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Theme issue contribution

Angry Citizens and Black Belt Employees: Cascading Classifications of and around a Predictive Algorithm

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Abstract
Over past decades, predictive algorithms have been used extensively as profiling tools in the private sector, but today they are also increasingly entering public sector domains. This article builds on an ethnographic study of the development of a predictive algorithm in a debt collecting public sector organization. The algorithm was designed to profile citizens on the basis of their calculated 'readiness to pay' their debt and to guide employees' case handling according to 'type' of citizen. The article examines how the classification of citizens produced by the algorithm was mediated by different visualizations and by organizational actors who superimposed new and different classifications (moral and emotional) onto those provided by the algorithm. The article draws on the concepts of nominal and ordinal classification to identify how intended non-hierarchical classification glides into new hierarchical valuations of both citizens and employees. Classifications were 'cascading' – a concept the article develops to account for how classification of and around the algorithm multiplied and had organizational ripple effects. Based on empirical insights, the study advocates an agnostic approach to how algorithmic predictions impact work, organizations, and the situation of profiled individuals. It emphasizes a dynamic and unstable relationship between algorithms and organizational practices.

Keywords: predictive algorithms; valuation; classification; cascading classifications; profiling of citizens

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Introduction

Over past decades, predictive algorithms have been used extensively as profiling tools in the private sector, especially in marketing, banking, and finance (e.g., Fourcade and Healy 2013). Today, predictive algorithms are also increasingly entering public sector domains such as health care (Amelang and Bauer 2019), social work (Eubanks 2018), policing (Brayne 2017; Benbouzid 2019), and education (Jarke and Macgilchrist 2021). Predictive algorithms score, classify, and 'profile' people or organizations based on data sets, generating statistical estimations of their likely future behaviour. The present-day explosion in digital traces enhances the possibilities for the algorithmic sorting of people into classificatory schemes (Jürgenmeyer and Krenn 2016: 178) and these new 'classification situations' (Fourcade and Healy 2013, 2017) have significant consequences for individuals as well as for organizations.

Scholars have examined how predictive algorithms affect organizations when they become part of everyday work practices and how algorithmic classifications shape employees' behaviour and decisions. For instance, clients' personal risk profile may be calculated to set the price of their insurance (Cevolini and Esposito 2020, 2022), or a social worker may decide to intervene in a family situation because the children are classified by the algorithm as being 'at risk' (Eubanks 2018). Much research on predictive algorithms has suggested that they reduce employee agency and lead to a bypassing of the heuristics that employees otherwise usually apply when making decisions (Kellogg et al. 2020: 373). As such, algorithms are often portrayed as highly agential, leaving employees increasingly disempowered. Other studies focus on the embedded values and biases of algorithms and how these biases reproduce inequality and discriminatory practices (Friedman and Nissenbaum 1996; O'Neil 2017) that lead to 'algorithmic oppression' (Noble 2018: 4), to the stigmatization of profiled individuals, and to toxic feedback loops with performative effects (O'Neil 2017).

While much research has demonstrated the strong agency and often discriminatory effects of predictive algorithms, some scholars have begun to bring in more nuance to studies of algorithms and challenge what can be perceived as an almost deterministic, or at least too linear, account of algorithmic agency. These studies devote more attention to 'algorithmic assemblages' (Lee 2021) where human agency also plays an important role and they argue for a more agnostic, symmetrical, and empirically attuned approach to how algorithms work in organizational practices (Seaver 2017; Dudhwala and Björklund Larsen 2019; Lee and Björklund Larsen 2019; Lee and Helgesson 2020; Lee 2021). In this vein, Lee and Björklund Larsen (2019: 2) posed a note of caution: 'might we risk losing sight of the practices, negotiations, and human action that algorithms always are intertwined with? Might we become so seduced by the algorithms that we forget the many social practices that surround them?'.

The point is not to deny that algorithmic classification and valuation are often very powerful and do structure 'life chances' in ways that reinforce inequality (Fourcade and Healy 2013). Yet, this literature highlights that predictive algorithms are many different things and that organizational contexts and human agency make a difference in relation to the algorithms' functioning and classifications, just like the specific design of the algorithms does. Taking inspiration from Lee and Björklund Larsen's question, this article advances a view attuned to the multiple classification and valuation practices that algorithms become entangled with in practice as people interact with them.

This article builds on an ethnographic study of a public sector organization ('the Center') that collects public debt. The Center developed and implemented a predictive algorithm designed to profile and sort citizens on the basis of their calculated 'readiness to pay' their debt and to guide employees' case handling according to the 'type' of citizen (cf. Deville 2012). Based on this study, we examine how classifications of the algorithms were moulded, reinterpreted, and modified in different ways to shape the organizational practices of which they became part. We develop the concept of 'cascading classifications' to account for how classifications of and around the algorithm multiplied. In this way, we theorize how classifications may condition each other and lead to new, sometimes surprising, or indirect classifications.

The concept of cascading helps us shed light on how classification of citizens in terms of their 'readiness to pay' became entangled with other classifications. Organizational actors superimposed new and different classifications onto those provided by the algorithm. The latter became entangled with classification of citizens in terms of motivation or attitude (who is willing to pay), the potential trouble they might cause (who is a 'difficult' person), or their emotional state (who is an 'angry' person). At the same time, employees had to be recategorized to match the algorithm's proposed citizen categories. Such an indirect organizational effect can also be captured by the concept of cascading classifications. To understand and qualify the many layers as well as the ambivalence of the cascading classifications, we draw on Fourcade's (2016, 2021) concepts of nominal and ordinal classifications, which particularly help us identify how intended non-hierarchical classification glides into hierarchical valuations of both citizens and employees.

Our analytical approach is inspired by Science and Technology Studies (STS) and Seaver's (2017) perspective on algorithms as 'sociomaterial tangles', which implies that "algorithms are not singular technical objects that enter into many different cultural interactions, but are rather unstable objects, culturally enacted by the practices people use to engage with them" (Seaver 2017: 5). Along these lines, we treat both human and non-human actors as mediators that never merely transport effects but transform them along the way (Latour 2005: 128). While the basic premise of STS is that the technological and the social mutually shape each other, the technological side has sometimes been given too much weight in accounts that ascribe strong agency to algorithms while reducing the role of human actors. In our analysis, we pay attention to how algorithmic design, visual cues, and other material aspects became entangled with organizational practices and were recalibrated (Dudhwala and Björklund Larsen 2019), reinterpreted, and sometimes even ignored (Plesner and Justesen 2023) by human actors in the organization.

Since there is increased interest in using predictive algorithms, knowledge about how employees work with and around them is important – including how the classifications and valuations they imply affect the relationship between public employees and the citizens they are supposed to serve. The article contributes by theorizing the cascades of classification which surround the development and implementation of a predictive algorithm. With this concept, we are able to analyse how an algorithm's classifications – and hence the values inscribed in it – are mediated by actors within organizational practices and have organizational ripple effects.

Valuations and algorithms in organizational life

Algorithmic society

Recent work on valuation has given us vivid descriptions of how big data and algorithmic tools allow for new ways of tracing, sorting, assessing, and ranking individuals and organizations. In the words of Jürgenmeyer and Krenn (2016: 178), we are witnessing the "emergence of a valuation regime which exploits the ever more abundant digital traces of our everyday lives to algorithmically sort and slot people into classificatory schemes". According to Fourcade and Healy (2013, 2017), this has significant consequences for individuals as the emergence of new 'classification situations' shapes individuals' life chances by the proliferation of algorithmic scoring and decision making.

Fourcade and Healy portray classification (in their case, credit scores) as "an active, independent force that structures people's life chances" (Fourcade and Healy 2013: 569), thus depicting the algorithmic classifications as agents per se. Several studies have shown how algorithmic classifications are also implemented in settings they were not intended for, such as when credit scores are used to assess job candidates (Jürgenmeyer and Krenn 2016: 179; O'Neil 2017). This kind of algorithmic creep may have serious consequences for the classified individuals and can lead to unequal service and treatment (Eubanks 2018).

Predictive algorithms and analytics differ from pre-programmed, deterministic ones that operate on the basis of a simple 'if … then' logic (Bucher 2018: 23). They build on often opaque processes using machine learning to analyse data, identify patterns (Burrell 2016), and make predictions about a likely future situation based on these data sets. In Bucher's terms (2018: 28), "machine learning is about strengthening the probability of some event happening, based on evolving information". Hence, predictive algorithms are concerned with possibilities and probabilities often expressed through calculation of risk scores and the profiling of individuals based on such quantification. These output scores are supposed to predict individuals' likely future behaviour, such as their risk of dropping out of school (Jarke and Macgilchrist 2021), their ability to repay a loan (Fourcade and Healy 2013), or the risk that they will commit a crime (O'Neil 2017).

Hopes are high regarding the usefulness of analysing big data and generating profiles of individuals' expected behaviour as a basis for decision making (Cevolini and Esposito 2020). However, the literature shows that organizational uses in practice are fraught with uncertainties. Predictive algorithms are often based upon limited and biased data (Jarke and Macgilchrist 2021) or dubious proxies (O'Neil 2017) that reinforce inequalities and discriminatory practices. While a critical literature highlights the problematic nature of an increasingly 'algocratic society' (Aneesh 2009), this approach leaves little room for human agency.

Enactment of algorithms in organizational everyday practices

Other studies have shown how it is precisely the uncertainties that allow for human agency and for mediation (Latour 2005) or even mitigation of some of the potential discriminatory effects. An increasing number of ethnographic studies demonstrate how algorithms are intertwined with everyday organizational life (e.g., Amelang and Bauer 2019; Dudhwala and Björklund Larsen 2019; Lee et al. 2019; Lee and Helgesson 2020; Plesner and Justesen 2023) and how they may have very different consequences. For instance, in their comprehensive review of the literature on everyday uses of algorithms in organizations, Kellogg and colleagues (2020) examined how algorithms produce new conditions for control in organizations. Drawing on labour process theory, they argued that employees are prompted to follow the recommendations of algorithms and act accordingly, even when, in principle, they have the autonomy to make a different decision.

Other organizational studies of algorithms portray them as more open to translation and interpretation, emphasizing the indeterminate outcome of using algorithms to solve particular tasks. These studies grant more agency to employees. Many of them are inspired by insights from STS, where sociomaterial sensibilities lead to a focus on how algorithms 'fold' heterogeneous data, methods, and objects with ethical and political effects (Lee et al. 2019), or where algorithms are viewed as enacted and as "the manifold consequences of a variety of human practices" (Seaver 2017: 4). Following the everyday lives of algorithms, as suggested by Neyland (2018), opens the way for analysing not only the ordered sets of instructions which comprise the algorithm, but also the various actions that the algorithm inspires.

Taking this approach, Dudhwala and Björklund Larsen (2019) showed how employees recalibrated the output suggested by algorithms when the output conflicted with their own knowledge, intuition, and judgement. They found that users often experienced a 'technological dissonance', i.e. a mismatch between their own expectations and the algorithm's output. This led employees to question the output and to 'recalibrate' it. Employees simply acted differently than the algorithm suggested. The recalibration of output could be based on different numbers from those provided by the algorithms, or on the employees' own experiences, or on their own contextual knowledge from elsewhere (Dudhwala and Björklund Larsen 2019: 11).

Amelang and Bauer (2019) demonstrated how a risk-predicting algorithm was embedded in everyday medical practices and gave rise to several translations and reactions. Staff members embraced some of the algorithmically based practices and resisted others. Here, the algorithm became both an external mediator *and* a source of authority. It was both used to reinforce arguments and was contested when it interfered with employees' intuitive grasp of the situation. Similarly, in their study of algorithms used in a laboratory for generating instructions for sample handling robots, Lee and Helgesson (2020) showed how employees made varying assessments of the procedures and outcomes of the algorithms. Algorithms were appreciated for their role in reducing human subjectivity in selection processes, but they were also criticized for destroying 'raw data'. Lee and Helgesson concluded that different 'styles of valuation' can coexist in the same organization around the same algorithms.

In a study of predictive algorithms in police work, Brayne (2017) described how massive amounts of heterogeneous data were constantly amassed in large databases, and based on the patterns identified, alerts were generated by algorithms. Brayne found that predictive algorithms did guide behaviour in some instances, while in other cases police officers would claim to have intimate knowledge that overruled the algorithm, e.g., about specific zones where they knew that crimes were likely to take place. In such situations, the police officers considered the algorithmic recommendations to be superfluous or unreliable. Eubanks's (2018) study of predictive algorithms that were supposed to identify child neglect highlighted how employees were encouraged to be sceptical of the scores and rely on their own experience.

Both the literature on organizational uses of decision support algorithms generally and predictive algorithms specifically alert us to their multiplicity and different effects in practice. Importantly, they illustrate various ways in which the agency of algorithms is curbed by humans' pushbacks, recalibration, overruling, or deliberate neglect. Algorithmic calculations and outputs have disparate effects, depending on how they become entangled with human actors' interpretations and calibrations, and as such, their outcomes may be enacted in various ways. One important aspect of predictive algorithms, which has effects in organizations, is their entanglement with classification and valuation practices.

Classification and valuation practices

Classification and valuation are at the core of the design and functioning of predictive algorithms (Fourcade and Healy 2013; Fourcade 2016, 2021; Bucher 2018) and one approach to studying the entanglements of algorithms and organizational life is to focus on how algorithms classify. Predictive algorithms extend and transform classification practices in several ways. In their seminal work on infrastructure and classification practices, Bowker and Star (1999) argued that "classification schemes always have the central task of providing access to the past" (255). Predictive algorithms expand the temporality of classification schemes. Based on past data, they attempt to provide access not only to the past, but to the present and the future. Besides this, algorithms are not only based on prior organizationally produced categorizations. Building on designer input, algorithms are designed to produce 'their own' classifications whose logic sometimes escape even the designers of the algorithm, such as in machine learning (Burrell 2016). On the one hand, algorithms make classification more explicit because the algorithms formalize and standardize much of the tacit categorization work embodied in professionals' everyday heuristics and work practices. On the other hand, algorithms also make many of the specific choices and values invisible because functions of the algorithms tend to be opaque for their users (Burrell 2016). Some scholars have emphasized that rather than viewing complex algorithms as 'black boxes' (Pasquale 2015) that need to be 'opened up' for scrutiny, algorithms are never completely opaque or transparent (Lee 2021: 78). Instead, opaqueness and transparency are situated, enacted, and dispersed as part of specific assemblages (Lee 2021: 78).

Classification orders the world by dividing and grouping people or things in particular ways according to certain principles depending on purpose and context, and classification practices are always entangled with valuation (Kjellberg et al. 2013: 17). Valuation is a process (Kornberger et al. 2015), and valuation practices depend on classification as the basis for comparing and assigning worth to different people or objects (Lamont 2012). At the same time, it is well-established that classification practices as such are imbued with values and norms. In Fourcade and Healy's (2017: 287) terms, scores and classifications are "dual to one another", and scores are "categories all the way down".

For analytical purposes, however, it makes sense to distinguish between different ways of connecting classification and valuation. Taking inspiration from mathematics, Fourcade (2016; 2021) distinguishes between different principles of classification, which she refers to as nominal, cardinal, and ordinal. These classification practices are ideal types. In practice, they always overlap and intersect, implying that "much of social life around the world takes place at the intersection between judgements of kind and judgment of worth" (Fourcade 2016: 179).

Nominal categories are judgements of kind. Linnaeus's classification of plants in the eighteenth century is an example of classification based on kinds (Fourcade 2016: 176). Other examples could be when gender is described in binary terms or other identity categories are essentialized. Nominal classification establishes knowledge about essences by grouping together people or things with perceived resemblances and differentiating them from other kinds. As ideal types, nominal classifications are flat and horizontal and often appear as if they were natural and neutral differences, but practice looks different. Nominal classifications have often been imbued with inequality and discrimination, as in racism, sexism, etc.

Whereas nominal classification builds on a qualitative ontology, cardinal judgements are quantitative, aggregative, and compare different elements. Ordinal judgements are oriented towards commensuration based on relative ranks. In contrast to the horizontal ontology of nominal classification, ordinal classification is, by definition, vertical and tends towards scoring and quantitative commensuration (Fourcade 2016: 178). Fourcade elaborates:

> Unlike mere nominal difference, ordinal relations imply different valuations, a distinction of (at a minimum) two levels, highest and lowest, above and below. In the old Parsonian vocabulary, they are 'evaluative'. Unlike cardinal judgments, which are focused on magnitudes, ordinal judgments are

> interested in relative ranks, no matter the size of the difference. (Fourcade 2016: 178).

Hence, ordinalization involves rankings and tends to be competitive and fluid. Historically, ordinal classification has been tied to ideals of political liberalism and meritocracy because it judges individuals based on their performance instead of on their belonging to a certain kind (Fourcade 2016, 2021). Sorensen and Roberson (2020) illustrated this reorientation in their study of OECD education governance where they demonstrated how modes of comparison have shifted from nominal classification of countries (related to a 'modern' versus 'traditional' distinction) to ordinalization where countries are compared and ranked based on output indicators. This change marks a reorientation from 'being' to 'behaviour' as the foundation for judgement. However, as Fourcade (2021: 163) remarks, "ordinal citizenship often reproduces those very categorial inequalities it was meant to circumvent, albeit through different means". Digital technologies support the shift towards ordinalization as "computers are by nature oriented to sorting: they 'order' the world by spewing out priorities and queues" (Fourcade 2021: 162). In that sense, "digital citizenship [...] dwells in ordinality" (Fourcade 2021: 162). Credit scoring is an example of this.

Increased interest in using predictive algorithms raises important questions about their uses in practice, including how employees work with and around them and how the classifications and valuations they imply affect the relationship between public employees and the citizens they are supposed to serve. The literature discussed in the two sections above on recalibration of algorithms and on different modes of classification provides a foundation for understanding situations where predictive algorithms become entangled with classification and valuation as well as with human agency in practice.

Empirical context and methodology

This article builds on an ethnographic study conducted in a Scandinavian public organization, pseudonymized as 'the Center', whose main function is to collect public debt (unpaid parking tickets, day-care bills, nursing home services, etc.) from citizens and to give advice on debt repayment options (e.g., dividing citizens' debt into monthly instalments). The Center was a small unit in a larger department within a big public organization. It was led by a team of managers and project managers and employed around 30 caseworkers. A significant part of employees' daily work consists of taking phone calls from citizens, clarifying their queries about their bills and debts, and advising them about repayment options. In some ways, the caseworkers' job resembles call centre work since, equipped with headsets at their desks, they take calls in sequence and are monitored in terms of processing time, client waiting time, and other performance measures well- known from other call centre contexts (Winiecki 2009).

However, employees and managers repeatedly emphasized that the centre should not be considered a call centre, and that efficiency and reduction of case processing time were never goals in themselves. In contrast to many call centre employees, who receive minimal training, the Center caseworkers are trained and skilled clerks with a broad knowledge of finance, legal regulations, IT systems, communication, etc. Rendering high quality casework and treating citizens fairly and equally were viewed as essential by both the caseworkers and their managers, who emphasized in interviews and at meetings that good casework often requires time and attention because the specific nature of each individual case demands careful consideration of the citizens' entitlements.

A goal of the Center is to encourage citizens to set up debt repayment agreements. Such agreements benefit the financial situation of the public organization and is supposed to make it easier for citizens to repay their debt. Sometimes citizens refuse to repay their debt (typically an unpaid parking ticket) because they think it is unfair. In other instances, the citizen's financial situation makes it difficult for them to repay the full amount at once. Therefore, the Center's employees and managers see it as a success if citizens can repay in monthly instalments. Such agreements can be concluded during the phone calls between staff and citizens. The high complexity and variation in the calls (regarding the types and amount of debt, individuals' financial and personal situations, attitudes, etc.) require good caseworker skills, including strong communication and people skills.

The Center had already digitalized many work processes. For instance, all cases were digitized and personal data, such as age, address, unpaid bills, photos of their car in the case of a parking ticket, memos from previous encounters with the Center etc., were readily available on employees' screens when a citizen contacted the Center. During our fieldwork, we witnessed how the Center management continuously sought to advance the digitalization agenda and to implement new digitalization initiatives, even in areas where technologies were untested and success uncertain, such as it was the case for the predictive algorithm, which is the focus of this article. A member of the management team with a background in the financial sector had first-hand experience with credit scoring and when a funding opportunity occurred within the overall organization, the Center applied for funds to develop a similar algorithmic tool for profiling citizens and matching them with the right employee. The Center relied on IT support from a unit in the larger department, so it turned to this IT unit for help in developing the algorithm. The operation of the Center as well as the municipal services in general obviously already relied on various algorithms (understood simply as computers' procedures for problem solving), but this project was talked about and promoted as the first experiment with a *predictive* algorithm. The stated goal of the project was to improve the efficiency and quality of the casework by providing a better and faster service. Another motivation for developing the algorithm, however, was the wish to experiment with emerging technologies so as not to fall behind in the race towards more digitalized public organizations (Plesner and Justesen 2023).

Data collection and analysis

The ethnographic fieldwork took place over a period of 12 months in 2018–2019. This allowed us to follow the development and subsequent implementation of the algorithmic profiling project. Data were collected through participant observation, qualitative interviews, and review of relevant documents. We attended staff meetings and meetings of the management team. All caseworkers in the Center were supposed to be affected by the introduction of the algorithm, and we observed a selection of different caseworkers' everyday work, both before and after the introduction of the algorithm. We sat next to them with headsets, listening in real-time to their phone conversations with citizens and observing their screens during and between calls. In addition to numerous informal conversations, we twice conducted semi-structured interviews with eight caseworkers (before and after implementation of the algorithm except that one caseworker was interviewed only once as he resigned before the implementation) as well as with managers, project managers, and the IT staff responsible for the development of the algorithm. These interviews were recorded and transcribed, as were several of the meetings. In sum, we conducted 60+ hours of observation, including 278 phone conversations between caseworkers and citizens, conducted 22 interviews, and collected key policy and procedure documents as well as PowerPoint presentations.

Data were analysed by reading the entire material in several rounds, thereby familiarizing ourselves with the data before entering a thematic coding process (Braun and Clarke 2006). As this was an ethnographic study conducted over several months, and because it included different kinds of data, we ended up identifying many different themes that pointed in quite different directions. One cluster of themes related to categorization and this cluster was related to the algorithmic profiling project. In this cluster, we grouped data related to categorization of both citizens and employees, matching of citizens and employees, design choices such as algorithmic variables deployed to construct the categories, visualization of the different categories, etc. We analysed the data by focusing specifically on 'classification' and 'valuation', striving to be open towards many different types of both, and organizing the analysis to display the multiplicity of classification and valuation practices emerging throughout the Center's work with the predictive algorithm. In the following analysis, we show the classification work involved in designing the algorithm and we outline how algorithmic outputs were recalibrated and led to multiple new classifications and valuations. In doing so, we highlight how valuation had cascading effects throughout the organization.

'It's about making the right match': Designing an algorithmic profiling tool

Developing the rationale for a predictive algorithm

The Center developed their new predictive algorithm to be used as a profiling tool for increasing knowledge about citizens and qualifying employee intervention based on this knowledge. The idea was that this would provide instant knowledge about callers and their likely future behaviour, whereby they could be matched with the caseworker who possessed the most suitable skills for handling precisely this 'type' of citizen. Based on the algorithmic profiling of each citizen who called the Center to clarify their debt situation, the algorithm would match citizens and caseworkers by automatically directing the call from a particular category of citizen to a particular category of employee. A Center manager described the purpose of the project in the following way:

> It's about making the right match. It's about giving the citizens the right service – the right matching of citizen and caseworker, thereby actually supporting the caseworker's job in an intelligent way. Whereas previously, they had to make their own judgment, like, 'hmm, this is the type of citizen I'm talking to' […]. Now, the majority of citizens who call will be sorted for you [by the algorithm].

The manager presented the algorithm as a way of providing knowledge about citizens by classifying them in a new way. It was intended to sort citizens for the employees, thereby supposedly replacing 'their own judgment'. In this manager's view, the previous, 'analogue', mode of knowing the citizen was a less valid source of knowledge. The different citizen types represented by the algorithmic profiling tool were considered to be pre-existent, but invisible or unclear, and the idea was that the algorithm could make these types visible, as would subsequent management intervention encouraging staff to utilize or adapt to the algorithm's profile categories.

Knowledge provided by classification of the algorithm were meant to become the basis for two types of intervention. One type was concerned directly with citizen service. It was assumed that knowledge of 'type' would enable better service because it would be the 'right service' targeted precisely to this type of citizen. Another intervention was more indirect and organizational. To ensure the right match, the employees also needed to be categorized in a new way – the assumption being that employees had different skills, and some would be better than others at 'handling' certain types of citizens. It was also assumed that such knowledge would enable employees to apply particular skills and communication strategies matching a specific profile. Even if the employee already had access to ample digitized information about the individual caller, this new tool was supposed to provide them with an extra layer of information about the *type* of caller. The extra layer required a notification – a visual cue on the screen – that would signal a categorization instantly.

In interviews with the Center managers and project developers, they repeatedly stressed that the algorithm's classification of citizens were not intended to be hierarchical. The categories were not supposed to be ratings or rankings that assigned different worth to citizens. They were, it was emphasized, merely categories that would provide valuable information about how best to handle a particular citizen call. In that sense, they were presented as nominal rather than ordinal categories (Fourcade 2016). The algorithm was supposed to signal different citizen *types* in a *non-hierarchical* manner. Often explicitly invoking key public values, both employees and managers stressed that all citizens were entitled to a fair and equal service no matter how they were classified by the algorithm. No citizens were more worthy of receiving good service than others. In that sense, strong egalitarian values and a public sector ethos were combined with the design of the algorithmic project from the beginning.

Such values of equality and fairness were important not only for ethical and professional reasons, but also for legal ones. The organization's legal department was active in ensuring the legality of the predictive algorithmic project and prepared a document stating that in their interpretation, the project was compliant with legislation. If the project entailed discrimination or unequal service it would be illegal, but according to the assessment, the purpose of the project was to ensure that every citizen obtained the best service by matching them with that caseworker who was best suited to handle their specific case. It can be argued that there was a tension built into the algorithm from the beginning: citizens are classified but must be treated equally based on their individual case. As we will see, this ambivalence paved the way for recalibration as did the specific technological, communicative, and organizational design choices that had to be made, which will be illustrated in the following sections. It turned out that the initial classifications were followed by new, and sometimes surprising, classifications and valuations.

Entangled classifications: Ready to pay?

Despite the ambition of designing a non-discriminatory algorithm that would produce purely nominal classifications, the design work was imbued with values and norms from its inception. This was reflected in the design choices of which variables would be used (cf. Friedman and Nissenbaum 1996; O'Neil 2017) and as the algorithm was designed to be a predictive tool, it also had to be decided what exactly should be predicted. After some negotiation this became the likelihood that the citizen would, as it ended up being phrased, be 'ready to pay' his or her bills, and thereby the likelihood that a payment agreement would result from the phone conversation. The management team and the designers had lengthy discussions about how to find proxies for 'readiness to pay'. Which indicators would point to a citizen's future behaviour in terms of their likelihood to be 'ready'? What would a 'ready' or 'not so ready' person look like statistically? Several potential variables were considered, such as age, gender, number of children, marital status, and residential district as well as debt and payment history. It turned out that some of these variables could not be used for legal reasons, while others required data that was unavailable. These discussions were part of a process whereby citizens were to be grouped nominally, i.e. based on resemblances and shared characteristics.

Eventually, the citizen's debt and payment history over the past two years became one of the variables, and the algorithm was designed to operate with three main categories of citizens based on what management decided to call the citizen's 'readiness to pay' – after having considered their 'willingness to pay' as an alternative. The categories were then termed 'high readiness to pay', 'medium readiness to pay', and 'low readiness to pay'. A category called 'unknown' was added, reserved for citizens who could not be recognized by the algorithm. This classification scheme was based on the assumption that citizens' phone calls to the Center had to do with payment of unpaid bills and not with efforts made by the citizen to clarify or contest their debt status as such. In fact, our data show that clarifying mistakes made by the authorities was a frequent topic of the calls. The 'readiness' variable was also based on the assumption that citizens already had the *ability* to pay their debt. Their likelihood of repaying was considered to be a function of their 'readiness', making the issue one of motivation, although the more explicit criterion of 'willingness' had been rejected in the naming. Furthermore, there was a built-in assumption that the more money citizens owed the authorities, the less they could be expected to be ready to pay.

While the designers sought to construct a set of categories that could inform the caseworkers about the citizens' assumed readiness to pay, the 'readiness' classification quickly intersected with other classifications that became superimposed on the profiles. Early in the design process, the persons classified were ascribed value as 'easy' (the ones in the 'high readiness' category), 'difficult' (the 'low' category), and 'worth spending extra time on' (the 'medium' category, where it was hypothesized that people could be convinced to pay if an effort was made by caseworkers). Here, nominal classifications seemed to glide into ordinal classifications, which contradicted the egalitarian values that were otherwise inscribed in the project. The very terms high, medium, and low suggest a hierarchy, and hence an ordinalization, and when this vertical classification became linked with notions of 'easy' and 'difficult' citizens, a seemingly technical classification became entangled with a moral evaluation.

Distinctions regarding citizens' 'readiness' were not only about semantics. The categories were supposed to influence the behaviour of the caseworker in the sense that they should adjust their response to match the citizen profile. As a rule, caseworkers were supposed to spend less time on citizens categorized as having 'low readiness to pay' because they were considered less likely to repay anyway. A project manager explained this logic:

> Okay, maybe it's fine to say that we need to talk less with these people [those classified by the algorithm as 'low readiness to pay']. Maybe this is where we can become a bit more efficient because we shouldn't waste half an hour on a call when we know that they usually don't pay and will never pay. In that case, it is better just to forward their call to [name of another public authority]. We just test to see whether they have changed their minds, because of course, we have the Public Administration Act, the legal stuff, and the equal service stuff [the law on citizen social services], but we need to become quicker at detecting if they want to pay – if they have changed their attitude and perhaps become more ready to pay and more willing to pay.

The tension between different classifications and valuations are clear because the project manager recognized the importance both of equal service and of giving people a chance to show that they had 'changed their attitude'. Still, an implication was that on average the caseworkers would spend less time on 'these people' and that the 'low readiness to pay' citizens should be approached differently from citizens in the other categories. The classification of assumed readiness became the basis for a new politics of differentiated treatment. In the quote, the project manager also presented the predictive algorithm as if it were a simple and deterministic algorithm rather than a machine learning-based probability model with relatively high statistical uncertainty. This understanding was reflected in the manager's description of the project's efficiency potential: "We think we can save some time there, because *we know they will never pay*, no matter the amount of tools and good conversations we have with them, so we need to save time there, not in the 'want to pay' or 'will maybe pay'" (emphasis added).

Talking in statistical terms, the project manager explained that 'the likelihood that they will ever make an instalment plan is zero'. He suggested not spending much time on these citizens, but rather, to 'spend our resources on the medium group, where you may say that if we do it right, we can actually make them pay, whereas if we don't, they won't pay'.

Here, the category 'low readiness to pay' was described by the project manager as predictive of a citizen who will 'never pay', such that 'readiness' becomes a matter of 'willingness'. In many ways, this statement was puzzling as the project manager clearly knew about the uncertainties and probabilities of the algorithm. It seemed that even if the algorithm had primarily categorized a citizen on the basis of their payment history, a pretty solid narrative followed, portraying the citizen as someone who would never pay. Already in the design phase, valuations of the different categories adopted a moralizing tone and an indication of the development of a particular approach to some citizens is also illustrated in the following quote from the project manager:

> Again, in the red boxes, we don't want to listen to all that whining – bam – we just need to get to the point where we know if they want to pay or not. Because if you want to, we are very happy to help, but otherwise, we cannot be bothered.

This section points to cascades of classification and valuation practices that predictive algorithms generate in an organization. It illustrates how moral categories became entangled with the readiness to pay classification produced by the algorithm. The next section demonstrates a further step in this trajectory by showing how yet another new classificatory logic was prompted by visual translation of the categories.

Visualization and valuation

Based on the algorithm's classification of the caller, the phone call would be directed to a caseworker who was considered a good match for this particular type of citizen. If the algorithm should operate efficiently in informing the caseworkers about the caller's profile, the task would be to figure out how exactly to convey the information on 'type' in practice. The caseworker only had a few seconds before answering the call, so communication needed to be instant. The solution was to install pop-up icons on the caseworker's computer screen. When citizens called and entered their personal ID number, icons would immediately appear on the caseworkers' screens, signifying the category of the caller and thereby his or her assumed 'readiness to pay'. This raised the more specific design question for the project management team about how to visualize the three different citizen categories. A project manager told us that they considered several options before deciding on a set of yellow emoticons. At first, they had considered traffic lights, and even different kinds of animals, but in the end, the management team and project managers decided to launch a competition among employees, asking them to come up with ideas for icons.

The selection of icons for the three 'readiness to pay' categories ended up being a happy smiley with a thumbs-up gesture for 'high readiness to pay', a semi-happy smiley for 'medium readiness to pay', and a frowning, thumbs-down emoticon for 'low readiness to pay'. In addition to the three different emoticons, the design team added a ghost icon to signify 'unknown citizens' and an icon showing a monkey, which would indicate that the system had made an error. As we will show in the next section, visualizing the different categories with these emoticons led to new types of classification that became absorbed into those already established through the design phase.

Classification of moods and temper: 'If I see it's the angry one, I put up my defenses'

Once the algorithm was up and running, caseworkers and managers began to discuss citizens using the algorithm's three main groupings (low, medium, or high readiness to pay). This discussion was prompted by the emoticons that now appeared on their screens, although the implementation was still only partial, and many calls would go through without pop-up icons. It turned out that the categorized citizens were not so much discussed in terms of their 'readiness to pay' or their actual financial situation. Instead, employees as well as their managers repeatedly talked about the profiled citizens' expected moods and temperament. The emoticons with various facial expressions led to translations of the initial classification. This seemed to be supported by the fact that even though the traffic light symbol had been discarded and the smileys all had the same yellow colour, there continued to be talk about some citizens being 'red'. One employee explained, 'if the red smiley comes up and indicates that this is a difficult citizen, you think, "Oh", and you take a sip of water before answering, and you may already be gearing up towards a tough conversation'.

The yellow frowning thumb-down emoticon was sometimes referred to as a 'red smiley' and conceived as a warning sign, where the caseworker should be prepared for trouble. In this way, a new classification of the caller's emotional state was superimposed on the 'readiness to pay' classification. In line with this, many employees referred to the frowning emoticon as 'the angry one', associating the expression of the icon with the mood of the caller. A caseworker reflected on how the emoticons impacted her work: "[The emoticons] are helpful … I think it will be nice to be prepared for someone who is really angry. Because they can be really angry." Being prepared was important, she said, because it was very hard to be "yelled and screamed at".

The idea that icons helped the employees prepare mentally for the call was repeated by several caseworkers. One of them explained:

> you just need a split second to prepare mentally. If I see it's the angry one, I put up my defenses, I pay attention on a different level, I don't handle emails at the same time, I am fully focused. Because I know I need to pay attention, not necessarily because it's an angry citizen [on the phone], but because it can be a difficult case.

Here, the knowledge-intervention nexus departs from the rational and efficiency oriented ideal presented by managers where the knowledge provided by the algorithm would be about the statistically calculated likelihood that the person on the line would be ready to set up a payment agreement and the intervention should fit the classification of this likelihood. Instead, caseworkers interpreted the knowledge provided by the algorithm as knowledge about mood and temper, and their intervention was calibrated to handle possible emotional outbursts: 'Knowing' that the caller might be an 'angry one' led to increased mental focus, preparedness, and 'putting up one's defences'. Here, the encounter is imagined and described in affective terms (cf. Deville 2012).

Classification practices relating to assumed emotions show that the classifications inscribed in the algorithm during the design phase were not simply duplicated in practice. Rather, they evolved and became entangled with new concerns and different classifications and valuations. Employees superimposed their own classifications onto those of the algorithm, and employees' classifications seemed to be based on the visualization of the categories (the emoticons) rather than on the 'readiness to pay' terminology. Like the 'readiness to pay' classifications, the emotion classifications are behavioural categories where the nominal and ordinal intersect because although the emotional categories were not an explicit ranking of citizens (ordinalization), the emotional descriptions had moral undertones. In this sense, employees recalibrated the algorithmic output by ascribing different values to citizens. However, as the next sections show, this way of classifying citizens in terms of their emotions did not stand alone among the employees. They intersected with other ways of classifying citizens.

Everyday classification in action

The employees' mood categorizations of citizens were in many ways puzzling. During our fieldwork, we listened to more than 200 phone conversations conducted by different caseworkers, both before and after implementation of the algorithm. During these conversations, citizens were, in fact, very rarely angry. Callers might at times express frustration with their personal financial situation, or because mistakes had been made. In a few instances they even cried.

However, we saw no connection between these expressions of emotion among callers and the specific icons displayed on the employees' screens. Overall, our observation data showed that the vast majority of citizens was calm and polite, very often calling to clarify a question, to resolve some misunderstanding, or to establish a repayment agreement on their own initiative. The caseworkers were also friendly and polite and, in general, the encounters showed little tension. Many of the calls included laughter on both sides and ended with the citizen explicitly thanking the caseworker for helping them resolve the issue. When we discussed our observations with caseworkers in-between calls, they agreed.

This relative lack of tension in the actual encounters suggests that caseworkers deployed much more fluid classification in practice, nuancing them based on their experience and knowledge of the specific case. Our observations of the phone encounters with citizens showed that caseworkers paid little attention to the emoticons in these situations. Instead, they quickly tuned in on the caller's question by listening and asking clarifying questions, while at the same time quickly navigating through various digital documents and payment regulations on their double screens to resolve the issue.

As part of the Center's efficiency ambitions, employees had been provided with a set of standardized phrases and questions that varied according to the citizen categories, the idea being that communication with a citizen classified as having a 'low readiness to pay' should be different from communication with a citizen whose readiness to pay was classified as 'high' or 'medium'. As we saw in the previous sections, the goal was for caseworkers to spend less time on citizens classified as having 'low readiness to pay'. However, we never observed an employee use the script cards or the standardized phrases in practice. Instead, their interventions were adapted to the specific cases at hand.

'Supermen' and 'black belts': Classification of employees

The algorithmic profiling project also led to other types of categorization processes in the Center. These were not inscribed into the algorithm as such, but instead an indirect consequence of the profiling project with organizational effects, derived from the fact that the project was intended to match citizens with the appropriately skilled caseworker. Hence, employees had also to be formally categorized in a new way. From listening to conversations among both managers and employees, we could detect that before the introduction of the algorithm, some kind of informal hierarchy already existed among employees. This informal ranking was based on how quickly and competently staff members were able to conclude their conversations with citizens and set up the much-desired repayment agreements. For instance, both before the algorithm project and during its implementation, one particular employee was frequently praised as the quickest and best phone agent by both colleagues and managers. It was also known that statistics on employee productivity were available, and in the open office setting, employees and managers could easily overhear how calls were handled.

But now that employees were to be placed in categories in order to be matched with citizens, the more informal hierarchies among employees in the Center were affected by the work with categorizing citizens. There was some confusion about how to carry out employee classification in relation to the citizen categorizations. Even managers disagreed about whether the categorization should be about degrees of employee competence. For instance, one manager used the term 'lowest level' when she described how the employees were divided into the new 'match groups'. She explained that the goal was not to keep employees in their groups, but to allow them to work with their competencies so that everybody would be able to take all kinds of calls. When all staff members would one day reach that level, it would only make sense to use the match groups for new employees: 'They enter at the lowest level and work themselves up through the systems' she explained. Another manager expressed the opposite viewpoint, emphasizing that classification of employees did not operate within a hierarchy of some being more skilled than others:

> We quickly found out that it was really important that we repeatedly said out loud, 'This is not good-better-best'. And when that was established and people realized that's how it was, then it was accepted. But in the beginning,

> it was a bit unpleasant because people thought they were being categorized in that way.

Even if the idea was described as matching citizens with 'the right' caseworker, the process of placing employees in different groups meant that they attached value to themselves and their colleagues. Employees used terms such as 'being supermen' or 'having the black belt'. For instance, when we asked an employee how the process of categorizing employees took place, she was not quite sure. She guessed that two of the managers had tried to assess employees' skills, placing most of them in the middle group. She described the matching process as a typical ordinal classification: 'Well, I know that some are placed up there at the top, but I think … but I can also hear that sometimes when you need their help, they can … actually, they say precisely the same as the rest of us.'

When prompted by the interviewer to elaborate what being 'at the top' implied, the employee explained that "those who are supermen at the phones, if that makes sense".

Another employee explained how calls from the 'difficult citizens' would be directed to the most efficient employee mentioned above, the one considered a brilliant handler of all kinds of calls: 'The idea is that the difficult citizens are directed over to him so he can deal with them and convince them that they should pay'. As described by management, and by the efficient employee himself, this was not how the match was supposed to be carried out. Employees who were good at convincing citizens to set up instalment plans should deal with those in the 'medium readiness to pay' group and not waste their time on the 'low readiness' callers. But this was not the understanding of this employee:

> Interviewer: 'Which group do you think you will be placed in?'
>
> Employee: 'The second [medium], the … you know, I haven't reached the taekwondo black belt yet, that calls for years of experience, and I'm not there yet.'

Another employee described his competencies and categorization as follows:

> Employee: 'Yes, I can handle all types of calls […].'
>
> Interviewer: 'So, you are in the … what do they call that group?'
>
> Employee: 'They just call it black belt.'

> Interviewer: 'They call it black belt – would you say it's a kind of elite group?'
>
> Employee: 'Yes, that just sounds a bit stupid […]. We just call it black belt.'

Like managers, employees could shift between different employee classifications where the nominal and ordinal intersected. In one interview, an employee used the metaphor of steps on a staircase to portray a hierarchy, while at the same time insisting that this was not a matter of good, better, and best. In the first part of the interview, the employee described how he was 'placed on a stair step', where he could advance: 'If I want to move up a step, it's easy for me to identify, to say that I would like to move up to this category instead.' Later, however, he portrayed the categorization of employees as non-hierarchical, emphasizing that this is not about climbing stairs:

> This is not about good, better, best in that sense, it's more about where I have my strengths. We have another colleague who can handle 100 cases per day when we are busy. He can handle all types of calls, without doubt, he can handle the most difficult ones when you need to talk to the citizen for a long time, but he really shines when it comes to the middle category, where citizens need a gentle push to agree to set up an instalment plan. He is much better than me in that category, which doesn't mean that this category is easier, it's just another tool that is needed in that conversation, so it's not about good, better, best, in that staircase sense.

These examples show how both managers and employees made attempts to entertain the idea of purely nominal (non-hierarchical) classification, where each employee was a type with different, but equally valuable skills. At the same time, however, it was notable how the ordinal (hierarchical) classification of citizens in terms of their difficulty led to a corresponding ordinal classification of employees. In this sense, the hierarchical imagery entered into discussions of how employees were to be allocated to different types of citizens, especially the 'difficult' ones. 'Angry citizens' should be matched with 'blackbelt employees'. We understand this as a cascading effect: the valuations of citizens led to new valuations of employees, even though these valuations were neither inscribed into the predictive algorithm, nor a direct result of its operation.

Discussion

This article has explored how a predictive algorithm aimed at profiling citizens and matching them with appropriate caseworkers became entangled with different classification and valuation practices when it was implemented in a public sector organization. As is the case with any algorithm, the classifications were based upon values and normative assumptions related, e.g., to the choice of proxies for 'payment readiness'. As such, our findings are in line with other studies showing how algorithms have values inscribed into them by their designers (e.g., Friedman and Nissenbaum 1996; O'Neil 2017). However, the contribution of this article lies in elaborating how the algorithm's classifications – and hence the values inscribed in it – were mediated by actors in organizational practices. To describe how human agency and algorithmic classifications interact and become entangled with one another, and constitute new classification situations, we develop the concept of cascading classifications.

Cascading classifications

The term 'cascade' has two key connotations. It may refer to large amounts that occur at once, as in 'cascades of water' (Oxford English Dictionary). At the same time, cascading also denotes a sequential movement conveyed by the image of a waterfall or a sequential linking of elements (Oxford English Dictionary). In an STS context, Latour (1986) talked about cascades of inscriptions, but without conceptualizing cascades as such. Ruppert and colleagues (2013: 31) refer to Latour's usage when they write that "It is through such cascades of inscriptions – for instance from reams of data to indices – that simpler and more mobile digital inscriptions are often generated". However, based on our findings, we can elaborate on the concept of cascading to better understand the opposite movement, whereby the 'simple' classifications are cascading and thereby become multiplied rather than simplified. In our case, cascading is the output of rather than the input to predictive algorithms.

Our analysis demonstrated how classification of citizens in terms of their 'readiness to pay' became entangled with a cascade of other classifications. Organizational actors superimposed new and different classifications onto the ones provided by the algorithm when citizens were classified in terms of motivation or attitude (who is willing to pay), the potential trouble they might cause (who is a 'difficult' person), or their emotional state (who is an 'angry' person). In these classifications the nominal and the ordinal intersected and they involved moral evaluations, albeit always in an ambivalent manner. The ambivalence was related to the fact that a strong public sector ethos and values of fair and equal treatment had a major influence on caseworkers' everyday interactions with citizens. Democratic values of equality and fairness intersected with undertones of moral judgements about unwilling, difficult, or angry citizens, and those were talked about as not always worth spending time on. The moral evaluations about indebted citizens resonate with research on debt: there is always a moral aspect to any debt relationship (Fourcade and Healy 2013; Fourcade 2021). Referring to Nietzsche, Fourcade (2021: 163) writes that the domain of credit and debt 'is one of the most potent sites for the social distribution of feelings of superiority, moral desert, shame and guilt'. However, while managers and employees in our study sometimes voiced their moral judgements, such valuations were also contested by caseworkers, who emphasized public sector values and the right of all citizens to fair and equal service as a principle of good casework practice. In such cases, the guiding valuation principle was the maintenance of a strong public sector ethos and in the concrete situations and encounters with citizens' caseworkers often used their room for manoeuvre to ignore the 'readiness to pay' categories as well as the visual cues.

One type of cascading effect implied that citizens were routinely talked about as 'happy' or 'angry'. Another type of cascading effect led to employees being talked about as 'having the black belt' (or not). The latter was one of several indirect organizational effects of the introduction of the algorithm. Not only did it produce new ways of classifying citizens, it also led to new categorizations of employees as they became linked to their respective 'match group'. The numerous new classification activities revolving around the introduction of the algorithm can be thought of as processes of making the organization 'algorithm-ready'. These insights about classification and valuation practices related to predictive algorithm contributes to the literature that challenges tech determinist approaches (e.g., Dudhwala and Björklund Larsen 2019; Lee and Björklund Larsen 2019; Lee and Helgesson 2020; Lee 2021), helping us understand in more detail how human agencies become entangled with the digital, with organizational effects.

Human agency and enactment of the algorithm

Hype around the expansion of algorithmic society might lead us to overlook the uncertainties and grey zones that allow room for human judgement and recalibration (Dudhwala and Björklund Larsen 2019). While several studies have shown how some predictive algorithms structure people's life chances in credit institutions or other settings (Fourcade and Healy 2013), or how they can lead to algorithmic oppression (Noble 2018), many organizations still find themselves at the 'data frontier' (Beer 2019) where hopes are highly inflated compared to everyday organizational realities (see also Plesner and Justesen 2023).

Our study has illustrated that predictive algorithms in some contexts end up being less powerful than commonly assumed in the critical literature. Algorithmic output can be enacted in many ways (Seaver 2017) and thereby be subject to significant recalibration. Our analysis showed that sometimes the predictive algorithm sparked caseworkers' interpretation and activities, whereas at other times, the algorithm's classification was downplayed or completely ignored (cf. Plesner and Justesen 2023). Employees were not blindly prompted by the icons in casework practice, nor were they left disempowered or frustrated, as the literature emphasizing the close link between algorithms and organizational control has argued (Kellogg et al. 2020). Instead, employees would still deploy their own judgement of the situation, often overruling the algorithmic prompts and carefully designed icons. Hence, we found that the original classification situation was less determinant than demonstrated in other case studies of algorithmic prediction (Fourcade and Healy 2013). While there can be no doubt that predictive algorithms can lead to discrimination, oppression, and increased inequality (Fourcade and Healy 2013; O'Neil 2017; Noble 2018), our study shows that there is more to algorithms than steering and oppression. Algorithms in practice can be many things. Algorithms are sociomaterial tangles (Seaver 2017) with different effects depending on context. As such, actors may not only mediate but also mitigate discriminatory classifications and consequences of the algorithm in some situations.

While our study has pointed to the role of human actors in recalibrating algorithmic output, this does not imply that the algorithm was open to any sort of interpretation. Specific design choices shaped the ensuing classification processes, involving a cascading of classification. Emoticons that functioned as visual indicators involved a translation of the 'readiness to pay' classifications into emotional categories. People's readiness to pay morphed into a characterization of people as either willing or uncooperative persons. Such design implications are well-known from other algorithmic projects, such as Amelang and Bauer's (2019) study of risk scoring in the health-care sector. In their case, developers attempted to avoid symbols such as traffic lights because they were considered 'too judgmental' (Amelang and Bauer 2019: 484). Our study also shows that despite similar attempts to avoid judgementalism, visualization remains open for resignification and becomes entangled with valuation.

Concluding remarks

The article was motivated by the spread of predictive algorithms into ever more contexts but offers an alternative to alarmist and tech determinist accounts of the effects of such algorithms. Drawing on an ethnographic study, it demonstrated how algorithms are enacted differently in different contexts and how actors may recalibrate algorithmic output, classification, and valuation. While values and normativities are always inscribed in predictive algorithms, their effects are not determined, but emerge in the classification work surrounding it in specific situations. With the focus on classification and valuation practices, our study extends the critique of 'monolithic accounts' of technologies (Lee and Helgesson 2020) that tend to underestimate the agency of technology users and which portray the values of algorithms as being blindly duplicated in practice without any sort of mediation, distortion, or resistance. We contribute to the literature by showing in empirical detail how classifications of and around an algorithm were enacted in multiple ways and how nominal and ordinal classification intersected in these processes. We theorized this as cascading classifications, by which we mean classifications that multiply around an algorithm in ways that are neither deterministic nor arbitrary; they may be prompted by visual designs, as when emoticons prompt classifications of emotion, or they may emerge when employees are recategorized to fit the logic of an algorithm.

Our study is based on a single ethnographic study, but it may inspire future research to similarly pay attention to differentiated, coexistent, dynamic, and cascading classifications circulating among algorithms, employees, and managers. Classification and valuation have a 'career'. They can develop in surprising and sometimes internally inconsistent ways, and we need more empirical knowledge about how this unfolds in different empirical contexts. Much of the literature on predictive algorithms has relied on private sector cases. The present study contributes to our understanding of public sector organizations' adoption of this type of tool, and we suggest that given the spread of predictive algorithms in the public sector, future research should pay more explicit attention to the public sector as a particular context of digitalization (Plesner et al. 2018; Plesner and Justesen 2022) since it can be expected that a public sector ethos colours the valuations attached to predictive algorithms.

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