Big Data, Algorithms and Artificial Intelligence

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Introduction

The emergence of big data and artificial intelligence (AI) has brought about unprecedented changes in the ways we live and know together. These technologies are often regarded as the defining general-purpose technologies of the early 21st century. However, the potential risks and harms associated with them, including lack of transparency, misinformation, bias, worker exploitation, environmental impacts, and concentration of power have raised many concerns and controversies. Science and Technology Studies (STS) and neighbouring fields have been instrumental not only in rendering these issues visible and in sparking lively debates about the development, implementation, and governance of these technologies, but also in engaging in critical scholarship, policy advice, and activism.

Big data refers to vast amounts of structured and unstructured digital data generated from various sources, including social media, electronic sensors, and transactions. Digital algorithms are sets of instructions designed to handle data and perform specific tasks, such as data analysis, prediction, and decision-making. Artificial intelligence (AI) is an area of computer science that involves machines performing tasks typically attributed to human cognition, such as identifying patterns and making decisions. In healthcare, for example, AI is used to develop personalised medicine and support diagnosis and treatment decisions, raising questions about algorithmic bias, patient autonomy, and the role of medical professionals. Similarly, in law enforcement, AI systems are implemented to support decision-making around predictive policing, criminal sentencing, and facial recognition for surveillance, prompting concerns about discrimination, civil liberties, privacy, and power distribution in society. In the advent of escalating automation, generative AI is likely to transform not just the entertainment sector by producing cultural commodities like music and videos without the direct participation of human creators, but also impact democracies with a flood of misinformation, as well as communication as a whole by enabling broad access to means of production such as programming code, while imposing significant demands on resources such as energy, raw materials, and human labour, and exacerbating social inequalities.

Discussions around the intersection of computers and humans, machine intelligence and human cognition, and the shaping of technology by social, cultural, and political practices, have a long history in fields such as anthropology, philosophy, sociology, but also human computer interaction or social computing. Today, STS serves as a common ground for scholars from various backgrounds to critically study AI, big data, and algorithms. Incorporating STS insights helps data science adopt critical perspectives for technology design and implementation in academia and industry. Indeed, STS offers valuable theoretical and methodological tools drawing from social constructivism and feminist epistemology. It helps to emphasise methodological symmetry, revealing power structures and inequalities in knowledge production. Feminist critiques challenge traditional knowledge dichotomies, stressing the situatedness of knowledge and its embodiment in the creation of machine intelligence. Actor-network theory highlights distributed agency across human and non-human actors in the study of algorithms, while studies of imaginaries of AI expose underlying values and cultural norms in technology promotion and politics. Focusing on infrastructure and processes of infrastructuring allows for the study of social media platforms and other socio-technical systems. Additionally, contemporary STS scholarship benefits from exchange with new materialist schools of thought, postcolonial studies and critical race theory. Utilising a diverse methodological repertoire—including ethnographic, historical, discourse analytical, cartographic, digital, and mixed-methods approaches—STS enables researchers to analyse the sociality of data and algorithms and contributes robust empirical evidence to ongoing debates.

This entry offers a glimpse on STS approaches to big data, algorithms, and AI, demonstrating their intertwined history. It highlights recurring themes, such as the quest for intelligence and the materiality of knowledge, the controversy around a technocratic notion of objectivity, culminating in the search for technology governance.

The quest for intelligence

The non-linear history of Western artificial intelligence (AI) research involves many fields such as psychology, cybernetics, robotics, and artificial life, and has always been tied to corporations and military funding programs. STS scholars have engaged with the evolving relationship between humans and machines, particularly with the aspiration to develop 'thinking machines' (Adam, 1998) that simulate and surpass human intelligence from the beginning of the debates (Collins, 1990; Forsythe, 1993). During the first wave of AI, which spanned from the mid-1950s to the mid-1970s, human cognition was theorised using abstract, rationalistic models that employed symbolic manipulation and rule-based systems to replicate logical reasoning and problem-solving. However, early AI research also faced critiques that challenged its technoscientific power rooted in social irresponsibility and economic excess (Taube, 1961). These critiques were part of a larger tradition of humanist scepticism that addressed the rapid advancements in automation, digitization, and the increasing social complexity of technosciences during the twentieth century.

Critics have warned against the power imbalances and inequalities that AI could exacerbate, particularly in the context of critical theory, where it was posited that AI would subvert direct experience and cause human estrangement. Joseph Weizenbaum, who created the Eliza chatbot, emphasised the distinction between computer power and human reason, while questioning the blind faith in computers. He argued that the central question should not be whether computers could perform certain tasks, but rather if they should (Weizenbaum, 1976). Today, these questions persist in discussions surrounding 'artificial general intelligence' (AGI), defined as possessing the ability to understand, learn, and apply knowledge across a wide range of tasks at a level equal to or beyond human capabilities. Criticisms from the past remain relevant and have inspired the burgeoning STS community, which contributed a lot to the debates during what is now referred to as the second wave of AI.

The second wave of AI research in the 1980s and 1990s focused on developing expert systems using predefined rules and heuristics to emulate human domain knowledge. However, the emergence of the connectionist paradigm changed the focus to neural networks, enabling these networks to learn without the need for explicit instructions. During this period, the critical discourse shifted from exploring the conditions of possibility of AI to examining the practical implications, particularly in already implemented expert systems such as medical diagnosis support systems and military command and control systems (Suchman, 2007).

STS scholars at the time addressed the limitations of rule-based systems and symbolic AI, which struggled to manage complex and ambiguous information, and lacked comprehensive notions of human intelligence or knowledge subjects (Adam, 1998). Lucy Suchman's work on human-machine interaction presented a persuasive anthropological case against the dominant theory of rational choice showing that human actions are perpetually formed and reformed through dynamic engagement with both the material and social environments (Suchman, 1987). Harry Collins was concerned with the dimension of `tacit knowledge`. He designated that 'machine-like actions' are equally applicable to tasks assigned to humans as to those embedded in 'intelligent machines' (Collins, 1990). These scholars were also interested in the cultural assumptions about human autonomy and the characteristics that make humanness a unique property of our species.

STS's goal has always been not just offering critiques, but also actively contributing to productive interventions and improvements within the field under study. Scholars then emphasised the need to incorporate insights from sociological thought into AI development (Woolgar, 1985). Others conducted ethnographic field studies to gain insights into the day-to-day practices, interactions, and negotiations that contribute to the development of AI (Forsythe, 1993). Susan Leigh Star investigated how social metaphors can be productively used as ‘boundary objects’ in the design process to better understand the social implications and implicit expectations and to improve human-computer interaction (Star, 1989). STS scholars have also delved into the evolution of information theory and cognitive sciences, examining how the notions of cognition, expertise, the body, and experience have been shaped by informationalism, computational reductionism, and functionalism (Hayles, 1993).

STS scholars have critiqued and intervened in AI and robotics by emphasizing the importance of embodied knowledge and challenging the notion of a ‘universal knower’ and the ‘view from nowhere,’ drawing on feminist epistemology to illuminate the fluid boundaries between humans and machines (Suchman, 2007). Donna Haraway's *Cyborg Manifesto* introduced the concept of a cyborg—a hybrid entity that challenges conventional boundaries (Haraway, 1991). Haraway's scholarship advocates the intricate interdependence between humans and machines, examining how technology shapes bodies and identities with the capacity to both constrain and augment individual capabilities, as well as communities and solidarity. Several years later however, subsequent internet and AI developments faced criticism for their excessive sway over human autonomy and identities, ultimately turning its users into products.

Data power

The advancement of neural networks was initially slow due to limited computational power and challenges in training such systems. However, in the 2010s, the steady increase of computing resources, open-source code sharing, machine learning, together with the availability of vast amounts of data from sensors, digital platforms and archives propelled neural networks into the forefront of AI applications. Machine learning (ML) today spans various fields, including computer vision, NLP, and robotics. The third wave of AI is data-driven and adapting machines to real-world environments by learning from sensory data, across diverse contexts resulting in applications like recommender systems, image recognition, language translation, automated surveillance, predictive analytics, and autonomous vehicles. The fourth wave of AI, from the 2020s onwards, focuses on generative AI, which creates new content based on existing data, such as text, code, images, video, or sound. The rise of large language models (LLMs) and the popularity of chatbots based on these models have reignited the quest for machine intelligence. LLMs detect and predict patterns in text data during their training, enabling them to generate seemingly coherent and contextually relevant responses – albeit without comprehension, hence the term 'stochastic parrots' (Bender et al., 2021). Because these models excel at reproducing natural language, they are often mistakenly perceived as possessing human-like intelligence and cognition. Thus, lately, AI has emerged as particularly data-hungry, requiring significant quantities of data for ML and generative AI training and testing.

Ubiquitous efforts of datafication enabled the generation of vast quantities of diverse, digital data by systematically converting social interactions, behaviours, and processes into machine-readable formats, thus giving rise to what is now called the era of big data (van Dijck, 2014). Big data encompasses two distinct yet interrelated aspects: (1) the vast volume of data generated from a multitude of sources, and (2) the methods employed to manage and analyse these datasets. Conventional data processing methods struggle with unstructured data, especially when real-time analysis is needed. Big data techniques, however, manage the storage, processing, and analysis of vast, dynamic datasets, aiming to extract insights, make predictions, and decisions. These methods require extensive infrastructure, with data size, speed, and complexity dictating processing demands and the capacity required by capable institutions.

Central to the STS approach to big data is a critique of the prevalent technological determinism and data-centric positivism that governs the prevailing discourse on technological capabilities (boyd and Crawford, 2012). The recurring theme is the persistent belief in objective knowledge, but from an empiricist, data-driven angle (Kitchin, 2014). This perspective highlights the sufficiency of data-driven discoveries and correlations for comprehending intricate phenomena, while minimising the importance of theory and causation in scientific knowledge production. José van Dijck uses the term 'dataism' to describe this widespread belief in objective quantification and complete representation of human behaviour or other phenomena through digital systems (van Dijck, 2014). Instead of perceiving data as a 'raw' and neutral resource, critical scholars regard it as an inherently relational and historically situated phenomenon, influenced by social, economic, and political factors. Debates concerning expertise and authority in knowledge production - particularly prominent during the Cold War era - were refreshed with the issue of fake news and post-truth in public discourse.

The STS community explores data practices across diverse fields, such as Critical Data and Algorithm Studies, Software Studies, Surveillance Studies, Platform and Infrastructure Studies, and App Studies. These areas converge on the concept of data as power, addressing disparities between data producers and those impacted by data and how data is employed to exercise control over individuals and societies. Such studies examine the implications of datafication on individuals' lives, in particular when they serve both as resources and targets of automated scoring (Eubanks, 2018). Similarly, the concept of ‘data politics’ is used to study how data subjects are governed and how they can participate in ‘data regimes’ (Dalton et al., 2016) asserting their rights and engaging in everyday acts of data politics, asserting agency and reclaiming data privacy and sovereignty. Following closely how data is produced, collected, analysed, circulated and used for example to influence, target, surveil and campaign reveals how data evolves into a transferable, tradable intangible good (Beaulieu and Leonelli, 2022). Datafication research probes complex power dynamics, encompassing areas like education, labour, healthcare, marketing and privacy.

The concept of ‘data journeys’ (Bates et al., 2016) tracks the pathways of data in production, processing and circulation, highlighting the liveliness of digital data, including data generated by smartphones, wearables, and sensors that accompany us (Lupton, 2016). Data journeys reveal the intricate socio-technical infrastructures and resources underpinning the digital sphere, effectively ‘re-materializing’ it by pointing to the tangible components and interconnections. Beyond data extraction from daily life and natural resources for network and device construction, ‘data colonialism’ or ‘digital colonialism’ (Arora, 2016) shed light on labour exploitation, including gig work, content moderation, and ML training .

From the perspective of big data and AI, STS has also explored the transformation of the science system. The intersection of STS and data science, especially the social data subfield, offers opportunities and challenges, as both fields consider data science's pervasion a socio-technical endeavour (Ribes, 2019). Data science ‘labs’ now operate in the public sphere, experimenting on platforms like social media and search engines. Consequently, critical scholarship calls for increased reflection and transparency, such as in dataset construction and evaluation.

STS frequently informs diverse types of data activism or algorithmic activism (Milan and van der Velden, 2016), such as ‘data feminism’ (D’Ignazio and Klein, 2019), and a broad range of interdisciplinary public interest research. These activities around the world strive to empower marginalised groups to leverage data, data science, algorithms, AI, participatory methods, and co-design to develop alternative social, political, and economic models that challenge prevailing power structures.

Algorithmic agency

The study of big data is intrinsically connected to and overlapping with the critical scholarship on algorithms, sharing common concerns and objectives, focusing on understanding the socio-technical dynamics, power relations, and ethical implications of data-driven systems (Gillespie, 2014). By automating data handling and analysis towards decision making and prediction, algorithms have become widely used tools of management and control in many domains. In STS, the notion of algorithm is a powerful sensitising concept for the study of the technoscientific practices of big data and AI. There are calls for research into the 'history and mythology' of algorithms, exploring how they replaced self-critical reasoning and became indicative of a general mode of social order (Ziewitz, 2015). Illustrating such a mode of social order reveals the many algorithmic forms of bureaucracy and its impact on society. Algorithmic management should not only boost performance but also make it comparable and auditable. Imaginaries of a better management or administration led to a wide application of automated decision making in public services and many other domains. Everyday automation has long become an interesting object of investigation and critique, such as automated hiring decisions, content moderation, management of refugee camps, automated welfare decisions, educational technologies and many more.

Algorithms act as gatekeepers and significantly contribute to processes of visibility, creating reality through their ordering power and shaping cultural structures of meaning. The concept of algorithmic agency builds on this relational perspective of power, which is not controlled by a single actor. Algorithms are not neutral or passive tools but instead reflect certain positions and values. Considering agency not simply as autonomy, but as means for social change is essential for understanding the allocation of power in the digital transformation. Research on algorithmic agency is exploring how users can exert control over data streams and algorithms, which social actors and regulations can intervene in digital practices, and how complex algorithms and data-driven systems can be scrutinized and held accountable (Couldry and Powell, 2014; Kennedy et al., 2015).

The issue of trust and accountability in algorithmic decision-making is a central challenge in the field. Black-boxed algorithms, where the process of decision-making is unclear, pose a significant challenge to society (Pasquale, 2015). STS scholars have employed various strategies, including source code analysis and ethnographic studies, to gain insight into algorithms and their cultures (Kitchin, 2014; Seaver, 2017). Computer and data scientists have also explored transparency and explainability in algorithms to ensure reliability and ethics. The question of whether trustworthiness should be integrated into technology design or addressed through institutional and legal frameworks remains a central debate. Identifying and minimizing harms in automated decision making is a core aim of algorithmic auditing. This is commonly understood as the process of analysing and evaluating algorithms for potential biases, discrimination, and other ethical concerns, and to make visible and evaluate their broader social, legal, and environmental impacts, including labour conditions. The debate thus revolves around questions of regulation, institutionalisation, and validation. The need for international standards and certifications, as well as the development of adequate audit methods for algorithms and data is also important to ensure consistency and transparency across different contexts and jurisdictions (Sandvig et al., 2014).

Any effective regulation or validation procedure requires a deep understanding of technology design and culture, and STS has successfully devised numerous approaches to ‘open the black box.’ Ethnographic studies of the production of AI technologies show the behind-the-scenes processes of algorithm development (Jaton, 2017). Florian Jaton highlights the embodied labour of programming, the epistemic cultures and the interconnected activities involved in ground-truthing, programming, and formulating data relations. However, this process can be problematic, as the definition of what constitutes the ‘correct’ answer is highly situated and influenced by social, cultural, and political factors. This can result in biased classifications that perpetuate existing power structures and reinforce systemic inequalities. Undoubtedly, bias is one of the most prominently debated issues in the context of algorithmic power (Benjamin, 2019). Thus, historical bias is one of many notable concerns in predictive analytics, which utilises statistics and ML to forecast future outcomes. As models are trained on past data, they risk favouring or harming specific groups due to biased data and historical patterns. Scrutinising training and validation data is crucial to avoiding biased classifications. Joy Buolamwini's experience with facial recognition software failing to recognize her face until she presented a white mask led to an investigation into the ‘coded gaze’ and revealed predominantly Caucasian male training data (Buolamwini and Gebru, 2018). Buolamwini's findings inspired successful activism against this discriminatory technology around the globe.

In *Algorithms of Oppression*, Safiya Noble highlights the role of a non-diverse workforce in data science and big tech in perpetuating discriminatory actions and automation. She demonstrates how search engines, in what she calls the "most unregulated social experiment of our times" (2018: 6), privilege whiteness and discriminate against people of colour, especially women, due to concentrated power, profit motives, and workforce homogeneity. However, Noble critiques the ‘big data optimism’ belief that increased workforce diversity alone would resolve algorithmic biases, arguing that this ‘complacent’ perspective unfairly shifts responsibility onto individuals rather than organisations (Noble, 2018).

Ethics and governance

From Italy's temporary ban on the AI chatbot *ChatGPT* in March 2023 to a call for a global AI governance board later the same year, these reactions reflect the growing concern over the use of big data and AI. Datafication's pervasiveness has left many individuals feeling disempowered and politicians confused, leading to decreased public trust in AI due to scandals, biases, and privacy breaches. This has spurred a focus on AI ethics and regulatory frameworks, addressing AI limitations and false claims. AI ethics, trustworthy AI, and responsible data concepts emerged in the 2010s, featuring soft governance and expert-led policy discussions (Mittelstadt et al., 2016). Formalising fairness for ML models facilitated some standards and requirements but was sometimes misused to distract from fundamental issues. The AI industry's view of ‘democratising’ its technology referred rather to making it accessible to all computer owners. This is why critical communities - countering this simplistic notion of democratising AI - are still working on self-regulation guidelines for corporations and government bodies to counter the trend of ‘automating inequality’ (Eubanks, 2018). At the same time employee protests against big tech firms highlighted issues like women's rights, alignment with controversial policies, and military funding. Moreover, there is a growing awareness of the necessity of open data and open methods to scrutinise commercial, academic as well as public use of AI, as illustrated by the FAIR principles (findable - accessible - interoperable - reproducible) and CARE principles (collective benefit - authority to control - responsibility - ethics) for data governance (Beaulieu and Leonelli, 2022).

Over time, critical voices have coalesced into distinct communities, promoting interdisciplinary collaboration through various institutions and conferences. Until this day, the field of AI ethics is a central focus in these discussions, serving as a nexus for scholars and practitioners from diverse fields to convene and address the ethical, social, and political implications of AI technologies, emphasising the necessity for responsible and inclusive AI systems (Mittelstadt et al., 2016). As technical communities grapple with the complexities of integrating fairness, accountability, and transparency into AI systems, broader attention has been directed towards the ‘planetary costs’ of AI (Crawford, 2021). The *Anatomy of an AI System* is a critical cartography of the materiality of the data industry and their huge infrastructures, produced by Vladan Joler and Kate Crawford that highlights the complexity and resource needs of an AI-driven home assistant. The map is a visual representation of the global interdependencies of resources, capital, infrastructures, and human labour, as well as the extractive logics intrinsic to AI (Crawford and Joler, 2018). Mapping reveals the global distribution of automation's costs and benefits, especially concerning environmental and social impacts. The map demonstrates the intricate and frequently opaque nature of those interdependent relationships, which subsequently extends to the delineation of responsibilities and the establishment of ethical and regulatory frameworks.

In response to the acknowledged challenges and risks posed by AI technologies, we recently saw a shift from questions of ethics to those of governance. A range of measures have been implemented, including the formation of ethics boards, audits, frameworks, and guidelines, alongside initiatives aimed at fostering ethical awareness among AI developers and data scientists in academia, industry and policy. However, it could be observed that during major layoffs in big tech, ethics teams are often the first to be let go. Alternative ethical frameworks for AI governance, anchored for example in feminist ethics of care (Taylor, 2020), or advocating for a reimagining of AI for the common good, have challenged the prevailing tendencies of the big tech industry to take over or 'own' the ethics agenda (Metcalf et al., 2019). Comparative analyses of international and national AI strategies for research and industry reveal dominant socio-technical imaginaries that portray AI as an inevitable, disruptive force, a grand legacy and key international competition (Bareis and Katzenbach, 2021). Governance strategies closely align with economic objectives, utilizing AI not only as a subject of governance but also as a tool for enhancing policy monitoring and governance effectiveness.

STS scholars have played a significant role in critiquing and shaping responsible and inclusive technologies, emphasising the importance of power relations and social contexts in knowledge production. By connecting feminist, racial, and social justice approaches to technology to interrogate power relations, critical scholarship highlighted the need for reimagination of human–computer relationships while dismantling systems of oppression. It problematised rationalist notions of intelligence, techno-solutionist notions of ethics, as well as colonial ideologies in global information ecologies. As AI governance becomes increasingly important, STS will play a vital role in researching, collaborating, advising, and intervening at the intersection of legal, policy, research, and industry. Taking into account not only general data protection or anti-discrimination regulations, but also the infrastructural and material dimensions of big data and algorithms, and AI, their extractive logics, and the need to intervene in the respective epistemic cultures, STS will be able to contribute to alternative perspectives and visions. However, despite the robust empirical foundation of STS engagement with AI, there is a pressing need to refine ethnographic methodologies and gain access to field sites to effectively comprehend the societal impacts of AI and intervene in collaborative working environments.

Key Readings

Beaulieu A and Leonelli S (2022) *Data and Society*. London: Sage Publications.

boyd d and Crawford K (2012) Critical Questions for Big Data. *Information, Communication & Society* 15(5): 662–679.

Crawford K (2021) The atlas of AI: Power, politics, and the planetary costs of artificial intelligence. New Haven: Yale UP.

Couldry N and Powell A (2014) Big data from the bottom up. *Big Data & Society* 1(2): 2053951714539277.

Eubanks V (2018) *Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor.* New York: St. Martin's Publishing.

Forsythe DE (1993) Engineering Knowledge: The Construction of Knowledge in Artificial Intelligence. *Social Studies of Science* 23(3): 445–477.

Kitchin R (2014) *The data revolution: Big data, open data, data infrastructures & their consequences*. London: Sage Publications.

Noble SU (2018) *Algorithms of Oppression: How Search Engines Reinforce Racism*. New York UP.

Suchman L (1987) *Plans and situated actions: The problem of human-machine communication*. Cambridge UP.

Suchman L (2007) Feminist STS and the Sciences of the Artificial. In: Hackett EJ et al. (eds) *The Handbook of Science and Technology Studies*. Cambridge MA: MIT Press, 139–164.

Van Dijck J (2014) Datafication, dataism and dataveillance: Big Data between scientific paradigm and ideology. *Surveillance & Society* 12(2): 197–208.

Other References

Adam A (1998) *Artificial Knowing: Gender and the Thinking Machine*. Milton Park: Routledge.

Arora P (2016) Bottom of the data pyramid: Big data and the global south. *International Journal of Communication*. 10: 1681–1699.

Bareis J and Katzenbach C (2021) Talking AI into Being: The Narratives and Imaginaries of National AI Strategies and Their Performative Politics. *Science, Technology, and Human Values* 47(5): 855-881.

Bates J, Lin Y-W, and Goodale P (2016) Data journeys: Capturing the socio-material constitution of data objects and flows. *Big Data and Society* 3(2): 205395171665450.

Bender EM, Gebru T, McMillan-Major A, et al. (2021) On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? In: *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, 610–623.

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

Buolamwini J and Gebru T (2018) Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification. In: *Proceedings of the 1st Conference on Fairness, Accountability and Transparency*, 77–91.

Collins HM (1990) *Artificial Experts: Social Knowledge and Intelligent Machines*. Cambridge MA: MIT Press.

Crawford K and Joler V (2018) Anatomy of an AI System. Available at: https://anatomyof.ai/

Dalton CM, Taylor L, and Thatcher J (2016) Critical Data Studies: A dialog on data and space. *Big Data and Society* 3(1): 205395171664834.

D'Ignazio C and Klein L (2019) *Data Feminism.* Cambridge MA: MIT Press.

Gillespie T (2014) The Relevance of Algorithms. In: Gillespie T, Boczkowski P, and Foot K (eds) *Media Technologies: Essays on Communication, Materiality, and Society*, Cambridge MA: MIT Press, 167–194.

Haraway D (1991) *Simians, Cyborgs and Women: The Reinvention of Nature*. Milton Park: Routledge.

Hayles NK (1993) The Materiality of Informatics. *Configurations* 1(1): 147–170.

Jaton F (2017) We get the algorithms of our ground truths. *Social Studies of Science* 47(6): 811–840.

Kennedy H, Poell T and van Dijck J (2015) Data and agency. *Big Data and Society* 2(2): 2053951715621569.

Lupton D (2016) *The Quantified Self.* Hoboken: Wiley and Sons.

Metcalf J, Moss E, and boyd d (2019) Owning ethics. *Social Research: An International Quarterly* 86(2): 449–476.

Milan S and van der Velden L (2016) The Alternative Epistemologies of Data Activism. *Digital Culture and Society* 2(2): 57–74.

Mittelstadt BD, Allo P, Taddeo M et al. (2016) The ethics of algorithms: Mapping the debate. *Big Data and Society* 3(2): 2053951716679679.

Pasquale F (2015) *The Black Box Society: The Secret Algorithms That Control Money and Information.* Cambridge MA: Harvard UP.

Ribes D (2019) STS, Meet Data Science, Once Again. *Science, Technology, and Human Values* 44(3): 514–539.

Sandvig C, Hamilton K, Karahalios K et al. (2014) *Auditing Algorithms: Research Methods for Detecting Discrimination on Internet Platforms.* 64th ICA Meeting 22(2014), 4349-4357.

Seaver N (2017) Algorithms as culture: Some tactics for the ethnography of algorithmic systems. *Big Data and Society* 4(2): 205395171773810.

Star SL (1989) The structure of ill-structured solutions: Boundary objects and heterogeneous distributed problem-solving. In Gasser L and Huhns MN (eds) *Distributed Artificial Intelligence*, Burlington: Morgan Kaufmann, 37–54.

Taube M (1961) *Computers and Common Sense: The Myth of Thinking Machines.* New York: Columbia UP.

Taylor L (2020) The price of certainty. *Big Data & Society* 7(2): 2053951720942539.

Weizenbaum J (1976) *Computer power and human reason: From judgment to calculation*. New York: WH Freeman.

Woolgar S (1985) Why not a Sociology of Machines? The Case of Sociology and Artificial Intelligence. *Sociology* 19(4): 557–572.

Ziewitz M (2015) Governing Algorithms: Myth, Mess, and Methods. *Science, Technology and Human Values* 41(1): 3-16.