What Data Can Do: A Typology of Mechanisms

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This article offers an analytical framework for understanding the effects of data on the social world. Specifically, I ask: What happens when new data —digital or not—is introduced in a given context? Drawing on a mix of historical and contemporary examples, I provide a typology of 5 mechanisms: tracking, homogenizing, triaging, nudging, and valuating. I then demonstrate how this framework can change how we understand two empirical cases involving data-driven software programs, one in Web journalism and the other in criminal justice. Based on this analysis, the article makes three main points. First, at a time of rapid technological development, we should pay particular attention to what is not changing with digitization. Second, we need further theoretical integration in the rapidly growing field of critical data studies. Third, I suggest that the umbrella concept of "data" should be broken down into smaller and more manageable components depending on the mechanisms scholars are interested in studying.

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In 1948, Alfred Kinsey and his colleagues published their report *Sexual Behavior in the American Male*, which received copious media coverage in the United States. Following the publication, some readers strongly disagreed with the numbers. As an anonymous writer explained in a letter to Kinsey, "I have lived with one woman for 46 years and I do not agree with your findings . . . when you show as one magazine reports that 62% of adult women practice masturbation—you're nuts" (Igo, 2008, p. 255). Yet people's representations of sex also evolved due to the sheer availability of these statistics. As anthropologist Margaret Mead wrote at the time, "Until the Kinsey report was published, people hadn't known whether they should have more sex or less. Now many are rushing to buy the book just to look themselves up" (Igo, 2008, p. 262). According to historian Sarah Igo, this change in how people understood their sexual lives was largely due to the statistical and quantitative nature of Kinsey's data: "The figures Kinsey unleashed carried a great deal of weight *because* they were numbers: spare, clear, and direct" (Igo, 2008, p. 247, emphasis in original).

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As the Kinsey example reveals, data—digital or not—often has strong effects on the representations and identities of the people whose lives and activities are being quantified. The repercussions of the Kinsey report on how Americans made sense of sex —and, through sex, of their own practices—introduces some of the central questions for this article. Data and data-driven systems increasingly mediate large parts of our lives, from how we stay informed to what we buy, how we vote, and how we work. Data also occupies an important place in our current representations. From mythologies about the higher intelligence of "big data" (boyd & Crawford, 2012) to the promise of "artificial intelligence" or the rise of algorithmic "imaginaries" (Bucher, 2016), we project multiple and complex meanings onto digital metrics.

Given how ubiquitous metrics have become in our lives, this article poses the question: What happens when data is introduced in a given context? Specifically, how does the introduction of data affect the people and entities being quantified? The article offers a theoretical framework for thinking about the social effects of data. Specifically, I provide a typology of mechanisms by which data can affect its "subjects"—that is, the people and activities undergoing quantification. The concept of mechanism comes from analytical sociology, where mechanisms have been defined as "constellations of entities and activities that are linked to one another in such a way that they regularly bring about a particular type of outcome" (Hedstrom, 2005, p. 11). In line with recent interpretations, I consider the concept of mechanism to encompass a wide range of entities and activities, from individual actors to technological artifacts, discourses, routines, organizational dynamics, and field structures (Knight & Reed, 2019). For the purposes of this analysis, I define "data" as any kind of numerical information that can be used for reference, analysis, calculation, and computer operations.

With these definitions in hand, the article begins by offering a brief overview of the history of data in contemporary societies. Then, drawing on a mix of historical and contemporary examples, I provide a typology of five mechanisms through which data operate in the social world: tracking, homogenizing, triaging, nudging, and valuating. I put this framework to use drawing on two empirical cases involving data-driven software programs: Chartbeat, in Web journalism, and COMPAS, in criminal justice. The article concludes by discussing three key implications of this analysis for the burgeoning field of critical data studies. First, whereas existing research overwhelmingly centers on computational technologies, I argue that focusing on data affords a different time frame, in turns enabling researchers to focus on what is not changing when new forms of data are deployed in the social world. Second, I call for further theoretical integration in critical data studies and argue that developing a layer of "middle-range" theories (Merton, 2007) is crucial to map the concrete impact of digital systems across social contexts. Third, I suggest that the umbrella concept of "data" may need to be broken into smaller, more manageable components, allowing a more precise lens for scholars to study different mechanisms.

Data, Old and New

Data is defined here as any kind of numerical information that can be used for reference, analysis, calculation, and computer operations. The word "datum" started being used in the 17th century to describe scientific evidence. According to the *Oxford English Dictionary*, the plural form of the noun, "data," was first used in the 1940s to refer to computer operations.[2]

Drawing on this definition, it is important to note that data is never naturally "out there": it is always collected, analyzed, and distributed for specific purposes. To borrow the expression of Lisa Gitelman (2013), "raw data is an oxymoron." In this view, data is always collected by humans or machines, for humans or machines. It can also be digital or analog. Although this article primarily focuses on digital data, it establishes parallels with a longer history—stretching back long before the emergence of computers—of what I call "analog data," meaning data gathered and processed without the use of digital technologies.

Recent decades have witnessed an exponential multiplication of digital data being collected, stored, and analyzed in various fields and sectors. A first explanation for this development relates to what is often described as the "affordances" of the Internet—that is, the range of activities enabled by digital technologies in terms of data capture, storage, and analysis. In the words of Shoshana Zuboff (2015), computer-mediated activities differ from previous waves of technological innovation because "when it comes to information technology, automation . . . not only imposes information (in the form of programmed instructions), but it also *produces* information" (p. 76, emphasis added). Given the rapid development of digital information systems, it has become easier than before to collect automatically the behavioral data produced through the overwhelming number of routine social activities that now take place online (Agre, 1994 Cukier & Mayer-Schönberger, 2013). The expansion of cloud computing and machine learning algorithms has made it possible to store, mine, and use these digital traces to personalize users' online experiences. It also enabled the development and consolidation of a complex economic infrastructure dedicated to the monetization of this behavioral data (Turow, 2011; Zuboff, 2019).

Yet it would be a mistake to focus exclusively on these recent technological developments when analyzing the impact of data in contemporary societies. The trust we put in numbers as transparent and objective measurements of the "real" world has a long history (Espeland & Stevens, 1998; Porter, 1996). Broader cultural and institutional factors have legitimized data as a valued way of representing the world and making decisions about it. Historians of science have analyzed the emergence of widespread beliefs in the higher value of "mechanical objectivity" and the aura of rationality that have accompanied numbers over the past three centuries (Daston & Galison, 2007). They retraced the development of aesthetic and moral principles that make us see data as "valuable and beautiful" (Halpern, 2015, p. 5). Over time, these positive meanings attached to numbers and data moved beyond the realm of science and engineering, making their way into public administration, nonscientific institutions, and everyday life (Igo, 2008; Porter, 1996).

A second and related thread of analysis ties the institutionalization of numbers and their growing legitimacy to economic production and to the cultural frames supporting the complexification of capitalism. Thus, social scientists have highlighted the longer arc of rationalization and quantification techniques. Key episodes in this long history include the rise of double-entry bookkeeping (Carruthers & Espeland, 1991; Weber, 1978), the birth of public statistics (Desrosières, 2002), the commodification and monetization of domains previously protected from quantitative appraisal (Marx, 1992; Simmel, 2011; Zelizer, 2010), the

[2] In spite of the original plurality of "data," I follow common usage of the singular form of the noun in this article.

role of numbers in sustaining colonialism and slavery (Browne, 2015), the development of quantitative measurements designed to increase worker productivity during and after the industrial revolutions (Edwards, 1979; Kellogg, Valentine, & Christin, 2020), and the multiplication of data-driven standards to support complicated logistics and supply chains (Star & Bowker, 2000). More recently, economic sociologists have pointed to the role of economics and ideologies of market fundamentalism in promoting numbers as well as quantitative frameworks, including cost–benefit analysis and mathematical equations, as fair and efficient assessments of value (Espeland & Stevens, 1998; Fourcade, 2011).

This brief overview clarifies two main aspects of data. First, data has a long history—one that predates the development of computer technologies. This suggests that whereas the scholarly focus on recent computational development is warranted, more attention needs to be paid to the continuity between analog and digital forms of quantification. Second, one cannot rely on purely technological or economic explanations when analyzing the predominance of data in contemporary societies: Cultural and institutional forces also played a central role in legitimizing data in various institutional domains. We will return to these points later.

A Typology of Mechanisms

In this section, I identify five key mechanisms through which data can affect the people and entities being quantified: tracking, homogenizing, triaging, nudging, and valuating. Because data collection has a longer history than the Internet, all the mechanisms delineated here apply both to analog and digital cases. Table 1 provides an overview of the five mechanisms, related concepts, data ideal types, analog and digital examples, and main references.

Before introducing these five mechanisms, however, two notes of caution are needed. First, the list of mechanisms presented here is not exhaustive: The five processes delineated below can and should be expanded. They were selected because they can help make sense of various cases across sectors, but there are certainly pathways that do not fit within this framework and would deserve more careful attention. Second, the mechanisms are likely to overlap in real-world examples: Two or more of them may characterize any given data process in action. This applies not only to the cases analyzed in the second half of the article but also to the examples illustrating each mechanism. In spite of this empirical overlap, I argue that these mechanisms should remain analytically distinct because they do not mobilize the same entities and do not bring about the same outcomes.

Table 1. A Typology of Mechanisms.

Mechanism	Related concepts	Data ideal types	Examples	Key References
Tracking	Privacy	Metadata	Bertillon system	Lyon
	Surveillance	Big data	Google/Facebook	Zuboff
	Internalization	Biometrics	NSA/ALPR	Brayne
Homogenizing	Commensuration	Price	Law school rankings	Espeland & Sauder
	Comparison	Ranking	Yelp/TripAdvisor	Orlikowski & Scott
	Mimetism	Rating	Kinsey survey	Igo
Triaging	Sorting	Algorithm	Online ads	O'Neil
	Bias	Artificial	Credit scores	Eubanks
	Inequality	Intelligence	Risk-assessment tools	Barocas & Selbst
Nudging	Reactivity	Indicator	KPI	Thaler & Sunstein
	Affordance	Metric	Uber	Muller
	Incentives	Measurement	On-demand platforms	Rosenblat
Valuating	Visibility	Index	Corruption barometer	Porter
	Articulation	Barometer	U.S. Trafficking in	Fourcade
	Legitimacy	Report	Persons Report	Merry

Tracking

The first mechanism, tracking, can be defined as the monitoring of human behavior and activities. Tracking data is typically collected at the individual level—it primarily documents individual characteristics (sex, age, income, etc.) and behaviors (location, time, activity, etc.). Tracking primarily operates through internalization: People who are being tracked tend to monitor themselves and normalize their behavior to avoid standing out.

Tracking initiatives started well before the emergence of digital technologies. For instance, in 1879, Alphonse Bertillon—a French police officer born into a family of statisticians—created a broad system of criminal identification that relied on systematic records of anthropometric measurements (height, foot size, weight, "mug shots," etc.) designed to help policemen determine whether suspects in custody had been involved in previous crimes. In that case as in many others, data was first collected as a documentation perceived to be valuable in and of itself before being used for more targeted goals such as incapacitation and the prevention of recidivism (Kaluszynski, 2001).

In recent decades, the development of ubiquitous computing and the recording affordances of "smart machines" (Zuboff, 2015) took tracking to new levels. Cookies, beacons, and related technologies made it possible to capture fine-grained information about Internet users' browsing histories and behaviors (Agre, 1994).

Following the development of server-based data collection, as well as transformations over time in the relations among advertisers, media companies, and content producers, online advertising turned to individual and behavioral targeting, which led to the emergence of a growing number of firms engaging in data brokerage, ad exchange, and real-time advertising auctions (Turow 2011). The result is a complex ecosystem of platforms and intermediaries, now largely dominated by Google, Facebook, Amazon, and Apple, controlling the data being collected in real time about Internet users' sociodemographic characteristics, networks, and behaviors. This is what Zuboff (2019) analyzes as the new form of "surveillance capitalism."

In addition to commercial tracking, governmental tracking also expanded dramatically. In the wake of the 9/11 terrorist attacks, the National Security Agency (NSA) collected billions of records, logging phone calls and texts from telecommunication companies—including 534 million call-detail records in 2017 (Savage, 2018). The NSA scandal may seem exceptional, but it is only the tip of the iceberg in terms of governmental tracking: Many other tracking initiatives emerged at the local level, often fueled by similar antiterrorist justifications and sources of funding. For instance, police departments now routinely rely on automatic license plate readers (ALPR) as well as data integration technologies that integrate disparate type of tracking data on a single platform to help with ongoing and future investigations (Brayne, 2017).

How does this multiplication of commercial and governmental tracking initiatives affect the people being tracked? Two frameworks have emerged to make sense of this question. A first approach frames tracking as an encroachment on privacy rights. Against the argument that people who have "nothing to hide" do not need to worry about tracking, legal scholars argue that tracking comes with a "chilling effect" (Solove, 2015)—one that can discourage meaningful social participation and democratic debate. A second approach understands tracking as a form of surveillance and control (Foucault, 1977; Haggerty & Ericson, 2003). In the words of David Lyon (2018), surveillance encompasses all "the operations and experiences of gathering and analyzing personal data for influence, entitlement and management" (p. 6). Here, the emphasis is on tracking as a specific kind of power that operates from a distance.

Both in the privacy and surveillance frameworks, an essential pathway through which data affects people is internalization. When personal data is gathered, the actors who are being tracked tend to monitor themselves and adjust their behavior. People do not know the specific ways in which data is recorded or analyzed: Opacity plays an essential role in the tracking process. Yet people know enough to be aware that their data may be used against them. As a result, they normalize their activities to avoid standing out. Note, however, that internalization is never complete. People can be unaware that they are being tracked; they can also find ways to minimize tracking through various obfuscation strategies (Brunton & Nissenbaum, 2015).

Homogenizing

The second mechanism through which data operates, homogenizing, refers to the process through which units become more similar across time and space. Homogenization as a mechanism in turn relies on commensuration and comparison through metrics.

Data travels well across time and space. This is because by turning qualities into unidimensional metrics, data tends to abolish complex contextual features (Espeland & Stevens, 1998; Fourcade, 2011).

The canonical medium for making things comparable or "commensurable," in Espeland and Stevens' (1998) formulation, is money, which Simmel (2011) described as the "great leveler." From Marx (1992) to Weber (1978), classical scholars noted the effects of prices—a key type of data—in making things comparable. In the process, they identified an important aspect: Data boils down essential differences among entities into mere differences in magnitude. In effect, data erases fundamental marks of the entities they represent, even as it facilitates comparisons—a transformation often criticized as leading to a loss of authenticity. In cases where the quantification process touches on an identity or property that is held sacred, this raises fears that authenticity is being destroyed by the "hostile" force of metrics (Zelizer, 2010).

Beyond prices, other types of data entail similar processes of commensuration. The case of school rankings gives a sense of how data-driven homogenization functions. Starting in the 1990s, the *U.S. News and World Report* started publishing quantitative rankings of the best law schools in the United States (Espeland & Sauder, 2016). Over time, these rankings became highly influential, shaping students' decisions while influencing donations and affecting the schools' financial resources. The rankings made it easier for students to compare different law schools, but also erased important differences among schools. For instance, law schools that historically had a mission of serving underprivileged or minority populations did not see these values reflected in the rankings: their numbers were compared with those of schools that did not have similar goals. The perception of the object being quantified became more homogeneous after ranking data was introduced.

Similar pressures toward homogenization play out in digital cases. Take the example of the hospitality industry: Crowdsourced platforms such as TripAdvisor or Expedia provide hotels with a flow of user-generated data about their performance. Customers can review hotels through ratings such as stars and numbers in a range of categories (service, room quality, etc.); they can also post comments and pictures. A boutique hotel with 10 rooms and a chain hotel with several hundred rooms can have similar quantitative rankings and ratings, even if the experience of staying in the two places is hardly comparable. As a result, workers often complain that these new metrics do not fairly represent their "core" identity. Yet the multiplication of online ratings also transformed the rules of the game: Hotel managers often adopted similar practices (such as providing a similar range of services to their guests) to score well and be visible on the platform (Orlikowski & Scott, 2014, p. 881; see also Ticona & Mateescu, 2018).

Triaging

The third mechanism through which data operates is triaging, or sorting things according to specific criteria of quality or urgency. The concept of triage comes from medicine, where it describes the degree of urgency assigned to treating different categories of patients. Yet triaging goes well beyond health care. In many organizations, data-driven triage is now used to sort people, objects, and situations into specific categories that are given predefined treatments. Data-driven triage in turn often reproduces bias, reinforcing inequalities among the people being classified.

Data-driven triage usually stems from a desire to standardize a given field of activity: In most cases, the turn to triage stems from a belief in the higher efficiency, objectivity, and reliability of mechanical decision making compared with subjective judgment (Timmermans & Esptein, 2010). Take the case of criminal sentencing in the United States: The 1984 Sentencing Reform Act created mandatory sentencing guidelines that constrained the range of punishments that judges could adopt based on the sentencing tables. Based on a defendant's criminal history (quantified into "criminal history points" ranging from 0 to 13+) and type of offense (categorized into 43 "offense levels"), the sentencing tables defined sentencing "zones" within which the length of incarceration had to be located. From the start, the sentencing guidelines were motivated by the desire to make criminal sentencing more consistent and objective through a standardized triaging mechanism, though their effects were not necessarily in line with these motivations (Espeland & Vannebo, 2007).

In recent decades, the amount of data-driven triage has increased exponentially, in large part due to the development of more sophisticated information systems and computational procedures. Algorithmic triage has become particularly important in institutions with scarce resources that need to be carefully allocated—from social services to hospitals, police departments, and public schools (Brayne, 2017; Eubanks, 2017; O'Neil, 2016). Yet such data-driven procedures have been found to reproduce and even reinforce social inequalities. This stems from what is often called a "garbage in, garbage out" process: Because the data used to train the algorithms is itself shaped by long histories of structural inequality and discrimination (Cottom, 2017), triaging algorithms mechanically reproduce these historical biases in their search for patterns. Drawing on metaphors of "weapons of math destruction" (O'Neil, 2016) and "automated inequality" (Eubanks, 2017), scholars have argued for in-depth auditing—and, in some cases, for the outright elimination—of algorithmic triage.

In addition to low-resource institutions, data-driven triage is also used in situations where the amount of data to be processed and the number of decisions to be made are too high for individual decision making. Prominent cases include high-frequency trading (MacKenzie, 2018), online advertising delivery (Sweeney, 2013), search engine queries (Noble, 2018), online content sorting (such as social media platforms' news feeds; Gillespie, 2014), and credit scoring (Fourcade & Healy, 2016). In all of these cases, complex computational procedures—often machine-learning algorithms—handle massive and constantly expanding amounts of digital data, classifying them and submitting them to a given "treatment." Thus, stocks presenting specific features at a given time point will be bought or sold; the eyeballs of Internet users with predefined sociodemographic and behavioral characteristics will be auctioned off and shown a given advertisement online; and a social media post with a specific author and content will be displayed on top of a user's newsfeed.

Here, again, problems of bias and disparate impact abound (Barocas & Selbst, 2016). For instance, the automated delivery of online advertising was shown to be more likely to suggest the term "arrested" for African American–sounding first names than for White-sounding first names (Sweeney, 2013). Similarly, men are more likely than women to see ads for high-paying jobs; low-income populations are more likely than middle-class users to see ads for for-profit colleges; and hiring algorithms tend to discriminate against women. In addition to the "garbage in, garbage out" explanation outlined above, machine-learning algorithms pick up on emergent patterns of discrimination. Thus, if more Internet users click on an advertising with the mention "arrested" when they search for African American–sounding first names, search engines' advertising algorithms are more likely to display such ads in the future. Such automated processes end up reinforcing existing inequalities and biases in the treatment and representations of minority groups (Noble, 2018).

Nudging

The fourth mechanism, nudging, refers to situations where data is mobilized to make people change their behaviors in ways that add some kind of value (broadly defined) to their activities. For instance, data can be used to incentivize workers to act in a given way—one that is considered to be preferable, either because it is economically more profitable or because it is more highly valued by the people in charge. A key aspect of this mechanism is what Espeland and Sauder (2016) call reactivity, namely the idea that people change their behavior when being measured and quantified.

Although Richard Thaler and Cass Sunstein (2008) popularized the concept of nudge relatively recently, data-driven nudging—which in many cases could better be described as a not-so-gentle shoving—has a long history in the workplace, first during the industrial revolution and later in the aftermath of Taylorism. As studies of factory floors have shown, the productivity of workers has always been carefully evaluated, directed, and disciplined (Burawoy, 1979; Edwards, 1979). Engineers took this monitoring to a new level at the turn of the 20th century through the "scientific management of work" and related initiatives based on a mix of automation, financial incentives based on individual outputs, and the identification of efficient practices through careful measurements.

Since the 1930s, incentive-based management has grown exponentially. Recent developments include the spread of key performance indicators (KPIs); the multiplication of data-driven software suites such as Salesforce, for management and customer service; as well as the institutionalization of performance and financial ratings for firms. Beyond the for-profit sector, processes of data-driven nudging have also been deployed in fields where the value of the output being produced is more complicated to measure. For instance, scholars have analyzed the uses and misuses of performance indicators in public schools (O'Neil 2016), international organizations (Davis, Fisher, Kingsbury, & Merry, 2012), and public administration (Porter, 1996).

Digital nudging is even more pervasive. Online data is frequently used to manage, incentivize, and control workers' production, especially when their work is mediated through digital platforms (Kellogg et al., 2020). For instance, Rosenblat (2018) shows how Uber uses frequent algorithmic nudges to influence its drivers. These nudges include surge pricing predictions, notification pushes, and weekly performance reports. Based on this data, Uber encourages drivers to work longer hours ("Make more money, don't stop now!") as well as adjust their behaviors to maximize client satisfaction (Rosenblat, 2018; see also Shestakofsky, 2017). Similarly, platforms for on-demand care workers encourage them to complete their profiles and report their earnings to the Internal Revenue Service through specific interfaces and design choices on the platform (Ticona & Mateescu, 2018).

Yet it would be mistaken to assume that nudges are always successful. In fact, data-driven nudging often fails. Actors develop many strategies of resistance, including foot-dragging, gaming, and open critique (Christin, 2017). For example, several scandals broke out about how public school teachers "creamed" and "cheated" on their students' standardized examinations to receive additional resources (Muller, 2017). Similarly, the Internet is full of actors and companies that find ways to "optimize" (which often means manipulate) search engine and social media metrics to gain visibility (Petre, Duffy, & Hund 2019; Ziewitz, 2019).

Interestingly, many of these "gaming" strategies can lead to homogenizing. This is what happened in the case of law schools when they started gaming the *U.S. News & World Report* rankings, as we discussed above (Espeland & Sauder, 2016). That said, nudging and homogenizing remain analytically distinct mechanisms. For instance, there can be homogenizing without nudging. In the case of law schools, it is reasonable to assume that *U.S. News & World Report* did not plan to nudge law schools in a particular direction; instead, they justified the creation of the rankings as a means to provide more information to prospective students (and, in the process, to increase their circulation figures).

Valuating

The last mechanism, valuating, refers to the ways in which data can increase the value and legitimacy of the people and entities it represents. The introduction of new data often changes the dynamics of valuation and evaluation at stake in a given social context (Lamont, 2012). In some cases, data is created for precisely that purpose: the impetus behind data collection is to make the things and people being measured more visible. Indeed, quantification is often mobilized by social groups unsatisfied by the status quo to amplify their claims (Porter, 1996).

Why is data associated with valuation? A first pathway is institutional: Creating data takes a lot of work. In particular, coming up with meaningful and reliable measurements that match existing standards and can travel across organizations and systems requires time and effort (Desrosières, 2002; Star & Bowker, 2000). Distinct constituencies often disagree about what is being measured, how, and why (Fourcade, 2011). Resolving such differences requires entrepreneurship and political skill. Thus, once data is created, it benefits from the invisible institutional work that went into its creation. Consequently, data often acquires visibility beyond the place where it originated. Second, as we discussed earlier, data often benefits from an aura of rationality and scientific credibility that gives it a particular worth (Daston & Galison, 2007). Thus, when numbers are introduced, they often trump other types of criteria in anchoring and shaping individual decision making. As a result, the entities being represented through data become more visible than their nonquantified counterparts.

Take the example of social movements and advocacy groups, which have long relied on quantification to make their concerns more legitimate and facilitate the institutionalization of their cause. One can think of the development of pollution ratings (Sharkey & Bromley, 2015) or the rise of corporate social responsibility ratings. Nongovernmental and international organizations also rely on metrics to measure entities that are notoriously hard to define and assess. For instance, Transparency International, a nongovernmental organization, promotes several anticorruption measurements—including the Global Corruption Barometer and the Bribe Payers Index—that have become important indicators in the structuration of the field of anticorruption policies. Complex (and contested) statistical constructs such as the World Happiness Report or the U.S. Trafficking in Persons Report (Merry, 2016) also make the entities being represented legitimate in political debates, both at the national and global levels.

Two Empirical Examples

This section puts the previous typology to use by examining several empirical examples through the lens of the five mechanisms delineated above. Specifically, I focus on two digital cases: Chartbeat, a Web analytics software program used in Web newsrooms; and COMPAS, a predictive risk-assessment tool used in criminal courts. The examples were chosen to present significant variation in terms of scale, kind of data, and motivation behind the technology (see Christin, 2017). Table 2 provides an overview of how the five mechanisms apply to the two cases.

Table 2. Empirical Examples.

	Tracking	Homogenizing	Triaging	Nudging	Valuating
Chartbeat	Yes	Yes	No	Yes	Yes
COMPAS	Yes	No	Yes	No	Yes

Chartbeat in Web Journalism

When the news moved online, marketing departments started using server-based data to assess the preferences of their readers. Editorial departments followed suit and started to rely on analytics software programs providing fine-grained audience data for editorial use. Chartbeat is the most popular of these programs: the dashboard displays real-time data to journalists and editors about the number of concurrent visitors, the average time spent by readers on each article, the number of likes, shares, and tweets, as well as rankings of the most popular articles on the website.

From a design perspective, the primary "subjects" of Chartbeat (i.e., the people primarily concerned by this technology of quantification) are the journalists themselves: The software program collects information about online users, not to monitor readers, but instead for the explicit purpose of managing the popularity of news articles and their authors—that is, Web journalists. Thus, I examine the effects of the software program on journalists, not readers.

Given this information, how does Chartbeat affect Web journalists? First, Chartbeat clearly works as a tracking technology: It monitors the popularity of journalists' stories. This in turn is a good case of "refractive surveillance" (Levy & Barocas, 2018): Data recorded about one group (e.g., readers) is repurposed over time to control another group (e.g., workers). Journalists in turn often internalize this pressure, although their reactions depend on the newsroom under consideration (Christin, 2018; Petre, 2015).

Second, the software program clearly has homogenizing effects: Whereas journalists in print newsrooms traditionally relied on the assumption that articles were incomparable across categories (section, type of article, length), Web analytics make it possible to directly compare the popularity of stories about different topics. In most newsrooms, journalists have access to these metrics. As a result, mimetic practices—often labelled "clickbait"—have emerged.

Third, Chartbeat works as a nudging technology: In most newsrooms, journalists are encouraged—implicitly or explicitly—to maximize traffic numbers by tweaking headlines and picking topics that appeal to the readers' interest. For instance, traffic targets (both individual and collective) structured the work dynamics of Gawker Media newsroom, where editors and writers alike describe the process as "stressful" (Petre, 2015).

Chartbeat also functions as a valuating technology: It makes the entity being measured—the popularity of articles—a more prominent and legitimate set of criteria guiding editorial decisions in Web newsrooms. This is particularly striking in comparison to print newsrooms, where journalists traditionally ignored feedback from their readers (Gans, 1979).

That said, Chartbeat is not a triaging technology: There is no automatic categorization or predefined treatment based on the number of page views or social metrics that articles receive. Journalists and editors usually take Chartbeat data into consideration when making decisions about topics or placement, but this is only one piece of information among several considerations, and the process is not automated.

COMPAS in Criminal Justice

Turning to the case of criminal justice, risk-assessment tools are predictive algorithms used to assess the risk of recidivism (or failure to appear in court) of defendants. Based on a statistical analysis of sentenced cases, risk-assessment tools assign a "risk score" to defendants based on a number of variables (age, gender, criminal record, type of offense, etc.). COMPAS (Correctional Offender Management Profiling for Alternative Sanctions), one of the most widely used of these programs, is a product of the for-profit company Equivant. COMPAS relies on a survey of 137 questions administered to defendants, computing several risk scores that range from 1 to 10.

What are the mechanisms through which COMPAS affects the people being quantified—that is, defendants? COMPAS functions as a tracking technology, in the sense that it monitors, aggregates, and records data about the activities and attitudes of defendants to "manage" them—namely, sentence them. As a result, defendants are likely to adjust their behavior and respond to the COMPAS survey in ways that they believe will minimize their risk score.

COMPAS also relies on triaging. Based on their risk scores, defendants are classified into distinct categories ("low," "medium," and "high risk"), with different color codes. Depending on their category, distinct treatments follow: high-risk defendants are more likely to receive an incarceration sentence, whereas low-risk individuals usually get probation, although this depends on the court. As many other triaging technologies, COMPAS has been found to be biased against African American defendants (Angwin, Larson, Mattu, & Kirchner, 2016).

COMPAS certainly works as a valuation technology, in the sense that it increases the visibility and legitimacy of what it purports to measure: The program focuses on the defendants' "risk" to public safety—a notion that is often elusive in criminal justice. By relying on standardized calculations to quantify risk, such instruments put risk-related values such as deterrence and incapacitation at the center of the criminal justice process.

That said, COMPAS does not come with homogenizing effects on its "subjects"—that is, on defendants. This is because an overwhelming majority of defendants do not know what their own risk scores are: The software program and its output remain opaque. Given this opacity, defendants cannot compare or "commensurate" their respective risk.

Similarly, COMPAS does not function as a form of nudging for the defendants: It does not seek to change their behavior. COMPAS affects the decision-making process of judges and prosecutors—the ones making the decisions about defendants—but not the attitudes of the defendants themselves. I will return to this point in the discussion.

Together, Chartbeat and COMPAS give a sense of how the five mechanisms analyzed here may apply to empirical cases. Yet the actual ways in which these software programs affect the people using them often depends on the specific features of the institutional contexts within which they unfold. Thus, Chartbeat has different effects depending on the newsroom, and COMPAS is used differently depending on the jurisdiction under consideration, as I have explored elsewhere (Christin, 2017, 2018).

Discussion

This article offers a theoretical framework to analyze the range of effects that data can have on the people and entities being quantified. Through the five mechanisms delineated above, I seek to change how we think about data, online and off-line. In this discussion section, I highlight three implications of this approach before turning to avenues for further research.

First, by explicitly focusing on data instead of computational technologies, this article argues that we need to pay close attention to what is not changing with digitization. To date, the growing field of critical data studies has primarily focused on computational technologies and digital sociotechnical systems, drawing on concepts such as protocols, algorithms, analytics, platforms, and artificial intelligence. Such a focus on computational technologies is justified given the breadth and pace of ongoing technological developments, yet it runs the risk of overemphasizing change. Instead, placing data at the center of the argument affords a longer time frame—one that predates the development of digital technologies. Interestingly, the five mechanisms analyzed here appear to apply equally well to analog and digital data. Such an approach in turn raises further questions about the study of data. In particular, one might ask: Why are the effects of data so stable over time? This suggests that, instead of a big data "revolution" (Cukier & Mayer-Schönberger, 2013), we may simply be witnessing an intensification of mechanisms that have already been in place for more than two centuries.

Second, this article seeks to contribute to the structuration of the interdisciplinary field of critical data studies (see Iliadis & Russo, 2016, for an introduction). To date, most instances of research examining the social effects of data have gravitated toward two opposite intellectual poles, which one could describe as respectively "overgeneralized" and "undergeneralized." On the overgeneralized side, theoretical analyses have taken a macrolevel view, examining the broad ethical, legal, and political repercussions of data on the social fabric. Yet by adopting such a bird's-eye view, such theoretical approaches often fail to pay close attention to the role of organizational and field-level processes in modulating the impact of the technologies they examine. On the undergeneralized side, in-depth qualitative monographs have focused on a given site and provided fine-grained examinations of the repercussions of data on the institution under consideration. Because of their monographic focus, however, such studies are often limited in how much they can generalize or extrapolate to other cases. Relatively absent is what sociologist Robert Merton (2007) calls a "middle-range" space of intellectual production. Middle-range theories seek to identify theoretical frames "applicable to limited conceptual ranges" (p. 457), instead of all-encompassing abstractions. This is precisely what the typology of mechanisms provided in this article hopes to provide. The five mechanisms delineated above are tools for mapping the concrete impact of digital systems across contexts.

This leads me to the third contribution of this article. Based on this typology of mechanisms, the analysis presented here suggests that the umbrella concept of "data" may need to be broken into smaller, more manageable components. As can be seen in Table 1, researchers tend to use different concepts to talk about data depending on the mechanisms they are interested in studying. For instance, researchers who examine tracking processes tend to talk more about big data, metadata, and biometrics, whereas scholars interested in homogenization are more likely to focus on prices, rankings, and ratings. Scholars focusing on triage often rely on the concepts of scores, algorithms, and artificial intelligence, whereas people who work on nudging pay closer attention to indicators and metrics, and researchers studying valuation typically focus on indexes and barometers. These differences indicate that as the field of critical data studies grows and the range of phenomena under scrutiny expands, the all-encompassing concept of "data" may need to be considered in conjunction with smaller components, depending on the outcomes scholars want to study.

To conclude, the current framework could be expanded in several ways. First, this analysis primarily focuses on the effects of data on the "subjects" of quantification—the people and entities being quantified. But data can come with important effects on other categories of actors, transforming the representations and practices of the people who collect, analyze, and use it. Data can also affect third parties: neither subjects nor users, but wider constituencies such as public opinion or public administrations. Further research is needed on the effects of data for these other categories of actors, as well as the interrelations that emerge among producers, users, subjects, and the public.

There is also more work to be done in delineating the role of factors that are not fully developed here. For instance, information sharing practices need further attention. Several mechanisms analyzed above require human access to the data (e.g., homogenizing, nudging, evaluating) whereas others thrive on opacity (e.g., tracking, triaging). How does the kind of access people have to data being gathered about them shape the effects of such data? Another aspect relates to the intentions of the people and organizations collecting, analyzing, and storing data. Some of the mechanisms above describe intended effects (e.g., nudging, valuating) whereas others focus on unintended effects (e.g., tracking, homogenizing, in most cases). How should we think about these intended versus unintended effects of data? Last but not least, future research should examine how the different mechanisms can build on one another. For instance, tracking appears to be an obligatory passage point for many of the other mechanisms analyzed above, whereas valuating seems to be a necessary consequence of datafication.

A promising avenue of research in teasing out these questions is to examine how data is organized, shared, and visualized. Again, data does not exist "out there": it is always collected and organized with specific users and purposes in mind. In line with recent work on the politics of data visualization (Kennedy, Hill, Aiello, & Allen, 2016), scholars could further explore the conventions and choices that shape how data is displayed to various audiences. For instance, could we associate "homogenizing" with a specific subset of visualization strategies (say, rankings and lists), and "valuating" with others (say, barometers and maps)? We need to pay closer attention to the technical, aesthetic, and moral choices guiding how data is "appresented" through screens, graphs, and dashboards (Knorr-Cetina & Bruegger, 2002).

Conclusion

This article offers a theoretical framework to analyze the effects of data, which I argue operates through five key mechanisms: tracking, homogenizing, triaging, nudging, and valuating. Each of these mechanisms comes with discrete effects on the people being quantified, online or off-line. The second part of the article applies this framework to two empirical cases with distinct characteristics. Based on this analysis, I make three contributions. First, by focusing on data instead of technological or computational power, I adopt a longer historical perspective and focus on what is not changing whenever data, whether digital or analog, is introduced in a given context. Second, in the spirit of theoretical integration, I provide a middle-range framework that can be implemented across sites in critical data studies. Third, I suggest that the umbrella concept of "data" may need to be broken down into smaller and more manageable elements.

With this framework in mind, we can now return to the 1940s and the Kinsey reports mentioned at the beginning of this article. What were the effects of this data on its subjects, broadly defined by Kinsey himself as the American population at large? Kinsey's project was widely perceived as a form of tracking and an intrusion on people's privacy; people reacted to it by internalizing the numbers, as noted by Margaret Mead. The reports also came with homogenizing effects, by making all sexual activities (including homosexual sex) commensurable—a fact that many readers vehemently criticized. They certainly played a central role in making sex a topic of public discussion, valuating and normalizing a wide range of sexual activities in the public eye. Yet the reports did not function as a form of triage, in the sense that being classified in one group or another did not entail immediate and predefined consequences, nor did Kinsey rely on nudging—the project was promoted as an empirical and objective description, not a moralizing one.

Right after Kinsey's reports were published, a columnist complained: "We have been so *statisticized* in the United States that nothing is sacred anymore" (Igo, 2008, p. 235, emphasis in original). More than half a century later, data-driven mediations have become more ubiquitous and multiform than this columnist could have imagined. The analytical distinctions presented here are a first step to refining our understanding of what data—digital or not—can do when it becomes part of our daily lives.

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