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Daniel Marciniak

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Algorithmic policing: an exploratory study of the algorithmically mediated construction of individual risk in a UK police force

Daniel Marciniak

University of Hull, Kingston upon Hull, UK

ABSTRACT

Predictive policing has captured the imagination of both enthusiasts hoping to improve public safety and opponents raising concerns around algorithmic bias and opacity. Based on seven in-depth interviews with officers in a UK police force, this article examines the dynamics of how automated risk scores institutionalise an individual-focussed threat-harm-risk strategy aimed at preventing repeat offending. Born out of the need to prioritise work given budget cuts, the risk scores alleviate fears of missing opportunities for prevention and render professional decision-making defendable. Rather than replacing professional judgement, the article finds that officers maintain discretion in a process of co-construction by scrutinising the risk scores and weighing them against other priorities and operational constraints. In a climate of austerity, a concern arises from the scores' potential to drive short-term selective incapacitation rather than prevention through supportive measures.

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Introduction

'Habitual offender', 'chronic offender', 'usual suspects', 'frequent offenders', and the 'felonious few' – the focus on individuals deemed dangerous and risky has a long history in policing (Pratt 1996, Lawrence 2017, Werth 2019). Algorithmic tools for risk assessment promising precise and continuously updated forecasts of future offending have brought a renewed interest in focussing police strategy on those likely to offend. Based on in-depth interviews with police officers in a mid-sized English police force, this article analyses the dynamics of the tool's institutionalisation, its role in police officers' discretionary decision-making on resource allocation and prioritisation of tasks, and how resource constraints limit preventative measures.

Algorithmic risk assessments can be situated in a wider trend towards 'predictive policing' that emerged in the context of budget cuts after the 2008 financial crisis as a way to quantitatively organise police work to achieve 'more with less' (Beck and McCue 2009). It refers to the use of a wide range of techniques '[…] to identify likely targets for police intervention and prevent crime or solve past crimes by making statistical predictions' (Perry *et al.* 2013, p. 1). Part of a transformation of policing practices towards risk scores, prediction, automatic alerts, and more exhaustive and integrated databases (Brayne 2017), predictive policing builds on a large body of empirical literature highlighting the success of policing strategies targeting 'hot spots' and individuals (Braga *et al.* 2018, 2019). It automates processes that have long existed in the criminal justice system, such as actuarial tools for individual risk assessment like Correctional Offender Management Profiling for Alternative

CONTACT Daniel Marciniak D.F.Marciniak@hull.ac.uk

Sanctions (COMPAS) and statistics-driven patrol deployments like CompStat (Feeley and Simon 1994, Harcourt 2007, Willis and Mastrofski 2012, Wilson 2019).

Predictive policing can be divided into approaches that target likely locations of crime (place-based predictive policing) and, as is the focus of this article, those that predict (re)offending or victimisation (individual-based predictive policing). Focussing on the practice of place-based predictive policing, researchers engaging with police officers, analysts, and software developers have highlighted the influence of patterns of past policing and assumptions about crime on predictions, the interpretative work of analysts and officers, the organisational tensions around its adoption, and its depoliticisation of public policy issues (Maguire 2018, Tulumello 2018, Benbouzid 2019, Kaufmann *et al.* 2019, Ratcliffe *et al.* 2020, Shapiro 2019, Egbert and Leese 2020, Brayne 2021, Duarte 2021, Lally 2022, Sandhu and Fussey 2021, Waardenburg *et al.* 2022). Reflecting a research agenda interested in the social embeddedness of algorithms (Kitchin 2017), or 'algorithms as culture' (Seaver 2017), the need to examine questions relating to the production, use, and consequences of predictions also apply to the less-studied practice of individual-based predictive policing. Here, approaches vary in terms of the type of prediction and policing strategy (Ferguson 2017, p. 34ff): They employ (combinations of) actuarial approaches (using group characteristics like offending history, age, and gender) and social network analysis. Associated policing strategies include focussed deterrence through direct contact, incapacitation prioritising arrest, and public health approaches offering support through social services. Approaches also vary in the scope of individuals affected and in sophistication ranging from manual rating to machine learning. Examples of this variation are Chicago's Strategic Subject List (Saunders *et al.* 2016), Durham's HART (Oswald *et al.* 2018), London's Gangs Violence Matrix (Densley and Pyrooz 2020), Los Angeles' LASER (Brayne 2021, p. 56ff), and New Orleans' use of Palantir (Ferguson 2017, p. 40ff) – of which in the context of civil rights concerns, ineffectiveness, and difficulty of maintenance only the Gangs Violence Matrix is still in operation. The tool subject to this article is among the more sophisticated approaches: it applies machine learning to criminal records to make automated predictions about re-offending for all suspects and convicted offenders in the police database. Spurred by budget cuts, the police force seeks to reorient prioritisation from crime types to 'risky' individuals providing regularly updated, automatic risk scores to officers. The strategy aims to prevent further offending through earlier incapacitation and support.

Predictive policing has stimulated a critical debate on the use and misuse of data in policing. Critics have voiced concerns around data quality in terms of errors, underreported crimes, and discriminatory biases, as well as around feedback loops leading to over-policing (Joh 2016, Lum and Isaac 2016, Ferguson 2017, Raso *et al.* 2018, Richardson *et al.* 2019, Scannell 2019). Other concerns relate to the lack of transparency and accountability that these systems afford – especially when owned by private companies and protected by copyright law or nondisclosure agreements (Joh 2016, Ferguson 2017, Raso *et al.* 2018). Directly impacting individuals' lives, these concerns weigh heavy for individual-based predictive policing and they are widened further by concerns around false positives, guilt by association (to a statistical category or as part of a social network), prejudgement of suspects, and double jeopardy (Harcourt 2007, Schlehahn *et al.* 2015, Oswald *et al.* 2018, Egbert and Leese 2020, p. 30). Yet, as proponents will point out, human decision-making is imbued with many of the same issues while algorithms can in principle be scrutinised and adjusted (Berk *et al.* 2009). Given its potential in reducing crime-related harm, much depends on the particularities of how predictive policing is implemented (Ferguson 2017, p. 187ff). With individual threat, harm, risk scores touted as one of the main elements of the digital transformation of policing in the UK (NPCC and APCCS 2020), this article provides a preview of what is likely to come for British policing.

The article first gives a brief account of the risk modelling undertaken by the police force subject to this study. It then sets out the analytical frame through which the risk scores become visible as a managerial tool positioning the risk scores as 'obligatory passage points' (Callon 1986) in decisions on resource allocation. The article introduces an Actor-Network-perspective on discretion to facilitate the analysis of the scores' role in officers' decision-making. The main findings are organised into three parts: the first part analyses how the risk scores institutionalise threat-harm-risk assessments, the second shows how the risk scores become a part of officers' professional judgment, and the third warns that in the wider context of budget cuts for social services short-term incarceration rather than long-term prevention programs may become the main route of action.

Towards a prioritisation by risk

Years of austerity politics and the promise of doing 'more with less' have driven the adoption of predictive policing in multiple UK police forces (Babuta 2017, Couchman 2019). Police budgets decreased until 2015 and are returning only now to 2010 levels (Home Office 2021). In the face of rising demand and fewer resources, the police force in this research introduced data dashboards monitoring every aspect of police work from statistics on calls for service and criminal cases to officer workloads. This platform includes the automated risk ratings for offenders that are the focus of this article. The risk scores are influenced by a criminological discourse that seeks to combine risk of reoffending and likely harm. Recent debate associated with evidence-based policing and intelligence-led policing has shifted focus from the mere frequency of offending, as discussed since Wolfgang *et al.*'s (1972) seminal cohort study of youth offending in Philadelphia, to weighting offences according to the harm they cause as estimated using sentencing guidelines (Sherman 2007, Ratcliffe and Kikuchi 2019). A prominent example of this is the 'Cambridge Crime Harm Index' (Sherman *et al.* 2016). Mirroring Wolfgang *et al.*'s (1972) study, Liggins *et al.* (2019) use the index to attribute the majority of harm to a group of 'felonious few'. It is this group of offenders that the police force seeks to identify and intervene with earlier to reduce future demand on the service.

Conceptually, the risk scores are similar to assessments commonplace in UK police forces which use the THRIVE (Threat, Harm, Risk, Investigation, Vulnerability, Engagement) model to assess calls for service (Walley and Adams 2019, p. 2). However, the force aims for these assessments to be made not only for calls for service but for every job across the organisation. They replace a previous prioritisation of work by crime type with the simultaneous dissolution of priority crime teams focussing on specific forms of crime.

In continuous use since 2016, the scores are the product of a score for risk of reoffending and a harm score. Risk of reoffending is calculated based on a Chi-square automatic interaction detection (CHAID) decision tree trained on two years of data from a cohort of prolific offenders. The model relies solely on data about offending behaviour (time since last offense, number of offenses, average time between offenses) within the last 2 years and categorised by offense type. To get a final score, the risk of reoffending value is multiplied with a harm score: each crime type is assigned a harm value (e.g. 100 for murder, 40 for burglary), which are then added up over an offender's career. Compared to Sherman *et al.*'s (2016) Cambridge Harm Index, the weights are adjusted to prioritise violent crimes over property crimes. Both scores take only offenses into account for which a conviction has been achieved or the court decision is still outstanding. Limiting themselves to offense-related data and prioritising serious crime, the developers intended to reduce the influence of biases inherent to police records. To what degree this is successful, is outside the scope of this article.

Officers can see the total score, as well as its elements of risk of reoffending, harm score, and, additionally, a recency score reflecting the recently incurred proportion of an offender's harm score. They have access to offenders' case files through the same platform. Moreover, the platform provides an explanatory spreadsheet detailing how the risk of reoffending is calculated.

Risk scores as managerial tool to drive strategy

Given the long lineage of 'dangerousness' and the 'chronic offender' in policing (Pratt 1996, Lawrence 2017, Werth 2019), the novelty of individual-based predictive policing lies in the automation of risk assessments rather than in the assessments themselves. The risk scores can be interpreted as a form of 'social sorting' (Lyon 2003) presenting a 'rational' solution to the management problem of attending to perpetrators and victims of crime given limited resources – a 'modern' solution to an old police function of monitoring the 'usual suspects'. A similar argument is made by Benbouzid (2019) about the use of predictive policing to allocate and monitor patrols. But unlike predictive policing programs for patrol management which simultaneously record officer movements (Benbouzid 2019), or the wide-spread managerial use of performance scores and the associated 'target culture' in policing (Power 1997, de Maillard and Savage 2012, Beer 2016), the risk scores in this study do not immediately translate into a form of oversight. Rather, this article argues that the scores reify a strategic decision to prioritise police work based on 'threat-harm-risk'-assessments replacing the previous focus on crime types. The scores' ability to reorganise priorities lies in becoming what Callon (1986) calls 'obligatory points of passage'. Useful as a heuristic device for reflecting upon the ordering of socio-material processes, the term describes a relation in which an actor-network (that is, the risk scores constituted by databases, servers, developers, and algorithms) renders itself indispensable to the interests of other actor-networks (investigations, offender management, neighbourhood policing, etc) (Callon 1986). To decide which individuals to prioritise, officers need to consider the risk scores. The scores become central to resource meetings where senior officers with less direct connections to the field use them as a reference point. They also become a new professional risk to officers, who fear being held accountable for not using the risk scores in case of a subsequent incident. In this they match with what Power (2004) describes as a replacement of vulnerable professional judgement with defendable process – a tendency also observed for offender management in the UK and Canada (Robinson 2003, Hannah-Moffat *et al.* 2009).

Algorithms and discretion

The potential for bias in automated decision-making like the use of risk scores has caused concern in recent years (Gandy 2009, Pasquale 2015, Eubanks 2018, Benjamin 2019). With developers' assumptions rendered opaque and black-boxed into an 'objective' score (Kaufmann *et al.* 2019), the fear is that biased risk scores replace professional judgement much in the same way that Feeley and Simon (1994) saw penal managerialism replace clinical approaches. Police officers would follow the prioritisations indicated by the scores without understanding their functioning, replicating biased patterns of past policing (Joh 2016, Ferguson 2017). Particularly in the case of risk scores for individuals a long-held reservation is that an offender's grouping in terms of the variables entering the analysis becomes more important than the circumstances of the individual case (Harcourt 2007, Schlehahn *et al.* 2015). Proponents of predictive policing argue, on the contrary, that predictive policing may reduce human bias and increase transparency. In contrast to biased human decision-makers, the input variables could be selected purposefully and predictions could be checked for discriminatory biases (Berk *et al.* 2009, Perry *et al.* 2013, Brantingham *et al.* 2018). This tension between automation and discretion mirrors a long-standing debate in legal scholarship and policing research on the role of laws, regulations, and policies in shaping or curtailing police discretion (Davis 1969, Pepinsky 1984, Campbell 1999, Lipsky 2010), as well as the tension between policing as 'craft' and standardised, 'evidence-based' approaches to policing (Willis 2013).

Yet, technical systems seldom merely replace individual judgement but rather transform it, encourage resistance, and have unintended effects. The relationship is more complicated than the '[…] dystopian cul-de-sac […] of penal agents as executive automata or docile bodies entrapped in the 'iron cage' of an over-rationalized criminal justice system' Cheliotis (2006, p. 314) ascribes to Feeley and Simon's (1994) actuarial justice thesis: Already in the development of predictive policing software, Kaufmann (2018, 2019) and Kaufmann *et al.* (2019) argue that algorithms and police practice co-constitute each other with practice shaping desired solution and data inputs, and algorithms targeting changes in practice. Studying analysts judging the validity of place-based predictions, Egbert and Leese (2020) show that analysts tinker with settings, correct inputs, and overrule results (albeit bolstered by deciding as a team). In Waardenburg *et al.*'s (2022) research, intelligence analysts curate and largely abandon automated predictions because police managers expect explanations for why an area should be targeted. Similarly, research on patrol officers following place-based predictions finds that scepticism toward the software's capabilities and appropriateness can lead to resistance in adoption (Ratcliffe *et al.* 2020, Brayne and Christin 2020, Sandhu and Fussey 2021). More importantly, offender managers studied by Hannah-Moffat *et al.* (2009) and Robinson (2003) use their discretion over data input to obtain risk scores matching their own judgement and preventing perceived racial bias in risk assessments. In line with this research, this article describes a complex process of co-construction of risk in which officers filter the database according to their own criteria, critically engage with the scores, and defend strategic priorities not reflected in the scores.

Employing Actor-Network-Theory to describe officers' interactions with the risk scores as a process of co-construction aims to overcome the structure/agency dualism inherent to discussions of discretion. As John Law writes, 'Should a habit etched into the mind (or the body?) be treated as a calculation? Is there not, in fact, a large territory between explicit calculation on receipt of signs on the one hand, and 'automatic' response to the input of signs on the other, a territory that may pertain to both of these' (Law 1991, p. 171f). This perspective on discretion goes beyond the classically discussed human factors of police decision-making (Dymond 2020). As Fussey *et al.* (2021) argue, policing technologies can be conceptualised to possess 'affordances' (Hutchby 2001) that shape their use in a non-deterministic way. Artefacts do not determine their use through some inherent properties, nor do their uses depend solely on the users' interpretation of the object.

Methodology

The article's findings are based on seven in-depth interviews with police officers of a mid-sized English police force in a variety of functions: A Business Intelligence Manager coordinating adoption of the data platform, a Tasking Coordinator, a Chief Inspector and a Neighbourhood Sergeant covering neighbourhood policing, a Detective Chief Inspector, and two Offender Managers. These interviewees are part of a list of 'power users' introduced by the Business Intelligence Manager. 'Power users' are early adopters who gave feedback to the developers or ranked high in the automatically recorded measures of engagement with the software. They are likely to have embraced the technology more enthusiastically than their colleagues. But they also have more experience with it and can point to infrequent issues. Six interviewees were male, one female. Aged between 40 and 65, all had substantial experience in their roles. Given this profile of interviewees, the article does not seek to provide a representative description of officers' engagement with risk scores, but to contribute to the formation of an empirically informed frame for future research into risk scores in policing.

The police force was chosen because exploratory conversations with contacts in multiple UK police forces pointed to it as one of the more advanced approaches to predictive policing and an example for other police forces to learn from. Interviews were carried out in 2018 as ethnographic interviews employing a conversational style loosely guided by a list of possible questions and accompanied by demonstrations of the software. Questions addressed the role of data in decision-making, its relationship with professional experience, perceived changes brought about by the data platform, and associated opportunities and risks. Interviews lasted around an hour each and were audio-recorded. The officers seemed keen on explaining their work and interviews developed as conversations. Transcripts were exploratorily coded to elicit themes from the material. The researcher was shown an anonymised version of the software and higher-level statistical dashboards.

Interviews provide a valuable inroad to studying an algorithm like the risk scores as a sociotechnical system in which the scores become alive only through police officers' interpretations. Future research could build on this not only with a wider selection of participants but also with observations of tasking meetings and decision-making to go beyond officers' self-perceptions. Interviews with users are just one of many approaches to studying algorithms reflecting other aspects outside the scope of this article, like an evaluation of accuracy, biases, and effectiveness or the production of the algorithm and its inputs (Kitchin 2017, Seaver 2017, Christin 2020).

The research was approved by the university's ethics procedures. Interviewees were provided with an information sheet and consent form.

Findings

The findings are presented in three sections: the first section addresses the scores' adoption and how they become institutionalised in decision-making around resource allocations, the second analyses the process of co-construction of risk in which officers scrutinise the risk scores and weigh them against other priorities, and the third section problematises how austerity limits officers' options for supportive measures thus contributing to a cycle of (re-)incarceration.

Institutionalising threat-harm-risk assessments

As the mere existence of risk scores on the police force's data dashboard does not in itself ensure that the scores become part of officers' regular decision-making, this section sheds light on the factors that lead to the scores' institutionalisation. It first identifies objectivity, traceability, and external authorities as sources of legitimacy before outlining the organisational dynamics that create accountability to the risk scores.

To what extent all officers in the police force believe in validity and legitimacy of the scores is outside the scope of this study. Nonetheless, interviews with the most active (and positively inclined) users give an overview of the different arguments brought forward in favour of the scores. Reflecting the academic discourse on algorithms and big data (Chan and Bennett Moses 2016), one central factor legitimising the risk scores are appeals to 'objectivity' in contrast to flaws in human judgements. The Tasking Coordinator welcomed the risk scores replacing officers' 'knee-jerk' assessments, 'factualising the issues', and the Chief Inspector referred to them as 'putting a little bit of science into that'. Officers make this objectivity argument both referring to anecdotal evidence of correct and usually unexpected predictions, and, from the side of those creating the scores, to statistical measures of prediction accuracy and comparisons with manual ratings. Yet, interviewees knew only in general terms how the risk scores are produced – despite the availability of explanatory documents on the platform, the simplicity of the model's inputs, and its intelligibility as a decision tree. The risk scores' legitimacy relied more on trust gained from plausibility which is reinforced by the ability to trace recency and severity of offending behaviour, as reflected in the scores, to the underlying case files. The platform is explicitly designed so that it 'empowers' its users, as the Business Intelligence Manager put it, to engage with the scores and make them part of a co-constructive decision-making process as described in the next section.

Interviewees dismissed concerns around bias with reference to actions being limited to (mostly already known) top offenders with high harm scores for crimes that are usually not recorded through police-initiated contact, arrests being made reactively based on outstanding warrants, and proactive measures focussing on support. 'This is about getting upstream and […] managing offenders, rather than just targeting them' (Business Intelligence Manager). As discussed later, a lack of resources may tip the balance from support to incapacitation. Quantitative analysis outside of the scope of this article would be needed to examine the extent to which policing biases are reflected in data, predictions, and subsequent actions.

To further underline the risk score's legitimacy, interviewees name other organisations using similar scores: Examples of this are the OGRS scores developed by the Home Office to predict reoffending (Howard *et al.* 2009) and the Cambridge Harm Index (Sherman *et al.* 2016). As Brayne (2021, p. 23) notes, new technologies are often adopted for the legitimacy gained from imitating authoritative actors.

Ascribing legitimacy to the risk scores consequentially forces engagement – a decision to act or to ignore the scores. This is a double-edged sword because, on the one hand, officers welcome the scores as a way to address their fear of missing a crucial detail about a case given their high workloads, particularly for events that could denote what officers referred to as an 'escalating' risk. The following quote demonstrates this:

> What DataVis[1] is really good for is that we, as our team, we can't keep an eye on everyone arrested for burglary or robbery all the time. It's just not possible. We're not here 24/7. […] So, what DataVis is really good for is bringing up people that we might not have seen before. Might think, 'Haven't seen that thing before. That's a high score. They're escalating. They've got a previous for burglary. Let's take a closer look through it'. (Offender Manager 2)

On the other hand, the scores create a new professional risk: as much as officers perceive it as a protection against missing important cases, missing an important case despite an automated warning is now a risk to the individual officer and the organisation as a whole. Multiple interviewees were aware of this, as a Chief Inspector described,

> It's a little bit concerning for me, because I do fear the time when we go to something, the information is on DataVis saying this is a really high risk, we've got to do something. We're not aware of it. And someone turns around and says, 'It was there. Why didn't you do it?' and someone is then held to account. That's the fear for me. (Chief Inspector)

This fear resonates with Douglas' (1992) theorisation of risk as the moderns' logic of apportioning blame which then structures action towards avoiding this blame. Thus, the mere existence of the risk scores makes it difficult to ignore them.

Consequentially, the scores become what Callon (1986) would call an 'obligatory passage point' of the decision-making process. Risk assessments cannot be produced without passing through the risk scores. In tasking meetings, the risk scores form a point of reference against which decisions must be justified – especially when the decision is to ignore the scores. The following quote expresses this need of taking decisions with respect to the scores:

> Even if we assess [the score] and say, 'Okay, we can see where it's gone up, but it's all because of historical stuff and, actually, there isn't anything happening. They have that high score, fine at least we looked at it and made that decision'. (Chief Inspector)

In being consistently added to decision-making processes the risk scores reify the force's risk-threat-harm strategy. This matches with findings by Robinson (2003) and Hannah-Moffat *et al.* (2009) for probation where risk scores render decisions defendable.

The use of risk scores, notwithstanding arguments for increased efficiency and 'objectivity', is first and foremost born out of the need to prioritise work given budget cuts brought about by the austerity regime of successive governments. Legitimised by the 'objectivity' narrative, the traceability of underlying files, and the use of similar scores in other areas, the risk scores become 'obligatory points of passage' (Callon 1986) for decision-making reinforced by managerial oversight. Yet, the main reason for the risk scores' adoption may be intrinsic to the scores themselves: they provide a double-edged sword that promises a solution to increased workload, but simultaneously creates new professional and organisational risk where the scores are ignored. As discussed further below, this generates a particular dilemma where risk scores cannot be acted upon because of resource constraints. In the context of budget cuts, the ability to diagnose problems at a distance, without the necessity for detailed tacit knowledge, also spurs concerns of a centralisation of policing and what one interviewee called 'faceless policing'. Based on research in Scotland and the Netherlands, Terpstra *et al.* (2019) describe this trend as 'abstract policing'. However, as the next section demonstrates, the scores do not supplant professional decision-making but become part of it.

Co-construction of risk

Although risk scores form, as argued above, an 'obligatory passage point' in attributing resources, the platform's affordances also give leeway for interpretation and other ways of prioritising work persist. This section analyses risk assessments as a process of co-construction showing how officers (a) assert priorities by filtering the list of offenders, (b) assess the risk score by tracing underlying files, (c) weigh the scores against other priorities, and (d) negotiate the temporalities of changing scores and the duration of any measures chosen.

While all individuals in the database are ranked by risk, officers need to filter the list to include only individuals of relevance to them. For example, officers narrow their selection to offenders within their catchment area. This filtering can reflect various priorities: The Chief Inspector described filtering by release from custody to be aware of who may soon be a problem in the neighbourhood, the Business Intelligence Manager described a scenario of filtering by age for those focussing on minors, or filtering by offense. One of the Offender Managers suggested reordering the list according to the recency score reflecting an 'escalation' of offending. By way of filtering the risk scores, officers can thus align the scores not only with their area of responsibility but also with their own priorities. This process is similar to the 'little analytics' in big data described by Amoore and Piotukh (2015) where the choice of filters determines the threshold of perceptibility.

Once an officer has filtered the list according to their needs, they assess the individuals at the top of that list. Here, the names often coincide with individuals they are already familiar with, and the risk scores accordingly only give an affirmation of the officer's professional knowledge. For cases new to the officer, they then check the underlying case files. This is an important affordance of the software as together with the conceptual simplicity of the predictions (recency and severity) it allows officers to reason about what may have triggered the score. Consequently, officers may spot data errors that cause a heightened risk score. Such a case was described by a Chief Inspector:

> […] we had one person that featured on the most wanted list a few weeks ago. […] she'd been arrested as part of a murder inquiry, but that was over 20 people arrested to probe that murder inquiry. […] they were not charged, but that has raised their risk score. That's always the danger if you just use data alone, you have to apply human intelligence, and you have to question, 'Well if I'm not aware of it, what is there in the background?' At least, the system does enable us to look at that background very quickly through all the records, […] and then we've removed them from that list. (Chief Inspector)

Errors like this can happen easily. An offender manager, for instance, pointed out that the difference between being recorded as a suspect or witness was just a tick box. Whereas in the past a paper file would have collected dust in the archive, these small errors can now cause substantial changes in the scores. Consequentially, maintaining the database and correcting errors becomes a new task to all officers.

Of course, some cases are neither known to the officer nor based on erroneous data. If the officer assesses that there might be a previously overseen risk, this can trigger further action. For example, one officer reported,

> I had a domestic incident: […] It was the sort of thing where a neighbour phoned saying, 'This has happened. I'm really, really concerned'. […] Officers had gone out and said it was two brothers. […] Somehow, randomly, that incident had come up on DataVis and it had a really high risk score, and someone had the common sense to look at why. They brought it back to me and said, 'I'm a bit concerned about this job'. I looked at it and, actually, when we saw the history of the young kid that made the threat, he was a person that could go and grab a knife and stab his brother. That information was there. You could understand how officers wouldn't have picked it up at the time, but that really surprised me. […] We put in place much more rigorous safeguards as a result of that. […]. (Chief Inspector)

Even if it relates to few cases, as multiple interviewees suggested, this is where risk scores most resemble the logic of 'automated suspicion' and related legal concerns described by Joh (2016). The algorithm brings new individuals to increased police attention. To what extent this is genuinely a new capability, or it is mostly replacing the resources lost due to budget cuts cannot be answered – especially since the scores are not based on new data, like surveillance data or social media monitoring, but on police files which would have gone through officers' hands.

So far, the interactions described in this section refer to officers' shaping and tracing of the risk scores. However, not all priorities are reflected in the scores. The list of individuals who may receive police attention is not limited to those with a high score. In their prioritisations, officers bring other concerns to the table. First, there are cases that the software does not reflect. For example, risks of offenders from outside of the force's geographical boundaries would be underestimated due to missing records, or cases that escalated quickly but without historical precedent would escape the ratings. As the Detective Chief Inspector explained,

> Where you've got a bucket, which is empty because you've not offended before and you haven't got that history of risk, to go high-risk is harder to spot sometimes. […] The example there would be a lady who started receiving things through the post, and that escalated to be notices around that she was gonna be killed, animals left. There was an incident where she was then stabbed. That wasn't quite so clear on DataVis because, one, it was fast-moving, but secondly, there was no precursor […]. (Detective Chief Inspector)

Consequentially, officers would keep track of cases that stand out to them given their professional experience.

Second, some priorities are not covered by individual risk. A neighbourhood sergeant, for instance, explained that community priorities around perceived public disorder would be as important as the high-risk offenders foregrounded by the software:

> We also have people that we know are high risk in the centre. But the way it might be reported, and the way stuff's done, they're not necessarily DataVis priorities, but they are community priorities, especially the street community people here. We got lots of people who are involved in drugs, sort of low-level offending, regular low-level offending. They don't hit the marks in the same way necessarily. […] There's no substitute for the people, and you really see that when you've got good beat managers and good PCSOs that they can tell you immediately, not just say it's wrong, but why the data doesn't collect it. (Neighbourhood Sergeant)

This demonstrates that risk scores do not fully replace other modes of prioritisation. Risk scores can be mobilised or put aside according to priorities that are not all encoded in the software but part of the professional culture. Yet, as evident from the sergeant's insistence on knowing why something is not reflected in the data, the risk scores form, as argued in the previous section, a central point of reference against which decisions need to be justified.

Against the background of missing resources, the question of which of the high-risk individuals to focus on becomes less a question of assessing the veracity of the scores and more a practical question of how many offenders officers can deal with. This leads to an arbitrary list of offenders tracked according to available resources. Moreover, the choice of which offenders to deal with becomes highly dependent on professional judgement when new offenders appear at the top of the list and no resources are available. In the Chief Inspector's words:

> […] I can guarantee you next week or in two weeks' time, when my next task meeting is, there will be a couple of different names in there. So, do I stop doing these because working with them is going to be three, six months? Do I now bring in other people, but then that's adding to my list, and I've just said capacity is an issue? Or do I take one point in time and say, 'No, we're going to do these, screw anything else, we'll just focus on that.' There's no policy, there's no procedure, it's done on gut, gut instinct, it's done on a sense of knowing what people are committed with, and just trying really to manage maybe the top one or two. (Chief Inspector)

The risk scores require a dynamic assessment of who (over someone else) to attend to. This and the question of when some form of intervention could be most successful is entirely up to professional judgement. An example is judging when someone might be open to receiving support, as the Neighbourhood Sergeant described:

> […] we saw somebody trying to fill up their housing sheets in the doorway where they were sleeping. […] they were trying, which for us would be an indicator that this person might be at that point where we can [help]. (Neighbourhood Sergeant)

The Chief Inspector's statement above is also a testament to the limits of the approach – only the knowledge of offenders does not make the resources appear that are necessary to deal with them.

Altogether, much of the prioritisation of policing tasks is done in engagement with the risk scores and based on professional experience: filtering, checking case files, arguing for alternative priorities, weighing courses of action. Particularly options to filter the list of offenders and to review underlying case files are crucial affordances of the platform's design that allow for the risk scores to become an integral part of discretionary decision-making.

Austerity limiting options for action

As shown above, risk scores do not by themselves remove resource constraints on police action. This section examines the actions officers take based on the risk scores and discusses the stated goals to reduce demand and to prevent crimes considering resource limitations for police and social services under austerity budgets. At the time of the interviews in 2018, the lack of resources was a major concern for the interviewees. Since then, spending on police and social services has increased but has yet to reach levels of 2010 (Home Office 2021). This section first discusses post-incident measures, such as investigations and arrests, and then preventative measures such as support in rehabilitation and the use of restrictive orders. While the first set of measures may reduce demand in preventing further reoffending, they do not address underlying issues and mostly follow a strategy of selective incapacitation. The second set of measures raises the question of why supportive measures should be restricted to high-risk offenders and to what extent a lack of social service support leads to preferential use of restrictive orders.

Depending on their role, the actions that interviewees take based on the risk scores vary between punitive and supportive actions. Detectives and tasking unit employ the risk scores to prioritise investigations and arrests focussing on outstanding warrants for high-risk offenders and cases in which a high-risk offender is a suspect. This changes prioritisation away from crime types to a focus on individuals:

> So, it's about getting the proportionate resources. […] this person here might actually be wanted for a shoplift […], they're not there as a priority because it's a shoplifting offense; they're there because they're a really nasty individual […]. (Business Intelligence Manager)

Prioritising arrest of high-risk offenders even for minor offences aims to prevent further harm to the public from likely serial offenders. What was self-explanatory to the interviewees, raises concern in the literature: Similar to concerns legal scholars had for 'bad character' provisions in the Criminal Justice Act 2003 allowing character evidence in court (Parsons 2007), Schlehahn *et al.* (2015) caution that such an approach may lead to prejudgements of suspects and miscarriages of justice. Future research will need to explore the extent this happens in practice. Moreover, the context of lacking resources forces the moral question if all crimes (and their victims) deserve equal amounts of investigative resources or if one crime should receive more attention than another of the same type because it is perpetrated by someone who is likely to commit a series of crimes (see also Harcourt 2007, Sherman 2007).

Resources and the lack thereof also play a factor in the second form of prioritisation which is more preventative: prioritisation for support and control, or what one interviewee called 'take the carrot or we will beat you with the stick'-approach. Offender managers and neighbourhood policing officers prioritise individuals either for supportive or restrictive measures. These measures are part of a legal framework for actuarial risk management procedures for offenders that began to take shape in the 1990s and early 2000s comprising of restrictions, conditions, sanctions, and enforcements organised through agency cooperation between police and social services (Kemshall 2010, Wiliams and Nash 2014). Supportive measures include contacting social services to provide support on, among others, drug and alcohol abuse, accommodation, mental health, and education and employment. For example, Multi-Agency Public Protection Arrangements deal with registered sex offenders, violent offenders sentenced to 12 months or more, and those that 'pose a serious risk of harm'. Instated by sections 325–327 of the Criminal Justice Act 2003 these arrangements exist across England and Wales and are led by police, probation, and prison services with other authorities like Children's Services and Adult Social Care, Health Services, Youth Offending Teams, local housing authorities and jobcentres under duty to co-operate. Beyond formal arrangements, officers may have relations with private rental teams or community groups through which they seek support for an offender. In terms of restrictive measures, the most relevant measure relies on Criminal Behaviour Orders (CBOs) instated in the Anti-Social Behaviour, Crime and Policing Act 2014 first introduced with the Crime and Disorder Act 1998 (Brown 2020). The Crown Prosecution Service's guide to relevant case law paints a picture of the wide range of possible restrictions such as prohibiting begging in a specified area, wearing clothing with an attached hood, being drunk in a public place, associating with or contacting specified individuals, or possessing drug paraphernalia (Levy and Hall 2019). Violations are punishable by a fine and/or imprisonment (up to six months on summary conviction and up to five years on indictment).

A neighbourhood sergeant described this use of court orders to control individuals:

> […] one of our guys who's wreaking havoc in the centre […]. The work went in to getting some form of control over his behaviour and it was only a couple of weeks ago, [we] managed to get a CBO on him. […] So that excludes him from the main areas [where he has been] offending. Putting conditions on, really controlling his movements and what he can do, because he was that problematic, he needed that element of control. […] it's generally orders, injunctions, CBOs, we got community protection notices and warnings that they dish out here like confetti at times, but anything that will just give us a little extra control over their behaviour. […] I think [the responsible officer's] vision is to see him locked up. (Neighbourhood Sergeant)

Particularly in a context of resource-deprived social services due to the same austerity conditions that motivate the use of risk scores, the use of ASBOs/CBOs as a fast route to re-incarceration confirms some of the fears from when ASBOs were first introduced by Blair's government; namely, ASBOs circumventing prosecution under criminal law through the use of civil law and eroding principles of due process, proportionality, and protections of young people (Squires 2006, Burney 2008, Crawford 2009). Moreover, just as the prioritisation of investigations raises a question of fairness towards victims, the prioritisation of offenders for support in finding adequate help by social services raises the question of why other offenders should not receive equivalent support – this is central to the shift from rehabilitation as welfare to rehabilitation as risk management described by Garland (2001, p. 176) and exacerbated by budget cuts. Beyond this moral question, it is also unclear to what extent focusing support measures on those deemed risky according to the algorithm is effective compared to focussing the same resources on other groups of offenders (Harcourt 2007). Furthermore, as long as social services are not adequately funded and remain privatised, many of the underlying factors of offending remain and reincarceration becomes the main outcome (see also Mann *et al.* 2020).

Conclusion

Based on in-depth interviews with early adopters, this article offers a complex picture of the role of risk scores in individual-based predictive policing. Adopted to make officers' workload more manageable by (a) preventing future offending of high-risk offenders and (b) providing a safeguard against missing cases that require further police attention, the scores institutionalise a 'threat-harm-risk' strategy focussed on individuals rather than crime types. An 'objectivity' narrative supported by the traceability of underlying files, and the use of similar scores by other authorities, ensure the scores' perceived legitimacy. Risk scores render decisions defendable turning them into an 'obligatory passage point' for resource decisions.

Unlike probation officers adjusting inputs to bring risk assessments in line with their professional judgement (Robinson 2003, Hannah-Moffat *et al.* 2009), there is little officers can do to manipulate the risk scores apart from correcting underlying errors. However, officers' decision-making is not determined by the algorithm. Instead, an Actor-Network perspective on discretion reveals the entanglement of officer and technology in co-constructing risk. This platform's design allows officers to filter risk rankings and scrutinise underlying case files. Officers assert their own priorities by weighing scores against priorities not reflected in the scores and they choose individuals from the ranking given available resources and prospect for successful intervention. Thus, even if the scores cause concern for a more centralised, 'faceless' policing that relies more on paper trails than tacit knowledge – reflecting Terpstra *et al*.'s (2019) diagnosis of a turn towards an 'abstract police', officers need their professional knowledge to make sense of the scores and integrate them with other priorities. Rather than risk being the central feature of policing as described by Ericson and Haggerty (1997), this article shows that risk is only one of several concurrent factors like the availability of resources or concerns for the public perception of policing that order police priorities.

Principled concerns around who decides the weighting of harms, the inclusion of spent sentences, and limited access to the algorithm need further public debate. However, the main concern highlighted in this article stems from the socio-political context in which the risk scores institutionalise a strategy of policing the 'usual suspects': the scores purport to be a way out of the pressures from increasing demand and decreasing budgets; to enable police to do 'more with less'. Indeed, officers report that the software prevents them from missing cases due to their workloads. Yet, austerity politics affecting all the social services surrounding policing limit options for supportive measures, leaving punitive measures like criminal behaviour orders and arrests. Thus, the warning here is that better prioritisation may not automatically lead to better outcomes. With a continued lack of funding, the police may become very efficient in arresting the highest-scoring offenders, but the cycles of incarceration continue, and little is done in preventing future harm. On the contrary, the individualistic focus on risk scores hides the wider issues that contribute to criminality. It remains to hope that budgets for policing and social services continue their return to previous budgets and that the introduction of automated risk scores does not cement the shift from a welfarist paradigm of rehabilitation addressing all offenders to a risk paradigm addressing only those deemed most dangerous noted already by Garland (2001).

Manning's (2008) study on the adoption of CompStat is a warning that policing can be resistant to change through technologies. Moreover, the interviewees' characteristics as enthusiastic, early adopters should lend some caution to generalising this study's findings. The findings highlight how the technology's affordances are essential to the co-constructive production of risk. Other software packages will work differently, other prediction algorithms will be less intelligible. Similarly, other socio-political contexts will come with different problematizations. This leaves large scope for studying individual-based predictive policing as situated practice both qualitatively examining 'algorithms as culture' (Seaver 2017) and quantitatively assessing policing outcomes, shifts in decision-making, and biases. Reference to threat-harm-risk scores in the National Policing Digital Strategy (NPCC and APCCS 2020) suggests that automated risk assessments may well be the future of resource allocation in British policing – a direction that requires substantial debate.

Note

1. Pseudonym.

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ORCID

Daniel Marciniak http://orcid.org/0000-0002-1843-120X

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