8. The Organization in the Loop: Exploring Organizations as Complex Elements of Algorithmic Assemblages

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Abstract
Organizations are a highly relevant contexts for understanding the interactions of algorithmic assemblages and the unfolding of algorithmic regimes. We argue that organizations must be understood as social systems that enable and restrict how algorithmic regimes unfold. We make this conceptual argument by analysing the algorithmic assemblage in the case of predictive policing in Germany and subsequently compare our insights with the case of hospitals which serve as our secondary case. Our analysis focuses on three crucial organizational dimensions: goals, differentiation, and goal conflicts. We argue that taking these dimensions into account sensitizes researchers not only to how organizations empower algorithmic regimes, but also to the frictions and breaks they cause.

Keywords: goal conflicts; differentiation; predictive policing; hospitals

Introduction

Algorithmic regimes unfold their social relevance not only in private settings like online shopping, fitness tracking, streaming, or dating, but also in organized settings, meaning in organizations. They operate in and between organizations by supporting how tasks are carried out, by optimizing organizational processes, or by enabling new forms of interorganizational collaboration. Hence, organizations become important contexts that shape how algorithmic regimes unfold—in the focal organizational settings themselves and by the same token in society at large (see Jarke et al. and Egbert, in this volume).

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Despite their pivotal role for and in algorithmic regimes, though, organizations are not currently receiving much scholarly attention. The observation that it is not only humans and algorithms “in the loop” (Danaher, 2016), but also organizations, constitutes our point of departure and informs our main research question: What is the role of organizations as elements and contexts of the embeddedness of algorithmic systems? To elucidate this question, we explore two different empirical settings which both present prominent yet sufficiently different cases of organizations embedding algorithmic systems. Our primary case is predictive policing in Germany. Predictive policing algorithms are designed to support the police in their task of preventing crime by directing organizational attention to geographical areas of heightened risk of burglaries. Our secondary case, which we primarily use as a contrast, involves algorithmic systems in hospitals that support different organizational tasks such as accounting and diagnosis.

Drawing on empirical data from the literature and our current research, we use these two cases to make the conceptual argument that organizations are active contexts deeply affecting how algorithmic systems unfold by both enabling and restricting this unfolding. To build this argument, we first demonstrate that current research does not pay sufficient attention to organizations when discussing algorithmic systems. Next, we depict organizations as social systems that decide upon their formal processes and structures (Luhmann, 2018). In particular, we highlight organizational dimensions that are important for understanding the interplay of algorithmic systems and organizations: organizational goals, organizational structure, and goal conflicts. The focus on organizational goals allows us to identify the tasks algorithmic systems are supposed to support, while focusing on organizational structure raises a question of which organizational unit is using them. Considering goal conflicts reveals how algorithmic systems compete for organizational resources that are also relevant for fulfilling other tasks. We analyse our primary case by means of these analytical dimensions before turning to our secondary case. In both cases, we demonstrate the organizational impact on algorithmic regimes. In the conclusion we reflect on our analysis in this chapter before pointing to directions for future research.

The Problem of Omnipresent but Conceptually Opaque Organizations

In critical algorithm studies, the meso-level of organizations is not a central point of interest. Rather, prominent scholars argue that we may be witnessing a shift towards the decentring of organizations as "digital data objects … become central reference points of organizational knowledge making and action" (Alaimo & Kallinikos, 2021, p. 3). However, this tendency does not lead to the dissolution of organizations as complex structures (ibid., p. 15; Kallinikos & Hasselbladh, 2009). Scholars studying algorithms often share a lively interest not in organizations, but in the politics put forward and enforced by algorithmic systems, as in the influential work of Virginia Eubanks, who has analysed the connection between digital tools and their consequences for dealing with and overcoming poverty. Her call for "dismantling the digital poorhouse" (Eubanks, 2018, p. 204) remains paradigmatic for the strong focus on the policy level when studying algorithms (Allhutter et al., 2020; Amoore, 2013; Bucher, 2018; Crawford, 2021; Gillespie, 2010; Hansen & Flyverbom, 2015). When organizations are more explicitly addressed, the focus often falls on certain types of organizations, especially on platforms (Egbert, 2019; Gillespie, 2018; Plantin & Punathambekar, 2019). Platform organizations, though, represent a technology-focused type not easily comparable to more traditional but societally crucial organizations such as bureaucracies or businesses.

Current research demonstrates that organizations are producers as well as users of algorithmic systems. Organizations assume these roles when firms like Amazon use algorithms to optimize the storage of products in their warehouses (Danaher, 2016), when states automate the calculation and payment of benefits (Eubanks, 2018), when architectural offices use computational design to model their buildings (Boeva & Kropp, in this volume), or when courts use algorithmic systems like COMPAS to assess the likelihood of recidivism risk among defendants (Christin, 2017).

Despite this omnipresence of organizations as users and producers, at a conceptual level they remain opaque in their functioning, as they are often reduced to mere sites or "settings" (Schubert & Röhl, 2017, p. 2) for algorithmic systems in use, mainly when algorithms are analysed ethnographically (Christin, 2020; Kitchin, 2017, p. 24f.). In this way, it is less the organized nature of courts, planning and construction companies, Amazon's storage centres, or the bureaucratic organization of welfare states that is of interest when the embedding of algorithmic systems and the interactions in the algorithmic assemblage are being analysed. Instead, these empirical studies focus primarily on specific social fields or working areas (e.g., journalism, justice, police, commerce, architecture) and the types of algorithmic technologies in use (e.g., audience analytics, predictive analytics, decision support and recommender systems, computational design). In sum, organizations are "backgrounded" (cf. Zerubavel, 2015, p. 86) by such an approach as they only appear as layers, sites, or settings of the algorithmic assemblage.

We take issue with reducing organizations to mere background settings or simple contexts for three reasons. The first reason to foreground instead of background organizations is that algorithms operate as elements of algorithmic systems in complex socio-technical arrangements or, as Kitchin (2017, p. 18) puts it, in socio-technical assemblages. For understanding algorithms, it is thus crucial to understand them as

> relational, contingent, contextual in nature, framed within the wider context of their socio-technical assemblage. From this perspective, "algorithm" is one element in a broader apparatus which means it can never be understood as a technical, objective, impartial form of knowledge or mode of operation. (ibid.)

Such a *relational understanding* necessitates exploring the interactions between the elements of the apparatus and therefore depends on separating them analytically (Jarke & Zakharova, forthcoming). Omitting such an analytical separation may lead to problematic cause and effect attributions to the whole assemblage. From an organizational perspective, there is a need to study organizations as specific and complex elements of the algorithmic assemblage.

The second reason for foregrounding organizations is that algorithmic regimes are, in a Foucauldian sense, powerful socio-technical assemblages of knowledge production and circulation that share particular characteristics (see Jarke et al., in this volume). Taking the notion of assemblages and algorithmic regimes into account then means that a careful analysis of assemblages must pay attention not only to the *enabling* forces of algorithmic regimes but also to the *breaks, restrictions, and barriers* of these regimes. Such a *bidirectional sensitivity* demands an analytical frame conducive to avoiding the risk of overestimating the transformative powers of algorithmic assemblages and regimes. As many algorithmic regimes are embedded within and between organizations, this state of research also requires considering the role of organizations as active contexts (Büchner, 2018; Büchner & Dosdall, 2021).

Third, foregrounding organizations offers an analytical point of reference for comparing the complex social embeddings of algorithmic technologies called for by Christin (2020, p. 907), among others. We therefore agree that practical strategies like that of "a similarity-and-difference approach to identify the specific features of algorithmic systems" (ibid.) are fruitful and necessary, for example, in an analysis of how the police and legal professionals use predictive algorithms (Brayne & Christin, 2021). We add to this, though, that such an approach additionally requires attention to organizations, as such a meso-level focus supports cross-case comparisons, thereby opening up a mid-level for studies between micro practices and policies.

Organizations as Complex Elements of Algorithmic Assemblages and Algorithmic Regimes

Early in the debate on the power of algorithms (see also Milan, Lopez, and Egbert, in this volume) and following Latour (2005), Neyland and Möllers (2016, p. 3) proposed to "understand the algorithm-in-action as situated." They further argue that algorithms possess an "associational life" and derive their social power "through algorithmic associations" (ibid., p. 1). To investigate these "algorithmic associations," metaphors play an important role for scholarly thinking about the embeddedness and the relational character of algorithms. In this line of thought, Neyland (2015) suggests associative metaphors such as "algorithmic account" to understand the algorithm in relation to the organizational work putting it to use. Christin (2020, p. 906), on the other hand, proposes the metaphor of "algorithmic refraction" for "paying close attention to the changes that take place whenever algorithmic systems unfold in existing social contexts—when they are built, when they diffuse, and when they are used."

We agree that metaphors play an important role to "bypass algorithmic opacity and tackle the complex chains of human and non-human interventions that together make up algorithmic systems" (ibid., p. 907). At the same time, concepts from organizational sociology also hold great promise and offer more clarity for analysing the complex relations of algorithmic assemblages. In particular, this is the case as they allow us to see that organizations are *active contexts* shaping digital transformation (Büchner, 2018; Büchner & Dosdall, 2021). This theoretical approach directs our attention to the variegated and heterogeneous ways in which organizations inscribe themselves into algorithmic assemblages.

Organizations, Decisions, and Agency

Organizational sociology has undergone a change of focus, with work now being the dominant point of scholarly interest (Barley & Kunda, 2001; Orlikowski & Scott, 2016). This has led to a situation in which scholars no longer treat organizations as a "distinct layer of social life" (Besio et al., 2020, p. 413). Recently, though, scholars such as Du Gay (2020; Du Gay & Vikkelsø, 2017), Besio and colleagues (2020, p. 413), or Schwarting and Ulbricht (2022) have demanded more analytical attention to the characteristic social form of organizations. Their call is echoed by researchers who point out that AI and digitalization are constrained by socioeconomic and organizational factors that shape their implementation (Fleming, 2019, p. 9).

We follow organization-sensitive works by understanding organizations as social systems that differentiate themselves from their environment by taking decisions (Luhmann, 2018; March & Simon, 1958). Among other things (cf. Luhmann, 2018), organizations decide about their goals, their members, and their structure. Understanding organizations as decision-making systems emphasizes that organizations are not just passive objects but have an agent-like quality; they are active entities, after all (Brunsson & Brunsson, 2017; King et al., 2010). However, emphasizing the ability to make decisions implies neither that organizations are deterministic nor that they are fully autonomous. Formal structures come with informality (Barnard, 1938), that organizational rules inform only a part of the decisions required to be made in organizations (Reynaud, 2005) and that attempts at implementing formal control structures often lead to nothing other than unforeseen processes of change (Chown, 2021). With regard to autonomy, organizations follow societal institutions (Meyer & Rowan, 1977) and their logics (Ocasio, Thornton, & Lounsbury, 2017) as they are important sources of legitimacy—a fact increasingly recognized by research on algorithms (cf. Caplan & boyd, 2018). The high variety of organizational forms is testament to the agentic quality of organizations.

Overall, we argue that organizations are active and complex, not passive and one-dimensional contexts—an insight that directly impacts the analysis of algorithmic regimes. For the analysis of algorithmic regimes, this means that organizations and their ability to take decisions influences how algorithmic regimes unfold—just as algorithmic regimes, in an iterative process, influence organizations. However, due to the lack of research on the former, we focus on the question of how organizations bear upon algorithmic regimes. We now turn to our analytical dimensions.

Structure, Goal, and Goal Conflicts as Analytical Dimensions

To elucidate the role of organizations in the algorithmic assemblage, we focus on three dimensions of organizations which we subsequently discuss in their relation to algorithmic regimes. In this section we present our three analytical dimensions leading our conceptual argumentation. First, we focus on the structure of organizations before, second, we turn to the role of organizational goals. Third, we discuss goal conflicts in organizations. While organizations are social orders with more than these elements (Ahrne & Brunsson, 2011), structure, goals, and goal conflicts are near-universal characteristics of organizations and thus should be generally applicable for future analysis.

Our first point of analytical interest focuses on organizational goals as all organizations pursue certain goals. To operationalize their goals, organizations usually define subgoals for which they assign responsibility to specialized units (Cyert & March, 1963; March & Simon, 1958). This already indicates that goals also bear upon organizational structure. What is of relevance here, though, is that defining these subgoals is necessary because abstract goals like providing security in the case of police organizations or providing public health in the case of hospitals need to be put into practice. Consequently, organizations do not just pursue one but *multiple* (*sub*)*goals*. The multiplicity of goals is amplified by a high degree of institutional complexity (Greenwood et al., 2011), which requires organizations to conform to an increasing number of external and, at times, contradictory demands (Bromley & Powell, 2012; Brunsson, 1985; Meyer & Rowan, 1977). Taking organizational goals into account thus sensitizes us to ascertain for which goals organizations implement algorithmic systems—and for which goals they do not do so.

Our second point of analytical interest is the differentiated order of organizations (Luhmann, 2018; March & Simon, 1958). While the extent of differentiation depends on the characteristics of the focal organization, almost all organizations differentiate in line with their internal division of labour. Organizational differentiation allows for processes of specialization, which, in turn, make it possible to designate responsibilities and subsequently delegate tasks and responsibilities to specific units. Taking differentiated organizational structures into account, thus, sensitizes us to ascertain which organizational unit is algorithmically supported—and which is not.

Our third and last point of analytical interest are goal conflicts. Due to the existence of complex environments and multiple goals, goal conflicts often are unavoidable. This is the case if pursuing different goals requires drawing on the same pool of resources. Thus, organizations with more resources are less afflicted by goal conflicts than organizations with fewer resources (Nohria & Gulati, 1996). However, what exactly counts more or less depends, among other things, crucially on the number of duties an organization is tasked with and its ability to defer these tasks to future handling. This indicates that the type of organization also matters. For example, organizations like the police or hospitals must often respond immediately to emergencies, requiring the triage of existing resources to address some goals, all the while postponing other goals to a time when the required resources are free again (Faraj & Xiao, 2006; Geiger et al., 2021). However, multiple or even contradictory goals do not necessarily need to become problems, as organizations must *not actively pursue all their goals simultaneously* (Greve & Teh, 2018). Furthermore, they have different means of easing the tensions resulting from contradictory goals, i.e., by prioritizing specific goals for some time at the expense of others (Ramus et al., 2021), by relying on a loosely coupled structure (Weick, 1976) or by resorting to symbolic actions (Brunsson, 1989). Another popular means to solve conflicts are projects (Button & Sharrock, 1996; Midler, 1995) as they often come with their own resources and therefore tend to ease resource tensions; this is an effect that even holds in the case of digitization projects, which often underestimate the resources necessary for successful digital innovations (Büchner et al., forthcoming).

Introducing the Leading and Contrasting Cases

We develop our conceptual argument by two reference cases. For the purposes of our analysis, we refer to both cases intentionally in an uneven manner. We focus on the case of predictive policing as our primary case and turn only occasionally to the secondary and mainly contrasting case of hospitals. The following introduction to our cases mirrors this analytical focus by describing predictive policing in more detail than the case of hospitals.

Predictive policing has gained prominence over the last decade as it uses algorithms to detect increased risks of criminal actions (Brayne, 2017; Egbert & Leese, 2021; Wilson, 2019). For the police, detecting these risks is attractive as it enables patrolling areas at risk of higher criminal activity. This, in turn, holds the promise of preventing criminal activity before it even happens. In Germany, the police use predictive policing technology primarily to detect areas with a higher-than-usual risk of burglaries (Egbert, 2020). Unlike the police in the United States, for example, predictive policing technologies are hence not used to surveil and detect individuals (Brayne, 2017); they are confined to flagging areas subject to an increased risk of burglaries. Another difference between the United States and Germany is that in the past, private companies like Palantir played only a minor role in providing the algorithmic infrastructure for predictive policing. Instead of buying surveillance software, most *Länderpolizeien* (state police forces) have opted to develop their own, even though there are some notable exceptions like the police of Hesse which early on cooperated with Palantir.

Predictive policing relies on the premise of "near-repeat" (Bernasco, 2008). Near-repeat is a behavioural heuristic assuming that some criminal activities entail an increased future risk of the same criminal activity occurring again. In the case of theft, this is due to successful burglaries flagging certain quarters for other burglars as a rewarding area or because perpetrators gain a boost from previous burglaries as they can parlay their gained knowledge to burgle similar targets (ibid.). In any case, *only professional* and not one-time perpetrators are expected to repeat their criminal activities. What follows from this for predictive policing technologies is that the *ascribed professionalism* of a criminal act is a major factor in determining the risks of future burglaries for certain areas (Kaufmann et al., 2019). Once the data on burglaries detected and identified as professional are fed into the database, the risk for future near-repeat burglaries is algorithmically determined. The police can then allocate their patrol forces to prevent future burglaries. Summing up, the algorithmic system of predictive policing is embedded into the police as an organization to predict the likelihood that a specific type of crime will occur. Its output of flagged high-risk areas enables actions to be taken to prevent the forecasted repetition of this crime from happening.

To analyse the case of predictive policing, we primarily use published studies on the subject but view and reinterpret them through our organizational lens (Büchner & Dosdall, forthcoming; Egbert, 2020; Egbert & Leese, 2021; Sandhu & Fussey, 2021). For our contrast case, we use selected empirical illustrations from an ongoing ethnographic study ("Digital Cases," funded by VolkswagenStiftung, 2020–2023) that analyses the role of digital infrastructures in treating patients in a German university hospital. As in many other hospitals, this hospital has a long tradition of being quantified and highly datafied (Reilley & Scheytt, 2019) and of using algorithms for different purposes, ranging from accounting to monitoring and supporting diagnosis (cf. Maiers, 2017; Bossen & Markussen, 2010). We conducted fieldwork by accompanying and interviewing physicians and nurses in day and night shifts for 12 months while also talking to specialized staff with key positions in off-patient work, such as in-house staff from medical informatics

Zooming into Organizational Embeddings

In this section, we draw on the notion of "zooming in" (Nicolini, 2009) to analyse the organizational situatedness of the assemblages of algorithmic systems. Our analytical premise is that organizations empower algorithmic systems and regimes by formally deciding upon their use and the intended area of application. Thereby, organizations endow these algorithmic regimes with agency as they are now part of organizational decision-making processes. This process, though, also creates frictions and tensions for how algorithmic regimes unfold.

In the following, we identify these frictions and tensions along the outlined dimensions of organizational structure, goals, and goal conflicts. First, we show how organizational differentiation engenders a compartmentalization of predictive policing, thereby restricting a full unfolding of the transformative powers of the algorithmic regime, and then we compare this to the case of hospitals. Second, we relate predictive policing to the different goals police organizations pursue before turning to hospitals. Third, we demonstrate how algorithmic systems are affected by goal conflicts and how emerging new goals can influence the unfolding of algorithmic regimes. Here, too, we subsequently refer to selected illustrations from the ethnography of a hospital. Before we begin our analysis, we note that in both our cases, algorithmic regimes are not limited to temporally bounded projects as found in the building sector, where they influence design, planning, and monitoring of construction work (Boeva & Kropp, in this volume). Instead, they are part of the continuous organizational activity.

The Role of Multiple Organizational Goals for the Algorithmic Assemblage

Our point of departure is that organizations have multiple goals, as we have argued in the theoretical part of this chapter. *Two main goals* characterize police organizations. First, the police are responsible for *fighting crime*. Formally, this involves enforcing the law by apprehending offenders as well as ensuring public safety by dealing with imminent dangers threatening the public. The latter includes but is not tantamount to fighting crime as it includes broader yet concrete dangers. A second goal lies in the *prevention of crime* and thus in inhibiting criminal activity from occurring in the first place. Regarding this organizational goal, the police assume a sentinel role different from its apprehension role (Nagin, 2013), which is characteristic of police work related to apprehending offenders.

If we relate these organizational goals to each other in terms of organizational significance, it is well documented that, while important and effective (Weisburd et al., 2017), *prevention work plays a minor role* in most police organizations when compared to crime fighting. One of the reasons is that prevention "lacks glamour; apprehensions offer the excitement of the chase" (Sherman & Weisburd, 1995, p. 646). The case of the police, hence, underscores that organizations do not necessarily assign equal significance to all their organizational goals all the time (Audia & Greve, 2021), as some goals align for some groups more convincingly than others with what is perceived to be the organizations' main goal.

The cited lack of glamour characteristic of prevention work is exacerbated by the ambiguous nature of prevention. By definition, prevention is only successful in the case of a non-event. What remains unknown in the case of a non-event, though, is whether anything would have occurred anyway, or whether actions actually prevented criminal activity. As a result, it is hardly possible to measure the success or failure of prevention. The low visibility and, by the same token, inability to measure the organizational goal of prevention, underscores its more minor role for the organization.

Relating predictive policing to the goals of police organizations thus reveals that predictive policing as used in Germany is related to an organizational goal that in most police organizations is subordinate to the deeply ingrained primary goal of crime fighting. This is undoubtedly one of the reasons why numerous studies show that algorithmic regimes in the field of predictive policing, at least for now, fall short of their predicted transformative potential (Egbert & Leese, 2021; Sandhu & Fussey, 2021). However, our main point is a conceptual one: organizations implement algorithmic systems to support some goals but not necessarily others. This bears upon how the algorithmic assemblage is constituted and how algorithmic regimes unfold in organizations—in the case of predictive policing in Germany, in a somewhat limited way.

In contrast to the police, hospitals use various algorithmic systems for more central and prominent organizational goals, primarily for the diagnosis and treatment of patients and the billing process. Early warning systems and algorithm-based diagnosis suggestions are institutionalized elements of hospital work in many fields. They are used to identify patterns indicating abnormalities in visual representations such as X-ray scans and MRT images or to count, identify, and categorize medical materials, such as analyses of blood samples. In our case, medical staff, therefore, avoided the buzzword "algorithms" when describing concrete algorithmic assemblages used in various devices measuring medical data as a physician in the researched hospital states:

> What we do is, you look at the summary from the machine and these machines that have already been the normal practice when I was trained as a doctor: The machines suggest an indication. That's what they do at the end of the day; they suggest an indication.

In a second regard, we mentioned that hospitals use algorithmic systems for the billing process. In Germany, public hospitals can only charge predefined treatments and services laid down in the diagnosis-related groups (DRGs). The classifications include primary and secondary diagnoses, procedure codes and demographic factors. Many hospitals provide coding staff with algorithmic support systems integrated in broader software systems. These systems suggest specific codes and thereby aim to increase hospital income.

In the case of the hospital, the organization uses algorithmic support not only to support diagnosis but also for the billing and coding of nearly all illnesses and treatments as well as for the support of diagnosis. Here, algorithms suggest clusterings and groupings of diagnosis and treatments. In comparison, algorithmic systems in the hospital case are tied to more central and highly relevant goals than in the case of the algorithmic system of predictive policing in Germany. This is particularly clear regarding billing, which is not a relevant goal for the police that is not burdened with acquiring funding for its operation.

The Role of Internal Differentiation of Organizations in the Algorithmic Assemblage

For many authors, predictive policing holds the promise of fundamentally changing how police work is done (Brayne, 2017; Flyverbom & Hansen, 2019; Wilson, 2018). Upon closer inspection through an organizational lens, the German case showcases that predictive policing is much more confined in its organizational outreach than these claims suggest, especially when paying attention to the internal differentiation of the police.

The German police is differentiated according to a combination of regional and functional principles (Frevel & Groß, 2016). Functionally, the organization is differentiated between the uniformed *Schutzpolizei* (uniformed police), who are primarily but not solely responsible for dealing with imminent dangers and thus providing public security, and the plain-clothes *Kriminalpolizei* (criminal police), who are primarily but not solely responsible for criminal investigations and thus with apprehending offenders. Both organizational parts are further differentiated according to particular tasks. In the case of the uniformed police, which is the part of the organization that uses predictive policing, the overall goal of ensuring public safety includes a broad spectrum of tasks, such as dealing with traffic accidents, patrolling areas, receiving complaints, testifying in court, finding and logging evidence, reacting to emergencies, and documenting all of these activities. Furthermore, a variety of other specialized units exist to police waterways, demonstrations or highways.

We do not need to delve deeper into the differentiation of police organizations to make clear that preventing burglaries is just one among various other tasks the uniformed police must deal with. Thus, while the term "predictive policing" gives the impression of organization-wide change, in fact, predictive policing bears primarily upon a relatively small part of organizational activity.

Relating this insight to the algorithmic regime of predictive policing reveals two essential aspects. First, the algorithmic system of predictive policing is directed to support and change the work of only one part of the German police, the *Schutzpolizei*. Second, within the *Schutzpolizei*, predictive policing is relevant for only a minor part of the activities the police are engaged in: preventing burglaries. This is not to say that it is unlikely that the technology diffuses to other task areas in the organization, as some authors predict (Egbert, 2020; Egbert & Leese, 2021; Wilson, 2018). We surmise, though, that such a diffusion process will unlikely be broad and homogeneous. Rather, we expect that such a process would affect the police heterogeneously due to its differentiated structure.

To contextualize this point with regard to the case of hospitals, we return to the coding process mentioned above. This process defines what a hospital can charge for a specific treatment. Here, organizational differentiations also influence the algorithmic assemblage as the algorithm is not used at the ward itself but by a specialized coding department operating separately from the ward. Thus, the data work involved in the coding process does not lie with the doctors but is outsourced to a specialized department. The coding staff in the department we researched was formerly part of the ward, but is now exclusively responsible for this coding work.

The point we want to stress regarding the coding department is that *functional differentiation is not neutral to the algorithmic assemblage*; the specialized unit is not only another setting in which the algorithmic system is applied, but is also detached from the work of frontline operatives. If the coding were to take place on the ward, it would likely influence the doctor's work more directly, for example, by impacting decisions about necessary or profitable medical treatment. Accordingly, the functional differentiation between the coding department and the frontline doctors buffers any direct effects on the medical practice of the ward.

The Role of Existing Goal Conflicts in Organizations and New Goal Conflicts in the Algorithmic Assemblage

In this section, we discuss the role of goal conflicts in the algorithmic assemblage of predictive policing. Our starting point is that, as we have seen above, both police and hospital organizations serve not only one but multiple purposes, which also differ in their relevancy. We have seen that multiple goals can engender goal conflicts when organizations have to draw on a limited pool of resources to meet these goals. This is exacerbated when multiple goals need to be addressed simultaneously and thus cannot be brought in a sequential temporal order to decrease the pressure on the organizational pool of resources.

Predictive policing promises to render police work more efficient. The claim of higher efficiency is grounded in the idea that police work is no longer informed by unreliable experience or officers' whims but by a dense data basis. Paradoxically, while *promising higher* efficiency due to the datafication of police work, predictive policing requires considerable *additional data work*, especially *documentation work*, that in itself exerts considerable stress on organizational resources. The reason for this additional data work is that predictive policing requires police officers to meticulously document burglaries to feed these data back into the database used by the algorithmic system to enable future prognosis. Not doing so can lead to detrimental vicious circles; bad data (Richardson et al., 2019) can spiral through the system and reduce the quality of future prognosis, which, in turn, can lead to a loss of acceptance in the organization for using the technology. Furthermore, the increased data work is not offset by additional organizational resources. Not surprisingly, the time requirements of ensuring a sufficient data basis for predictive policing often conflict with other duties.

Closely related to the data-intensive nature of predictive policing is another source of goal conflicts that stems from the necessity that the police often must rapidly respond to emergencies and thus must reassign resources on short notice. From the perspective of police officers, this means that the same organizational unit responsible for patrolling areas which are algorithmically flagged as having a higher risk of burglaries is also responsible for responding quickly to a broad range of emergencies ranging from domestic violence to car accidents. The resulting conflict between the goals of prevention and dealing with emergencies is regularly resolved in favour of responding to emergencies. The result, as a recent study notes, is that officer attention is often redirected by the demand for immediate intervention (Egbert & Leese, 2021, p. 105). This, however, results in algorithmic prognosis not being followed through systematically due to the interference of goal conflicts.

The entanglement of algorithmic systems in goal conflicts and their influence on the unfolding of algorithmic regimes also becomes virulent in the hospital, especially regarding algorithm-based early warning systems. Early warning systems aim to support the detection of critical changes in a patient's condition (Maiers, 2017). Many of these systems combine different vital signs of patients and set off an acoustic and visual alert if conditions deteriorate, which allows staff to react immediately. However, the goal of improving the monitoring of *single patients* stands in contrast to the goal of ensuring that *all patients on a ward are sufficiently monitored in a given shift*. Therefore, the doctors and nurses on the intensive care unit (ICU) hospital underlined the importance of learning not only to "read the alerts correctly," but to learn to move and act in a calm and concentrated way in the ecosystem of constant visual and auditive signals characteristic of an ICU.

This mode of semi-attention indicates that the omnipresence of goal conflicts in organizations makes frictions in the embedding of the algorithmic assemblage likely and a simple unfolding of an algorithmic regime less likely. Just as in the case of the police, the goal of optimizing the monitoring of single patients in the hospital is challenged by parallel and conflicting tasks that often occur in an unplanned manner and call for situated actions. In the worst case, this goal conflict may cause more "algorithmic work," including checking if the alarm is indeed a warning to be taken seriously or merely an effect of the unavoidable over- and underfitting of these systems (Bailey et al., 2020).

We pointed out the extensive data work of manual documentation for police officers through the introduction of the algorithmic system. We also see indications that this kind of data work done by regular staff alongside the regular workload (Büchner & Jarke, 2022) will intensify goal conflicts in organizations. This is highly likely for administrations which cannot easily grow areas of activity or successfully compete for specialized and highly paid data professionals on the market. Due to resource constraints, we expect that organizations which have to produce data alongside their routine practices will accumulate increasingly problematic data in terms of data quality and will also challenge professionals' core tasks and motivation (Hoeyer & Wadmann, 2020).

In conclusion, we offer a conceptual question. The notion of goal conflicts due to limited resources may appear as a general and unspecific aspect at first glance. Resources are generally rather scarce than munificent, regardless of whether we look inside organizations or outside of them. However, when analysing algorithmic assemblages and the unfolding of algorithmic regimes, we should reflect that the plentiful investments in various digitization projects we witnessed in the last years cannot be taken for granted in the future. Especially in light of multiple societal challenges and crises, a continuation of this trend seems rather unlikely. In effect, manifest and latent goal conflicts that do not appear to influence algorithmic assemblages in the present might make a difference when compensation and resource flows for digital innovation projects decrease or even stop.

Rethinking the Algorithmic Assemblage with Organizations as Active Contexts: Enablement and Frictions for Algorithmic Regimes

Starting from a situated understanding of algorithms as part of a broader and complex assemblage (Kitchin, 2017, p. 18), we used an organizational sociology perspective to elucidate the interplay of organizations and algorithmic systems. To this end, we focused on the role of organizational goals, structures, and goal conflicts for the algorithmic assemblage and the according unfolding of the algorithmic regime.

Our analysis showed that organizations play a complex role that can hardly be condensed to one principle or one direction of influence. Instead, organizations enable *and*, simultaneously, restrict, break, and relativize the power of algorithmic regimes. In the case of predictive policing in Germany, we have argued that the unfolding of predictive policing is limited by the peripheral status of the goal of prevention for the police, which only informs a part of the task set of the uniformed police and goal conflicts stemming from increased data work as well as the need to react to emergencies. In a second step, we related these insights to our contrast case, a hospital. We pointed out that how algorithmic regimes are embedded and how they unfold differs between organizations and that these differences can be analysed by attending to general characteristics of organizations as complex social systems.

Reflecting upon our analysis, we conclude by identifying three challenges resulting from paying closer attention to the role of organizations in the algorithmic assemblage. First, the elaborated conceptual lens enables a bidirectional perspective by demonstrating that organizations not only empower but also restrict algorithmical associations in assemblages. This perspective challenges researchers to *systematically integrate these breaks, frictions, and relativizations* into the study of algorithmic assemblages and regimes instead of reducing their significance, e.g., by placing their hopes in future generations of algorithms which will supposedly overcome current limitations. While we agree that such processes of optimization will likely happen to a certain extent, we emphasize that the clarity of analysis of algorithmic assemblages and regimes does benefit from differentiating between future possibilities and actual configurations of algorithmic assemblages. Taking the complexities of organizations in the assemblage into account does not hinder researching future imaginaries and analysing the strong discursive powers in play (Jasanoff, 2015; Kitchin, 2014). In contrast, it might sensitize us to the importance of organizational changes and organizational alliances for algorithmic regimes to unfold their social power (Hanseth, forthcoming).

The second challenge is to rethink how we *cluster and lump together algorithmic systems and assemblage elements* for analysis. In this chapter, we chose an approach for studying our main case, which paid attention to the rather confined algorithmic systems of predictive policing for the prevention of burglaries. Others might opt for a broader understanding of predictive policing that includes a variety of phenomena outside of algorithmically enabled burglary prevention. How we cluster our phenomena creates systematic tensions; the tension between paying attention to the situatedness of an algorithmic assemblage, on the one hand, and the aim of identifying overreaching patterns or similarities of algorithmic assemblages and regimes, on the other hand. Although the latter is promising, this tension cannot easily be solved. This presents a disadvantage of "zooming out" when more and broader algorithmic systems are lumped together for analysis: our understanding of organizational (dis)embeddings becomes blurry.

The third challenge is also an invitation. We used our shared interest in the role of organizations in algorithmic assemblages and regimes to zoom into the problem of understanding the relation between algorithmic systems and organizations, not from a metaphorical, but from a conceptual angle. However, it also became clear that there is no lack of theoretical challenges when thinking along the lines of Latour about associations and analysing organizations as social systems at the same time. Since this analysis of the complex role of organizations will create some resonance and inspiration, these debates will most likely also do so. Such a dialogue would allow us to use the conceptual arsenal of organizational sociology more comprehensively, e.g., by paying attention to organizational and data culture, the logics of informality, or the reduction of complexity with the aim of inspiring future analyses and contributing to a better understanding of algorithmic regimes.

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