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What is algorithmic governance?

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Abstract

This article contributes a coherent framework to the rich literature emerging in the field of algorithmic governance while also resolving conflicting understandings. Tracing the history of algorithmic governance to the broad architecture of the universal Turing Machine, the article identifies a common thread of critical concern in the literature on algorithmic governance: the growing institutional capabilities to move contestable issues to a space of reduced negotiability, raising questions of social asymmetry, inequity, and inequality. Within the social context of algorithmic governance, the article highlights three general areas of concern where the social negotiability of processes is threatened: the problem of power (surveillance), discrimination (social bias), and identification (system identity).

KEYWORDS
communication & media, culture, gender, organizations & work, race & ethnicity, social stratification, sociological and social theory, sociology of knowledge, sociology of science and technology, technology

1 | INTRODUCTION

Algorithmic governance has become a new field of inquiry in the social sciences (e.g., Aneesh, 2006; Coletta & Kitchin, 2017; Danaher et al., 2017; Del Casino Jr. et al., 2020; Introna, 2016; Just & Latzer, 2017; Katzenbach & Ulbricht, 2019; Larsson, 2018; Yeung, 2018). It has gained sufficient analytical power as a concept to illuminate social asymmetries. Even so, it has also raised certain difficulties in the usage of the term "algorithm," whose valence is registered differently in computer science and social science. While computer science defines algorithms as abstract, formalized descriptions of computational procedures, the social sciences are criticized for interpreting them vaguely as code, programs, automation, or architecture (Dourish, 2016). We seek to contribute a coherent framework to the rich literature emerging in the field of algorithmic governance while also resolving conflicting disciplinary understandings. Tracing the history of algorithmic governance to the broad architecture of the universal Turing Machine, we identify a common thread of critical concern in the social science literature on algorithmic governance: the growing institutional capabilities to move contestable issues to a space of reduced negotiability in state, market, legal, and other structures. We use the term "negotiability" not as an evaluative standard but as a matter of concern implicit in diverse discussions about automation, discrimination, surveillance, employment practices, opacity, and transparency in the social science literature.

More specifically, we highlight three contexts of algorithmic governance: (1) a historical context–from the early semantics of algorithm to the broad architecture of the universal Turing Machine; (2) a disciplinary context–by distinguishing between two different horizons of computer science and social science as a way to resolve conflicting understandings; (3) a social context–by underlining three clearly defined domains of social concerns: the problem of power (surveillance), discrimination (social bias), and identification (system identity).

2 | THE PROBLEM OF ALGORITHMS IN THE SOCIAL SCIENCES

Let us first discuss some of the difficulties noticed in the usage of algorithmic governance and algorithms in general. As "algorithm" remains a term of art in computer science, Dourish (2016) argues, it is important to show "ethnographic responsibility" by not setting new references for the term. For example, concerns about the automatically adjusted credit score (Zarsky, 2016), automatic digital surveillance (Graham & Wood, 2003), or the automatic detection of plagiarism (Introna, 2016) are not about algorithms per se; their target is computer-based monitoring where algorithms may play a role but must not be equated with surveillance itself (Dourish, 2016). He also advises not to conflate *algorithm* and *code* because a single algorithm may have several code expressions in different programming languages. Attempts to present algorithms as automated, machinic, architected, or opaque may inadvertently confuse algorithms with technically different things (Dourish, 2016).

To address the critique, we adopt a three-pronged conceptual strategy: first, we recover the *historical context* of algorithm before its differentiation into current forms. Second, we present the development of two horizons of observation driven by different *disciplinary contexts* of computer science and social science. The caution with which recent studies (DuBrin & Gorham, 2021, p. 2) have distinguished the technical and social dimensions of algorithms necessitates an understanding of these two horizons. Complementing Seaver's (2017) response to Dourish (2016), we embrace rather than eliminate the incommensurability between the two horizons of observation. Finally, from the horizon of the social sciences, we develop the last section on the *social context* of algorithmic governance.

3 | HISTORICAL CONTEXT

3.1 | A brief history of "algorithm"

Historically, "algorithm" referred to the decimal number system developed in India. The Indians developed a set of nine numerals, to which they later added a symbol for zero [1 2 3 4 5 6 7 8 9, 0]. The Syrian scholar Severus Sebokht, who knew the use of these numerals, wrote in 662 A.D. of the Indians' "subtle discoveries in the science of astronomy, which are more ingenious than those even of the Greeks and Babylonians, and their method of calculation which is beyond description–I mean that which is done with nine symbols" (Burnett, 2006, p. 15). The diffusion of Indian numerals presumably spread through the ninth-century Persian mathematician Muhammad ibn Musa al-Khwarizmi's arithmetic treatise *Al-Khwarizmi Concerning the Hindu Art of Reckoning*, which was translated into Latin, *Algoritmi de numero Indorum*; Al-Khwarizmi's name (Algoritmi in Latin) gave rise to the term algorithm. Soon the Khwarizmi reference of the word was forgotten, and the term began to describe seven operations with Indian numerals, as mentioned in a 1240 manual titled *Carmen de Algorismo* composed by Alexandre de Villedieu (Ambrosetti, 2015).

Clearly, algorithm lacks, like all other terms, a transhistorical meaning. It wasn't until the 20th century that logician Alan Turing came up with the essential features of what is now called a general-purpose algorithm machine or Turing machine (Hopcroft, 1984), and the loose semantics of algorithm started yielding to its computer science form. Turing was inspired by German mathematician David Hilbert, whose 10th Problem at the 1900 Second International Congress of Mathematicians in Paris asked for a method to determine whether a polynomial equation with arbitrary rational coefficients is solvable in rational numbers. By seeking a general method for the provability of arbitrary statements in mathematical logic (*Entscheidungs* problem), Turing ended up proving that no such universal method could ever exist. But the bulk of his 1936 paper is about computable numbers, the numbers that can be calculated by a purely mechanical process. Growing up at a time when the idea that human beings were machines was common, Turing was inspired to explore the relationship between the human mind and computing machines (Petzold, 2008).

Focusing on automatic or a-machines, Turing developed an abstract model of computation involving automatic manipulation of symbols on a one-dimensional tape divided into squares. The symbols in these squares are not limited to numbers; they can be letters, even blanks. The mechanism that scans and writes, the machine's head, moves one square left or right, reading, erasing, or rewriting the symbol following a table of instructions. These instructions anticipate the modern definition of algorithm as "systematic procedure that produces—in a finite number of steps—the answer to a question or the solution of a problem" (Encyclopædia Britannica, 2006).

In this sense, the meaning of "algorithm" goes beyond mathematical symbols. An ordinary step-by-step cooking recipe is often used to explain the meaning of algorithm (Berkman Klein Center, 2019). We present Turing's hypothetical automatic machine as a quintessential model of algorithmic governance, transforming input into output in an automated sequence of computational steps.

3.2 | Turing Machine as an archetype of algorithmic governance

Turing's machine allows us to derive the logic of algorithmic governance from within the early developments in computing. By accessing this history of algorithm, we can connect to their formative logic, which becomes difficult to discern in contemporary complex technical developments. In this earlier archetype, current differentiations among code, algorithm, and program had not taken place. The key referent was a kind of mechanical process that would eventually be called algorithm — "a set of precise (but basically 'mindless') instructions for solving a problem" (Petzold, 2008, p. 60).

Algorithmic governance refers to the architecture of Turing machines in a broad way. Algorithms alone cannot govern any process. Unless the algorithm is part of the machine, the question of governance remains moot. No algorithmic system operates in a social vacuum (Just & Latzer, 2017). Indeed, Seaver (2017) approaches algorithms as "multiples," as heterogeneous sociotechnical systems, rather than rigidly constrained procedural formulas. Here algorithmic governance emerges as a structural coupling of various elements whose genealogy can be traced back to the archetype of abstract, automatic, programmable Turing machine.

Algorithmic governance can thus be defined as the probability that a set of coded instructions in heterogeneous input-output computing systems will be able to render decisions without human intervention and/or structure the possible field of action by harnessing specific data.

It is not surprising that the earliest expression of algorithmic governance in the social sciences appeared in the theory and concept of algocracy (Aneesh, 2006, 2009), which did not refer to algorithms in a narrow technical sense. Rather, it sought to distinguish the general logic of algorithmic governance from other systems of governance such as bureaucratic or market systems. The term "algocracy" does not pretend to refer to a precise set or kind of algorithms. Rather, just as the "bureau" in bureaucracy referred to all kinds of bureaux, offices, organizations, governments, and corporations following the legal-rational principles of governance, algocracy refers to a variety of programmable, input-output governance systems. For justifiable reasons, some studies use the terms "algocracy" and "algorithmic governance" interchangeably (Danaher, 2016), drawing parallels with bureaucracy and bureaucratic governance, and the ways in which the latter has historically constrained social negotiability (Porter & Haggerty, 1997; Seipel, 2020). However, if useful, one could reserve the term "algocracy" for the horizon of the social sciences while keeping "algorithmic governance" to refer to both technical and social processes.

This approach to algorithmic governance allows us to construct a common thread running through recent literature's diverse concerns about programmed events and their unequal consequences. It is important to point out that in and of itself, automatic or programmed nature of governance is not a matter of concern. For instance, a programmed peer-to-peer (P2P) network that allows "peers" (individual computer systems) to share files over the Internet can be thought of as an example of algorithmic governance, but it does not raise the same concern for the social scientist. The problem occurs when certain social processes deemed important for deliberation or contestation are moved to a space of reduced negotiability through algorithmic governance, pre-determining the range of possible events with programmed alternatives.

Clearly, the problem of reduced negotiability falls within the domain of social science, not computer science, even though both may need to work together to avoid the "translation" problems when policy goals are converted into computer code (Kitchin, 2017), as negotiability could vary extensively from one algorithmic system to another, depending on their respective structures, their applications, and the kinds of algorithms and data being used by them. While we derive algorithmic governance from an earlier history of computing, it is important to underscore the later development of two different horizons of social and computer sciences. A brief discussion of the disciplinary context enables us to highlight the social scientific approach to algorithmic governance as opposed to the computer science approach.

4 | DISCIPLINARY CONTEXT

4.1 | Computer science and social science: Two horizons of observation

It is expedient to think of computer science and the social sciences as two separate horizons of observation. The notion of horizon, derived from Husserl (1975), allows for a specific coherence and structural order to emerge in phenomena. That is, a social science horizon affords us a field of relations that is decisively different from a computer science one. The meaning of algorithms and algorithmic governance is realized differently in different realms. Indeed, the semantics of "algorithm" behaves like many other terms such as "gravity," whose meaning shifts from "alarming importance" in literature to "the force of attraction between physical bodies" in Newtonian physics to "an effect of the spacetime curvature caused by the uneven distribution of mass" in the Einsteinian model. The word "gravity" in itself is empty; it gains its specific meaning only after its insertion into a system of signification.

At its core, the disciplinary focus of computer science derives from technical efficacy, seeking to reach particular computational goals. While Dourish's (2016) distinction between algorithm and code is quite precise (e.g., an algorithm expressed in different programming languages emerges as different forms of code), these distinctions may be less relevant for the social sciences whose concerns are social, not technical. Thus, differences among programs, code, and pseudocode yield to a social concern about any system of input and output where in-between, intermediate processes are bracketed out and become less negotiable.

Technical efficacy and *social negotiability* emerge as two separate disciplinary foci in computer science and social science. This raises a question concerning the possibility of any traffic between the disciplines. One way to resolve the question of exchange is to think of computer science and social science as structurally open to each other but operationally closed (Luhmann, 1995 [1984]). For computer science to increase its internal complexity, it must be open to environmental stimulations (e.g., social contexts), but it must perform its operations in its own language. While social science may influence the type of computing projects pursued, it cannot affect the method of operation. As an analogy, a religious concern may put an external pressure on scientific practice (e.g., debates on cloning), but it cannot affect the scientific method.

There are a few scholars who move between these horizons in precisely this fashion. Due to their dual training, they use the structural openness of computer systems to take in the concerns of social science and translate them into the language of computer systems. Irani and Silberman's (2013) work on Turkopticon exemplifies this dual participation on either side of the divide. They successfully imported the sociologist's concern about worker rights and used it as a perturbation to create a browser extension that allowed workers to create reviews of employers on Amazon Mechanical Turk.

Generally, however, it remains difficult for such specializations to work in tandem. Moats and Seaver (2019) revealed the tensions between different fields while staging a collaboration between data scientists and social scientists. Some notice a dialog emerging between the two horizons with a constructive acknowledgment of the "limits of translation" (Poechhacker & Kacianka, 2021). There is an emerging focus on understanding the entire lifecycle of a sociotechnical algorithmic system where various actors—developers and decision makers—are obligated to justify their use, design, and decisions concerning the system (MacDonald, 2021; Wieringa, 2020).

From the social science perspective, algorithmic governance is a matter of concern not just because everything automatic and programmed is ethically compromised. In some cases, automatic processes may even be desirable for the mitigation of sensory overloads. One could philosophically criticize all automation, particularly its adverse effects felt in the sedentarization of the human body, but such a broad critique is beyond the pale of this article. For the sociologist, algorithmic governance raises concerns in cases where the social negotiability of processes is highly desirable but becomes unavailable. These concerns reveal an uneasiness about the emerging paradox of democratic structures based on negotiability and contestation. The legitimacy of liberal democratic processes is based on free and equal participation in the political community through processes of negotiation and contest: due process, electoral process, complaint process, committee work, unions, and other forms of deliberation. While such spaces do not always work in practice, they do refer in principle to a voluntary political order where the addressees of the law, after Kant and Rousseau, are also conceived of as its authors through informed participation and negotiation. In discussions of agonistic democracy, negotiation allows for the sublimation of antagonism while in deliberative democracy it may serve as the basis for consensus. With the rise of what Gillespie (2014) calls "public relevance algorithms," one's participation in public life is now deeply dependent on algorithmic selections of information.

From the single thread of negotiability, therefore, we can connect disparate concerns of the burgeoning literature on the programmed nature of algorithmic governance.

4.2 | Automatic and programmed: Algorithmic governance and negotiability

Automation, or the non-manual execution of a process, is not a characteristic exclusive to computer systems. Moreover, as discussed earlier, it is not a problem in itself. It becomes a concern when it enables the bypassing of negotiation in any social process. Worker control, for instance, is a fraught issue. Several studies have documented the increasing diffusion of automated control through algorithmic governance and its unequal effects, a fact also highlighted by the inquiries of US judges in lawsuits related to Uber and Lyft. In the case of Uber, passenger assignment, predictive scheduling, dynamic surge pricing, and semi-automated evaluations are contestable issues but moved out of the space of immediate negotiability (Rosenblat & Stark, 2016). Automated worker control has been a major theme in discussions of the future of labor in the sharing economy (Codagnone et al., 2016).

Once we think of algorithmic governance in terms not merely of algorithms but of the whole system, it is easier to see how the automatically adjusted credit score (Zarsky, 2016), automatic digital surveillance (Graham & Wood, 2003), or the automatic detection of plagiarism (Introna, 2016) can all be considered part of a governance assemblage where the space for immediate negotiability has been reduced in algorithmically managed input-output systems. We use the adjective "immediate" because any process can become negotiable at a future date through challenges in a court of law or activist protests. Algorithmic processes will inevitably produce errors characterized by colligation or insufficient interpretation in ways that are not fully accounted for by Fairness, Accountability, Transparency, Ethics FATE principles (Alkhatib & Bernstein, 2019).

As contested forms of social ordering (Katzenbach & Ulbricht, 2019), algorithmic operations could reassemble and restructure power relations and institutions at the expense of the disenfranchised and impoverished (Zarsky, 2014). Eubanks' (2018) metaphor of the "digital poorhouse" conveys a sense of this restructuring as it was meant to efficiently distribute financial benefits, though it only served the needs of a few. But the digital poorhouse, she argues, ended up enabling the policing and surveillance of vulnerable publics in the United States. It shepherded the majority of the working class away from public resources and minimized the scope for negotiability by limiting social mobility, criminalizing varied forms of resistance, and reinforcing the "race-class-incarceration nexus" (Lehman et al., 2018).

Negotiability is connected to another important component of democratic welfare regimes: due process. In Indiana's attempts to automate eligibility processes for the state's welfare system, Eubanks (2018, p. 77) laid bare the assumption that "it is better for 10 eligible applicants to be denied public benefits than for one ineligible person to receive them." There was no way for the individuals to challenge the assumption or the decisions made by the algorithmic system. Not until a class action lawsuit about the loss of due process was filed could the problem even be heard.

These features of algorithmic governance combine to produce stratifying effects. Scoring technologies, for instance, classify people according to credit risk, engendering differences in interest rates, loan structures, or access to rental markets for different classes of people, and act as the engine of class differentiation and reproduction (Fourcade & Healy, 2013). These processes remain inaccessible for immediate questioning or negotiation, making opacity an area of social concern.

4.3 | Opacity, failure, and negotiability

Given the automated, machinic, and programmed nature of algorithmic governance, it is not surprising that its opacity emerges as a major concern for the social scientist (Danaher et al., 2017; Zarsky, 2016). For example, opacity obscures "cheap, menial" labor behind a veil of code in MTurk (Irani, 2013, 2015). Algocratic systems also produce opacity through information asymmetries (McCarthy, 2015) inherent in systems of reputation, search, and finance (Pasquale, 2015).

A major consequence of opacity is the drastically reduced space and scope for negotiation. Here, one comes across impediments that are external to algorithmic governance per se, such as the proprietary opacity of algorithms. Owned and controlled by companies and governments, their precise mechanisms are hidden from view (Kitchin, 2017; Pasquale, 2015). Oftentimes, algorithms and associated code could be a result of collaborations, deriving from pre-existing packages of code and embedded into complex networks of other algorithms (Sandvig et al., 2014; Seaver, 2014).

Opacity can be particularly devastating in cases of failure. Scientific experiments fail more often than they succeed, but due to the inherently open process of negotiation, evaluation, and replication, failures can be identified, and unfruitful research, jettisoned. But if opaque systems fail, there is no way to know, challenge, or rectify the mistakes, as we noticed in the case of Indiana's welfare system. There are always possible "fissures in algorithmic power" – moments where such systems of governance might not function as expected (Ferrari & Graham, 2021).

In order to better understand the processes through which algorithmic governance systems are designed and implemented, Kitchin (2017) suggests unpacking the sociotechnical assemblage by going through its code documentation, mapping out genealogies of algorithms, reverse engineering to see the output under different conditions, interviewing coders, conducting user experiments and ethnographies of actual sites of production.

However, there is another kind of opacity—relating to machine learning systems—that is so machinic in nature that it is difficult to open up for scrutiny (Anderson, 2008; Burrell, 2016; Geitgey, 2014). When we feed data to the generic algorithm, which builds its own logic based on numerous variables under numerous conditions being transformed by multiple layers of neural networks, humans simply cannot comprehend the model the computer has built for itself. This model is not scientific; indeed, it exposes the limitations of scientific models and theories long based on elegance and parsimony (Anderson, 2008; Geitgey, 2014). When a machine learning system is fed thousands of scans, it learns to identify cancer cells in a new scan. But it does so without any recognizable rule; instead, it examines complex patterns of darker and lighter pixels, expressed as matrices of numbers. Rather than reducing phenomena to fit a simple model, machine learning systems can make models as big as needed, the workings of which may remain opaque (Weinberger, 2017). When a bank or a credit card company temporarily blocks a card on account of suspicious activity, the organization may not be able to specify how it was led to that decision. Attempts to recreate the situation that led to the hold are complicated by the transient nature of supporting conditions and circumstances. On the horizon of computer science, these complications can be associated with variations in the complexity of a given task, which then acts as a determinant of how opacity is understood (Vimalkumar et al., 2021).

Opacity in itself may not raise an immediate alarm for the social scientist. Deep learning algorithmic systems for cancer detection (Bazazeh & Shubair, 2016), galaxy detection (González et al., 2018), or farm management (Liakos et al., 2018) do not seem to pose an immediate threat to social processes, though it is always possible for such technologies to migrate out of their original purpose and be used for processes that may pose a threat. These systems become a matter of concern when they enter specific social arenas where it is important for the space for negotiation to remain open. We identify at least three such areas of concern within the social sciences: surveillance, social bias, and individual identity.

5 | SOCIAL CONTEXT

One of the difficulties with algorithmic systems is that they can simultaneously be socially neutral and socially significant. For example, physicists have painstakingly identified and classified galaxies by eye for a long time. Looking into artificial intelligence (AI)-based solutions, they stumbled upon facial recognition algorithms. After all, to a computer, faces and galaxies are both just data. Their work on further identifying abnormal-looking galaxies whose light is bent by curved spacetime raised a social concern about how such work might migrate out of the lab: "What if physicists made an algorithm for galaxies, but somebody else repurposed it for surveillance" (Chen, 2020).

5.1 | Surveillance: The problem of unverifiable power

Since Foucault (1979), surveillance as a form of unverifiable power has been a topic of rich research (Lyon, 2007). It is a form of power that can be deployed in all kinds of places for all kinds of motives. "It is increasingly difficult to suggest that surveillance serves a coherent purpose" (Haggerty, 2006, p. 28). As Gilliom (2006, p. 114) argues, "one of the greatest challenges facing the emergent field of surveillance studies will be developing a grasp on the chaos." While the problem of surveillance has often been equated with the loss of privacy, its effects are wider as it reflects a form of asymmetrical dominance where the party at the receiving end may not know that they are under surveillance, and thus, would have no ability to contest or negotiate for better terms of engagement.

Algorithmic systems intensify the pre-existing authority of quantification, which simplifies, classifies, compares, and evaluates within the larger penumbra of disciplinary power (Espeland & Sauder, 2007; Espeland & Stevens, 2008). Quantification reflects a quest for what Porter (1995) calls "mechanical objectivity," which constrains discretion. Quantitative models have also been shown to have led Wall Street banks to moral disengagement (Beunza, 2019). From social credit scoring to facial recognition technologies, algorithmic systems may enable surveillance by state, corporate, and private actors without gaining legal authority or furnishing any space for negotiation. With an increasing tendency to program certain outcomes in advance, algorithmic systems impose compliance on people and commodify patterns of behavior (Zuboff, 2019) within the political economy of pervasive data colonialism (Couldry & Mejias, 2019).

Arrays of “profiles” that derive information from online activity become the basis for surveillance, and the asymmetries of algorithmic governance emerge in ways that align with how these systems seek to stratify populations and exercise authority over them (Rouvroy & Berns, 2013). The use of such profiles has accompanied a rise in algorithmic management and workplace surveillance with implications for workers' income and their well-being, social inequalities and numerous welfare states (Wood et al., 2019).

Under the individualizing gaze of algorithmic governance, the goals of equity and inclusion may prove to be little more than sociological fantasies. Eubanks (2018) highlights problems of inclusion and exclusion that emerge from systems that are designed to serve agendas of state surveillance and large-scale classification of populations. Here, biases are said to emerge and bear an effect on decision-making after the process of data collection is complete. Such processes of datafication can often be “dehumanizing and violent” (Sadowski, 2020).

5.2 | Social bias: The problem of discrimination

Machine learning algorithmic systems depend on the quality of data used for training them. In 2016, for example, Microsoft released an artificial intelligence twitter chatbot named Tay, which was designed to become “smarter” with user interaction. But it was shut down within a day when it started tweeting anti-Semitic, racist, and sexist insults as it learned from other Twitter users. One of the tweets stated, “I (expletive) hate feminists and they should all die and burn in hell,” proving correct an old programming adage: garbage in, garbage out (Cherelus, 2016). The problem of discrimination in algorithmic systems has been investigated in domains as varied as facial recognition (Buolamwini & Gebru, 2018), search engines (Noble, 2018; Sweeney, 2013), and language (Caliskan et al., 2017).

Social inequalities can be reinforced and amplified by algorithmic governance. First, existing inequalities, unfairness and discrimination get translated into biased data sets, and once installed, those inequalities can be amplified by algorithmic decisions based on biased data sets (Katzenbach & Ulbricht, 2019). The integration of algorithmic governance into our routines over time may be taken for granted as societal infrastructure, allowing inequalities to become durable (Gorwa et al., 2020; Plantin et al., 2018). Situating the problem of racializing visual technologies like face recognition in longer histories of photographing black bodies, Ruha Benjamin (2019) shows how algorithmic governance perpetuates anti-Black racism through the codification of racial stereotypes and the carceral surveillance in the name of law. Commercial facial-recognition systems make mistakes with Black faces at far higher rates than they do with white ones (Lohr, 2018), partly because the widely used training set was mostly male and white (Raji et al., 2020). Richardson et al. (2019) argue that predictive policing systems are often built on data produced during periods of flawed, racially biased, and sometimes unlawful practices of “dirty policing.” Algorithmic assemblages of power and misrecognition also envelop migrant and refugee populations as one notices in the case of Syrian refugees (Kasapoglu et al., 2021). Some studies point out that the solution to misrecognition may not lie in a greater accuracy of vision, which cannot avoid the mistakes when certain bodies are already perceived as dangerous (Neyland, 2016; Suchman, 2020; Wilcox, 2017).

Other studies have shown that the blind application of machine learning risks amplifying biases present in data; for instance, gender stereotypes such as the association between *receptionist* and *female* in natural language processing (Bolukbasi et al., 2016), or the replication of biases in the gig/sharing economy (Shorey & Howard, 2016). Models of machine learning are also implicated in the production of identities, bringing us to the third aspect of our discussion of the social context.

5.3 | Individual identity: The problem of identification

In the era of big data and machine learning, it is important to recognize that these data are collected mostly by default. They lack any explicit orientation to specific end uses or collective meaning, thereby constituting a generalized digital behaviorism (Rouvroy & Berns, 2013), and allowing people to be sorted and slotted into categories of taste, worth, or riskiness (Fourcade & Healy, 2017). This enables constructions of identity that are neither stable nor preconceived. From one's credit scores (financial identity), buying habits (customer identity), medical records (health identity), risk scores (criminal identity) to one's demographic characteristics such as age, gender, income, region and education, algorithmic systems are simulating persons without their knowledge and assimilating their data into profiles in order to meet certain conditions of communication. Such constructions have been labeled "system identities" (Aneesh, 2015).

System identities represent persons as dynamically forming clouds of data (Aneesh, 2015). Such algorithmic identities suffer from a paradox: one is unable to identify with one's own identity, as it mostly remains unknown to the person, and challenges their self-perception (Burrell & Fourcade, 2021). One could argue that even racial identity is not necessarily something an individual identifies with. Yet, ethnic, racial, linguistic, national identities hail individuals through publicly assigned attributes. Digital constructions are detached from persons, and the capturing of "persons" in such constructions is only incidental. There is much discussion within privacy and security literature of a similar, though different concept, the data-double or database-self (Lyon, 2007; Simon, 2005) deriving from one's "digital dossier" (Solove, 2004).

The notion of data double assumes there is someone real behind the data. System identities posit no such substrate or foundation on which identity is based. It is not a double of any real person. A data scientist working for a political campaign, for instance, may *challenge* or *provoke* big data in such a way as to make it, to borrow from Heidegger (1977)–a "standing reserve"–which responds to the system according to the queries being asked of it. It may reveal new patterns of behavior useful for the campaign. These new behavior patterns can be named, producing a new identity for all the people who are covered by this pattern. While there is a clear functional significance for such identities for the system, they remain arbitrary from the individual's perspective. This form of "governance without a subject, but not without a target" is aptly termed "algorithmic governmentality" by Rouvroy and Berns (2013), a kind of system that "focuses not on individuals…but on relations."

The workings of system identity occur in the background beyond an individual's grasp, reducing negotiability and the possibility of resistance. Consider credit scores. They are simply financial data that change with new purchases, payment, non-payment, debt ratios, and time. At the point of request a score is algorithmically generated attesting to the credit-worthiness of the individual, but the mere fact of calling a credit score into existence and initiating a credit inquiry itself can change the given score. The individual is turned into a changing, dynamic, and contingent identity with a changing credit score. System identities may work independently from the subject, producing profiles that an individual may or may not have, or may develop in the future, or simply be confronted with.

The following table is a stylized summary of the above discussion regarding algorithmic governance in three different contexts: State, Market, and Lifeworld (Table 1).

One positive consequence of the diagnosis of algocracy and algorithmic governance has been the emergence of literature on the regulation of algorithms and policy proposals for making systems of governance available for examination. Here, we can see how computer systems are structurally open to concerns arising on the horizon of social science even if they remain operationally closed.

6 | TOWARDS THE REGULATION OF ALGORITHMS

Algorithmic governance can be complex and opaque not only to the participants but also to its creators, and thus difficult to incorporate into democratic structures where the negotiability of processes remains a pivotal concern. Its importance and its threats will only grow as time goes on. Some efforts at regulating algorithmic governance systems have already begun whose success and reach will become clearer only in the future. For example, there is a call for physicists to participate more actively in AI ethics conversations by improving algorithm "interpretability" and carefully analyzing algorithms and their irregularities to ultimately make them fairer (Thais, 2020).

While the understanding of algorithmic workings is still in early stages, the ultimate goal is to help develop precise ways to present an algorithm's margin of error, representing a new area of research called "uncertainty quantification" (Chen, 2020). In addition to "explainable AI" (Shin, 2021), "value-sensitive algorithm" designs are also proposed by

TABLE 1 Algorithmic governance as a matter of social concern

	State	Market	Lifeworld
		The problem of power	
Surveillance	Loss of privacy rights	Manipulation and information asymmetry	Dominance
	(e.g., protections of the fourth amendment)	(e.g., higher premiums)	(e.g., nanny cams, phone tracking)
		The problem of discrimination	
Bias	Reduced welfare & justice	Reduced opportunities for employment or products	Reduced opportunities
	(e.g., incarceration, equal opportunity housing)	(e.g., higher Annual Percentage Rate)	(e.g., app-mediated screening for race, gender, sex)
		The problem of identification	
Identity	Deviance profiles	Financial profiles, medical profiles	Social media profiles
	(e.g., risk scores)	(e.g., spam, lending, credit score)	(e.g., contextual advertising, political campaigning)

recognizing the "value-ladenness" of algorithm development and its ability to shape human life (Shin et al., 2019). By drawing a possible categorization of AI transparency, Larsson and Heintz (2020) argue for the need to develop a multidisciplinary understanding for the governance of AI in society. Similarly, Shin (2019, 2020) utilizes the matter of transparency to argue for the ways in which self-governance must be enacted in the context of algorithmic responsibility.

There is a call to go beyond the notion of informed consent. Algorithmic systems within a digital economy need to factor in a certain "qualified transparency" that should not demand an individual consumer's awareness regarding algorithmic decision-making and create experiences of "autonomy fatigue" (Larsson, 2018). European legislators have made progress towards substituting the act of "auditing" algorithms for one of "explaining" what they actually do. There is a strong emphasis on how the citizens affected by algorithmic systems must have the right to know how a decision was actually made (Goodman & Flaxman, 2017). It is still uncertain what might constitute a "sufficient" explanation, and more crucially, how such an explanation might be produced by the algorithmic system itself. This stress upon the need for human interpretability within the design of an algorithm also highlights the need for managing the association between the pre-supposed "objectivity" of an algorithm and the biased decisions churned out by them.

7 | CONCLUSION

The goal of this paper was to contribute a general framework to the literature on algorithmic governance in the face of challenges and difficulties regarding the use of algorithms in non-computer science literature. Addressing these challenges, we hope to have provided a clearer analysis of algorithmic governance by situating it within historical, disciplinary, and social contexts.

From within the disciplinary context of the social sciences, we identified "negotiability" as a common thread unifying diverse concerns about opacity, black boxing, discrimination, surveillance, and automated asymmetries in the social sciences. In this context, concerns about algorithmic governance can be summed up as the growing institutional capabilities to move contestable issues to a space of reduced negotiability. It is a deeply relevant issue for governments across the world that seek to improve public welfare systems, the scope for "immediate" negotiability with AI, and democratic engagement with their citizens (Criado et al., 2021).

Within the social context of algorithmic governance, we identified three general areas of concern where the social negotiability of processes is threatened: (1) the threat of unchecked surveillance; (2) the potential problem of social discrimination through an amplification of pre-existing biases in data sets; and (3) the problem of individual identification as we notice in asymmetrical generation of system identities. Different forms of regulation are being imagined and developed to tackle some of these general threats to the social negotiability of processes, as suggested by the emergent literature about the actual and possible regulation of algorithmic systems. A pathway emerges through the proposed "Social Construction of Algorithms" approach (Napoli, 2014), which seeks to further develop our understanding of FATE principles for algorithmic governance (Shin et al., 2019).

Future research may help broaden the theoretical and practical implications of algorithmic governance by identifying and classifying the rapidly rising algorithmic input-output systems in realms as varied as consumption, work, education, welfare, finance, and government. Efforts may be directed at understanding how negotiability varies among different types of algorithmic systems and among different domains. This would help determine how the spaces of negotiation, contestation, and deliberation are threatened in the larger context of equity and equality with implications for how algorithmic systems are created, and the policies or laws that govern them.

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REFERENCES

Alkhatib, A., & Bernstein, M. (2019). Street-level algorithms: A theory at the gaps between policy and decisions. In *Proceedings of the 2019 CHI conference on human factors in computing systems (CHI '19), Glasgow, Scotland, UK, May 2019* (pp. 1–13). Association for Computing Machinery.

Ambrosetti, N. (2015) Algorithmic in the 12th century: The Carmen de Algorismo by Alexander de Villa dei. In: *International conference on the history and philosophy of computing, Pisa, Italy, 8–11 October 2015* (pp. 71–86). Springer.

Anderson, C. (2008, June 23). The end of theory: The data deluge makes the scientific method obsolete. *Wired*. Advance online publication. https://www.wired.com/2008/06/pb-theory/

Aneesh, A. (2006). *Virtual migration: The programming of globalization*. Duke University Press.

Aneesh, A. (2009). Global labor: Algocratic modes of organization. *Sociological Theory*, *27*(4), 347–370. https://doi.org/10.1111/j.1467-9558.2009.01352.x

Aneesh, A. (2015). *Neutral accent: How language, labor, and life become global*. Duke University Press.

Bazazeh, D., & Shubair, R. (2016). Comparative study of machine learning algorithms for breast cancer detection and diagnosis. *In Proceedings of 2016 5th International Conference on Electronic Devices, Systems and Applications (ICEDSA), December 2016* (pp. 1–4). Institute of Electrical and Electronics Engineers.

Benjamin, R. (2019). *Race after technology: Abolitionist tools for the new Jim code*. Polity.

Berkman Klein Center. (2019) What is an algorithm? Available from https://dcrp.berkman.harvard.edu/tool/what-algorithm

Beunza, D. (2019). *Taking the floor: Models, morals, and management in a Wall Street trading room*. Princeton University Press.

Bolukbasi, T., Chang, K. W., Zou, J. Y., Saligrama, V., & Kalai, A. T. (2016). Man is to computer programmer as woman is to homemaker? Debiasing word embeddings. In D. D. Lee, M. Sugiyama, U. V. Luxburg, I. Guyon, & R. Garnett (Eds.), *Advances in neural information processing systems* (Vol. 29, pp. 4349–4357). Curran Associates, Inc.

Buolamwini, J., & Gebru, T. (2018). Gender shades: Intersectional accuracy disparities in commercial gender classification. In *Proceedings of the 1st conference on fairness, accountability and transparency, New York, NY, USA, 23–24 February 2018* (pp. 77–91). Proceedings of Machine Learning Research.

Burnett, C. (2006). The semantics of Indian numerals in Arabic, Greek and Latin. *Journal of Indian Philosophy*, *34*(1–2), 15–30. Springer.

Burrell, J. (2016). How the machine "thinks": Understanding opacity in machine learning algorithms. *Big Data & Society*, *3*(1), 1–12.

Burrell, J., & Fourcade, M. (2021). The society of algorithms. *Annual Review of Sociology*, *47*, 213–237.

Caliskan, A., Bryson, J. J., & Narayanan, A. (2017). Semantics derived automatically from language corpora contain human-like biases. *Science*, *356*(6334), 183–186.

Chen, S. (2020, September 22). To make fairer AI, physicists peer inside its black box. *Wired*. Advance online publication. https://www.wired.com/story/to-make-fairer-ai-physicists-peer-inside-its-black-box/

Cherelus, G. (2016, March 24). Microsoft's AI Twitter bot goes dark after racist, sexist tweets. *Reuters*. Available from https://www.reuters.com/article/us-microsoft-twitter-bot-idUSKCN0WQ2LA

Codagnone, C., Abadie, F., & Biagi, F. (2016). *The future of work in the "sharing economy." Market efficiency and equitable opportunities or unfair precarisation*? Report, Institute for Prospective Technological Studies, Joint Research Centre, European Commission.

Coletta, C., & Kitchin, R. (2017). Algorhythmic governance: Regulating the "heartbeat" of a city using the Internet of Things. *Big Data & Society*, *4*(2). 205395171774241. SAGE Publications Ltd. https://doi.org/10.1177/2053951717742418

Couldry, N., & Mejias, U. A. (2019). *The costs of connection: How data are colonizing human life and appropriating it for capitalism*. Stanford University Press.

Criado, J. I., Sandoval-Almazan, R., Valle-Cruz, D., & Ruvalcaba-Gómez, E. A. (2021). Chief information officers' perceptions about artificial intelligence. *First Monday*, *26*(1).

Danaher, J. (2016). The threat of algocracy: Reality, resistance and accommodation. *Philosophy & Technology*, *29*, 1–24.

Danaher, J., Hogan, M. J., Noone, C., Behan, A., De Paor, A., Felzmann, H., Haklay, M., Khoo, S.-M., Morison, J., Murphy, M. H., O'Brolchain, N., Schafer, B., & Shankar, K. (2017). Algorithmic governance: Developing a research agenda through the power of collective intelligence. *Big Data & Society*, *4*(2), 1–21.

Del Casino, V. J., Jr, House-Peters, L., Crampton, J. W., & Gerhardt, H. (2020). The social life of robots: The politics of algorithms, governance, and sovereignty. *Antipode*, *52*(3), 605–618. https://doi.org/10.1111/anti.12616

Dourish, P. (2016). Algorithms and their others: Algorithmic culture in context. *Big Data & Society*, *3*(2), 1–11.

DuBrin, R., & Gorham, A. E. (2021). Algorithmic interpellation. *Constellations*, *28*(2), 176–191.

Encyclopædia Britannica. (2006). Algorithm. Available from https://www.britannica.com/science/algorithm

Espeland, W. N., & Sauder, M. (2007). Rankings and reactivity: How public measures recreate social worlds. *American Journal of Sociology*, *113*(1), 1–40.

Espeland, W. N., & Stevens, M. L. (2008). A sociology of quantification. A sociology of quantification. *European Journal of Sociology/Archives Européennes de Sociologie*, *49*(3), 401–436.

Eubanks, V. (2018). *Automating inequality: How high-tech tools profile, police, and punish the poor*. St. Martin's Press.

Ferrari, F., & Graham, M. (2021). *Fissures in algorithmic power: Platforms, code and contestation*. Cultural Studies. https://doi.org/10.1080/09502386.2021.1895250

Foucault, M. (1979). *Discipline and punish* (tran. A. Sheridan). Vintage Books.

Fourcade, M., & Healy, K. (2013). Classification situations: Life-chances in the neoliberal era. *Accounting, Organizations and Society*, *38*(8), 559–572.

Fourcade, M., & Healy, K. (2017). Seeing like a market. *Socio-Economic Review*, *15*(1), 9–29.

Geitgey, A. (2014). Machine learning is fun. In: *Adam Geitgey – medium*. Available from https://medium.com/@ageitgey/machine-learning-is-fun-80ea3ec3c471

Gillespie, T. (2014). The relevance of algorithms. In T. Gillespie, T. Boczkowski, & K. Foot (Eds.), *Media technologies: Essays on communication, materiality, and society* (pp. 167–194). The MIT Press.

Gilliom, J. (2006). Struggling with surveillance: Resistance, consciousness and identity. In K. D. Haggerty & R. V. Ericson (Eds.), *The new Politics of surveillance and visibility* (pp. 111–129). University of Toronto Press.

González, R. E., Munoz, R. P., & Hernández, C. A. (2018). Galaxy detection and identification using deep learning and data augmentation. *Astronomy and computing*, *25*, 103–109.

Goodman, B., & Flaxman, S. (2017). European Union regulations on algorithmic decision-making and a "right to explanation". *AI Magazine*, *38*(3), 50–57.

Gorwa, R., Binns, R., & Katzenbach, C. (2020). Algorithmic content moderation: Technical and political challenges in the automation of platform governance. *Big Data & Society*, *7*(1), 2053951719897945.

Graham, S., & Wood, D. (2003). Digitizing surveillance: Categorization, space, inequality. *Critical Social Policy*, *23*(2), 227–248.

Haggerty, K. D. (2006). Tear down the walls: On demolishing the panopticon. In D. Lyon (Ed.), *Theorizing surveillance* (pp. 37–59). Willan Publishing.

Heidegger, M. (1977). *The question concerning technology, and other essays*. Garland Pub.

Hopcroft, J. E. (1984). Turing machines. *Scientific American*, *250*(5), 86–98.

Husserl, E. (1975). *Experience and judgment*. Northwestern University Press.

Introna, L. D. (2016). Algorithms, governance, and governmentality: On governing academic writing. *Science, Technology & Human Values*, *41*(1), 17–49.

Irani, L. (2013). The cultural work of microwork. *New Media & Society*, *17*(5), 720–739.

Irani, L. (2015). Difference and dependence among digital workers: The case of Amazon Mechanical Turk. *South Atlantic Quarterly*, *114*(1), 225–234.

Irani, L. C., & Silberman, M. S. (2013). Turkopticon: Interrupting worker invisibility in amazon mechanical turk. In *Proceedings of the SIGCHI conference on human factors in computing systems, Paris, France, April 2013* (pp. 611–620). Association for Computing Machinery.

Just, N., & Latzer, M. (2017). Governance by algorithms: Reality construction by algorithmic selection on the internet. *Media, Culture & Society*, *39*(2), 238–258.

Kasapoglu, T., Masso, A., & Calzati, S. (2021). Unpacking algorithms as technologies of power: Syrian refugees and data experts on algorithmic governance. *Digital Geography and Society*, *2*(2), 100016.

Katzenbach, C., & Ulbricht, L. (2019). Algorithmic governance. *Internet Policy Review*, *8*(4), 1–18.

Kitchin, R. (2017). Thinking critically about and researching algorithms. *Information, Communication & Society*, *20*(1), 14–29.

Larsson, S. (2018). Algorithmic governance and the need for consumer empowerment in data-driven markets. *Internet Policy Review*, *7*(2), 1–13.

Larsson, S., & Heintz, F. (2020). Transparency in artificial intelligence. *Internet Policy Review*, *9*(2), 1–16.

Lehman, C. R., Hammond, T., & Agyemang, G. (2018). Accounting for crime in the US: Race, class and the spectacle of fear. *Critical Perspectives on Accounting*, *56*, 63–75.

Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, *18*(8), 2674.

Lohr, S. (2018, February 9). *Facial recognition is accurate, if you're a white guy*. The New York Times. Available from https://www.nytimes.com/2018/02/09/technology/facial-recognition-race-artificial-intelligence.html

Luhmann, N. (1995 [1984]) *Social systems*. Stanford University Press.

Lyon, D. (2007). *Surveillance studies: An overview*. Polity Press.

MacDonald, T. W. (2021). "How it actually works": Algorithmic lore videos as market devices. *New Media & Society*. 146144482110214. SAGE Publications. https://doi.org/10.1177/14614448211021404

McCarthy, M. T. (2015). Toward a free information movement. *Sociological Forum*, *30*(2), 439–458.

Moats, D., & Seaver, N. (2019). "You social scientists love mind games": Experimenting in the "divide" between data science and critical algorithm studies. *Big Data & Society*, *6*(1), 1–11.

Napoli, P. M. (2014). Automated Media: An institutional theory perspective on algorithmic Media production and consumption. *Communication Theory*, *24*(3), 340–360.

Neyland, D. (2016). Bearing account-able witness to the ethical algorithmic system. *Science, Technology & Human Values*, *41*(1), 50–76.

Noble, S. U. (2018). *Algorithms of oppression: How search engines reinforce racism*. NYU Press.

Pasquale, F. (2015). *The black box society: The secret algorithms that control money and information*. Harvard University Press.

Petzold, C. (2008). *The annotated Turing: A guided tour through Alan Turing's historic paper on computability and the Turing machine*. Wiley Publishing.

Plantin, J. C., Lagoze, C., Edwards, P. N., & Sandvig, C. (2018). Infrastructure studies meet platform studies in the age of Google and Facebook. *New Media & Society*, *20*(1), 293–310.

Poechhacker, N., & Kacianka, S. (2021). Algorithmic accountability in context. Socio-technical perspectives on structural causal models. *Frontiers in Big Data*, *3*, 519957.

Porter, T. M. (1995). *Trust in numbers: The pursuit of objectivity in science & public life*. Princeton University Press.

Porter, T. M., & Haggerty, K. D. (1997). Trust in numbers: The pursuit of objectivity in science & public life. *Canadian Journal of Sociology*, *22*(2), 279.

Raji, I. D., Gebru, T., Mitchell, M., Buolamwini, J., Lee, J., & Denton, E. (2020). Saving face: Investigating the ethical concerns of facial recognition auditing. In *Proceedings of the AAAI/ACM conference on AI, ethics, and society, New York, NY, USA, 7–8 February 2020* (pp. 145–151). Association for Computing Machinery.

Richardson, R., Schultz, J. M., & Crawford, K. (2019). Dirty data, bad predictions: How civil rights violations impact police data, predictive policing systems, and justice. *New York University Law Review Online*, *94*, 15–55.

Rosenblat, A., & Stark, L. (2016). Algorithmic labor and information asymmetries: A case study of Uber's drivers. *International Journal of Communication*, *10*, 3758–3784.

Rouvroy, A., & Berns, T. (2013). Algorithmic governmentality and prospects for emancipation: Disparateness as a precondition for individuation through relationships? *Réseaux*, *177*, 163–196.

Sadowski, J. (2020). *Too smart: How digital capitalism is extracting data, controlling our lives, and taking over the world*. MIT Press.

Sandvig, C., Hamilton, K., Karahalios, K., & Langbort, C. (2014). Auditing algorithms: Research methods for detecting discrimination on internet platforms. In *"Data and discrimination: Converting critical concerns into productive inquiry," a preconference at the 64th annual meeting of the International Communication Association, Seattle, WA, USA, 22 May 2014* (pp. 1–22). International Communication Association.

Seaver, N. (2014) On reverse engineering. In: *Anthropology and algorithms – medium*. Available from https://medium.com/anthropology-and-algorithms/on-reverse-engineering-d9f5bae87812

Seaver, N. (2017). Algorithms as culture: Some tactics for the ethnography of algorithmic systems. *Big Data & Society*, *4*(2), 1–12.

Seipel, M. B. (2020). Robo-bureaucrat and the administrative separation of powers. *Cardozo Law Review. De Novo*, 99–111.
Shin, D. D. (2019). Toward fair, accountable, and transparent algorithms: Case studies on algorithm initiatives in Korea and China. *Javnost-The Public*, *26*(3), 274–290.
Shin, D. D. (2020). User perceptions of algorithmic decisions in the personalized AI system: Perceptual evaluation of fairness, accountability, transparency, and explainability. *Journal of Broadcasting & Electronic Media*, *64*(4), 541–565.
Shin, D. D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human-Computer Studies*, *146*, 102551.
Shin, D. D., Fotiadis, A., & Yu, H. (2019). Prospectus and limitations of algorithmic governance: An ecological evaluation of algorithmic trends. *Digital Policy, Regulation and Governance*, *21*(4), 369–383.
Shorey, S., & Howard, P. (2016). Automation, big data and politics: A research review. *International Journal of Communication*, *10*, 5032–5055.
Simon, B. (2005). The return of panopticism: Supervision, subjection, and the new surveillance. *Surveillance and Society*, *3*(1), 1–20.
Solove, D. J. (2004). *The digital person: Technology and privacy in the information age*. NYU Press.
Suchman, L. (2020). Algorithmic warfare and the reinvention of accuracy. *Critical Studies on Security*, *8*(2), 175–187.
Sweeney, L. (2013). Discrimination in online ad delivery. *Queue*, *11*(3), 10–29.
Thais, S. (2020). Physicists must engage with AI ethics, now. *Physics*, *13*, 107.
Vimalkumar, M., Gupta, A., Sharma, D., & Dwivedi, Y. K. (2021). Understanding the effect that task complexity has on automation potential and opacity: Implications for algorithmic fairness. *AI Fairness, Trust, and Ethics*, *13*(1), 104–129.
Weinberger, D. (2017, April 18). Our machines now have knowledge we'll never understand. *Wired*. Advance online publication. https://www.wired.com/story/our-machines-now-have-knowledge-well-never-understand
Wieringa, M. (2020). What to account for when accounting for algorithms: A systematic literature review on algorithmic accountability. In *Proceedings of the 2020 ACM conference on fairness, accountability, and transparency, Barcelona, Spain, January 2020* (pp. 1–18). Association for Computing Machinery.
Wilcox, L. (2017). Embodying algorithmic war: Gender, race, and the posthuman in drone warfare. *Security Dialogue*, *48*(1), 11–28.
Wood, A. J., Graham, M., Lehdonvirta, V., & Hjorth, I. (2019). Networked but commodified: The (dis)embeddedness of digital labour in the gig economy. *Sociology*, *53*(5), 931–950.
Yeung, K. (2018). Algorithmic regulation: A critical interrogation. *Regulation & Governance*, *12*(4), 505–523.
Zarsky, T. (2014). Understanding discrimination in the scored society. *Washington Law Review*, *89*(4), 1375–1412.
Zarsky, T. (2016). The trouble with algorithmic decisions: An analytic road map to examine efficiency and fairness in automated and opaque decision making. *Science, Technology & Human Values*, *41*(1), 118–132.
Zuboff, S. (2019). *The age of surveillance capitalism: The fight for a human future at the new Frontier of power*. Public Affairs.

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