



Extending the framework of algorithmic regulation. The Uber case

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Abstract

In this article, we take forward recent initiatives to assess regulation based on contemporary computer technologies such as big data and artificial intelligence. In order to characterize current phenomena of regulation in the digital age, we build on Karen Yeung's concept of "algorithmic regulation," extending it by building bridges to the fields of quantification, classification, and evaluation research, as well as to science and technology studies. This allows us to develop a more fine-grained conceptual framework that analyzes the three components of algorithmic regulation as *representation*, *direction*, and *intervention* and proposes subdimensions for each. Based on a case study of the algorithmic regulation of Uber drivers, we show the usefulness of the framework for assessing regulation in the digital age and as a starting point for critique and alternative models of algorithmic regulation.

Keywords: algorithmic regulation, artificial intelligence, automated decisionmaking, big data, quantification.

1. Introduction

The continuous proliferation of digital technologies into more and more areas of social and political life brings with it a reconfiguration of social ordering mechanisms. Automatic information and decisionmaking systems are increasingly used to structure social processes, guide or replace human judgment, and influence behavior. This development has been reflected in various social sciences. The academic debate assumes that recent developments in data collection, data analysis, and data use are profoundly changing the mechanisms for producing social order – rendering them more granular, invasive, and powerful (Zuboff 2019) or more responsive and networked (O'Reilly 2013).

A sophisticated and widely cited approach to conceptualizing how digital technologies change social ordering mechanisms has been proposed by Yeung (2018) with her concept of "algorithmic regulation." Yeung defined "algorithmic regulation" as "decisionmaking systems that regulate a domain of activity in order to manage risk or alter behavior through continual *computational* generation of knowledge from data emitted and directly collected (in real time on a continuous basis) from numerous dynamic components pertaining to the regulated environment in order to identify and, if necessary, automatically refine (or prompt refinement of) the system's operations to attain a prespecified goal" (Yeung 2018, p. 507). In a first step toward a taxonomy of algorithmic regulation, Yeung introduces conceptual distinctions in how systems of algorithmic regulation set goals, gather information, and modify regulatee behavior.

Yeung makes an invaluable contribution to understanding the significance of digital technologies for regulation, sparking a lively academic debate. We subscribe to her definition, while emphasizing that "algorithmic regulation" covers a broad range of phenomena – both rather trivial algorithmic systems like traffic light circuits and more complex, AI-based ones.¹ We contend, however, that further conceptual elaboration is needed to systematically investigate how pervasive computer technologies change regulatory arrangements and enable new ones to be established; the conditions under which algorithmic regulation systems can be effective, efficient, lawful, and

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legitimate; and how algorithmic regulation is shaped by organizational cultures, politics, and other factors. In this article, we therefore aim to complement Yeung's taxonomy in providing the conceptual means for more detailed empirical research and systematic theory development. We draw on two streams of literature that provide a deeper understanding of how numeric descriptions of the world, on the one hand, and material artifacts, on the other, are involved in processes of social ordering: the literature on quantification, classification, and evaluation, and science and technology studies. We also draw on selected insights from other relevant fields of research, such as democratic theory.

In the following sections, we briefly review the literature on algorithmic regulation and related phenomena (Section 2.1), explicate our understanding of regulation (Section 2.2), and outline how research on regulation and governance can benefit from a refined conceptual apparatus for (algorithmic) regulation (Section 2.3). We then delineate the contributions of quantification, classification, and evaluation research and science and technology studies for better understanding algorithmic regulation (Section 2.4). In the third section, we present our analytical framework, which draws on Hood *et al.* (2001) and Yeung (2018) in distinguishing an epistemic, a normative, and an effective dimension of regulation, but proposes a shift of conceptual focus by analyzing them as *representation*, *direction* and *intervention* and introduces a number of subdimensions for each of them (Section 3). Section 4 shows the usefulness of the framework through a case study of Uber and its strategies for regulating drivers. A summary and an outlook conclude the article (Section 5).

2. Toward an analytical framework: Previous work and challenges

2.1. Reviewing the literature on algorithmic regulation

Over the past two decades, a number of scholars have contributed to making sense of what we call algorithmic regulation, often using related concepts such as “algorithmic management” (Lee *et al.* 2015), “algocracy” (Aneesh 2009), or “governance by algorithms” (Just & Latzer 2017).² While these contributions have provided valuable insights, the literature shows at least four shortcomings. First, many empirical studies have increased our knowledge on how digital technologies are used to establish and perpetuate specific forms of social order in manifold areas such as work organization (Aneesh 2009; Lee *et al.* 2015), media selection and consumption (DeVito 2017; Just & Latzer 2017; Festic 2020), and academic writing (Introna 2016). Some studies have highlighted specific aspects of algorithmic regulation, such as its propensity for “reality construction” (Just & Latzer 2017). In the absence of a sufficiently general conceptual apparatus, however, many of these important but domain-specific findings have yet to be systematically linked. If scholarship is to provide more general diagnoses about contemporary forms of social ordering, for example by way of comparative research, a more systematic conceptual framework is necessary.

While this first set of studies lacks the conceptual means for bringing order to the (conceded) heterogeneity of algorithmic regulation, the second overemphasizes its homogeneity. These analyses provide general characterizations of algorithmic regulation, treating the phenomenon monolithically, often with a normative evaluation. O'Reilly (2013), for instance, gives an optimistic account of algorithmic regulation, envisioning its potentials rather than analytically dissecting it, and Morozov (2014), in a critical reply, shares this approach. Some recent studies draw a more complex picture of the properties and risks of algorithmic regulation while maintaining a rather essentialist view on the phenomenon itself (e.g. König 2019). A more nuanced understanding of contemporary regulation would, however, benefit from a more detailed analytical perspective on its inner workings.

Third, while data clearly play an important role in many studies on algorithmic regulation, there is little differentiation between data types or between “data practices” (Lupton 2016). In their input-throughput-output model of algorithmic selection, for instance, Just and Latzer noted that “there is a wide spectrum of input sources, depending on the field of application” (Just & Latzer 2017, p. 241). Yet, few studies systematically analyze what kinds of data are used in algorithmic regulation, how they are produced, and how they are linked to the objects they are to represent (for exceptions, see Johns and Compton (2020) and Bellanova and de Goede (2020)). A pronounced focus on data and data-related practices, however, is important if we want to establish what is special about algorithmic regulation. Similarly, the social sciences so far lack the conceptual

means for distinguishing, at least heuristically, the various ways in which “throughput” in systems of algorithmic regulation is organized.

A fourth category of analyses sets out to gain a better understanding of the inner workings of algorithmic regulation. Beginning in the 1990s, scholars like Reidenberg (1998), Lessig (1999), and later Aneesh (2009) have explored how computer code, through affordances and constraints, structures the behavior of those interacting with it. In essence, this line of research investigates the extent to which code figures as a functional equivalent to other ways of creating social order, such as law or markets. While laying the foundations for studying algorithmic regulation, this perspective has often concentrated on only one way in which behavior is influenced through code: the opening or closing of possible paths of action, for example, through the design of graphical interfaces.³

This brief review⁴ shows a number of open research issues calling for an integrated framework for systematic research: connecting empirical research from different fields, shedding light on the diversity of forms of algorithmic regulation, reflecting on the impact of datafication on regulation, and addressing the role of technology in changing behavior. In an attempt to tackle these tasks, we argue for a broad concept of regulation (Section 2.2), a nuanced taxonomy (Section 2.3), and acknowledgement of two streams of research that are productive for regulation and governance studies: quantification, classification, and evaluation research and science and technology studies (Section 2.4).

2.2. Benefits of a broad concept of regulation

The concept of regulation provides a common denominator for relating the various studies mentioned earlier and enabling fruitful comparative research. With Julia Black, and in line with Yeung (2018), we understand regulation as “the sustained and focused attempt to alter the behaviour of others according to defined standards or purposes with the intention of producing a broadly identified outcome” (Black 2002, p. 26). To give an exact account of what we understand by regulation, we relate it to the five dimensions in which, as Koop and Lodge (2017) have shown, understandings of the concept differ. First, we agree with the vast majority of scholars that regulation is inherently intentional (Koop & Lodge 2017, p. 102), thus excluding non-intentional sources of social order such as tradition. Second, we hold that regulation may operate through both direct interventions addressing target behavior and indirect interventions addressing its context (Koop & Lodge 2017, p. 98). Following Black (2002, p. 22) and Yeung (2018, p. 507), we thirdly assume that regulatory activity is not limited to state actors but can be pursued by a variety of organizations.⁵ Fourth, our concept of regulation is not limited to interventions in a particular type of activity, for example in the economic field, but also encompasses interventions in all other kinds of activity. Finally, for an activity to be identified as regulation, regulator and regulatee need not necessarily be separate entities: we see the self-regulation of organizations as a subtype of regulation. In keeping with Black’s epithet “sustained” and in addition to the five dimensions highlighted by Koop and Lodge (2017), we speak of regulation only where altering behavior is attempted on a continuous basis, thereby excluding singular attempts (Levi-Faur 2011, p. 5).

This rather broad understanding of regulation is compatible with more widely used narrow conceptions. It includes, but is not limited to, cases of “intentional intervention in the activities of a target population, where the intervention is typically direct – involving binding standard-setting, monitoring, and sanctioning – and exercised by public-sector actors on the economic activities of private-sector actors” (Koop & Lodge 2017, p. 105). This means that the analytical distinctions introduced in Section 3 can yield useful insights even if one chooses to speak of regulation only in such a narrow sense. However, we contend that only a broad concept of regulation enables an adequate understanding of the transformations of social ordering in the digital age. Because private companies, civil society organizations, and other non-state actors play a major role in using digital technologies to alter people’s behavior (Zuboff 2019; Ulbricht & Yeung 2020), a narrow, state-centered conception of (algorithmic) regulation risks neglecting a significant — and possibly growing — share of the processes by which social order is established in contemporary societies. Likewise, only a broad understanding of regulation allows similarities and differences to be detected in how public agencies and private organizations use digital technologies to attain their goals. This is, however, crucial – for instance in mapping instrument diffusion from the private to the public sector.

2.3. The need for a more nuanced taxonomy

As David Levi-Faur has argued, one of the three main questions in studying regulation, besides “Who are the regulators?” and “What is being regulated?”,⁶ is “How is regulation carried out?” (Levi-Faur 2011, p. 7). Finding a structured answer to this question requires a set of categories apt for capturing the essential characteristics of individual cases of regulation. In studying single instances of regulation, a lack of well-defined categories may be compensated through “thick descriptions.” But when considering more complex questions – where the “how” of regulation is examined in relation to other variables or compared across multiple cases – clear-cut categories are indispensable. In the literature on regulation and governance, at least four sets of such complex questions can be found, which in the future might also be fruitfully posed with respect to algorithmic regulation.

The first set is concerned with the relationship between modes of regulation and its effectiveness and efficiency (as perceived by the regulator). Research following this line of inquiry would typically examine which configurations of regulatory systems enable the effective and/or efficient attainment of predetermined goals, which configurations do not, and why (e.g. Karlsson-Vinkhuyzen & Vihma 2009; Koutalakis *et al.* 2010).

Second, regulation and governance studies are often concerned with questions of legitimacy and lawfulness. Research in this line is interested in the degree to which different configurations of regulatory systems conform to the normative expectations of regulatees and to legal and constitutional norms, and in the factors determining the degree of conformity, such as accountability mechanisms or due process guarantees. Two cases in point are the debates on the legitimacy (Kemmerer *et al.* 2016) as well as the lawfulness (Alemanno & Spina 2014) of behaviorally informed approaches to regulation and those on the legitimacy (Yeung 2018, pp. 516–518; König 2019) and lawfulness (Bygrave 2019) of algorithmic regulation. A further example is the inquiry into the legitimacy of the European data protection regime provided by Yeung and Bygrave (2020) in this issue.

A third line of research often pursued focuses on the “politics of instrument selection,” that is, “the interests or ideas that shape the choice of tools” (Hood 2006, p. 470). Contributions following this tradition trace the specific configurations of regulatory systems back to a variety of factors, such as (political) culture (Wildavsky 1987; Linder & Peters 1989), beliefs in the superiority of certain instruments, or economic interests (Hood 2006, pp. 475–476).

Fourth and last, scholarship on regulation and governance has for at least two decades been concerned with how exactly pre-digital instruments of regulation differ from digital instruments, and what general changes these digital instruments have brought about in the overall systems of regulation into which they have been introduced (Margetts 1999; Hood & Margetts 2007; Gritsenko & Wood 2020).

Answering these questions with regard to algorithmic regulation, and thus advancing the relatively young field of research on algorithmic regulation, requires an analytical apparatus that is both sufficiently general to accommodate all instances of regulation *and* adequately differentiated to capture the internal varieties of algorithmic regulation, as well as its differences from other forms of regulation. Hood has acknowledged the need for a framework independent of technological peculiarities: “[...] only by applying technology-neutral analytical frameworks can we identify what precisely alters when technology changes” (Hood 2006, p. 477). Technology-neutral categories are especially important for analyzing “hybrid” systems of regulation – where only some operations are performed algorithmically while others continue to be performed by human agents – as well as their development over time (Hood 2006, pp. 477–478). For this reason, we have chosen dimensions and subdimensions that apply to any kind of regulation. To meet the second criterion – adequate sensitivity – we propose distinctions able to capture where instances of algorithmic regulation differ from one another, as well as from other forms of regulation.

2.4. Contributions of quantification, classification, and evaluation research and science and technology studies

In developing our analytical distinctions, we draw on two lines of research especially helpful in understanding algorithmic regulation. First, we consider the broad literature on quantification, classification, and evaluation, which discusses, among other issues, the causes and consequences of growing reliance on numbers in all areas of society (e.g. Miller & Rose 1990; Sauder & Espeland 2009; Heintz 2010; Mau 2019). Because this stream of research sheds light on the role of numeric representations of the world in social ordering processes, it is

especially important for understanding forms of regulation that rely on continuous flows of automatically generated digital data. Some of this research has focused on the role of quantification in administration and its impact on public services, giving important impetus to the study of regulation (Mennicken & Lodge 2015; Kurunmäki *et al.* 2016). The work in quantification, classification, and evaluation research shows that, as translation into the world of numbers necessarily implies contingent reductions of complexity, “different modes of quantification are associated with different modes of government” (Diaz-Bone & Didier 2016, p. 15); that numbers allow for the comparability of the otherwise incomparable, that is, for social commensuration (Espeland & Stevens 1998; Heintz 2010); and that quantitative methods of evaluation tend to favor self-disciplining through anxiety, resistance, and allure (Sauder & Espeland 2009).

Second, we use selected insights from science and technology studies (STS) because of its distinct focus on the importance of material artifacts in establishing and perpetuating social order (e.g. Latour 1990a, 1990b; Akrich 1992; Star 1995). This perspective is especially helpful for understanding forms of regulation that, in order to gather, transport, and process digital data, depend on ever more complex and dispersed material infrastructures, and which increasingly modify behavior through the design of material or graphical environments. Such a perspective takes a direction similar to the research done on the role of technology and design in regulation (Yeung 2008). Among its insights is the usefulness of a symmetric form of analysis that does not *a priori* favor human actors over technical artifacts when explaining social order (Latour 2005); the crucial importance of sociotechnical practices by which society is perpetually shaped (Law 2017); and the fact that engineers and computer scientists invariably inscribe particular, value-laden assumptions into the technologies they build (Akrich 1992).

3. An extended framework of algorithmic regulation

Our starting point for the analysis of algorithmic regulation is the framework developed by Hood *et al.* (2001), who adopt a cybernetic approach, analyzing regulation along the three dimensions information gathering, standard setting, and behavior modification.⁷ Information gathering is mainly concerned with the *epistemic* practices⁸ inherent in regulation. In standard setting, we find the many, mainly *normative* choices to be made when defining the means and ends of regulation. Behavior modification, finally, encompasses the *effective* dimension of regulation, that is, the means by which individuals and societies are acted upon. In constructing her systematization around these three dimensions, Yeung (2018) has taken a valuable step toward a conceptual framework, which we extend by further analytical distinctions inspired by STS and quantification, classification, and evaluation research.

Furthermore, we propose a terminological reconfiguration for the dimensions of algorithmic regulation. Departing from Karen Yeung's and Hood, Rothstein, and Baldwin's terminology comes at the cost of conceptual homogeneity. It does, however, have three analytical benefits. First, it makes use of the full range of insights provided by cybernetics – the school of thought also underlying Yeung's and Hood, Rothstein, and Baldwin's approaches. Second, this reconfiguration consequently broadens the empirical scope of each dimension, thus focusing academic scrutiny on aspects of regulatory systems potentially relevant for their performance that would otherwise be neglected. Third, by making more explicit the constructivist⁹ principles of cybernetics, our terminological reconfiguration provides contact points for a more systematic dialogue between the study of regulation and relevant neighboring fields of social research.

Instead of the term “information gathering,” we suggest “representation.” This choice indicates a broader empirical scope: it stresses that this dimension is not restricted to the mere collection of static and objective information unambiguously supplied by the available data but relies on the creation of internal models of the pertinent environment, and hence includes premises about what and what kinds of information are gathered. It thus reflects a wider understanding of classical cybernetics and systems theories, which have pointed out that information is never simply gathered but brought about, framed, and interpreted according to system-specific patterns (Bateson 1972). The constructivist perspective implied in the concept of representation also ties in more closely with the fields of critical data, code and algorithm studies (boyd & Crawford, 2012; Kitchin 2017) and their tenet that “raw data” is an oxymoron” (Gitelman 2013). Moreover, the term enables a conversation with

accounts of representation in political theory (Saward 2006), with quantification and classification studies that investigate representations of populations and citizenries (Desrosières 2011), and with STS perspectives on the interrelation between political representation and knowledge production (Latour 1993, especially pp. 27–29; Brown 2009).

In place of “standard setting,” we opt for “direction,” mirroring the expression “director” in cybernetics (Beer 1966; Dunsire 1978; Hood 2007). Echoing cybernetic parlance, we understand the direction dimension of regulatory systems to comprise the elements determining the system’s desired states, the means of measuring the degree of these states’ realization, and the threshold at which the difference between *ought* and *is* becomes significant enough to warrant countersteering – in short, we understand the direction dimension to cover the entirety of normative choices inherent in the design of a regulatory system. While standards, understood as definitions of desired states, undoubtedly constitute a decisive share of the normative choices to be made in regulation, this broader definition draws attention to other aspects, such as the choice of indicators or (horizontal or vertical) interlockings between standards. This wider focus allows for more fruitful conceptual exchanges with various fields of social research concerned with “normativity in action,” such as the sociology of evaluation (Lamont 2012), the STS literature on the inscription of values into technology (Akrich 1992), and moral philosophy, especially in the subfield of data ethics (Mittelstadt *et al.* 2016).

As an alternative to “behavior modification,” we advocate the term “intervention.” The former might imply that behavior is an object that can be adjusted at will, which has long been refuted by regulatory studies demonstrating that interventions often have effects that differ from the original intentions in magnitude or even direction. “Intervention,” by contrast, speaks to the insight of second-order cybernetics and related modern systems theories that the targets of regulatory action – be they organizations, individuals, or non-human entities – behave according to their own dynamics, only some of which can be brought at the disposal of regulators, and even then only partially. Understood in this way, the intervention dimension of regulation comprises all means used in attempting to alter the processes that determine an entity’s behavior. This terminological readjustment therefore not only offers a more accurate semantic reflection of insights already common in the study of regulation and governance (Baldwin *et al.* 2012, pp. 68–82). It also allows for a more symmetric perspective on the rather direct instruments that have long been at the center of attention in regulatory studies, such as “sticks” and “carrots,” and on more indirect or long-term approaches to facilitating behavior change, such as the creation of particular dispositions in order to achieve the regulatory goal. By widening the empirical focus, this reconfiguration connects the “tools of government” perspective (Hood 1983) in regulatory studies to other fields of research concerned with steering complex and dynamic systems. This includes, for instance, governmentality studies (Miller & Rose 1990) that build on Foucauldian concepts of power and subjectivation, stressing the intricate feedback loops between governing and attempting “not to be governed like *that*” (Foucault 2007, p. 44), and the critical scholarship on the rise of behavioral governance (Jones & Whitehead 2018), which shows the increasingly experimental nature of regulation and its reliance on A/B/N testing and sandboxes. The term “intervention” thus suggests an ambivalent and therefore empirical perspective on the chances of success in regulation and governance.

Two further clarifications are needed. First, our framework is a toolbox for empirical research; it is intended to enable comparative research to advance theory development on algorithmic regulation and its many forms. The aim of the framework is thus analytical rather than explanatory: we make no assumptions about how the framework’s elements are causally linked. Second, it is important to clarify the vantage point from which our framework analyzes systems of algorithmic regulation. It can best be described as the “architects’ perspective.” This means that the framework can be used to characterize systems of (algorithmic) regulation on the basis of their design principles – rather than how they play out on the ground, as typical for studies in the field of algorithmic regulation (Ulbricht & Yeung 2020). Yet, while our perspective does not distinctly address possible unintended deficits or surpluses in ordering effects of regulatory efforts (like subversion, gaming the system, and anticipatory compliance), this does not provide a principled argument against our framework. On the contrary, only by relating the design of systems of algorithmic regulation, for which our framework provides key categories, to the analysis of their factual performance can we examine *why* some types of algorithmic regulation fulfill their goals while others do not.

3.1. Representation

The *representation* dimension of regulation encompasses the assembling of knowledge about the aspects of a system deemed relevant for regulating it. Taking a key insight of STS as a point of departure – that knowledge is never simply there, but produced and shaped by social circumstances – we argue that *representing* involves an epistemic construction based on information or data, as well as their interpretation with the aim of obtaining “knowledge about current or changing states of the system” (Hood *et al.* 2001, p. 23).¹⁰ Analyzing, as this dimension suggests, how the system to be regulated is epistemically represented within regulatory processes then also sheds light on how it is represented in the political sense of “making present again” (Pitkin 1967). It is by acknowledging the long history of quantified governance that we can affirm that the conditions for numerical representation have become more and more favorable. In the early 19th century, the “avalanche of printed numbers” (Hacking 1982) in alliance with the “rise of statistical thinking” (Porter 1986), created a new strategic form of social power (Foucault, 2008; for a later period see Beniger 1986). Today, predictive analytics and machine learning are powerful tools for coping with our contemporary avalanche of numbers triggered by datafication phenomena like growing web traffic, the expansion of social media, the multiplication of sensors through smartphones, and cyber-physical systems, as well as the general digitalization of organizational workflows. To analyze the representational dimension, and inspired by STS and quantification studies, we focus on feature selection, data point production, and interpretation modes, as well as the adaptivity and opacity of these processes.

The insights provided by quantification studies imply, first, that to regulate means to reduce the complexity of the world to a specific segment of reality. This is the process of *feature selection*. Features might be fields in a form, variables in a database, the field of view of a CCTV camera, and so on. A clear example of such modeling is to be found in the Unified Modeling Language (UML) of software engineering, which provides standards for formalizing feature selection (Fowler 2003). The abstractions performed in the feature selection process provide the basis for regulatory capacities to operate efficiently and on scale. Like a map that allows control over a territory, they figure as technologies that enable “government at a distance” (Miller & Rose 1990, p. 9).¹¹ Today, large-scale digital data sets drive the construction of such abstractions through what Adrian MacKenzie calls vectorization: the transformation of real-world entities into vectors in a feature space that “subsumes all contextual, indexical, symbolic or lived differences in data” (MacKenzie 2015, p. 434). Such abstraction enables transitions between contexts and thus increases the radius of possible action (Latour 1990a, p. 50). Increasingly formalized forms of representation facilitate mechanization (Heintz 1993, p. 64), but might also lead to a degree of self-referentiality (Agre 1992) that decouples regulation from lifeworld experience. What is more, since regulatory representation cannot possibly generate a 1-to-1 correspondence with the regulatee, it is always tailored to concrete, local, and pragmatic concerns (Star 1995, p. 91).

Drawing on the insights of STS, which have long argued that more attention needs to be paid to scientific and technical measurement practices (Latour & Woolgar 1979; Pine & Liboiron 2015), the second aspect of representation we deem relevant for analyzing (algorithmic) regulation is the actual *production of data points*, digital or not, corresponding to the features selected. Rather than being simply read off reality, data points are the result of sometimes complicated socio-technical networks.¹² They might originate from questionnaires, surveys, or interviews, be given by regulatees to prove compliance, produced by the sensors of smartphones or other connected devices; they might be the outcome of conscious or unconscious online behavior, recorded by human observers, purchased from such third parties as data brokers or manually added as data labels in order to be used in supervised machine learning. As these practices rely on a number of implicit or explicit assumptions about relevance and representativeness, the informational basis for regulation is characterized by a latent “politics of measurement” (Scott 1998, p. 27) that opens up questions of sampling, unequal visibilities, and thus of social justice. This becomes apparent, for instance, in the debates and negotiations on the legitimacy of using digital trace data (Ulbricht 2020) or the concerns with biases in computer (Friedman & Nissenbaum 1996) and specifically machine learning (Chouldechova 2017) systems.

Importantly, representation is never given by measurement alone: it requires concentrated and narrated form to be of practical use. The third aspect of representation is therefore the *interpretation of data*. This constitutes another kind of modeling: the process of turning a collection of data into a coherent representation of the world, as with the paradigmatic mathematical fitting of functions to data points. Apart from unstructured interpretation, a number of modes of interpretation are available, such as organizational guidelines, expert knowledge, and

algorithmic instruments, which we summarize as *epistemic tools*: specific procedures for generating actionable knowledge, to be used in a strategic situation, from data or information.¹³ If the production of data points according to the features selected serves primarily to “accumulate time and space” (Latour 1990a, p. 31) in a single control center, it unfolds its regulatory potential as a form of actionable knowledge only through the “spatial, temporal, or spatio-temporal segmentation of the world” (Bowker & Star 1999, p. 10) by means of classifications that enable decisions. Machine learning promises to be an effective tool for regulation precisely because it can produce such classifications automatically and from complex data sets (Bechmann & Bowker 2019). Like files in bureaucracy, it is a “source of an essential power” in that it allows a few individuals – bureaucrats or data scientists – to “consider millions [of people] as if they were in the palms of their hand” (Latour 1990a, p. 55). A crucial facet of this aspect of representation is the distinction between *descriptive* and *inferential* tools.¹⁴ Descriptive tools focus on the collected data as they are, whereas inferential tools indirectly determine hidden features or future developments by probabilistic means. Given the complex dynamics of social processes and the resulting limitations to the temporal validity of statistical generalizations, linking data to predictions is political insofar as it involves contingent choices between different ways of representing populations. From a scholarly perspective, it is therefore important to analyze how this “production of prediction” (MacKenzie 2015) operates. With regard to algorithmic instruments, data can be modeled in a number of ways, varying in use cases, assumptions, and consequences. Examples include simple, predefined deductive models (e.g. “IF speed > 100; THEN fine”); fixed statistical models, that is, models derived from training data that are applied to new cases (which corresponds to standard supervised learning); dynamic statistical models, in which new training data are constantly added to update the model (i.e. online machine learning); mathematical optimization procedures, by which allocation or coordination is analytically optimized with regard to a given measure; and computer simulation methods by which scenarios of interest to regulators are explored so as to design appropriate regulatory processes. In practice, systems comprising multiple such algorithmic instruments and other epistemic tools are common.

Representation processes are characterized by two further properties – adaptivity and opacity – which also concern the other two dimensions of (algorithmic) regulation (direction and intervention), but will be considered in detail here. First, relations between feature selection, data production, and data interpretation might exhibit different degrees of *adaptivity*. For instance, with increasing data availability and better machine learning algorithms, we observe an algorithmization of feature selection: features are not specified in advance of data collection but sorted by relevance *ex post* by statistical algorithms. But data sources and interpretation might also become more flexible in themselves. It is therefore important to take into account the temporalization of knowledge enabled by algorithmic systems (Slota & Bowker 2016, pp. 541–542), considering the “trade-off between exploration and exploitation” – between experimenting with new strategies and relying on well-tried ones – “in governance systems [that] is rooted in a much more fundamental tension between the dual needs for institutional stability and change” (Duit & Galaz 2008, p. 320). Especially in the field of state regulation, dynamic forms of representation can be at odds with standards of steadiness, stability, and predictability.

The second property of representation is variation in accountability, transparency, explainability, and the centralization of information, which we summarize under the term *opacity*. There are two types: sociomaterial opacity arises through the concentration of massive data sets in the hands of a few private companies (Fourcade & Healy 2017a) or other organizations, through centralized decisions about feature selection and categorizations, or through the inaccessibility of closed-source algorithms. Epistemic opacity (Humphreys 2004), by contrast, is the inherent methodological intransparency of approaches like machine learning or computer simulation.¹⁵ Sociomaterial opacity has often been a source of conflict, for instance where users on social media platforms dispute the validity of inferred categories, such as sexual orientation or health status. Reversely, the deliberate establishment and maintenance of opacity has been brought forward as a value and right in itself (programmatically Glissant 1997; with respect to algorithmic systems, see Ananny & Crawford 2018) and demanded by data subjects. For instance, the intensive debate about privacy and data protection discusses what kinds of data can legitimately be gathered, combined, and re-used and under what conditions (Bayamlioglu 2020; Kosta 2020). In many cases, representation practices have triggered resistance, but if challenging the epistemic assumptions of organizations requires yet more epistemic tools and authority to be mobilized, “[t]he cost of disagreeing” (Latour 1990a, p. 34) might increase. Whether asymmetry and opacity will lessen trust in regulation or rather habituate users to

interacting with the “sealed surfaces” of user interfaces (Mühlhoff 2018; own translation) is an open empirical question.

3.2. Direction

The second, primarily normative dimension of algorithmic regulation is *direction*. It concerns the regulator's choice of desired states and of ways to render them actionable. In this regard, Yeung distinguishes between the fixed and adaptive specification of desired states, that is, those deterministically configured once and for all and those that can change over time, for example, through dynamic machine learning¹⁶ (Yeung 2018, p. 507). In an age of smart devices that are increasingly able to adapt to changing situations, this distinction is essential in describing the normative dimension of algorithmic regulation. As quantification, classification, and evaluation research has pointed out, however, it is not only the degree of adaptivity that characterizes how intentional activities, such as regulation, are performed, but also the general normative orientations, the varying forms of their operationalization and hierarchization as well as their opacity.

The ways in which normative choices in any regulatory system, including systems of algorithmic regulation, come to bear on its interaction with regulatees depends significantly on how and how far these choices have been formalized and operationalized as the premises of routine decision-making. In order to be able to grasp these differences in formalization, we propose to differentiate three subdimensions: general goals, standards, and indicators.

The least formalized aspect of the direction dimension refers to the *general goals* ascribed to a particular system of (algorithmic) regulation, that is, the ends to which regulation as an intentional endeavor is performed. These goals tend to be rather abstract, such as “economic success” in private enterprises or “effective implementation of law” in administrative bodies. As classical works from sociology (Weber 1958) as well as recent works from valuation studies (Boltanski & Thévenot 2006) point out, these goals typically reflect the larger social context into which an organization is embedded, for example, the economy or the state, and its general imperatives. This issue becomes vivid when organizations at the interface of multiple social contexts come into conflict with their regulatees, or have to decide internally, about which context's goals to pursue, for instance, when security agencies need to balance security concerns against civil rights. However, no general goal “speaks for itself.” In other words, because one and the same general goal may justify multiple courses of action, general goals lack the degree of determination necessary for effectively guiding regulatory operations. They therefore need to be formalized to become social realities.

The second subdimension for analyzing direction procedures in systems of algorithmic regulation thus focuses on the product of such formalization: *standards*. For our purposes, we speak of standards as substantially formalized definitions of desired states or processes that are backed up by institutional mechanisms deployed to monitor their implementation (cf. Bowker & Star 1999, pp. 13–14; Timmermans & Epstein 2010, pp. 70–71). For instance, while “economic success” is a general goal, “customer satisfaction” is a standard in that it defines a manifest benchmark for evaluating decisions and actions, and in that the degree of its realization can be – and, indeed, regularly is – monitored with the intention of countersteering if necessary. As observed by Susan Leigh Star and Martha Lampland, standards are often “nested inside one another [...] somewhat like a set of Russian dolls (maitruska)” (Star & Lampland 2009, p. 5). This nesting becomes particularly relevant in algorithmic regulation, as computer systems allow for the relatively easy combination of more stable general goals and adaptive standards, and even substandards, resulting in what we call *standard cascades*.¹⁷ These substandards can be implemented *internally* through subcategories developed by the regulating entity itself, such as “punctuality” as a part of the standard of “good workplace behavior,” or *externally* by including actors other than the regulator, as in the rating systems implemented at cash registers through which companies evaluate their employees on the basis of customer ratings.

In order to make the degree to which actual behavior conforms to relevant standards accessible and assessable, effective direction in regulatory systems depends on the use of *indicators*. Indicators can be understood as representations of certain aspects of the world that have been endowed with the authority to determine whether and to which degree standards have been fulfilled. They figure as “judgment devices” (Chiapello & Godfroy 2017), providing guidance for deciding how to categorize, for example as “satisfactory” or “non-

satisfactory,” certain actions, states, and so on. Although there are many historical examples of qualitative indicators, such as regular dispatches by local administrative bodies to centers of feudal rule, the prevalence of numerical indicators is a key characteristic of contemporary societies. The relative unambiguity of numbers, as compared to the indeterminacy of natural language (Yeung 2008, pp. 91–92; Hildebrandt 2018, p. 3), appears to contribute in two aspects to the contemporary large-scale use of numerical classifications (Fourcade & Healy 2017a): socially, numbers are more likely to reduce contingency in communication and to produce acceptance and consensus, enabling – or at least promising – coordinated action across regions, cultures, and times (Porter 1996; Heintz 2010, pp. 170–172; Espeland & Stevens 2008); technically, numbers can easily be processed by algorithmic systems, thus allowing for the automation of evaluation and decision-making, which is a central feature of algorithmic regulation.

Despite their appearance as neutral representations of the world, indicators regularly become politicized. As we know from valuation studies and the history of science, what counts as an adequate measurement of reality has evolved over time (Daston & Galison 2007). Novel types of indicators are still in the process of proving their value: while big-data-based economic forecasting and online-based price indicators are gaining increasing authority, the value of big-data-based population measurements (as opposed to traditional statistics) is still hotly debated (Grommé 2018). Conflicts about indicators are hence conflicts about priorities in societies and about epistemic authority. Similarly, other subdimensions of direction often become the object of contestation, as this dimension touches essential aspects – “who gets what, when and how” (Lasswell 1936) – of the political nature of decisionmaking. In the directive dimension, the very nature of regulatory systems is at stake: What purpose should be served? Against what indicators should regulators measure success and compliance? And who decides and monitors these processes? Most market-based quantification practices, as critics remark, serve the purpose of exploiting values created by users (Fourcade & Healy 2017a, p. 290). In addition, the capacities and incentives to influence “classification situations” (Fourcade & Healy 2017b) are unevenly distributed among social groups, with low-income populations having the least agency, middle income populations experiencing high stress, and high-income populations having more freedom in relation to data-driven classifications (Fourcade & Healy 2017b, pp. 38–45).

Like adaptivity, *opacity* is also to be considered in the direction dimension. According to contemporary critics (Morozov 2014; Johns 2017, p. 26; König 2019), normative choices are less likely to be put to debate in algorithmic regulation than in other forms of governance. Relying on algorithmic regulation often means replacing other forms of regulation or governance more open to participation and deliberation (Yeung 2017), marginalizing “the sorts of early stage ‘who’ or ‘in whose interest’ questions that are routinely asked in conventional governance practice” (Johns 2017, p. 26). The perceived lack of legitimacy of goals, standards, and indicators in algorithmic regulation is often attributed to the opacity of algorithmic systems and to the emphasis on efficiency rather than political contestability (Hildebrandt 2018; König 2019). Credit scoring systems, for example, often do not reveal what kinds of individual behaviors or characteristics are used to determine a person’s creditworthiness. Similarly, little is made public about how exactly large search engines determine the order in which research results are displayed.

3.3. Intervention

The *intervention* dimension of (algorithmic) regulation, finally, encompasses all attempts to move regulatees toward a desirable state. In this dimension, Yeung distinguishes two *degrees of automation*: systems that “automatically administer a specified sanction or decision” and those that merely provide recommendations to human decision-makers (Yeung 2018, p. 508). In addition to the degree of automation, we draw attention to a number of analytical distinctions regarding interventional strategies.

From the intervention perspective, regulation is successful insofar as undesired forms of behavior are made improbable and desired forms probable (cf. Schneider & Ingram 1990, p. 513). There are two basic ways to achieve this, as Latour illustrates with his vignette about a hotelier trying to ensure that guests leave their room keys at the counter before going out: acting on the customers and their sense of morality, or acting on the key itself by attaching a weight to it that makes it uncomfortable to carry around (Latour 1990b). For Latour, this is a

distinction between *incorporation* and *excorporation*. Elaborating on these two notions is a useful way of discerning types of intervention in (algorithmic) regulation.

Behavior can, on the one hand, be influenced simply by changing or creating properties of the regulated entity – this is *incorporation*. One common method is to facilitate the internalization of norms and values or, in Foucauldian terminology, “subjectivation” (Foucault 1990), as in many recent forms of “lifelogging” and related practices of digital self-monitoring. Another incorporate way to influence behavior described by Foucault is “discipline,” that is, the creation of bodily routines (Foucault 1995). This technique is not limited to 19th century factories or barracks, as in Foucault’s study, but extends for instance to contemporary “conditioning technology” (Fogg 2003). As argued by the authors of the Berlin Script Collective (2017, p. 24), “conditioning technology is used to permanently change user behaviour by creating habits or even addictions, in other words: to inscribe a specific behaviour in users.” The concept of incorporation also helps explain how non-individual and even non-human behavior is influenced by working on the inner properties of the respective entities: the behavior of machines can be regulated by changing their design, the behavior of organizations by altering their statutes, and even the behavior of organisms can be modified through breeding or genetic engineering (Yeung 2008).

On the other hand, behavior can be influenced through *excorporation*. This means taking regulatees as given and instead changing the environment in accordance with those properties of the regulatees that regulators assume to be (co-)determinants of behavior – in Latour’s case, adding a weight to hotel keys (environment) means exploiting an aversion to carrying bulky objects (property). The term “environment” is used here in the broadest sense to denote anything outside the regulated entity that is relevant for its behavior, including both material (e.g. architecture) and social environments (e.g. institutions). In the case of technologically mediated interventions, the artifacts themselves, for example keys or computer programs, provide the environment that can be designed to facilitate the desired behavior. Akrich (1992, pp. 207–208) shows how assumption-laden the design of technological devices is: “[...] when technologists define the characteristics of their objects, they necessarily make hypotheses about the entities that make up the world into which the object is to be inserted. [...]. A large part of the work of innovators is that of ‘inscribing’ this vision of (or prediction about) the world in the technical content of the new object.” For such attempts to be successful, however, it is necessary for anticipated and actual regulatees to be sufficiently similar (Akrich 1992, pp. 208–209).

Extending this insight from the design of technological artifacts to the design of all things intended to modify behavior, including regulatory systems, we can distinguish *excorporate* interventions in terms of the properties of the regulatee that they seek to utilize (cf. Schneider & Ingram 1990). Drawing on sociological literature, the Berlin Script Collective (2017, pp. 11–12) discerns three *kinds of influence*: *coercion* by material restraint or threat of physical harm, *inducement* through economic costs and benefits, and *initiating re-interpretation* by providing information. This approach is congruent with Vedung’s (1998) classical tripartition of “sticks,” “carrots,” and “sermons.” What is added is the insight that these kinds of influence can operate in three kinds of “media”: social interactions, social structures, and technological artifacts (Berlin Script Collective 2017, pp. 8–20). It is evident, however, that all three kinds of influence make use of regulatees’ (assumed) rational capacities: in each case, interventions (re)arrange the environment, for example, through mandatory law, taxes, or information campaigns, in such a way that the desired behavior becomes the most (instrumentally or normatively) rational option.

Although these three kinds of influence cover a large part of contemporary interventional techniques, we propose two extensions. First, in light of the increasing proliferation of psychologically informed modes of influence (e.g. Jones *et al.* 2013), we also consider techniques that exploit non-rational regulatee properties. We subsume this type of instrument under the umbrella term *influence through non-rational properties*.¹⁸ This technique makes use of those behavior-shaping features of human cognition that diverge from the ideals of “full rationality” and/or operate subconsciously, prominently investigated under the moniker “heuristics and biases” (Kahneman *et al.* 1982). Here, intervening means purposefully (re-)arranging elements of the environment that are assumed to affect non-rational and/or subconscious properties of cognition and thus behavior (for digital environments, see Yeung 2017). For example, a cognitive feature discussed among behavioral economists is “status quo bias,” people’s tendency to value the current situation higher than possible changes (Kahneman *et al.* 1991). This tendency is often utilized through “defaults,” that is, by making the desired behavior the standard option, for

example, through pre-ticked boxes on e-commerce websites (van Boom 2011). Influence through non-rational properties could be further differentiated in terms of the various cognitive features regulators aim for.

Second, and motivated by a plurality of reflections on human and non-human agency in STS and other fields of research, we point out another type of intervention neglected in Vedung (1998) and misleadingly subsumed under “coercion” by the Berlin Script Collective (2017): material restraint, that is, influence through the opening or closing of possible courses of action in environments to which regulatees are exposed. To stress that these environments are not necessarily material but also virtual, we use the term “*architectural constraint*” (cf. Lessig 1999; Grimmelmann 2005). What distinguishes coercion from constraint is again revealed by the assumed properties of regulatees. To use coercion presumes that, if high enough penalties are attached to a course of action, regulatees will no longer want to pursue it. Like inducement and the initiation of re-interpretation, this strategy thus operates on “volitional” theories of the regulatee. The application of architectural constraint, by contrast, draws on “capacity-focused” theories, that is, theories about what average regulatees are, in principle, *able* to do, regardless of what they *want* to do. Prison bars, for example, are designed to keep inmates inside by making it physically impossible for people to squeeze through. Similarly, many computer programs induce certain courses of action, for example, creating a password, by making all other actions temporarily impossible (cf. Lessig 1999; Aneesh 2009). In both cases, behavior is influenced by making all but the desired courses of action practically *impossible* — which is quite different from making them *unattractive*, since in the latter case compliance can be circumvented by accepting sanctions or evading perception. We therefore count architectural restraint as a fifth type of excorporate intervention.

As with the representation and direction dimensions, interventional techniques may also be characterized with regard to *adaptivity* (e.g. when interventions change in accordance with psychometric measurements) and *opacity* (e.g. subtle behavioral interventions (“nudges”) vs. explicit threats). Which interventions are legitimate and adequate is controversial. Normative preferences on the degree to which adaptivity and opacity are acceptable and whether regulation should be attained through incorporation or excorporation often depend on the area (e.g. schools or prisons), cultural orientation (e.g. hierarchical or horizontal), political preferences (e.g. liberal or republican), and other factors. Instruments from both basic modes of intervening have been praised for better effectiveness or condemned as manipulative. There is, for instance, an ongoing debate on whether utilizing non-rational behavior is a legitimate way to address citizens (Kemmerer *et al.* 2016).

The key aspects of the framework are summarized in Table 1. It is important to note that the three dimensions should not be understood as successive stages and are by no means isolated, but rather empirically

Table 1 An analytical framework for studying algorithmic regulation

Dimension	Subdimension	Specification (if applicable)
Representation	Feature selection	—
	Production of data	—
	Data interpretation	Epistemic tools
	<i>Properties</i>	Descriptive/inferential <i>Adaptivity</i> <i>Opacity</i>
Direction	General goals	—
	Standards	Standard cascades (internal/external)
	Indicators	—
	<i>Properties</i>	<i>Adaptivity</i> <i>Opacity</i>
Intervention	Degree of automation	—
	Strategies of influence	Incorporation Excorporation (coercion, inducement, initiation of re-interpretation, influence through non-rational properties, architectural constraint)
	<i>Properties</i>	<i>Adaptivity</i> <i>Opacity</i>

intertwined. Furthermore, the subdimensions are not exhaustive and can be complemented by further aspects should empirical research suggest any.

4. Applying the framework: Algorithmic regulation of Uber drivers

As we have argued in Section 2.2, one benefit of a sufficiently general conceptual approach is its scope. Examples of algorithmic regulation can therefore be found in the political, economic, and legal spheres and on an intraorganizational, local, regional, national, and global scale. This framework aims at scrutinizing a broad range of phenomena like workplace management systems that increasingly include wearable tracking devices; computer-assisted forms of organizing the criminal justice system such as predictive policing products or recidivism prediction software; the automated curation of media content practiced by Facebook or the far-reaching vision of a unified citizen score in China. Such a wide perspective has two main advantages. First, it reveals that, despite their diversity, these phenomena share crucial characteristics along certain dimensions. Second, it provides grounds for comparative analysis across different spheres and segments of society. The direction dimension, for instance, might assume a characteristically different form in a (democratically constituted) political context than in an economic context.

In order to show how the framework structures empirical analysis and generates value for theory development, we apply it to a specific case: the algorithmic regulation of Uber drivers. Founded in 2009, the peer-to-peer ride-hailing platform Uber is a market leader in private individual transportation and one of the pioneers of what is often called the sharing economy. Essentially, it provides smartphone applications that enable users to offer taxi services or hail drivers for a ride. Uber matches supply and demand, thereby virtually eliminating the considerable transaction costs resulting from the search associated with the traditional taxi model (see Rogers 2015). Although Uber also regulates its customers, the subsequent analysis focuses on the regulation of people working as drivers. Drivers have to register with the driver app and then indicate whether they are currently available for work or not. If they are, they will eventually be matched with a waiting customer, whom they can accept or decline. If they accept, they are expected to pick up the customer at the place indicated by the app and drive them to the destination. Afterwards, the driver receives a rating from the customer ranging from one to five stars. In the following, we will look more closely at the three dimensions of representation, direction, and intervention.¹⁹

4.1. Representation

First, our framework focuses on how regulatees and the environment are represented by Uber, that is, through which aspects drivers are modeled, how data is gathered, and how it is then interpreted to shape drivers' work process. Uber's feature selection and production of data points rely mainly on the various kinds of data that can be recorded through its app and smartphone sensors but has recently also started making use of custom hardware with sensor functionality, like the Uber Beacon.²⁰ The data collected include the locations of drivers and customers, but also aspects of drivers' driving behavior, for example, braking and acceleration (Rosenblat 2018, p. 139). Furthermore, map data, traffic information, and the location of other drivers are taken into account. However, other aspects possibly relevant for service delivery are, to our knowledge, not considered, such as altruistic and non-economic driver motivation or the current weather. It has to be stressed that what kinds of data are gathered is defined by Uber alone to the exclusion of both customers and drivers.²¹ The digital models resulting from feature selection and data production constitute the basis for interpreting data in Uber's regulatory scheme, allowing automated "governance at a distance." As regards the algorithmic instruments used as epistemic tools, only partial assessment is possible, since "a giant infrastructure consisting of thousands of services and terabytes of data supports each and every trip on the platform" (Viskic 2018). For the routing of cars on the map, for instance, Uber uses increasingly intricate optimization algorithms operating on the multilayer Uber Map Model (Viskic 2018). The interpretation used for coordinating the work process is largely descriptive in the sense that drivers are sent to areas where customers have already expressed the need for a ride. However, there appear to be a number of inferential elements. For instance, when planning the routes for Uber Eats, a recent food delivery service, machine learning is used to schedule food pick-ups and delivery, and to optimize many other parts of the customer experience (Waliany *et al.* 2018). Furthermore, the patent for Uber's "surge pricing" feature, which

dynamically adapts prices in areas where demand is high in order to prevent driver shortages, seems to indicate a prediction of future supply and demand (Novak & Kalanick 2013, p. 4). Surge pricing can also serve to illustrate both adaptivity and opacity regarding Uber. The “real time” updating of prices (Uber 2019a) through the surge pricing algorithm allows the system to be highly adaptive to shifts in the relation between supply and demand. But even though it is widely discussed among drivers, the concrete workings of the elementary algorithmic instruments remain black-boxed and show a high degree of sociomaterial opacity (Rosenblat & Stark 2016, p. 3766), even to attempts to methodologically reconstruct them (Chen *et al.* 2015, p. 11).

4.2. Direction

Being a publicly traded company, Uber’s general goal can be assumed to be profit maximization, which is broken down into a number of standards that Uber deems apt to achieve that goal: they include optimally matching drivers with passengers for short pickup times, suggesting routes chosen by Uber, achieving smooth driving behavior, realizing a maximum price for the ride, and improving customer experience. These standards constitute what we refer to as internal standard cascades, and are often dynamic and experimental in nature. An example is Uber’s “Experimentation Platform” (Deb *et al.* 2018), with which it systematically varies the ride parameters that appear to be reliable indicators of a good customer experience.²² The details of these internal standard cascades, however, are not public. Here, too, it is insightful to mention those standards that are, judging by the current state of empirical research, *not* deemed relevant by Uber for the regulation of its drivers, such as drivers’ health and well-being or ecological aspects. The Uber system also uses external standard cascades. Through the use of a universal rating system as an indicator of reputation, directive procedures are partly delegated from the company to customers. After each ride, passengers evaluate drivers through a five-star rating system, without restrictions on their choice of criteria. This feature makes the regulatory process decentral²³ and adaptive, because behavior that earns drivers five stars one day may not do so the next day. Unlike other star-based rating systems, Uber’s scale is very demanding: drivers who do not meet an average of around 4.6 stars cannot continue to work as Uber drivers (Rosenblat & Stark 2016).²⁴ Like the rankings studied by Sauder and Espeland (2009), the star system therefore functions as a disciplinary practice, normalizing specific forms of delivering a service. Voluntarily providing water bottles to customers, for instance, has in many regions become an implicit norm perpetuated by the feedback system, to the point where Uber now recommends it as best practice to new drivers.

4.3. Intervention

With regard to intervening, too, rather than acting as a neutral intermediary between customers and drivers, Uber clearly exerts systematic influence. Although there is little evidence of intentional attempts to facilitate incorporation, it is noteworthy that empirically the internalization aimed for in such strategies often also results indirectly from excorporation, for example, when drivers report about “Waking up dreamin’ of surge [pricing]” (Rosenblat & Stark 2016, p. 3766).²⁵ For the use of excorporation itself, there is stronger evidence, suggesting that all five types described in Section 3 are employed by Uber. First, *fear of coercion* is used in the mechanism that drivers whose ratings fall below a certain level or who repeatedly decline ride requests or cancel rides lose access to their accounts and are excluded from the Uber market. Before this happens, the drivers receive warnings, which are directly intended to change their behavior. Second, Uber uses fine-grained and dynamic *monetary inducement* to facilitate favorable allocation between supply and demand. This is achieved through “surge pricing,” the temporary, local rise in fares mentioned earlier, which is temporarily highlighted in red on the driver app interactive map, together with a multiplier indicating the scale of the price increase. Third, driving assistance by the Uber system corresponds to the *initiation of re-interpretation*. The most obvious means is the navigation function of the driver app, which ensures drivers reach their destinations, preferably by a recommended route. Drivers accordingly require no local knowledge of streets and routes. As a fourth instrument, Uber makes use of the *non-rational characteristics* of drivers. For instance, people’s “loss aversion,” a phenomenon well-documented in behavioral economics, is specifically exploited: when drivers are about to log off, they receive a message reminding them of the money they would “lose” by ending their shift. For instance, one message reads: “Are you sure you want to go off-line? Demand is very high in your area. Make more money, don’t stop now!” (Rosenblat & Stark 2016, p. 3768). Finally, *architectural constraint* is used to ensure driver compliance. This is illustrated by the app’s interface, which

does not allow for official cancellation of a ride once it has been accepted – an option usually within the professional discretion of “ordinary” taxi drivers. Thus, when Uber drivers approach their assigned riders and discover that they are, for example, heavily intoxicated, the app effectively reduces drivers’ choices to either providing the ride or not picking up the rider and waiting until the system cancels the ride due to exceedance of a predefined waiting time. In this case, drivers are treated as having failed to meet their obligations and risk exclusion from the Uber market. All five types of excorporate intervention strategies seem to operate in a highly automated way, meaning that their implementation does not require interpretation by another human actor. However, we do not know whether a decision to exclude a driver from the Uber market is double-checked manually. Similarly, with regard to adaptivity, the scholarly community knows little about whether interventions change in accordance with data gathered on individual drivers, for example, in terms of their ratings. It is, however, clear that the integration of various modes of intervening into a seamless user experience introduces a certain degree of opacity.

An analysis using the proposed categories allows us to confront the narrative of a non-hierarchical “sharing economy” with the actual ways in which Uber regulates its workforce, which often resembles procedures in conventional enterprises. But the framework also points towards possible distinctive traits of algorithmic regulation: insofar as Uber is representative of more general aspects of algorithmic regulation, it indicates a trend towards more decentral, reputation-based, experimental, and dynamic systems of regulation.

5. Conclusion

To characterize algorithmic regulation in its diversity, we need empirical analysis and comparative research: across sectors, regions, technologies, and organizations. This requires a conceptual framework that addresses the increasing importance of quantitative modeling, score-based systems of evaluation, and virtual choice architectures for regulation. In order to better grasp these kinds of phenomena increasingly characterizing regulation in the digital age, we have proposed a systematization that – building on the instructive work of Yeung (2018) – understands regulation as encompassing three dimensions: *representation*, *direction*, and *intervention*. By connecting Yeung’s approach with quantification, classification, and evaluation research, as well as science and technology studies, we have developed an analytically differentiated framework for dissecting regulatory phenomena along these dimensions. Based on the algorithmic regulation of Uber drivers, we have been able to show how the conceptual framework helps us understand and characterize a specific case of algorithmic regulation. Such a characterization, then, lays the groundwork for answering the central questions in regulation and governance research outlined in Section 2.3.

When it comes to exploring how *effective* and *efficient* regulation is achieved, the algorithmic regulation of Uber drivers shows that apps allow for the combination of various modes of incorporate and excorporate instruments for influencing behavior that, especially in concert, seem to be very powerful. We observe that apps construct subjectivities and hierarchies of professional worth and self-valuation that are useful for regulation (e.g. the “good driver”). This observation raises the question of how much room is left for professional discretion, as well as everyday resistance and subversion, when non-compliant behavior is almost impossible due to the constant threat of exclusion and sophisticated technical means for measuring compliance. In this sense, the peril of exclusion from the Uber labor market figures as an ever more credible “shadow of hierarchy” (cf. Héritier & Lehmkuhl 2008) that shapes drivers’ daily routines.

Regarding the *legitimacy* and *lawfulness* of regulation, it is important to note that algorithmic regulation at Uber attributes very limited opportunities to regulatees to develop skills, interact with the regulator, contribute to the regulatory system – or at least understand its inner workings. Many critics have pointed to the unclear legal status of drivers and raised questions of liability and social insurance. From a regulatory perspective, it is also important to examine whether the relationship via app allows for the development of trust, corporate identification, and socialization – factors that have proven important in organizational governance (Gunningham 2012).

The Uber case also allows for conjectures about the factors contributing to a specific *choice of regulatory instruments*. Uber’s mix of instruments, with relatively little (though not none) recourse to fear of coercion, at least superficially accords with its rhetoric of acting not as an employer, with the typical privileges and duties accompanying this status, but as a neutral intermediary merely providing market access and information. In effect, “the company produces the equivalent effects of what most reasonable observers would define as a managed labor force” while “render

[ing] the impression that Uber has a limited managerial role over driver behaviors” (Rosenblat & Stark 2016, p. 3777). This choice of apparently effective, yet seemingly innocuous instruments may, as research suggests, indeed be typical for “platform capitalism” (Srnicek 2016) at large where companies de facto “exercise monopoly control without the burden and responsibilities of direct ownership” (Rahman & Thelen 2019, p. 184).

When it comes to *comparing pre-digital and digital regulatory instruments*, the tripartite analysis helps show that the digital transformation affects each dimension differently: compared to traditional approaches to regulating taxi drivers, representation now has a wide range of new instruments at its disposal, making it more encompassing, adaptive, and opaque. Direction, through external norm cascades, becomes more decentral, reputation-based and responsive. Intervention, finally, does not involve fundamentally new instruments but rather a strikingly broad range and intricate combinations of them. What does appear to be new, however, is the dramatic cost reduction for employing architectural constraint due to the nature of digital environments. These shifts, in conjunction with increased information and communication asymmetry between regulators and regulatees, suggest that algorithmic systems might bring with them a fundamental reconfiguration of the bureaucratic model of organization as a resource for regulation, pushing the “informal organization” (Luhmann 2018) further to the margin in favor of formalized processes.

In brief, the framework can make at least four contributions to the current debate on algorithmic regulation, governance, and management. First, it sheds light on and differentiates the ways in which behavior can be influenced through technology by taking into account a number of different theoretical angles. Second, focusing not only on the overall influence of technology on social relations, but looking more precisely at data, models, and standards allows us to trace how different kinds of regulation are composed. What specific configurations of representation, direction, and intervention are empirically prevalent or inherently well-matched remains a question for further research. Third, this framework helps us make sense of the digital transformation precisely because it is not limited to it; rather, we can compare digital and non-digital modes of regulation, and can thus determine what is and what is not unique to the digital age. Last, it promises a deeper understanding of political struggles around algorithmic regulation by directing attention to the regulatory dimensions that are being politicized – from gender categories on social media platforms to controversies about “nudging.”

Moreover, a better understanding of the inner workings of concrete instances of regulation *by* technology is likely to lead to better informed regulation *of* technology – in the case of Uber (Tzur 2017) and elsewhere. More generally, the framework can indeed serve as a starting point for critique and connect empirical studies about algorithmic regulation with theoretical and normative meta-interpretations of the politics of algorithms (Ulbricht & Yeung 2020). Demonstrating that algorithmic regulation, far from being a singular, monolithic approach, is a highly heterogeneous phenomenon, makes it clear that its design involves degrees of freedom. Representation, direction, and intervention can take many shapes and confront regulators with normative choices that have to be comparatively assessed (Ulbricht & Yeung 2020). Langdon Winner’s insight that “[t]he adoption of a given technical system unavoidably brings with it conditions for human relationships that have a distinctive political cast – for example, centralized or decentralized, egalitarian or inegalitarian, repressive or liberating” (Winner 1980, p. 128) – remains valid in the digital age. Pointing this out, as we have done schematically in Section 3 with respect to the analytical differentiations proposed in this framework, appears to be a fruitful endeavor for critical scholars of regulation and governance. If we agree with Winner that “people are often willing to make drastic changes in the way they live to accord with technological innovation at the same time they would resist similar kinds of changes justified on political grounds” (Winner 1980, p. 135) – we are well advised to take a closer look and engage in deliberation about the alternatives available.

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Endnotes

- ¹ Here, we understand algorithmic systems, in a very broad sense, as systems that – in a specified and unambiguous manner – perform operations on discrete and quantified objects (Totaro & Ninno 2014). We therefore accord with the understanding of computer science but do not share its focus on effective computability.
- ² Throughout this article, we treat the scope of the concept of *governance* (e.g. Rhodes 1997) as practically coextensive with that of a wide concept of *regulation*, as proposed by Black (2002) and Yeung (2018).
- ³ For a notable exception discussing various means of influence through computer interfaces, see Fogg 2003.
- ⁴ A further extensive discussion of algorithmic regulation is provided by a recently published edited volume (Yeung & Lodge 2019a), in which many contributions take a more problem-oriented perspective, rooted in legal studies and computer science, regarding the risks and promises of algorithmic decision-making with respect to data protection, administrative procedures, and fairness criteria. Such a focus on issues of legality and implementation is urgently needed and we aim to complement it with an analytical perspective firmly rooted in the social sciences.
- ⁵ However, we exclude individual (psychological) self-control and influence in informal groups, like child-rearing in families, from the scope of the concept.
- ⁶ With regard to the “what” of algorithmic regulation it seems reasonable to take an agnostic perspective, focusing on the assumptions that regulators themselves hold about regulatees. We therefore treat related questions, for example, whether regulation aims at individual or organizational behavior, as an empirical rather than analytical question.
- ⁷ From a cybernetic perspective, every control system depends on these three dimensions, sometimes referred to as detectors, directors, and effectors (Hood 2007; Dunsire 1978, pp. 59–60) or sensors, actuators, and control algorithms (Cristianini & Scantamburlo 2019). Although the terminology of detectors (or sensors) and effectors (or actuators) is established in many fields, such as robotics, the term director appears to be more common for goal setting in specifically social contexts (e.g. Yeung 2018, p. 507; Yeung & Lodge 2019b, p. 5).
- ⁸ Here we take “epistemic” to refer to anything relating to knowledge. As epistemic practices, we understand “the socially organized and interactionally accomplished ways that members of a group propose, communicate, assess, and legitimize knowledge claims” (Kelly & Licona 2018, p. 140).
- ⁹ Constructivism, in our understanding, stresses that knowledge is never merely “found” in the world but always constructed, and thus contingent on the point of view of those producing it (see Hacking 2000). Cybernetics supports this constructivist view insofar as it stresses that every description of cybernetic systems is made from the point of view of an observer, who is another cybernetic system (Foerster 2003).
- ¹⁰ That algorithmic regulation involves new forms of “computational generation of knowledge” is recognized, among others, by Yeung and Lodge (2019b, pp. 4–5). Although their edited volume consciously decides not to focus on this epistemic dimension, we aim to give it a central position in our framework, as we think it is essential to the mechanisms of algorithmic regulation.
- ¹¹ These “methods of long distance control” have been captured by John Law in the concept of “emissaries” (Law 1984) as well as by Latour (1990a) in the concept of “immutable mobiles.”
- ¹² The contribution by Matus and Veale (2020) in this volume shows succinctly how such networks can be analyzed as global supply chains.
- ¹³ Here we subscribe to a rather canonical understanding of the relation between data, information, and knowledge, where information is understood as organized data and knowledge refers to data organized in such a way that it “can be acted upon” (Flyverbom & Madsen 2015, p. 128).
- ¹⁴ This differentiation resembles Yeung’s (2018) distinction between reactive and preemptive forms of information gathering, but in our case focuses on data interpretation rather than on the temporal orientation of regulatory interventions. We use this slightly different terminology to avoid confusion with such regulatory approaches as preemption, precaution, and preparedness (Anderson 2010; Aradau & van Munster 2012).
- ¹⁵ The difference between sociomaterial and epistemic opacity becomes tangible in recent debates around attempts to create “explainable AI,” which address the problem that AI systems are often incomprehensible despite complete access to their internal procedures.
- ¹⁶ Defined as the “programming [of] computers to optimize a performance criterion using example data or past experience” (Alpaydin 2010, p. 3), machine learning enables a continuous adaptation to new data points.
- ¹⁷ Standard cascades are not to be confused with what have elsewhere been described as norm cascades (Sunstein 1996). Bowker and Star (1999, p. 14) briefly refer to “cascades of standards” in Internet communication, however they appear to have in mind merely a large quantity of somehow interrelated standards and do not elaborate the concept further.

- ¹⁸ We avoid the term “nudge” which, in addition to being used fuzzily even by its originators (Selinger & Whyte 2012), denotes only one approach for utilizing non-rational behavior among others, some of which are considerably older.
- ¹⁹ For empirical descriptions, we draw on the works of Chen *et al.* (2015), Lee *et al.* (2015), Rosenblat and Stark (2016), Scheiber (2017), and Rosenblat (2018), as well as Uber’s website and “Uber Engineering” Blog.
- ²⁰ The Uber Beacon is a piece of hardware that can be installed in drivers’ cars and, among other functionalities, records GNSS, IMA, and barometer data (Uber 2019b).
- ²¹ It should be mentioned however that a recent Uber project aimed at including drivers into a redesign of the driver app’s user interface.
- ²² Such heavy reliance on A/B/N testing is typical not only for ride-hailing businesses (Scheiber 2017) but also for the optimization strategies of the digital economy at large (Stark 2018) and moreover resembles the randomized control trials gaining popularity in policy design (Pearce & Raman 2014).
- ²³ The significant role of reputation systems for control over decentralized activities is a well-studied and, though now facilitated by digital technology, historically common phenomenon (Greif 1993).
- ²⁴ However, there appear to be ways to regain access to the platform after completing a third party quality improvement course (Uber 2019c).
- ²⁵ The quality improvement course mentioned in Footnote 24 may, however, be counted as an attempt of facilitating incorporation by Uber, since it aims at making drivers internalize the company’s expectations regarding acceptable service delivery.

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