely data from other institutions, particularly health and social care data, contain bias due to longstanding race- and class-based prejudice. For instance, the unequal treatment of Black people, particularly Black women seeking medical treatment through the NHS and the overuse of forcible detention (via the Mental Health Act 1983) in the Black community (Joint Committee on Human Rights 2020) are just two examples of biased data absorbed into predictive systems that may come from organisations external to the police.

Runaway feedback loops can be created whereby the police are repeatedly sent back to the same neighbourhoods or focus on the same groups (Richardson et al. 2019). Ferguson (2017a: 1148) notes how the confirmation feedback loop "equates those currently in the system with those who need to be policed by the system." This creates more data, which feed back into the system, which further influences future decisions (Ensign et al. 2018). Harcourt (2007: 147) describes "The Ratchet Effect" as a type of increasing disproportionality whereby "a distortion occurs when profiling produces a supervised population that is disproportionate to the distribution of offending by a racial group." The longer this occurs, the more skewed the sample gets, as the data fed into the system reinforces the initial bias, which subsequently reinforces the feedback loop (Lum and Isaac 2016).

Qlik Sense

Increasing numbers of police forces in England and Wales are testing and implementing predictive policing systems (Couchman 2019). At least eighteen predictive tools are in use by UK police forces with many more suspected to be in operation, but no definitive list exists (Zilka, Sargeant, and Weller 2021). The ability to store and process large volumes of data, alongside third-party off-the-shelf software and the growth in data analytics companies, have made predictive policing systems far more accessible to police forces who may not have (had) in-house expertise (Linder 2019). Many police forces have also turned to technological solutions in light of reductions in funding.

Systems in the UK include PredPol, implemented by Kent Police in 2013 but abolished five years later due to difficulties in assessing whether the technology had helped to reduce crime (BBC News 2018). Other systems such as Durham Police's HART model are used to assist decision makers in custody suites to establish whether a person's risk of future offending designates them as eligible to take part in a four-month programme instead of being prosecuted (Oswald et al. 2018; Zilka, Sargeant, and Weller 2022). Merseyside Police use predictive crime mapping (Couchman 2019), whilst West Yorkshire Police have developed Patrol Wise, a mobile application for patrol plans to reduce burglaries (Zilka, Cartwright, and Weller 2021), alongside Corvus IOM Case, a system that collates an array of data to create individualised risk scores based on reoffending (Zilka, Sargeant, and Weller 2022). In 2020, West Midlands Police withdrew their Most Serious Violence (MSV) predictive model that was part of the National Data Analytics Solution (NDAS) project in collaboration with Accenture. The model attempted to predict whether an individual would commit a violent crime within twelve months (West Midlands Police 2019). A coding error found in the training data set rendered the system unable to predict accurately (West Midlands Police 2020). The NDAS project is used by the National Crime Agency and seven other police forces (Zilka, Sargeant, and Weller 2022). While not unique in its use and development of predictive policing systems, the UK is in a period of significant development and implementation of such systems. This is happening at the same time as the ethical safeguards and scrutiny of those systems is emerging—yet, not always in tandem.

In this context, Qlik Sense, as part of a data-driven policing system with predictive applications, has benefited from the growing datafication of society at a time when policing is shifting from reactive to pre-emptive. Qlik Sense reaches into siloed systems and amalgamates the information into various dashboards displaying visualisations. It handles not only backroom and management tasks but also actively uses predictive analytics to identify the potential perpetrators and victims of crime. It also assists in connecting non-police organisations and partners, allowing the sharing of their data for a variety of different purposes. Qlik Sense acts as the infrastructure on which the operations of Avon and Somerset Constabulary sits.

Qlik Sense does not label itself as a predictive policing tool, nor does Avon and Somerset Constabulary, but rather in the vein of data analytics companies supporting "smart" decision-making; the rhetoric is far more benign. Qlik Sense "combines the power of artificial intelligence with the creativity of human intuition" that allows "deeper discoveries," operates "just like your mind works," provides "peripheral vision for your data that lets you spot hidden insights," and "empowers people to make discoveries" (QlikTech International AB n.d.a). Qlik Sense is marketed for a range of different business use-cases outside of policing and security (QlikTech International AB n.d.a, n.d.b), thus confirming the work of Linder (2019), who highlights the take-up of business technology in policing. Business technology avoids the fanfare, and the accompanying critical scrutiny of a fanfare announcement, that a predictive policing system may garner.

Avon and Somerset Constabulary's (one of the main contexts for this research) use of Qlik Sense shows a diversion away from clearly defined digital policing systems like Geolitica (formerly PredPol). Systems such as Geolitica are generally narrow in their focus, often with a single purpose, such as hotspot policing. Qlik Sense, however, is embedded into the fabric of the police force and is incorporated into nearly every aspect of its operations: from on-the-street policing to back-room processes like fleet management. In this sense, it acts as the underlying infrastructure for the police force through the appropriation of business software and technology into bespoke applications used for social control and the managerial and operational aspects of policing. Qlik markets itself as delivering impact through data integration and analytics business solutions (QlikTech International AB n.d.a, n.d.b, 2023), not as predictive or data-driven policing software.

Reflecting on the system as an "information infrastructure" (Bowker et al. 2010) of social control, the present research was inspired by literatures within infrastructure studies and platform studies (Plantin et al. 2018) in its aim to reveal the system as a network. Linder (2019: 78) has described systems like Qlik Sense as "surveillant assemblage-as-a-service." We do not explore Qlik Sense as a form of surveillance capitalism per se (Linder 2019; Wilson 2019; Zuboff 2019), but as a divested form of state infrastructure. Yet it does, as other data analytics services, appear to conform to a surveillant assemblage consisting of "heterogenous surveillance technologies, networked systems, databases, and users" (Linder 2019: 78), which also "territorialises" by connecting siloed spaces, practices, and data.

Approaching Qlik Sense: Visualising the Network

Following Duarte (2021), our research focuses on constructing the digital network that makes up Qlik Sense, to make the system visible and "tangible." It is not that Qlik Sense is secret of course. The company's website frontpage is beguilingly techy, promising dramatic insights from the magic of data analysis. The pages for the product that is Qlik Sense are more banal and look like an advertisement for a spreadsheet; it is business-like. Qlik Sense and Avon and Somerset Constabulary provide Qlik with glowing testimonies on the Qlik website (Dowey 2018) and YouTube channels (Qlik 2018). One of Qlik Sense's many tools is also, perhaps ironically, visualisation, and those testimonies boast of the ability to help visualise data, police operations, workload, and more. The visual metaphors are strong and alluring. Qlik Sense analytics help to get a "grip" on an event, otherwise perhaps ungraspable, to gain a "snapshot of a situation," to help "spot vulnerabilities" or "trends," and ultimately to "make sure officers are in the right place at the right time to pre-empt certain events from happening" (QlikTech International AB 2017), where "events" again belies the potentially gritty and banal nature of the kinds of crime Qlik Sense attempts to anticipate.

We decided to focus on the data(sets) and data sharing that facilitate Qlik Sense's operations as, without this component, the system would not be able to function. Concerns regarding the data aspect of the system have also been raised by Couchman (2019) and Dencik et al. (2018, 2019), who identify merging data sets and trace the origin of some of the data. Our methodology reveals the flow of data in and around Qlik Sense and creates a visualisation to reveal the data collection and sharing that occurs. The research shows what data are being collected, by whom or what, and where they originated. The intention is to reveal a macro-outline of the data-driven policing system, to explore and reveal what it is. The research was split into two phases. The first phase aimed to identify the applications used within Qlik Sense whilst the second used a social network methodology to visualise Qlik Sense as a network and identify the data flows to, and between, the applications. We set these out in more detail below.

It was anticipated that the data-sharing taking place would be both difficult to pinpoint and vast in its scope. To begin exploring the data being used by Qlik Sense, it was first necessary to identify the different applications facilitating the system. Some of the applications were found in existing literature (Couchman 2019; Dencik et al. 2018; Dencik et al. 2019; Eaton and Bertoncin 2018), but it was not possible to locate a complete or comprehensive list. Consequently, phase one of the research involved locating promotional material and official, publicly available videos of Avon and Somerset Constabulary discussing their use of Qlik Sense. These videos, found on the official YouTube channels of Qlik and Avon and Somerset Constabulary, were used to identify different parts of the system. Screenshots of the videos were taken and by zooming in, the individual Qlik Sense applications were often visible on the computer screens of the Avon and Somerset Constabulary staff talking in the videos.

While this is a far from perfect method that risks the possibility that many applications were missed, this method of data collection enabled the identification and accumulation of a significant number of applications used within Qlik Sense. The applications are individual programs built within Qlik Sense. For instance, operational applications such as a Call Handling application help the call handlers in the police control room manage incoming calls, a Fleet application allows the management of the police fleet of vehicles, and specific crime-based applications aim to predict who will be a perpetrator, or victim, of a crime.

We identified sixty-one Qlik Sense applications in phase one. In the second phase, a social network analysis methodology, inspired by a similar method recommended to the police by the UK's Home Office (2016) to identify those associated with gangs, was adapted to visualise, as a network, the data flows in and around Qlik Sense. The research employs a variant of what Pezzani and Heller (2013) have coined the "disobedient gaze." Their approach recognised the centrality of surveillance systems in border and migration management whilst it sought to use those very systems and techniques to make visible the management of migration and borders that can go broadly unseen. We do not suggest there is an active attempt to conceal parts of the Qlik Sense system, but rather that some parts and operations of this system receive less attention than others, making them hidden by default. The method was used to aggregate and analyse disparate pieces of data in various formats. This parallels the type of disparate data aggregation carried out by Qlik Sense itself, as one of its purposes is to bring together data in different formats and databases and aggregate it to make inferences.

Phase two followed a four-step approach. The first step involved limiting the research focus to the geographical area covered by Avon and Somerset Constabulary and the different components, such as departments and third-party organisations, that are involved in and facilitate Qlik Sense. The second step involved the selection of data. Social network analysis can be applied "to any data that highlights the relationships between things (e.g., individuals, objects, events etc.)" (Home Office 2016: 7). For the purpose of our research, a "relationship" comprises at least two entities (individuals and/or organisations) that have engaged in data-sharing of some sort and to varying degrees. The links (sometimes called "edges" in social network analysis) between nodes in our research signify a data-sharing relationship rather than a social relationship, as is often the case in social network analyses. Step three involved the collection of data in the form of an internet search based on known nodes of the network. Primary data in the form of official documentation, letters, and reports were sought that would confirm or infer the occurrence of data sharing. This was supplemented by academic literature that had already explored some areas of the network. The data-collection process was slow and repetitive and often involved looking for a single sentence within a document that confirmed a link of some sort. As more nodes were revealed, further searches were carried out on those nodes in an iterative process until a network became apparent. Where possible, multiple documents were used to confirm a link.

For step four, the free and open-source tool Obsidian was used to visualise the links in the network data-collection process and written in Markdown. Obsidian allowed the creation of a network by establishing links and by self-generating a graph to display these links.[6] Where possible, all the sources relied upon to create the network were inserted into the Internet Archive[7] to safeguard against any future changes.

There are limitations to this methodological approach that need to be taken into consideration when interpretating our findings. A lack of access to internal police processes, procedures, and practices means that the network presented is undoubtedly incomplete. In many instances, it was not possible to determine what data are being shared or the direction of the data flows. Further, the network may contain a duplication of applications. This is due to applications with similar names being visible in the network; for instance, there is an Arson application and an Office of Data Analytics[8] Arson application. The research relied solely on publicly available information. The links confirming a data sharing relationship between nodes are unweighted. Each link indicates data sharing of some sort, yet for some links the data sharing was specific down to identifying individual datapoints whilst for others the exact nature, content, and direction of the data sharing is not known. The research was an iterative process that was adapted as new data were found. During this process, we also came to recognise that the method itself was more reflective of a network analysis rather than a social network analysis. Thus, while our research was initially conceived as a social network analysis, the process of constructing and visualising the network meant that the network itself gradually became the main object of study, rather than the social structures that sit around it.

Analysing Qlik Sense

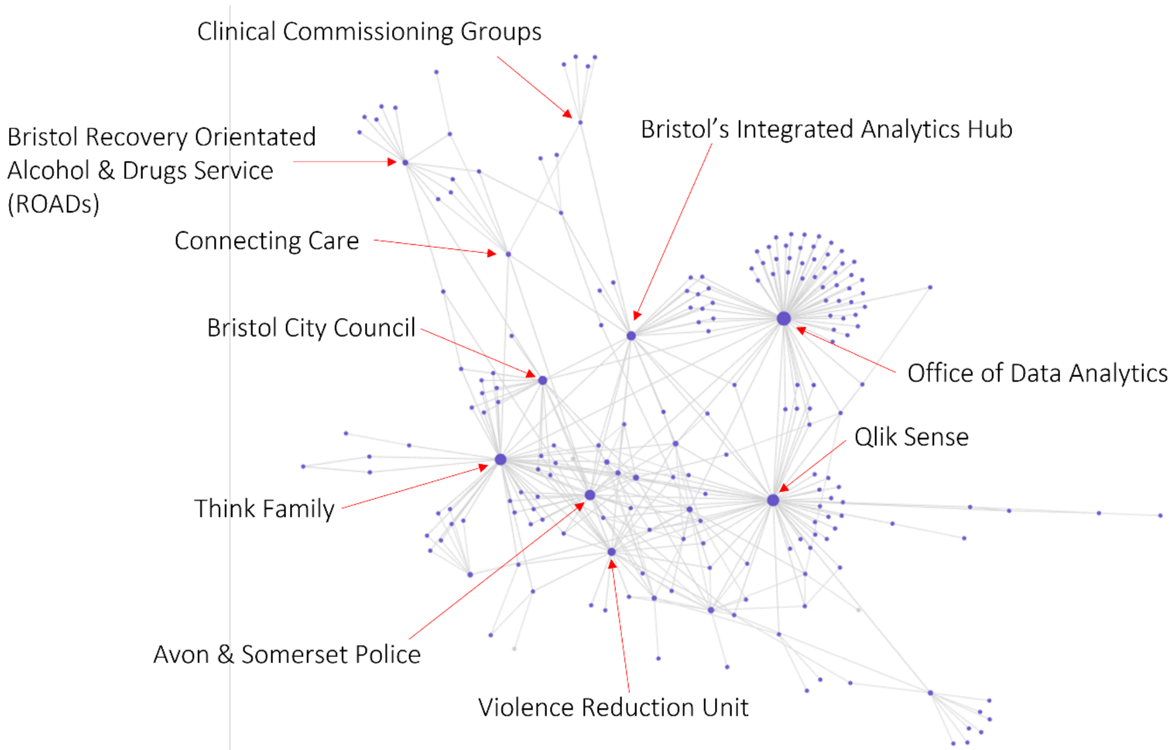
In this section, we draw out our key findings from researching the Qlik Sense network. In so doing, we first describe the network and the nodes within it as it materialised through our analysis before demonstrating how many of the data points serve as proxies for poverty, facilitated by "associate" data shared by organisations external to the police. The individual applications within Qlik Sense, each of which serve a different purpose, are used by thousands of police officers, civilian staff, and external partners across Avon and Somerset Constabulary in their daily operations (Qlik 2018). The managerial and operational aspects of Qlik Sense, seen through applications like the Supervisor App, which allows management to see everything an officer is doing, and My Work, a digital double of a police officer, provide the officer with all of their individual data, including personalised data quality statistics. This suggests that this system also fits with Benbouzid's (2019) view of predictive policing as a management tool intended to increase efficiency and productivity. Other Qlik Sense applications focus on crime, with some applications focusing on social care and community safety (e.g., road safety schemes). At least eighteen of the applications use predictive analytics and/or risk scoring with the aim of predicting suicide, violence, pleas, offenders, victims, vulnerability, road traffic accidents, child criminal exploitation, child sexual exploitation, serious youth violence, arson, missing persons, and domestic abuse.

Qlik Sense consolidates multiple and disparate data and databases, both internal and external to the police and presents the data in a variety of data dashboards and/or visualisations. Qlik Sense's data visualisations are used to assist officers and other police staff in their "real-time decision-making" with claims the Qlik Sense allows "everyone to make consistent decisions" through "data democratisation" (QlikTech International AB 2021). The macro visualisation of the network in Figure 1 contains all the applications in the Qlik Sense network, revealing their links to each other, the data they access, and the origins of some of

[6] We created an interactive version on GitHub (beta version). This is a snapshot at the time the research was conducted and may be subject to change as a result of further research being carried out: https://elle-lp.github.io/Panspectric-Network/.
[7] See https://archive.org/web/.
[8] The Office of Data Analytics is interchangeably called the Office for Data Analytics throughout the literature.

the data.[9] The data-sharing network consists of at least 195 nodes with a high number of links between them. The links are unweighted and there is no spatial dimension in relation to the distance between nodes. In some cases, the links represent specific data points being shared; others represent collaboration on a Qlik Sense application. In most cases, the direction of the data sharing is unknown, as is whether the data sharing is reciprocal. The links therefore represent a data sharing relationship of some sort but further research, going beyond publicly available information, is required to provide more specific and weighted descriptions of the links.

Figure 1*: The Qlik Sense Data Sharing Network*



The higher density of links a node has increases that node's size within the network. The most prominent nodes with the highest density of links are: The Office for Data Analytics[10] (seventy-one links), Qlik Sense (fifty-five links), Think Family (forty-eight links), Avon and Somerset Police[11] (twenty-eight links), Bristol's Integrated Analytics Hub[12] (twenty-seven links), and the Violence Reduction Unit (twenty-two links). The five largest nodes appear to function as an aggregator of information (the nature of this information is discussed below), whereby many smaller nodes feed directly into them. The larger nodes then become the point of contact for the other nodes in the network, with the larger nodes all having direct links with each other. Qlik Sense and Avon and Somerset Police are two separate nodes in the network, as it was not possible to establish the extent of their data sharing and, thus, data separation—if any. The research found the other nodes in the network either shared data with Qlik Sense or with Avon and Somerset

[9] The interactive version of the network provides greater detail than static images allow, but we include a brief overview of the network here.
[10] The Office of Data Analytics is based on the New York Mayor's Office of Data Analytics (MODA) and acts as hubs for multi-agency data sharing (Smith 2017).
[11] We use "Avon and Somerset Police" when referring to Avon and Somerset Constabulary's node in our network.
[12] Bristol's Integrated Analytics Hub is also known as Insight Bristol. Please note that some nodes, such as Think Family, Insight Bristol, and Bristol's Integrated Analytics may be merged together in future iterations of the network as in some cases they are the same organisation. They have been kept separate because they are separated within the reference material, but further research is required to assess whether they can be classed as one node.

Police, and sometimes with both. To ensure accuracy, a link was logged only if it was noted explicitly in the collected data. It should also be noted that Avon and Somerset Constabulary are the lead hosts of this branch[13] of the Office for Data Analytics so, in effect, Avon and Somerset Constabulary have three major nodes in the network.

The links that Qlik Sense has with the larger nodes show it may be able to connect to the whole network without needing direct links to every node. A proportion of the nodes connect to police databases such as STORM or Niche, making accessible data such as an individual's offending history, i.e., data that is likely to be considered police data by most people. There are also external organisations within the network that absorb data many people may not perceive to be police data, for instance education, health, and housing data. Nigel Colston, Chief Inspector of Avon and Somerset Constabulary, has confirmed Qlik[14] is used to share data with partners (Qlik 2018), including voluntary organisations (Dencik et al. 2018).

Data-sharing and External Organisations

There are data-rich nodes in the network that are external to the police. The data obtained ranges from information concerning substance abuse problems, domestic violence, housing, debt, mental health, disabilities, and welfare benefits, as well as data related to children such as education data and social services data. The two largest nodes are the Office for Data Analytics and Think Family (Insight Bristol), while there is a push for more external data sets to be fed into Qlik Sense. For instance, with respect to health data, Avon and Somerset Constabulary have expressed an interest in "integrating policing into healthcare pathways through the Connecting Care Partnership" (Smith 2017: 5). In a proposal, attached to Smith (2017: 5), a desire is expressed to make a "hub of hubs" or "to build the golden nominal." This is described as enabling the identification of social problems "upstream" so agencies can tackle them in advance (Smith 2017: 17). Connecting Care provides summaries of an individual's medical record allowing health and social care professionals to share information for a variety of reasons, including those relating to safeguarding and prevention. Examples of organisations able to view this information are Bristol's Drug Project (part of the ROADs node in the network), British Red Cross, care homes, sexual health clinics, and charities dealing with homelessness.[15] The idea is to connect to existing hubs, like Connecting Care, and to access all data from each public body through one place.

By constructing the Qlik Sense network, our analysis reveals large parts of the data-collection process are not carried out by the police but by organisations external to them. This affiliate data that exists externally to the police forms the basis for evidence collection that is used to inform police action through mechanisms such as risk scoring. As highlighted by Duarte (2021) and Egbert and Leese (2021), processes of translation occur internally within such systems. However, in the case of Qlik Sense, a wider chain of translation is also occurring between various outside organisations, all of which are grounded in different established practices and ethical considerations that are likely to shape individual approaches to data-sharing. Data are shared, often without the need for consent, through what Insight Bristol and Bristol City Council call "legal gateways." Legal gateways are provided in a list that sets out the laws that can be used as exceptions to share data without explicit consent. To exemplify this, Insight Bristol (n.d.a; n.d.b) provides a breakdown of which legal gateway(s) were used to share each individual data point in the Think Family node. It is not clear how much of this data sharing is reciprocal and which police data these external organisations are able to access, but some is viewable to them via Qlik Sense applications like the Community Safety Application. Additionally, work was ongoing (in 2019) to make data sharing more reciprocal, but further research is

[13] There are multiple branches across the UK. The branch referred to in this paper is the Office for Data Analytics (Avon and Somerset), led by Avon and Somerset Constabulary. Funding for the Office of Data Analytics project ended in 2019, and it is unclear whether those applications created with its input are still operational in Qlik Sense.
[14] In online promotional material, staff at Avon and Somerset Constabulary sometimes refer to Qlik Sense as "Qlik" during interviews. For clarity, Qlik Sense is but one of many products made by the company Qlik. A product list is available here: https://www.qlik.com/us/products.
[15] A full list of organisations able to view records is available here https://www.connectingcarebnssg.co.uk/what-this-means-for-me/who-sharesviews-my-information/. It is possible for an individual to opt-out of Connecting Care, but this does not stop information from being accessed if there is a safeguarding concern.

needed to ascertain what has happened since then (Avon and Somerset Police and Crime Commissioner 2019).

Feedback Loops and Affiliate Data

By enabling data flows from external organisations into police systems, decisions about interventions as "preventive" measures are being made based on "affiliate" data. It is unclear whether the data flows are reciprocal to allow affiliates to access police data. The Violence Reduction Unit (VRU) has a Qlik Sense application described as a "prioritisation tool" that uses SPSS, R, and Qlik Sense as well as IBM's i2 iBase to "assess those at risk and those with emerging risks" (Avon and Somerset Police and Crime Commissioner 2019: 27). It also uses police crime and intelligence data and "3 points of corroboration" to "show offending linked groups of people" (Avon and Somerset Police and Crime Commissioner 2019: 27). The VRU also calculates "risk of victimisation" scores. A breakdown of what data are used to facilitate such scores shows approximately half of the data stems from Insight Bristol and Somerset Transform, with the data points matching those used in the Think Family node (Avon and Somerset Police and Crime Commissioner 2021: 21). This data are used alongside police-collated data to create both victim and offender risk scores, with a focus on predicting vulnerability. The VRU node has links to many other nodes in the network, and whilst using standard police databases such as STORM, intelligence, past flags and warnings, and missing persons data, the VRU aims to include more data from health, education, and local authorities (Avon and Somerset Police and Crime Commissioner 2021).

Dencik et al. (2018) show how many of the risk models that focus on individualised risk scores work by comparing whether a person has a range of similar characteristics to others. This ultimately means that risk scores are based on associations and the categorisation of associations, e.g., a particular profile. Knowing how such associations are weighted would be required for further analysis, but such information was not revealed by this research. The organisation that collated the background data on which the VRU is based advise that there are a range of issues surrounding the violence related crime data. This includes the under-reporting of crime and limited data coverage, such as only 58% of crimes having data on the offender and only 32% having complete offender information such as gender, age, and ethnicity (The Behavioural Insights Team 2019). It was further noted that data on knife crime and domestic violence relies on police officers entering "flags" into the system (flags are used in the risk scoring) (Avon and Somerset Police and Crime Commissioner 2021), and there are no guarantees of their consistency (The Behavioural Insights Team 2019).

Bell's (2013) account of punishment in England suggests looking not at who is being targeted by the penal system but who is not. From this perspective, the Qlik Sense network reveals a focus on poverty and street-level crime bound together by violence. As we discuss in more detail below, many of the datapoints can be associated, sometimes spuriously, with low social economic status and poverty, with Qlik Sense applications focusing on the crimes associated with such social conditions (street violence, for example). What is missing is any reference to other crime types known to cause large amounts of social harm such as fraud, corruption, political, and other white-collar/corporate and organised crimes (Hillyard and Tombs 2017). Such crimes are much more difficult to investigate than those crimes on which the system is focused due to their relative invisibility (Whyte and Tombs 2005), which has resulted in a lack of data and research on such activities. The people who commit such crimes are rarely represented in any of the nodes making up the Qlik Sense network nor the data feeding them. Rather, the nodes in the system serve as proxies for poverty, as we explore below.

Proxies for Poverty

To demonstrate how nodes within the network function as proxies for poverty, we use the Think Family node, which makes certain populations visible within the network. Think Family is a separate system from Qlik Sense, developed by Insight Bristol (which is an integrated analytics hub) using staff from Avon and Somerset Constabulary and Bristol City Council (Dencik et al. 2018; Dencik et al. 2019; Families in Focus 2018). Think Family collates data on approximately 54,000 families in the Bristol Local Authority area (Independent Inquiry Child Sexual Abuse n.d.) and uses Qlik Sense applications such as The Early Help

Module Qlik App as a case management system (Families in Focus 2018). Think Family also draws on other Office of Data Analytics/Qlik Sense applications including risk models for child sexual abuse, criminal exploitation, and domestic abuse (Insight Bristol n.d.b).

In operational guidance, Think Family is described as a "data warehouse" (Families in Focus 2018: 15), collating a range of data relating to housing, education, social care, benefits, and police data, which it uses for predictive risk scoring (Insight Bristol n.d.b; Dencik et al. 2018). Examples of data points are teenage parent, accessed drug and alcohol support, mental health concern, child claiming free school meals, person in rent arrears, out of work benefits, linked as suspect/offender to an offence, and the vague other professional referral (Insight Bristol n.d.b). Many of these data points may not be data the police have traditionally had access to, indicating a type of function and surveillance creep in relation to the datasets being used, as noted elsewhere by Egbert (2019) and Wilson (2018). Those families who are identified as a risk and at risk have their progress tracked via this master data set and are required to show "significant or sustained progress or continuous employment" [16] as a marker of success (Bristol City Council 2015: 5).

Dencik et al. (2018, 2019) note how indicators used to assess risk within the Think Family node are more likely to apply to those affected by poverty and deprivation with many data points being proxies for poverty. The over-representation of poverty within predictive systems, in particular social care, is a recognised concern (Eubanks 2018). By creating the network, our analysis allowed the links between nodes to become visible, revealing that other nodes in the network were also drawing on the data collected by the Think Family node. Hence, Think Family may act to make certain groups more visible in the network. In this case, it is those who are likely living in poverty/relative deprivation (Young 2003).

This process of connecting affiliate data with police data risks creating a feedback loop whereby those with lower socio-economic status are disproportionately subjected to surveillance, leading to more regular predictive risk scoring, and potential interventions, whilst other groups within society become less visible to the system. The affiliate data are public sector data on a range of different social issues making visible those with certain characteristics. For instance, individuals seeking substance abuse support who sought private treatment are less likely to show in this public sector data, whilst not claiming benefits and being financially secure enough to not experience rent arrears, homelessness, or the need to rely on free school meals further decreases a person's visibility through these data-points. This matters because an individual's visibility within the Think Family node may result in them being more visible in other nodes, such as the Violence Reduction Unit, for example, which carries out predictive risk scoring in relation to vulnerability to violence.

[16] No further details are provided as to what this involves except that progress "will be assessed against a locally defined Family Outcome Plan" (Bristol City Council 2015: 5).

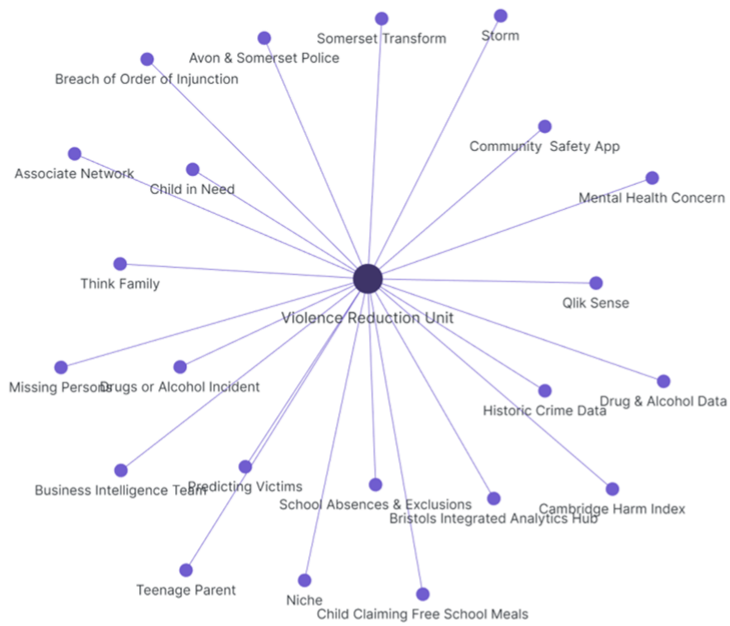


Figure 2: *The Violence Reduction Unit Note*

Conclusion

This research brought together disparate information from a range of sources into one place, making visible the data sharing required to operationalise such a system. The visualisation of Qlik Sense as a system revealed how non-police data are collated by certain nodes that act as hubs of information that then connect to Qlik Sense and/or its applications. Such a visualisation allowed us to describe and show what a data driven/predictive policing system *is* (Duarte 2021). Visualising and describing the Qlik Sense network is a first step to establishing how data from disparate organisations, some previously thought discreet from police powers and organisations, are being shared with the police and other agencies.

Sensitive data, such as mental health conditions and substance abuse, flow across digital thresholds from charities, healthcare, and non-police organisations into police applications where they are used in predictive risk scoring. This may be marking new collusions of knowledge and practice between organisations who do not traditionally perform police functions but who are supplying a form of intelligence without the police needing to investigate. Despite the legality of such data flows, questions arise as to who is responsible for data accuracy, the various points of translation along the data journey, and the ethics of large-scale data sharing—as well as, ultimately, who such systems serve.

The network further reveals interfaces between the police, data analytics, and other private companies through the flow of personnel and professionalised expertise. For instance, police staff are involved with non-police organisations to assist with the data analytics, raising questions of how police culture, values, and practices may be transferred to civilian organisations. The lack of fanfare regarding Qlik Sense shows it marks a diversion from previous forms of data analytics within a wider context of predictive policing systems and algorithmic policing practices in the UK. It is an aggregate of different digital tools brought together into one platform with bespoke applications containing tailormade data analytic tools that are visualised into dashboards to be interpreted. Qlik Sense applications filter part of the population of Avon and Somerset to identify those who may require pre-emptive social control.

The data flows into particular Qlik Sense applications are suggestive of forms of policing that target the poorest within society, with affiliate organisations playing an essential role in collecting the data. As Brayne (2017, 2021) describes, such surveillance is occurring through a range of different institutions collating data, and this provides a further example of function creep recognised in other systems by Egbert (2019) and Wilson (2018). The merging of police and affiliate data into Qlik Sense provides an example of the "collect it all" ethos of data driven systems.

This research provides insight into the rendering of individuals made visible through data rather than through a physical gaze, and this network visibility allows the maintenance of order, or *prepression* (Schinkel 2011), of those deemed a probable risk. We identify further research is required to explore the *in-situ* data practices and the use of algorithms and other technologies not only by the police but also all the organisations that supply data to them. The network visibility revealed by this research differs from the type of visibility made possible through algorithms, as the visibility is based on the use of public and charitable data. The data points used within Qlik Sense show those with lower socio-economic status are disproportionately focused upon, as the data flows from public services that many rely upon for support. The data points exclude those with the means to seek support elsewhere, making some groups invisible to the system and others highly visible. This exclusion of some populations and crimes, and the sustained focused on others, means, as our analysis demonstrates, that such systems are overly focused on the predictive or data-driven policing of poverty and, hence, we propose a new potential formulation to describe this surveillant-assemblage: Pred-Pol-Pov.

Acknowledgments

We would like to thank the anonymous reviewers for their constructive feedback. A special thanks to Professor Martin Albrecht without whom the online version of the network would not have been possible. The research of Pearson was supported by the EPSRC as part of the Centre for Doctoral Training in Cyber Security for the Everyday at Royal Holloway, University of London (EP/S021817/1).

References

Amoore, Louise. 2011. Data Derivatives: On the Emergence of a Security Risk Calculus for Our Times. *Theory, Culture & Society* 28 (6): 24–43.

Amoore, Louise, and Rita Raley. 2016. Securing with Algorithms: Knowledge, Decision, Sovereignty. *Security Dialogue* 48 (1): 24–43.

Andrejevic, Mark. 2017. To Pre-Empt a Thief. *International Journal of Communication* 11: 879–896.

Andrejevic, Mark, Lina Dencik, and Emiliano Treré. 2020. From Pre-Emption to Slowness: Assessing the Contrasting Temporalities of Data-Driven Predictive Policing. *New Media & Society* 22 (9): 1528–1544.

Aradau, Claudia, and Tobias Blanke. 2017. Politics of Prediction: Security and the Time/Space of Governmentality in the Age of Big Data. *European Journal of Social Theory* 20 (3): 373–391.

Avon and Somerset Police and Crime Commissioner. 2019. *Serious Violence Strategic Needs Assessment*. https://www.avonandsomerset-pcc.gov.uk/wpcontent/uploads/2021/09/FINAL-AS-SNA-Redacted.pdf.

———. 2021. *Avon and Somerset Violence Reduction Unit: Annual Report 2020/21*. https://www.avonandsomerset-pcc.gov.uk/wp-content/uploads/2021/02/VRU_Annual_Report_Jan_2020.pdf.

Barocas, Solon, and Andrew D. Selbst. 2016. Big Data's Disparate Impact. *SSRN Electronic Journal*, September 30. https://dx.doi.org/10.2139/ssrn.2477899.

BBC News. 2018. Kent Police Stop Using Crime Predicting Software. November 26. https://www.bbc.com/news/uk-england-kent-46345717 [accessed June 18, 2022].

Behavioural Insights Team, The. 2019. *Developing a Serious Violence Strategy for Avon and Somerset*. https://www.avonandsomerset-pcc.gov.uk/wp-content/uploads/2020/08/Developing-serious-violence-strategy-avon-somerset-min.pdf.

Bell, Emma. 2013. Punishment as Politics: The Penal System in England and Wales. In *Punishment in Europe: A Critical Anatomy of Penal Systems*, edited by Vincenzo Ruggiero and Mick Ryan, 55–85. London: Palgrave Macmillan.

Benbouzid, Bilel. 2019. To Predict and to Manage: Predictive Policing in the United States. *Big Data & Society* 6 (1): https://doi.org/10.1177/2053951719861703.

Bennett Moses, Lyria, and Janet Chan. 2014. Using Big Data for Legal and Law Enforcement Decisions: Testing the New Tools. *UNSW Law Journal* 37 (2): 643–678.

Bowker, Geoffrey C., Karen Baker, Florence Millerand, and David Ribes. 2010. Toward Information Infrastructure Studies: Ways of Knowing in Networked Environment. In *International Handbook of Internet Research*, edited by Jeremy Hunsinger, Lisbeth Kastrup, and Matthew Allen, 97–117. London: Springer.

boyd, danah, and Kate Crawford. 2012. Critical Questions for Big Data: Provocations for a Cultural, Technological, and Scholarly Phenomenon. *Information, Communication & Society* 15 (5): 662–679.

Brayne, Sarah. 2017. Big Data Surveillance: The Case of Policing. *American Sociological Review* 82 (5): 977–1008.

———. 2021. *Predict and Surveil: Data Discretion, and the Future of Policing.* Oxford, UK: Oxford University Press.

Brayne, Sarah, and Angèle Christin. 2020. Technologies of Crime Prediction: The Reception of Algorithms in Policing and Criminal Courts. *Social Problems* 68 (3): 608–624.

Bristol City Council. 2025. Information Sharing Agreement 02/15. https://www.bristol.gov.uk/files/documents/1395-bcc-police-think-family-tier-2/file [accessed March 31].

Chander, Anupam. 2017. The Racist Algorithm? *Michigan Law Review* 115: 1023–1045.

City of Chicago. 2016. Strategic Subject List - Dashboard. https://data.cityofchicago.org/Public-Safety/Strategic-Subject-List-Dashboard/wgnt-sjgb [accessed July 2, 2022].

Coleman, Clive, and Jenny Moynihan. 2010. *Understanding Crime Data: Haunted by the Dark Figure*. Croydon, UK: Open University Press.

Couchman, H. 2019. *Policing by Machine: Predictive Policing and the Threat to Our Rights*. I.IBERTY, January. https://www.libertyhumanrights.org.uk/wp-content/uploads/2020/02/LIB-11-Predictive-Policing-Report-WEB.pdf.

Crawford, Kate. 2021. *Atlas of A.I.: Power, Politics, and the Planetary Costs of Artificial Intelligence*. New Haven, CT: Yale University Press.

Day, Ronald E. 2014. *Indexing It All: The Subject in the Age of Documentation, Information, and Data*. Cambridge, MA: The MIT Press.

Deleuze, Gilles. 1992. Post Script on Societies of Control. *October* 59 (Winter): 3–7.

Dencik, Lina, Arne Hintz, Joanna Redden, and Harry Warne. 2018. *Data Scores as Governance: Investigating Uses of Citizen Scoring in Public Services*. Data Justice Lab, December. https://datajustice.files.wordpress.com/2018/12/data-scores-as-governance-project-report2.pdf.

Dencik, Lina, Joanna Redden, Arne Hintz, and Harry Warne. 2019. The "Golden View": Data-Driven Governance in the Scoring Society. *Internet Policy Review* 8 (2): https://doi.org/10.14763/2019.2.1413.

Dowey, Jonathan. 2018. How Avon and Somerset Combines Data and Experience for Better Police Work. Upshot by Influitive. https://upshotstories.com/stories/how-avon-and-somerset-combines-data-and-experience-for-better-police-work [accessed January 3, 2022].

Duarte, Daniel Edler. 2021. The Making of Crime Predictions: Sociotechnical Assemblages and the Controversies of Governing Future Crime. *Surveillance & Society* 19 (2): 199–215.

Eaton, Michelle, and Camilla Bertoncin. 2018. State of Offices of Data Analytics (ODA) in the UK. Nesta. https://media.nesta.org.uk/documents/State_of_Offices_of_Data_Analytics_ODA_in_the_UK_WEB_v5.pdf.

Egbert, Simon. 2019. Predictive Policing and the Platformization of Police Work. *Surveillance & Society* 17 (1/2): 83–88.

Egbert, Simon, and Susanne Krasmann. 2020. Predictive Policing: Not Yet, but Soon Preemptive? *Policing and Society* 30 (8): 905–919.

Egbert, Simon, and Matthias Leese. 2021. *Criminal Futures: Predictive Policing and Everyday Police Work*. London: Routledge.

Ensign, Danielle, Sorelle A Friedler, Scott Neville, Carlos Scheidegger, and Suresh Venkatasubramanian. 2018. Runaway Feedback Loops in Predictive Policing. *Proceedings of Machine Learning Research* 81(1): 1–12.

Ericson, Ricard V., and Kevin D. Haggerty. 1997. *Policing the Risk Society.* Toronoto, CA: University of Toronto Press.

Eubanks, Virginia. 2018. *Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor*. New York: St. Martin's Press.

Families in Focus. 2018. Families in Focus Operational Guidance V2. https://www.proceduresonline.com/bristol/cs/user_controlled_lcms_area/uploaded_files/Families in Focus Operational Guidance v2.pdf.

Ferguson, Andrew Guthrie. 2012. Predictive Policing and Reasonable Suspicion. *Emory Law Journal* 62 (2): 261–325.

———. 2015. Big Data and Predictive Reasonable Suspicion. *University of Pennsylvania Law Review* 163 (2): 327–410.

———. 2017a. Policing Predictive Policing. *Washington University Law Review* 94 (5): 1109–1189.

———. 2017b. *The Rise of Big Data Policing: Surveillance, Race, and the Future of Law Enforcement*. New York: New York University Press.

Haggerty, Kevin D., and Richard V. Ericson. 2000. The Surveillant Assemblage. *The British Journal of Sociology* 51 (4): 605–622.

Hälterlein, Jens. 2021. Epistemologies of Predictive Policing: Mathematical Social Science, Social Physics and Machine Learning. *Big Data & Society* 8 (1): https://doi.org/10.1177/20539517211003118.

Harcourt, Bernard E. 2007. *Against Prediction: Profiling, Policing, and Punishing in an Actuarial Age*. Chicago, IL: University of Chicago Press.

Hillyard, Paddy, and Steve Tombs. 2017. Social Harm and Zemiology. In *The Oxford Handbook of Criminology*, edited by Alison Liebling, Shadd Maruna, and Lesley McAra, 6th edition, 284–305. Oxford, UK: Oxford University Press.

Holmqvist, Caroline. 2013. Undoing War: War Ontologies and the Materiality of Drone Warfare. *Millennium: Journal of International Studies* 41 (3): 535–552.

Home Office. 2016. Social Network Analysis: "How to Guide." https://assets.publishing.service.gov.uk/media/5a819b0640f0b62305b8fdb6/socnet_howto.pdf [accessed October 20, 2022].

Independent Inquiry Child Sexual Abuse. N.d. Official Documentation ASP000279_006. https://webarchive.nationalarchives.gov.uk/ukgwa/20221215012028/https://www.iicsa.org.uk/key-documents/23441/view/ASP000279_006-007-010-012-018-019.pdf.

Insight Bristol. N.d.a. Think Family Data Process Map. https://www.bristol.gov.uk/documents/20182/34776/Think+Family+Data+Process+Map/c9a4c8f9-04a5-5655-346c-1470f83f1d1d [accessed July 8, 2022].

———. N.d.b. Legal Gateways. https://www.bristol.gov.uk/documents/20182/34776/Bristol+City+Council+Think+Family+Legal+Gateways.pdf/9dee4fa5-fb11-48c2-b08a-4fcdd4baad2a [accessed July 8, 2022].

Jansen, Fieke. 2018. Data Driven Policing in the Context of Europe. Data Justice Lab. Cardiff, UK: Cardiff University. https://datajusticeproject.net/wp-content/uploads/2019/05/Report-Data-Driven-Policing-EU.pdf.

Joh, Elizabeth E. 2015. The New Surveillance Discretion: Automated Suspicion, Big Data, and Policing. *Harvard Law & Policy Review* 10: 15–42.

Joint Committee on Human Rights. 2020. Black People, Racism and Human Rights. Eleventh Report of Session 2019–21. HC559. https://committees.parliament.uk/publications/3376/documents/32359/default/ [accessed May 20, 2022].

Lammerant, Hans, and Paul de Hert. 2016. Predictive Profiling and Its Legal Limits. In *Exploring the Boundaries of Big Data*, Volume 32, edited by Bart Sloot, Dennis Broeders, and Erik Schrijvers, 145–173. Amsterdam, NL: Amsterdam University Press.

Linder, Thomas. 2019. Surveillance Capitalism and Platform Policing: The Surveillant Assemblage-as-a-Service. *Surveillance & Society* 17 (1/2): 76–82.

Lum, Kristian, and William Isaac. 2016. To Predict and Serve? *Significance* 13 (5): 14–19.

Lyon, David. 2014. Surveillance, Snowden, and Big Data: Capacities, Consequences, Critique. *Big Data & Society* 1 (2): https://doi.org/10.1177/2053951714541861.

Magalhães, João Carlos. 2018. Do Algorithms Shape Character? Considering Algorithmic Ethical Subjectivation. *Social Media + Society* 4 (2): https://doi.org/10.1177/2056305118768301.

Maguire, Mike. 2012. Criminal Statistics and the Construction of Crime. In *The Oxford Handbook of Criminology*, edited by Mike Maguire, Rod Morgan, and Robert Reiner, 5th edition, 206–244. Oxford, UK: Oxford University Press.

Mann, Monique, and Tobias Matzner. 2019. Challenging Algorithmic Profiling: The Limits of Data Protection and Anti-Discrimination in Responding to Emergent Discrimination. *Big Data & Society* 6 (2): https://doi.org/10.1177/2053951719895805.

Mantello, Peter. 2016. The Machine That Ate Bad People: The Ontopolitics of the Precrime Assemblage. *Big Data & Society* 3 (2): 1–11.

Marsh, Andy, and Sean Price. 2020. Inphinity: Pushing the Boundaries | Sean Price & Andy Marsh. Inphinity, video. https://www.youtube.com/watch?v=FEQVSHviIEo [accessed July 3, 2022].

Mayer-Schönberger, Viktor, and Kenneth Cukier. 2013. *Big Data: A Revolution That Will Transform How We Live, Work, and Think*. Boston, MA: Houghton Mifflin Harcourt.

McCulloch, Jude, and Dean Wilson. 2016. *Pre-Crime: Pre-Emption, Precaution, and the Future*. New York: Routledge.

Mehozay, Yoav, and Eran Fisher. 2019. The Epistemology of Algorithmic Risk Assessment and the Path towards a *Non-Penology Penology*. *Punishment & Society* 21 (5): 523–541.

Meijer, Albert, and Martijn Wessels. 2019. Predictive Policing: Review of Benefits and Drawbacks. *Internation Journal of Public Administration* 42 (12): 1031–1039.

Minority Report. 2002. Steven Spielberg, dir. 20th Century Fox.

Nelken, David. 2012. White-Collar and Corporate Crime. In *The Oxford Handbook of Criminology*, edited by Mike Maguire, Rod Morgan, and Robert Reiner, 5th edition, 623–659. Oxford, UK: Oxford University Press.

O'Malley, Pat. 2015. Revisiting the Classics: "Policing the Risk Society" in the Twenty-First Century. *Policing and Society* 25 (4): 426–431.

O'Neil, Kathy. 2017. *Weapons of Math Destruction*. London: Penguin Random House UK.

Oswald, Marion, Jamie Grace, Sheena Urwin, and Geoffrey C. Barnes. 2018. Algorithmic Risk Assessment Policing Models: Lessons from the Durham HART Model and "Experimental" Proportionality. *Information & Communications Technology* 27 (2): 232–250.

Pasquale, Frank. 2015. *The Black Box Society: The Secret Algorithms That Control Money and Information*. Cambridge, MA: Harvard University Press.

Pezzani, Lorenzo, and Charles Heller. 2013. A Disobedient Gaze: Strategic Interventions in the Knowledge(s) of Maritime Borders. *Postcolonial Studies* 16 (3): 289–298.

Plantin, Jean-Christophe, Carl Lagoze, Paul N Edwards, and Christian Sandvig. 2018. Infrastructure Studies Meet Platform Studies in the Age of Google and Facebook. *New Media & Society* 20 (1): 293–310.

Qlik. 2018. Avon and Somerset Constabulary. Video. https://www.youtube.com/watch?v=PBvQUI83lfQ [accessed June 6, 2021].

QlikTech International AB. 2017. UK Police Force Visualizes Incident and Operations Data to Fight Crime Faster and Improve Public Safety. Qlik, January 11. https://www.qlik.com/us/company/press-room/press-releases/0111-police-force-visualizes-incident-operations-data-fight-crime-faster-improve-public-safety [accessed June 6, 2021].

———. 2021. Data Analytics Underpins 80% of UK Police Forces' Response to Covid-19. Qlik, May 13. https://www.qlik.com/us/company/press-room/press-releases/data-analytics-underpins-80-percent-uk-police-response-to-covid19 [accessed June 6, 2021].

———. 2023. About Qlik: Our Vision for a Data-Literate World. Qlik. https://www.qlik.com/us/company [accessed March 28].

———. N.d.a. Watch Qlik Sense Demo. Qlik. https://www.qlik.com/us/forms/success/demo/qlik-sense/thank-you [accessed June 10, 2021].
———. N.d.b. Qlik Sense | Modern Cloud Analytics. Qlik. https://www.qlik.com/us/products/qlik-sense [accessed June 10, 2021].
Richardson, Rashida, Jason M Schultz, and Kate Crawford. 2019. Dirty Data, Bad Predictions: How Civil Rights Violations Impact Police Data, Predictive Policing Systems, and Justice. *New York University Law Review* 94 (15): 15–55.
Royal United Services Institute. 2020. *Data Analytics and Algorithms in Policing in England and Wales: Towards a New Policy Framework*. https://rusieurope.eu/sites/default/files/rusi_pub_165_2020_01_algorithmic_policing_babuta_final_web_copy.pdf.
Schinkel, Willem. 2011. Prepression: The Actuarial Archive and New Technologies of Security. *Theoretical Criminology* 15 (4): 365–380.
Smith, John. 2017. Letter from Avon and Somerset Constabulary and Crime Commissioner to Devon and Somerset Fire and Rescue Service. September 29. https://fireauthority.dsfire.gov.uk/documents/s1785/Annex%20A%20to%20Report%20DSFRA1731.pdf.
Uchida, Craig D. 2009. Predictive Policing. In *Encyclopedia of Criminology and Criminal Justice*, edited by Gerben Bruinsma and David Weisburd, 3871–3880. New York: Springer.
Weber, Cynthia. 2007. Securitizing the Unconscious: The Bush Doctrine of Preemption and Minority Report. In *The Logics of Biopower and the War on Terror*, edited by Elizabeth Dauphinee and Cristina Masters, 109–127. New York: Palgrave Macmillan.
West Midlands Police. 2019. Ethics Committee Briefing Note. Project Reference DAL_2018_0001_IOM Model. https://www.westmidlands-pcc.gov.uk/wp-content/uploads/2019/05/Ethics-Committee-03042019-IOM-MODEL.pdf?x48248.
———. 2020. Ethics Committee: National Data Analytics Solution Submission to WMP Ethics Committee, March 2020. https://www.westmidlands-pcc.gov.uk/wp-content/uploads/2020/05/26032020-EC-Item-1-NDAS-Update.pdf?x41638.
Whyte, David, and Steve Tombs. 2005. From the Streets to the Suites: Researching Corporate Crime. *Crime and Justice Magazine* 62 (June): 24–26.
Wilson, Dean. 2018. Algorithmic Patrol: The Future of Predictive Policing. In *Big Data, Crime and Social Control*, edited by Aleš Završnik, 108–127. London: Routledge.
———. 2019. Platform Policing and the Real-Time Cop. *Surveillance & Society* 17 (1/2): 69–75.
———. 2020. Predictive Policing Management: A Brief History of Patrol Automation. *New Formations* 98: 139–155.
Wilson, Dean, and Leanne Weber. 2008. Surveillance, Risk and Preemption on the Australian Border. *Surveillance & Society* 5 (2): 124–141.
Young, Jock. 2003. To These Wet and Windy Shores: Recent Immigration Policy in the UK. *Punishment & Society* 5 (4): 449–462.
Završnik, Aleš. 2019. Algorithmic Justice: Algorithms and Big Data in Criminal Justice Settings. *European Journal of Criminology* 18 (5): 623–642.
Zedner, Lucia. 2007. Pre-Crime and Post-Criminology? *Theoretical Criminology* 11 (2): 261–281.
Zilka, Miri, Lawrence Cartwright, and Adrian Weller. 2021. Parliamentary Committee Written Evidence NTL0040. https://committees.parliament.uk/writtenevidence/39076/html/ [accessed February 23, 2022].
Zilka, Miri, Holli Sargeant, and Adrian Weller. 2022. Transparency. Governance and Regulation of Algorithmic Tools Deployed in the Criminal Justice System: A UK Case Study. In *Proceedings of the 2022 AAAI/ACM Conference on AI, Ethics, and Society (AIES'22), Oxford, UK, May 19–21*, 1–3. New York: Association for Computing Machinary.
Zuboff, Shoshana. 2019. *The Age of Surveillance Capitalism*. London: Profile Books Ltd.