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Algorithmic Silence: A Call to Decomputerize

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Abstract: Tech critics become technocrats when they overlook the daunting administrative density of a digital-first society. The author implores critics to reject structural dependencies on digital tools rather than naturalize their integration through critique and reform. At stake is the degree to which citizens must defer to unelected experts to navigate such density. Democracy dies in the darkness of sysadmin. The argument and a candidate solution proceed as follows. Since entropy is intrinsic to all physical systems, including digital systems, perfect automation is a fiction. Concealing this fiction, however, are five historical forces usually treated in isolation: *ghost work*, *technical debt*, *intellectual debt*, the labor of algorithmic *critique*, and various types of *participatory labor.* The author connects these topics to emphasize the *systemic* impositions of digital decision tools, which compound entangled genealogies of oppression and temporal attrition. In search of a harmonious balance between the use of "AI" tools and the non-digital decision systems they are meant to supplant, the author draws inspiration from an unexpected source: musical notation. Just as musical notes require silence to be operative, the author positions algorithmic silence—the deliberate exclusion of highly abstract digital decision systems from human decision-making environments—as a strategic corrective to the fiction of total automation. Facial recognition bans and the Right to Disconnect are recent examples of algorithmic silence as an active trend.

Key words: technocracy; algorithmic silence; history; labor; artificial intelligence; AI ethics; automation; decomputerization

1 Introduction

In 1948, in an article in *Business Week*, a Vice President at the Ford Motor Company coined the term "automation" to promote the use of mechanized self-governance in manufacturing. Since entropy, error, and deterioration are intrinsic to all physical systems, including digital systems, perfect automation is a fiction. Even still, economists, industrialists, and technologists continue to invoke idealizations of "automation" in their influential visions of society. In this article, the author challenges the heightened rhetoric major technology companies and computer scientists have recently used to characterise the autonomous and predictive capabilities of advanced digital decision tools, the current vogue of the automated society. The author shows how reports of a looming "AI Revolution" misrepresent the complex ways in which such tools have been used, in practice, to preserve the political status quo in the United States and United Kingdom.① Yet this article is not just a critique. In pursuit of a harmonious balance between the use of such tools, the use of the non-digital decision systems they are meant to supplant, and the modes of administrative labor required for each, the author draws inspiration from an unexpected source: musical notation. Just as musical notes require silence in order to be operative, the author argues that societies must strategically emphasize—rather than simply seeking to displace—non-digital decision systems by limiting their use of digital alternatives. To crystallize this point, the author introduces the concept of algorithmic silence: the

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① The author reserves his comments to the two countries about which he has most expertise.

designation of a deliberate exclusion of highly abstract digital decision systems from human decision-making environments. Recent bans on facial recognition technologies are an example of algorithmic silence.

While the rise of digital automation has afforded tremendous opportunities for social transformation, it has also disguised growing administrative burdens. This underappreciated coupling is, by my account, a key reason to normalize algorithmic silence. As the cost of digital decision systems decreases globally and their use becomes more prolific, the accompanying need for diverse types of administrative labor will escalate, perhaps precipitously. To evidence this trend, the author connects five realms of scholarship usually treated in isolation: *ghost work*, *technical debt*, *intellectual debt*, the labor of algorithmic *critique*, and various types of *participatory labor*. The author emphasizes the systemic impositions that digital decision systems make on human beings not only as workers and members of different racial, class, or gender groups, as other scholars have shown, but also as consumers, citizens, parents, or any other number of identity frames. These obligations compound in idiosyncratic proportions depending on one's entangled identities, and their harms should be mitigated in respect to these differences. Yet, the author adds, the potential also exists to forge a cross-cutting form of solidarity that addresses broad exposures to the Kafkaesque cacophony of digital decision systems in oversupply. Modes of collective restraint, such acts of algorithmic silence, could help distance AI development from technocracy and align it with traditions of de-escalation, such as decomputerization and degrowth.

2 Disingenuous Rhetoric and "The AI Revolution"

In popular use today, the term "artificial intelligence" is a palimpsest: etched over the disciplines' mid-twentieth century origins, rife with theories of neural activity, is a radical ethos of imminent social transformation via automation.② AI is a catch-all not just for a branch of computer science and its subsets, but for myriad other digital automation techniques as well. Yarden Katz excavates this layering to reveal how, in the early 2010s, major American technology firms lent panache to sales of their data science and machine learning products and services by perpetuating the existence of "The AI Revolution"[1]. Their campaigns publicly consummated[2] the field's longstanding but underappreciated entanglements with institutional patrons intent on developing sophisticated tools for social analysis and control[3]. These interventions capitalized on tropes of imminent technological potential inherited through Western myth, science fiction, religion, economics, and popular culture[4–9]. *Blade Runner*, for example, which builds its narrative around the existence of synthetic human-like "replicants", is set on November 20, 2019, the rough date of this article's writing[10]. The future, it seems, is now.

The AI Revolution, like the computer revolution, is not a real revolution[11, 12].③ Proponents do not seek to forcibly overthrow an existing social order. Far from it. As Katz shows, the AI Revolution is largely a conservative push to preserve and benefit from the political status quo, which, as this issue attests, is marked by historic levels of financial and informational inequality. A growing body of scholarship clarifies how such tool and services repackage and reinforce anti-black[13, 14], anti-poor[15], and chauvinist logics[16]—all under the pretense of progress and efficiency[11, 17–21]. The AI Revolution is thus genuinely political—just not in the ways it is made out to be[22].

Disingenuous rhetoric plays an important role in constructing civic imaginaries about the future. A critical audit of the evocative terminology used in and around AI research is long overdue[23–25]. A 1976 missive by an MIT AI engineer challenged the field's "contagious" use of wishful mnemonics: words that served as "incantations" for a desired result, rather than sober descriptions of a mechanism or function[23, 26–29].④ A recent framing captures this trick in action. In 2018, a team at the Toronto Rotman School of Management cast AI as "a drop in the cost of prediction"[30]. As prediction became cheaper, the team reasoned, it would be used to solve problems that were not traditionally prediction problems, such as autonomous driving. This

② A palimpsest is a manuscript on which later writing has been superimposed on earlier writing. Thank you to Sarah Dillon for this metaphor.

③ See Hicks for a critical take on how the 1950−1970s computer "revolution" in the UK served to entrench existing gender inequalities. Summary in Ref. [12].

④ Naming conventions were judged to have warped researcher's relationship to the epistemic significance of their designs. Artificial intelligence is itself a wishful mnemonic, unique from chemistry and physics in that the name portrays an intention. See Garvey for a survey of AI critique over the second half of the twentieth century and Dreyfus for a glimpse into various eras of critique.

is an insightful observation, but not necessarily for the reasons its authors intended. The AI Revolution does not mark a genuine drop in the cost of prediction, but it may, instead, mark a meaningful drop in the cost to feign prediction. Stated differently, it is becoming trivially easy to manufacture the pretense of "predicting" an outcome in areas where prediction, in fact, defies natural law.

Critics clarify that, at a technical level, contemporary AI capabilities are closer in substance to Katz's account than to the account put forward by those at the Rotman School[24, 31]. Most so-called "predictive" analytics lack the necessary relation to causality to genuinely foretell an outcome in advance. "I have not found a single paper predicting a future result. All of them claim that a prediction could have been made; i.e., they are post-hoc analysis"[31]. The term is mistakenly used to describe novel statistical correlations after events have occurred, rather than identifying a determinate causal mechanism beforehand. One example is the recently debunked claim that AI can "predict" someone's sexual preference from their photograph[32]. Prediction implies prophecy, which is intimidating and inaccurate. At a technical level, argues Momin M. Malik, the term "detect" is more precise, if still not totally satisfying.⑤

The risks involved in indulging such prophetic rhetoric are compounded in cases in which a user's environment can be altered to make a product appear more "predictive" than it is[33–35]. For instance, it is far easier for a driverless vehicle to appear autonomous within the perpetually dry city grid of Phoenix, Arizona, than it would be for that same vehicle to navigate the wet, twisted lanes of Aberdeen, Scotland. Phoenix has fewer characteristic features, which makes changes easier for an "autonomous" vehicle to infer. Disingenuous rhetoric arises when results from a constrained environment (e.g., Phoenix) are treated as universally applicable (e.g., adequate to navigate all locales, including Aberdeen). These claims are covertly subjective not just because they overstate the competency of the algorithmic system in question under the guise of technological objectivity, but also because they treat the value of certain constraints (e.g., a city in a grid formation) as self-evident, as if worthy of mass reproduction along with the new autonomous technology. "Prediction" rhetoric fuses a model with the environment it is most successful in, incentivizing the recreation of those constrained environments to accompany propagation of those models[36]. This conservative push for the hegemonic standardization of human environments and behaviors is especially pernicious when deployed in value sensitive domains like healthcare.⑥

These dynamics are not new. The profundity of automatic manufacturing has long been a matter of training audiences' perspective to notice certain contributing features at the expense of others. In the nineteenth century London, recounts Stephanie Dick, Karl Marx criticized Charles Babbage for anthropomorphising cogs and gears while simultaneously failing to recognize the humanity of his own craftsmen[38, 39]. When the term "automation" was coined in 1948 by a Vice President at the Ford Motor Company, economists, industrialists, and unionists seized the term—under inconsistent definitions—to articulate their own competing visions of society[40]. In present day, Astra Taylor coins the term "fauxtomation" to provide a more accurate characterization of the concealed chains of labor that sustain contemporary modes of digital automation[41]. The notion of "autonomy" is a fiction concealed through the chronic underreporting and/or dehumanization of living contributors, argues Taylor. It is a horizon sought for but never reached, like an asymptote stretching hopelessly toward zero.

Having briefly considered how various rhetorical maneuvres distort civic imaginaries of automation both past and present, it is appropriate to ask what is, in fact, required to sustain pursuit of the endless horizon that is ubiquitous digital automation. In the section that follows, the author connects five labor trends usually treated in isolation: *ghost work*, *technical debt*, *intellectual debt*, the labor of algorithmic *critique*, and various types of *participatory labor*. The author's aim in connecting these threads is to emphasize the *systematic* nature in which different modes of digital automation extract and appropriate human labor simultaneously. The shadowy politics active in these systems are perhaps best recognized in cases of piecemeal low-pay tasks, as in the category of *ghost work*. Here, industrial actors

⑤ Personal correspondence. Thank you to Momin for these critical readings.

⑥ Rhetoric of this type has already been found to obscure the flawed scientific foundations of such tools[37] and to legitimize pseudoscience in areas like criminal justice, human resources, credit scoring and in medicine.

dehumanize contingent workers to rationalize indecent conditions and maximize profits. Yet ghost work, on its own, is not fully illustrative of the broad spectrum of underappreciated impositions that digital automation makes upon human labor. The author explores four additional categories. As the author will show, *technical debt* and *intellectual debt* normalize poor craftsmanship and pseudoscience in the development of digital products and services, thereby offsetting an unspecified burden of maintenance and repair labor onto future generations. In a similar vein, the labor of *critique* and various modes of *participatory labor* help to sustain the acceptability and reliability of these products and services today. One wonders, in view of these labor trends: if software eats the world… who will digest it?

3 Performing "The AI Revolution" — A Taxonomy of Contingent Labor

3.1 Ghost work

The first category of labor to explore is *ghost work*, a phenomenon that reveals the banality of the AI Revolution in practice. Gray and Suri coined the term in 2019 to illuminate the opaque world of digital on-demand task fulfillment, in which online platforms aggregate piecemeal low-pay tasks and repackage them as the outputs of automation[42]. Examples of ghost work include rideshare driving and the search and categorization of micro tasks online. These platform systems emerged from decades of corporate led casualization and outsourcing, which normalized precarious modes of employment[43]. Their existence is critical to AI. For example, Fei-Fei Li's AI team at Stanford University estimated in 2007 that it would take nineteen years of undergraduate labor to create ImageNet, a large, gold-standard database of accurately labeled images. Using ghost work, the team accessed 49000 human contributors from 167 countries to produce the database in two and a half years[42]. ImageNet has been celebrated as a benchmark for computer vision algorithms; one that fueled a surge of media attention around AI techniques. Ghost workers, in contrast, remain "the AI revolution's unsung heroes"[42].

As the title suggests, ghost work is predicated on a status of tortured impermanence. Workers are hired as independent contractors rather than employees. This makes precise figures on the scale and nature of the phenomenon difficult to source. In 2017, the platform economy employed an estimated 70 million workers globally, with estimates for 2025 as high as 540 million (as cited in Ref. [44]). In the post-industrial economies of the US and UK, statistics indicate that ghost work is large and growing[42].⑦ Recent news around the poor performance of Facebook, Inc.'s platform content moderation algorithms provides a glimpse into how ghost work intersects with a well-funded and large-scale AI project. In this domain, content moderators are contracted to sort inappropriate content, often in conjunction with algorithmic systems. In 2009, Facebook was cited as paying twelve content moderators for its one hundred and twenty million users[45]. By 2017, this number allegedly grew to 4500 moderators. By 2019, it reached between 15000−20000 moderators for Facebook's two and a quarter billion users[46–48].⑧ Between 2009−2019 then, Facebook's content moderator-to-user ratio grew approximately sixty times.

Ghost work is core to the AI Revolution. Facebook is one of many corporations now intent on reconfiguring their business around AI and, consequently, precarious labor. In late 2017, YouTube LLC. declared it would hire 10000 content moderators for its 1.5−1.8 billion viewers, more than double the number of its current 5000-person employee base[49–51]. The most well-known ghost work platform is Amazon.com, Inc.'s Mechanical Turk (or MTurk) system, which provides businesses and consumers with structured access to a marketplace of low-cost and globally situated click workers. Between 2005−2016, MTurk grew five times, from approximately 100000 to 500000[42]. Amazon touts MTurk as "artificial artificial intelligence". In comparison, DefinedCrowd, one of many start-ups now competing with MTurk, claims eighty employees and 211468 click workers, more than the 163800 people working in oil and gas extraction across the United States[52–54].⑨ Sector analysts claim that the marketplace for third-party data labeling will grow six times by 2023

⑦ In 2016, twenty million workers were estimated to earn money via the completion of on-demand tasks in the United States. Estimates hold that analogous modes of semi "automation" could reconfigure 38 percent of US jobs by 2030. In developing countries, where much of ghost work is based, there are not even these figures.

⑧ In comparison, Facebook, Inc. reported 27705 employees in 2018.

⑨ At time of writing, competing outlets include: Alegion, Appen, Cape Start, Click Work, Cloud Factory, Cloud Sight, Data Pure, Defined Crowd, Figure8, Cloud AutoML Vision, hCaptcha, Gengo, Gems, Hive, iMerit, Labelbox, Lotus Quality Assurance, Micro Workers, MightyAI, OC Lavi, Playment, Reef, Scale, Superb, and TaskUs.

into a one billion dollar marketplace, with other estimates reaching as high as five billion dollars[55–57].

The federal government in the United States has yet to acknowledge or set labor protections for ghost workers, whose fight for recognition has only recently materialized into legislation in a handful of US states[58]. The job category "Content Moderator" remains unrecognized by the Bureau of Labor Statistics; it is also absent from the 21000 industry and 31000 occupational titles measured by the US Census[59, 60]. This uneasy status, along with the frequent lack of a shared worksite or uniform job title, deepens workers' precarity by adding friction to collective action and the protections it yields[42, 61].⑩

As in the era of Babbage, automation remains a matter of perspective. Regulators maintain a stubborn faith in narratives of imminent technological transformation. Despite the troubling size and character of the ghost work phenomenon, regulators fail to confront the possibility of its persistence, and thus fail to accept it as a site for reform. A 2015 World Bank report on online outsourcing claimed that forecasting beyond 2020 was "highly speculative" due to the sector's susceptibility to rapid technological change[62]. Gray and Suri challenge this idleness. They revisit how Microsoft leveraged Permatemp contracts as far back as the 1980s[42]. "We can not be sure if the 'last mile' of the journey toward full automation will ever be completed," they warn, adding that, "the great paradox of automation is that the desire to eliminate human labor always generates new tasks for humans"[42]. Even as technological boundaries change, workers' precarious status remains the same.

3.2 Technical debt

The second labor category to assess is *technical debt*. Technical debt is a form of delayed labor normalized through the acceptance of poor craftsmanship. In recent years, the programming community has used the term to characterize the compounding maintenance costs associated with poor design choices in program writing. Ward Cunningham coined the term in 1992, stating, "Shipping first time code is like going into debt. A little debt speeds development so long as it is paid back promptly with a rewrite... The danger occurs when the debt is not repaid. Every minute spent on not-quite-right code counts as interest on that debt."[63] Attempts at a framework for how to measure and monitor technical debt remain theoretical at best[64–69]. Estimates hold that in the development of machine learning systems, technical debt accrues at a rate comparable to that of a high-interest credit card[70, 71]. Researchers at Google, Inc. warn of compounding "correction cascades" in these fragile models, meaning hidden feedback loops, signal entanglements, and other technical challenges due to what they describe as the CACE principle, for "Changing Anything Changes Everything"[70].

Tomorrow's workers, both expert and not, will inherit the labor required to constantly repair and maintain this delicate infrastructure. That Facebook's moderator-to-user ratio increased sixty-fold between 2009−2019 speaks to the scope of the labor force required to algorithmically oblige evolving norms, customs, and laws in an ever-increasing number of overlapping domains. The European Commission, by analogy, employs a full-time "Protocol Service" to keep its human leadership tuned to ever-shifting cultural and political norms in national and regional contexts within that boundary[72].⑪ As the CACE principle distills, it is difficult to design AI systems that integrate a similarly fluid and complex set of concerns in real-time without human support. This difficulty rises further as developers attempt to model three dimensional environments. Sally Applin argues that software active in an "autonomous" vehicle must, in principle, seamlessly and unfailingly update across shifting municipal, city, regional, state/province, national, and international borders[73]. This software would also presumably register and integrate all relevant changes to the unfixed physical world (e.g., downed trees, new construction, etc.). These are Sisyphean undertakings. Narratives of an AI "revolution" belie the distribution of labor that make these performances of autonomy feasible at all.

3.3 Intellectual debt

As with technical debt, *intellectual debt* is a form of delayed labor. Zittrain uses the term to characterize the manner in which AI—and machine learning specifically—serve to "increase our collective intellectual credit line" by providing atomized solutions to problems without any clear explanation of the causal

⑩ Gray and Suri caution that no laws yet govern who counts as an "employer" or "employee" in this domain. Roberts explains that content moderators are also hired under the work titles "screener" or "community manager".

⑪ They are responsible to oversee appropriate gifts, actions, attire, and even choice in songs for events.

mechanisms involved[74]. In principle, access to this credit line could normalize widespread offsetting of theoretical explanation, where isolated decisions not to identify causal mechanisms accrue into a network of unchecked faith. Despite digital tools being the primary cause of this phenomenon, they are also held up as a primary solution, which fuels a feedback loop toward trained dependency and the centralization of power amidst cacophony. “A world of knowledge without understanding becomes a world without discernible cause and effect, in which we grow dependent on our digital concierges to tell us what to do and when”[74].

Influential figures in the American technology sector have extolled this horizon. In a 2008 article entitled “The End of Theory: The Data Deluge Makes the Scientific Method Obsolete”, Chris Anderson, chief editor of *Wired* Magazine, called on his readers to reimagine science in the mold of Google’s data-intensive advertising business. He celebrated an explanatory paradigm in which approximations to scientific truth follow from correlations found in massive stores of behavioral data, rather than from hypothesis and testing[75]. Also in 2008, Peter Norvig, Google’s research director, advocated to update the statisticians’ maxim “All models are wrong but some are useful”, to “All models are wrong, and increasingly you can succeed without them”[75].⑫ Weinberger, in a 2017 op-ed for *Wired*, reaffirmed Anderson’s vision for a new decade, claiming, “Knowing the world may require giving up on understanding it.”[76]

Intellectual debt is not unique to machine learning. As Zittrain notes, it is routinely accepted in areas of medicine. The drug Modafinil, for example, is sold with a disclaimer stating that its reasons for being effective are unknown. In the healthcare sector, however, such decisions face significant regulatory scrutiny and oversight. These burdens do not yet weigh as heavily on the tech establishment. Nor is mistrust of intellectual debt a guarantee that such heavy restrictions will naturally emerge over time. In the 1980s, automated and semi-automated document retrieval systems were met with a similar mistrust[77]. Indeed, the embrace of instrumentalist statistics in the United States can be traced back to the late nineteenth century[78]. Without regulatory oversights in place to ensure genuine social progress, the merits of which have already been overlooked by existing AI principles[79], this trend will likely burden tomorrow’s workers with the mountain of tedious responsibilities that accompany navigating an experimental turn away from the reliability of causation.

3.4 Critique

A fourth category of labor is *critique*. This category is broad: it could feasibly encompass the labor required to investigate, identify, articulate, remedy, and/or reject the degenerative aspects of “autonomous” systems. This characterization provides a wide enough berth to encompass the work of theorists like, say, Langdon Winner, activists like those in the Carceral Tech Resistance Network, and those whose labor sustains movements of technological prohibition like Neo-Luddism. The ACM FAccT conference, which highlights engineering critiques of algorithmic systems, offers a window into the growth of at least one aspect of this broad domain: since the conference was formed in the late 2010s submissions have increased roughly two times annually, from 73 in 2018 to 290 in 2020.⑬ While the growth of the AI industry is now regularly indexed by top universities and businesses[80], the growth of so-called AI Ethics, a contentious title for the body of criticism (as this issue conveys), is not as well understood.

Of note is that, at present, much of this labor is subsidized by the public. Of the seventy sets of recommendations on trustworthy AI produced between 2017−2019, industry produced roughly a fifth of submissions, and civil society and governments, together, roughly a half[81, 82]. Principled proposals for citizen juries and government-run data trusts extend, in their orientation, a similar expectation for the public to pay for the failures of automation. Zittrain, for instance, positions academia, along with public libraries, as the natural home for new modes of critique. He proposes that datasets and algorithms that meet a sufficiently broad level of public use could be tested by researchers to mitigate errors and vulnerabilities before they compound.

If adopted in tandem with structural reforms to labor standards, such proposals could bear fruit. Regrettably, most academic labor is now precarious and prone to exploitation. 73 percent of faculty in American higher education institutions work part-time or otherwise off the tenure track, which provides little job security[83]. 60

⑫ The first maxim is commonly attributed to the statistician George Box.

⑬ ACM FAccT (formerly FAT*) stands for Association for Computing Machinery’s Conference on Fairness, Accountability, and Transparency in machine learning. Thank you to Christo Wilson for the figures.

percent of higher education staff in UK universities struggle to make ends meet, with part-time and hourly paid teachers doing, on average, 45 percent of their work without compensation[84]. Meanwhile, in early 2020, Google, Inc.'s parent company Alphabet Inc. became the fourth US technology company to reach a market cap of over a trillion dollars, following Apple Inc., Amazon, and the Microsoft Corporation, with Facebook now close behind. The normalization of un- or low-paid critique thus threatens to normalize public responsibility for avoidable harms ill-managed by industry.

3.5 Participatory labor

The final category of labor the author assesses defies reduction to a single classification. This cluster encompasses the surfeit of unpaid and often unrecognized tasks and offerings undertaken by consumers, users, and citizens when they engage, passively and actively, with digital modes of automation. This includes but is not limited to:

• Do-it-yourself economies (e.g., self-checkouts, self-check-ins, self-booking systems, solve-it-yourself customer service);

• Open-source software economies (e.g., pro-bono support of for-profit infrastructures);

• Inference economies (e.g., proprietary model training via auto-complete, CAPTCHA or service fulfillment, such as traffic patterns inferred from a driver's rideshare activity without fair compensation);

• *Digital labor* and *informational labor* economies (e.g., online community management, such as the labor volunteered by women of color in response to misogyny and racism on platform systems[85–87]);

• Covert agency economies (e.g., the unacknowledged workarounds users employ to modify or overcome limited affordances in an algorithmic system[88]);

• Dark pattern economies (e.g., design affordances that trick a user into signing up for something they do not want[89]);

• Reputation maintenance economies (e.g., labor undertaken to maintain one's standing when it is impacted by a system's shortcomings or outright failings[90]).

These diverse types of labor substantiate the "human infrastructure" required to integrate digital automation into daily life[91]. When deployed into structurally racist, sexist, and ableist societies, such structures tend to disproportionately penalize marginalized groups[92, 93]. These burdens are normalized through appeals to a neoliberal conception of consent, which assumes a base level "capacity for consent" that is unsubstantiated in reality[94]. When collective harms are framed as the responsibility of each individual to navigate, only those with power can afford to understand and overcome them. Others face exile or deprivation when they try to resist. Robust taxonomies and lines of solidarity are needed to map, connect, reform, or reject these entangled forms of labor, and to identify the toll of their collective impositions. These taxonomies might also be used to build toward renumeration and reparation structures that recognize and respond to each party's contingent inputs[95, 96].

This brief survey of *ghost work*, *technical debt*, *intellectual debt*, the labor of *critique* and *participatory labor* highlights the significant labor—both in the present and in the future—that organizations depend upon to further the sales friendly mythos of AI. "We are all system administrators now, whether we realize it or not," write Dick and Volmer, who assess user-supplied maintenance in relation to Microsoft's Windows platform[97]. Much of what the author has covered here reduces to the extended labor economies of error and anomaly management. Given this common source, it is worth noting that the earliest pioneers of computing had not anticipated that such labor would be necessary. They believed, wrongly, that computers would not have bugs. In his autobiography, Maurice Wilkes, who developed EDSAC, the first practical use stored-program digital computer, grappled with the realization that a good portion of the remainder of his life would be spent fixing errors in his own code[98]. "Debugging had to be discovered," he recalled[98].⑭ In that era, and again with AI's maturation, the messy and irreducible complexities of material reality interrupt the principled but all too abstract aspirations of even the most accomplished computing engineers.

Since the development of EDSAC in the 1940s, the labor required to analyze, design, test, debug, and develop computer programs has become a recognized and deeply influential employment category known as, "Software Development and Programming". In the United States, it is one of the few employment categories to have emerged over the past century that employs a significant proportion of the population. As of 2010,

⑭ Emphasis mine.

there were thirty-five million computer experts employed around the globe, five orders of magnitude more than the initial group of scientists, engineers, and support staff working in the midcentury[99]. In 2016, 1.7 million were employed as software developers in the US alone, with an estimated 300000 expected to join in the decade to come[100]. Low-cost fauxtomation broadens this labor network even further, reaching into exploitational labor categories that remain to be taxonomized and acknowledged in the way that Software Development and Programming was during and after the 1960s.

Remaining to be seen, as responsibility for integrating these errors translates slowly into a tree of discernible job categories (e.g., content moderator, quality assurance officer for driverless vehicles), is the extent to which the accruing errors, harms, and sacrifices involved in adopting these systems should be absorbed by an already over-leveraged public. These impositions are particularly difficult to characterize, as is their chain of responsibility[101−103].⑮ By analogy, in 2016 analysts positioned medical errors as the third leading cause of death in the US[104, 105]. A 2018 report estimates that software bugs killed more than one thousand patients per year in the UK, with blame often passed on to doctors or nurses[90, 106, 107].⑯ A decade prior to the AI Revolution, the US Commerce Department estimated that computer users shared half the cost of the ＄22.2−59.5 billion lost annually as a result of inadequate software testing infrastructure[108]. These sacrifices—lost lives, lost wages, lost recognition, lost opportunity, lost insights, and lost time—are substantial, and they will grow larger still.

4 Automation's Impositions: A Structural View

The author's reason for connecting these threads is to draw attention to the outcomes of neglecting digital automation's systemic impositions, which entangle in ways that resist simple reduction. Notions of labor provide one lens into this change, as the prior sections demonstrates. Yet labor, alone, is not the only way to understand this change. As "predictive" technologies swell and rescript the logic of daily behaviors in healthcare, education, and beyond, competing automated systems will vie for citizens' finite time and encode their behavior with sophisticated interactivity[109]. Without adequate protections in place to monitor and/or meaningfully prohibit such impositions, low-cost decision systems will compound the public's digital obligations and slowly (or perhaps rapidly) sap their availability to non-digital systems. Existing terms of critique fail to capture the full character of this levy. Loss is treated in financial terms, as technical debt or intellectual debt, rather than a more profound loss of possibility. Ruha Benjamin subverts this trend when saying, in relation to technology's role in perpetuating anti-black logics, "Most people are forced to live inside someone else's imagination" (Ref. [110]; see also, in relation to critique of normative conceptions of time[111−113]).

An analogy is useful here as a means to characterize the scale of this type of systemic phenomenon and the related power that new vocabulary can have to communicate the complex reasons for an equally broad shift in course. The terms "global warming", "climate change", and "Anthropocene" introduced the public to the idea that local environmental harms, when taken in aggregate, amounted to a fatal error in cultural logic, one that now threatens the survival of our societies, with marginalized groups around the globe faced with the most dire risks[14]. These marquee terms speak to the sum-total harm caused by a complex web of operators whose default perspective was to treat carbon emissions as an acceptable negative externality. Emissions were considered someone else's problem—just as automation's impositions are now. "Global warming" and related terms interrupt that base assumption. They illuminate the inescapable hazards for everyone that accompany unrestrained material consumption.

That a climate crisis loomed in the late twentieth century was clear to many long before the invention of those aforementioned terms. In 1955, John Von Neumann, whose logical architecture laid the blueprint

⑮ Hobbyists, historians, and risk researchers maintain venues to catalogue and characterize the impact of poor error management in digital systems, but no sophisticated repository captures a broad picture of their aggregate toll, both economic and otherwise. For a moderated forum on the safety and security of computer and related systems see the Risk Digest. For a hobbyist's collection of serious or novel bugs see Huckle. For recent research on the role of error in the history of computing, see SIGCIS.

⑯ Elish calls this phenomenon of blame "the moral crumple zone" of automated systems. "Just as the crumple zone in a car is designed to absorb the force of impact in a crash, the human in a highly complex and automated system may become simply a component—accidentally or intentionally—that bears the brunt of the moral and legal responsibilities when the overall system malfunctions."

for the digital era, opined about this inflection point in an article entitled, "Can We Survive Technology?"[114]. During the first industrial revolution, he reasoned, "It was possible to accommodate the major tensions created by technological progress. Now this safety mechanism is being sharply inhibited; literally and figuratively, we are running out of room. At long last, we begin to feel the effects of the finite, actual size of the earth in a critical way."[114] John Von Neumann reckoned with technology's aggregate material implications. In this article, the author gestures to its aggregate temporal implications and administrative obligations.

As with climate change, the localized impositions of, in this case, low-cost decision systems, are dismissed by society at large as uncontentious in the short-term. Only once a ceiling asserts itself might this fleet of impositions be seen as degenerative and systemic. Regrettably, as with climate change, the existence of this ceiling is difficult to convey to the broader public—until it is not. Instead of fires, floods, and ecosystem collapse, temporal erosion may come to resemble, say, a latent denial-of-service (DoS) attack on a society's daily decision-making abilities. A DoS attack is a cyber-attack in which a communication pathway is flooded with enough superfluous requests to make it unavailable. By analogy, a poverty of time, caused by the proliferation of digital obligations and delights (deployed at low-cost), could hobble the public's collective capacity to consider or even imagine alternative modes of social organization, such as those that do not center on data, efficiency, or technological progress. Wood writes, from a related vantage, "Surely the most wretched unfreedom of all would be to lose the ability even to conceive of what it would be like to have the freedom we lack, and so dismiss even the aspiration to freedom, as something wicked and dangerous" (as cited in Ref. [92]).⑰

The difficultly of conveying this complex problem to the public is that time attrition is the product of a threatening system, not a threatening character or object. The harms of automation in oversupply are captured narratively in a folktale about The Sorcerer's Apprentice, in which an enchanted broom causes a flood by collecting and pouring out too much water for its new, inexperienced master. In the West, however, advanced automation is often personified, through characters like the Terminator, rather than being cast as infrastructural or distributed. These accounts of automation-as-individual, also captured in narratives about job losses to robots, distort the public's sensitivity to both the banality of the AI Revolution and its contingent harms. These stories convey a threat, but as with climate change, they may underemphasize the decentered nature of that threat.

Adding to the challenge of effective public communication of a world awash with low-cost decision systems is that skeuomorphs (i.e., features passed from one technology to another related technology, like the familiar "click" of a smartphone's shutter, which does not in fact exist or make a sound) have so far failed to preserve traditional prohibitory functions, such as those that ritualized natural limits and restraint. Digital automation techniques know no opening hours, holiday closures, snow days, sick days, periods of grievance, nor even strict regulatory limits on their collective impositions. These are the technological manifestations of the neoliberal attitudes that preceded them. Interventions in privacy law, labor law, consumer protections, and in the digital wellbeing movement add friction to select intrusions, as epitomized by worker's right to disconnect in France and Germany. Yet, as with climate change, reform is still often cast in relation to the individual, as if the potential to meter excess is somehow unavailable at the group level. This is a false restriction. Collective remedies, as always, remain viable.

The irony of this dilemma is that automation, at a certain level of proliferation, eventually fails to fulfill on its own celebrated purpose: to save time. The endless need to integrate different types of automation draws the ideal toward self-contradiction. Each new act of coordination creates a new labor requirement. This labor can be automated, but then that new automated system must be integrated, too. This feedback loop introduces new types of administrative obligations that, as the five labor trends outlined above adequately suggests, can be easily overlooked by those who benefit from their presence. As with climate change, marginalized peoples suffer these harms first. In the long run, however, as for the Sorcerer's Apprentice, a world awash with such obligations would presumably ensnare their elite creators as well by interweaving them in a society shaped by the same scripted logics they have used to control

⑰ Although this may sound alarmist, the emergence of light and sound pollution evidence how impacted parties can overlook what is lost amidst poor regulation. The author once met a child who had never seen the stars due to light pollution in his neighborhood.

others. The unrestrained use of low-cost decision systems would amount to death by a thousand paper cuts for a society callous to the compounding effects of such temporal pollutants.

By my account, the prolific use of digital decision systems, fueled by low marginal costs for proliferation and ascendant narratives of an imminent AI Revolution, marks a new stage in complex debates over the societal role(s) of automation. The characteristic the author seeks to denaturalize is the assumption that digital automation—by its own logic—merits recognition as a self-evident form of cultural progress. In the author's view, critics of automation who entertain this horizon (e.g., automation-as-progress) without also embracing acts of prohibition assume too readily that technical solutions can be found—eventually—and that, as a result, solutions should be labored toward. This endless-horizon narrative permits systemic harms to persist, with marginalized peoples bearing the brunt of tomorrow's maintenance. Acts of prohibition create decision making systems in which knowledge of such tools is not a prerequisite. With these spaces, critics endorse a growing distance between them and the non-expert communities they often aim to represent. Stated differently, advanced automation techniques may need to be resisted wholesale if tech ethics experts are to avoid becoming the technocrats they seek to displace.

5 On Formalization and Its Alternatives

One way to resist the encroachment of digital automation is to question the methodologies that clear a path for its use. One such methodology is the use of formalization to describe a system's presumed nature. In his introduction to Minsky's 1961 paper, "Steps Toward Artificial Intelligence", which laid out a research agenda for that discipline[115], guest-editor Harry T. Larson wrote, "When the practitioner has overcome his fear of the machine, and when the scientist and practitioner are communicating, the attack is relentless. The scientific mind has found an un-formalised field, and it cannot rest until it identifies, understands, and organizes basic elements of the field"[116]. Aspects of contemporary research on fairness, accountability and transparency in machine learning echo Larson's positivist dogma by implying that highly formalized engineering techniques will muster adequate solutions, rather than re-inscribing underlying harms or reifying ever more bureaucratization[78, 117].⑱ Intervening at the point at which attempts are made to formalize a social system helps to provide citizens the derivative economic or administrative relief needed to decide on a civic future for themselves. Operating this far upstream avoids their being automatically ensnared in debate over a decision tool or technique that continues ad nauseam.

To conclude, the author fosters a metaphor that he hopes will lend subtly to dialogue about how to reshape positivist inclinations in the automation space into something less brutal and domineering. In sheet music—indeed, in music composition generally—special notation is used to convey the role of a deliberative silence. These constructions build negative space purposefully, as a mode of art. Without rests, music would be cacophony. A recent wave of legal prohibitions on facial recognition technologies across American cities substantiate deliberative restraint in response to automation. US communities have opted to preserve what the author calls an algorithmic silence: the purposeful exclusion of highly abstract algorithmic methods from human decision-making environments. A silence of this type asserts that the value of such theory is worth more to the community when left unrealized. Such acts of prohibition leave room to incorporate holistic thinking about the myriad ways that advanced decision systems re-shape and bear upon human societies. Bans and moratoriums hold a space for reflection on the systemic burdens disguised by disingenuous rhetoric and incremental reformism. It provides the proverbial "frog" with the interruption necessary to recognize that it is in the proverbial "boiling pot".

Another benefit of this approach to resisting automation's impositions is that it reconfigures the distribution of labor involved in shaping the roles that digital decision systems ought to have in society. Algorithmic silence places the burden of proof on enthusiasts, rather than on critics, to prove why formal techniques and technological artifacts should be welcomed into a social system at all. Revoking entitlements to public goodwill reveals the actual toll of integrating such systems into daily life. Enthusiasts would need to prove ahead of time how their automated systems function without access to no-pay and low-pay surrogates to clean up the mess caused by piloting poor

⑱ Jones uses "data positivism" to describe this instrumentalist model of induction, which seeks functions that fit to the data, rather than functions that fit to a corresponding law of nature.

tech craftsmanship on the public. This tempts reflection on automation's full bill (and distribution) of costs, the nature of which transcend financial levees.

A third additional benefit to the normalization of prohibitions as a response to the excesses of an automated society is that this path would limit corporations' access to public coffers. By this route, universities and colleges would be spared reduction to the role of algorithmic custodians; history departments would need to be shuttered so that a new generation of scholars can find and resolve software errors on behalf of Facebook. Algorithmic silence asserts that the significant and underappreciated costs of experimenting with automation in the wild are paid for by the scientist and their patrons, rather than by the communities those groups treat as laboratories. Those who champion the horizon politics of automation, meaning the notion that decency will come "eventually" and that the status quo must remain until then, are handed responsibility for these "acceptable" burdens instead.

The motive power of a well-timed silence rings loudly. Rest, some forget, is its own vehicle. The ambience it creates is inhabitable and thus sacred. By this view, algorithmic silence is another safe road to progress. Sahlins—aware that declines in leisure time have been naturalized over centuries and can thus be denaturalized—famously memorializes hunter gathers as the original affluent society given that they toiled only three to five hours a day[118]. Via a far more theory-laden approach, Mejias introduces the term "paranode" to characterize the multitudes that lie beyond the network logics used in contemporary life to model and assimilate all that is social. A paranode is a place beyond the conceptual limits of networks[119]; a structural component that alters network outcomes but from outside the network's reach. An act of paranodality is one of disidentification with the logic of that network. Consider a broken URL, RFID (radio-frequency identification) blocker, or pirate radio. Each exists slightly beyond the validation of the networks designed to subsume it. By rejecting the hegemony of advanced decision systems, algorithmic silence fosters paranodality.

This account of paranodality from Mejias implies that those who resist disidentification from a network are more radical than those who cause it. By my account, those who reject algorithmic silence are tantamount to those who reject silence in music. This willingness to create cacophony is deeply political, since it is often not those enthusiasts who suffer its hazards. In response, these parties claim that acts of prohibition are antithetical to progress. This shaky platform would seek to undermine that silence is in fact co-constitutive of harmony; the two cannot exist apart. Writes musicologist Zofia Lissa, "In its symbiosis with sonority, silence is one of the structural elements of the sound fabric, though in itself silence is the very negation of a sound fabric."[120] Mejias, too, positions paranodality as intrinsic to a networks' structure. An attack on disidentification is thus an attack on the structure of the network.

At root, musical notation and network structures can be understood as metaphors for epistemic sovereignty in the face of technoscientific hegemony. Each makes a virtue of noncompliance. Algorithmic silence, likewise, provides an ambience that is, at first, epistemically nonhierarchical. What comes from this state, however, is unpromised. At best, respite from the perils of ubiquitous AI could provide a window into a way of knowing that colonialism has forcefully displaced; an occasion, per Nelson, to witness that "the human is not a problem to move beyond"[121]. Silence for the sake of silence constrains positivist technoscience by asserting arbitrary limits to its valorization of hyper rationalization and administration. It is an invitation to technocrats to stand outside of that rationalist bubble; to grieve, instead, the presumptuous fictions of progress and futurity. A chorus of algorithmic silences, the author wagers, could help to break the spell of AI by building harmony between its countless alternatives. Proponents of such techniques would arrive, instead, into the present, occupied as it is by the durability of imperialism[122] and the permanence of pollution[123]. Here, a different set of experts call the tune.

The growing ubiquity of advanced low-cost automation techniques has made strange bedfellows of those who seek the dangers of unrestrained automation. Military researchers, both in the US and India, have recently framed contemporary information flows as a growing *impediment* to their ideological aims rather than a cherished resource[124, 125]. "The desire to have maximum inputs for decision making is a tempting proposition but will have to be tempered with the necessity of giving a decision in time. As time pressures become more acute, we may well end up with ‘information decoherence’.”[126] This is a remarkable outcome given that the US military played a definitive role in pioneering modern information management techniques via the development of systems analysis, operations research, game theory, and digital computing and digital networking generally[127, 128]. For military researchers to insinuate the need to de-escalate information management is telling of the hazardous path dependencies of unrestrained automation. It speaks to a carrying capacity, or ceiling, after which even hardline proponents see diminishing returns from the logics behind mass automation. Cowan, similarly, debunks the popular myth that American domestic technologies saved domestic laborers time through automation. In fact, Cowan shows, such tools introduced more work for these laborers by upsetting the equitable models of labor distribution assumed in prior centuries[93].

In raising these critiques, and the unique possibilities afforded by the thoughtful use of prohibition amidst the rapid development of low-cost automated systems, the author seeks to emphasize the search for harmony in the development of digital automation regimes, particularly in the value-sensitive realm of democratic governance. It bears mention at this juncture that silence, on its own, is not harmonious, although the experience of it may be pleasing at times. Harmony, by definition, requires the thoughtful combination of positive expressions and their opposites, rather than simply the preservation of a dead signal or cacophony. The possibilities for proverbial harmony, in this regard, are vast[129]. In their 2020 book *Meaningful Inefficiencies*, for instance, Gordon and Mugar argue that public trust in civic organizations requires that such systems are designed *not* to be efficient[130].

In consideration of what precise balance to strike, it is worth considering that contemporary debates over acceptable levels of formalization and algorithmic management in a given context mirror a longstanding dilemma in American political theory about the appropriate balance between democratic representation and the agents who administer it. Herein lies a thorny trade-off: administrative decision makers in large-scale democracies, such as monetary experts, hold both the specialist knowledge to make an informed judgement and a capricious discretion over outcomes that no elected representative could ever hope to oversee. Sheer administrative complexity stifles democratic accountability by furnishing these experts with determinative rather than consultative capabilities[131]. Since there are too many experts for any elected representative to ever manage in these large systems, this group of specialists effectively skirt traditional modes of civic accountability.

The AI “revolution” teases this dilemma into new territory. As in industry, political administrators are easily tempted toward the presumed incentives of fauxtomation—efficiency, self-regulation, cost savings, etc.[79] This temptation leads them headlong toward a murky accounting of the contingent labor required to accomplish desired outcomes. The introduction of yet another layer of abstraction into state administration puts yet more distance between the public and their representatives[132, 133].⑲ Worse, Kafkaesque modes of administrative accountability fatigue the public’s sensitivity to their civic entitlements. “Decision-making structures become systems of domination”, warn Downey and Simons about the failings of contemporary pre-automated democratic procedures, “Nobody appears to have responsibility for the reproduction of injustice over time: not elected representatives, delegated agencies or private corporations”[131]. As in the American and Indian military contexts referenced above, complexity has exhausted the system’s potential for capacity.

The promise (or specter) of automation is that it can resolve complex administrative tradeoffs in a seemingly rational fashion. Regrettably, as demonstrated in the opening to this article, disingenuous rhetoric around the true capabilities of such techniques distorts a clear appraisal of their worth. Confusion over this accounting becomes, in the process, its own powerful form of deflection. When questioned by the US Congress and Senate about Facebook’s content moderation architecture in 2018, for instance, Mark Zuckerberg made frequent appeals to the efficacy of “artificial intelligence” to solve known problems[134], despite the

⑲ Lanius introduces how statistical technologies distort expectations about evidence amongst black and white communities. Hill shows how access to evidence from sophisticated analytical tools privileges those in the criminal justice system but penalizes marginalized individuals. Literature on the digital divide substantiates other disparities caused by the politics of digitization, such as the fact that the majority of content on the internet is in English, which alienates people who speak other languages, and that this content is most often developed for haptic interfaces on computers and smartphones, which alienates people with disabilities.

efficacy of such methods remaining untested. From this perspective, Zuckerberg's call for patience is in fact a call for the public to subsidize the status quo; to absorb the costs of his failure indefinitely in the hopes of an imminent technological solution—a simple expression of horizon politics in action. In the process, technical and intellectual debts continue to accrue, along with the social costs of abuse, harassment, and misinformation that traffic on his channels.

While Zuckerberg and Facebook can, for the moment, sustain this violent charade, it is less clear that a genuine large-scale democracy can do so as well. Consider the right to a public defender. This right is made trivial if that defender is too overburdened to adequately fulfil the duty, as is now the case in areas in the United States[135]. In this instance, a failure in due process negates the possibility to assert hard-won democratic principles; justice delayed is justice denied. While new technologies are held up as solutions as such problems, their total compounded administrative costs remain unclear at best, as the author has argued. At worst, sophisticated digital architecture is a known hazard to accountability. In an indicative case-study, Dick and Volmar capture what is called "dependency hell" in the use of Microsoft's infrastructure[97]. In this hell, individual components function precisely as intended but systemic failure results, nonetheless. "Who ultimately 'owns' a failure in a system like this?" they ask, "More importantly, who fixes it?"[97]

Algorithmic silence tempts these obscure politics into the light. The term connects acts of restraint that might otherwise be read as dissimilar. If ubiquitous automation is liable for its burdens and not just it promises, then bans on facial recognition technologies can be understood as of a kind with, say, the EU's Working Time Directive (2003/88/EC) and Right to Disconnect, which set out minimum requirements for rest in relation to telework. Each intervention imposes regulatory limits on the prospect of algorithmic optimization. Whether or not the human workplace or the human face is pliable to such techniques is made moot. Regulators, following public pressure, preserve the relatively intimate (if imperfect) modes of accountability permitted by human-to-human scale interaction.

The need to protect time and space from the AI Revolution echoes in literature on AI and medicine. Topol speculates that the core benefit of advanced decision systems will be time savings gained by experts moving away from automation[136]. US doctors currently face a degenerative cycle; more than 50 percent suffer burnout and 25 percent suffer depression—pressures that beget additional medical errors and strain, which exacerbate suffering and can lead to suicide[136]. Topol positions protections on time as a promising line of resolution to this feedback loop, not just for clinician's work/life balance, but also for patient outcomes. A study of 60000 caregiver visits identified the provision of additional patient-to-expert time as the most reliable path to decreasing hospital readmissions, as other studies support[136].⑳

In medicine, human-to-human accountability regimes led to improved outcomes. Summarizing one of several such studies, Topol writes, "Taking the computer out of the exam room and supporting doctors with human medical assistants led to a striking reduction in physician burnout, from 53 percent to 13 percent."[136] This solution is not new. On the contrary, Topol's thesis echoes the sentiment of William Osler, co-founder of John Hopkins Hospital, who wrote in 1895, "A sick man cannot be satisfactorily examined in less than half an hour."[136] Indra Joshi, Digital Health and AI Clinical Lead for NHS England, agrees. Joshi describes the experience of waiting in the journey for treatment—for results, a specialist, or a bed—not as a process, but as a state of being, "A feeling of being neither here nor there"[137]. This is the same torturous state of being that Zuckerberg, Facebook, and other influential proponents of ubiquitous digital automation advocate for and enforce through the tact they take to technological development[138]. Just hold on, the story goes, we are almost there.

To interrupt this rhetoric, critics must adequately diagnose its charm. Crucially, Zuckerberg and peers assume no finite constraints on time. This is their faux reality. Such appeals benefit from at least three levels of illocution[139] (Garvey characterizes the history of AI as a string of illocutionary acts or promises). Within AI, as the author has introduced, technical terms like "predict" describe a desired end state, not a procedure in time. The term "artificial intelligence" is an exemplar of this trend; a vague yet seemingly prophetic sign of a movement yet to come. Reckless critique overlooks this folly. It accepts

⑳ Giving a patient an additional minute with an expert reduced their probability of being readmitted by 18%, or 13% in the case of nurses. A separate study found that additional time with experts reduced hospitalizations by twenty percent.

AI rhetoric without scrutiny and diverts attention from wishful mnemonics to "wishful worries", Brock's term for "problems that it would be nice to have, in contrast to the actual agonies of the present"[140]. Meanwhile, a fleet of human contributions, both paid and unpaid, perform, unknowingly and knowingly, a broad array of discreet tasks that, if overlooked as systemic and connected, might lend AI an air of legitimacy and imminence. Like the Church-Turing Thesis, AI provides a tantalizing and multifaceted escape from the existence of time and space, but only for a privileged few.

To interrupt this wishful cycle, critics must situate AI within the post digital era, meaning the period in which, "The revolutionary phase of the information age has surely passed"[141]. Cut off from the ability to escape time or make vague appeals to imminent transformation, AI advocates would be pressed to justify their interventions on alternative grounds. One option the author has championed here is to audit the labor required to develop, deploy, maintain, critique, and use such tools. If this was a norm, a clearer picture of AI's proffered impact on labor could begin to emerge. More likely, expert-led calls for algorithmic accountability would be met with a charge akin to "Luddite!". The author, for one, fears that the history of Luddism is too disanalogous to today to accommodate the paradoxes of contemporary automation, replete as it is with the compounding intersectional realities of gender, race, class, coloniality, and globalization[21, 142]. Digital tools embody opportunities and risk across many layers simultaneously; their treatment deserves more nuance.

Enter algorithmic silence. If unburdened by the accumulated labor required to perform the AI Revolution ad infinitum, citizens would gain the incremental derivative economic or administrative relief needed to decide on a civic future for themselves. Their reliance on technocrats posturing as AI ethicists would be diminished in proportion to the nonproliferation of faux automation systems, since—in principle—the civic space in which they operate would be relatively less influenced by unrestricted impositions on their finite time. Algorithmic silence provides a content agnostic framework for solidarity across settings, be it restraint for workers, consumers, parents, prisoners, women, youth, etc. The prospect of solidarity across these contexts is, in principle, broad enough to answer orthogonal pressures from data science. Ribes, for example, shows how the term "domain" presupposes a role for computing in areas of life not yet conscripted into such methods[143−145]. For solidarity to emerge across countercultures, interventions must evidence a larger movement, whatever it may be called. Algorithmic silence is a step toward that end.

As critics mobilize against automation's harms, they must confront the possibility of achieving a Pyrrhic victory. Clearly articulated ethical principles would indeed be a positive result, but their enshrinement into law remains only half the battle (see also Ref. [146], this issue). Commitments to due process must also be considered, articulated, enacted, and enforced, or hard-won principles will be a farce, as is witnessed with overworked public defenders and caregivers. The politics of procedure and promise of automation merit deep contemplation in a moment when indigenous leaders and scholars in particular reaffirm ancient notions of accountability to place, planet, and people that stand to exceed the shortcomings of liberal democratic imaginaries[147−149]. Transformation is possible, but likely not via appeasement. By continuing to normalize the presumption that automation can be refined and improved—that satisfactory tech ethics can be articulated—those in the realm of automation development and critique point to a loadstar that either misguides them, or makes real a system of politics that, in fact, they endorse but have not yet been held accountable for.

6 Conclusion

Arthur C. Clarke's popular Third Law About the Future boasts, "Any sufficiently advanced technology is indistinguishable from magic."[150] This literary "law" is often cited in salesmanship that surrounds the AI Revolution. It is used to paint a boundary between those who create technology and those who merely witness it. In this article, the author has questioned that boundary by exploring the ways in which groups who experience the "magic" of digital automation is often made into co-managers of that performance via ghost work, technical debt, intellectual debt, the labor of critique, participatory labor, or some combination therein. The author questions how the experience of advanced technologies changes as onlookers participate in an increasing number of performances simultaneously, day after day, week after week, without structured relief to their expected vigilance. Clarke's "law" claims to speak to the performative aspects of a new technology. Yet, tellingly, it speaks not at all to experience of those performers whose labor substantiates the act.

Given the need for public awareness around the structural impositions caused by an automated society, as well as the risk of paternalism that accompanies unchecked faith in a technocratic expert-led resistance, it is worthwhile to question which vocabularies adequately capture the character of the phenomenon the author has engaged herein. Algorithmic silence resists the tradition of highly formalized and positivist articulations of social dynamics that prefigure and inform contemporary forms of digital automation. The concept, instead, reifies the virtues of deliberate relief from these types of knowing. At best, it affords collective freedoms from the onslaught of formalisms and encoded behaviors that are sure to accompany the prolific use of low-cost automation. Algorithmic silence treats rest as its own dignified vehicle to progress—one that could surface lines of solidarity across otherwise divisive relationships changed by a rising torrent of discrete obligations. With each passing day, the global community awakens to the reality that, as Dick and Volmar suggest, we are all system administers now (or will be, eventually). Servicing the need for spaces untouched by algorithmic enclosure would allow civic communities the distance to reflect on and shape this unfolding phenomenon for themselves—or at least see that it is occurring.

Acts of wholesale prohibition such as that which the author distills as algorithmic silence tempt reflection on the ethos of entitlement that sustains contemporary myths about digital automation and a looming AI Revolution. If judged in relation to time and space, as opposed to the timelessness of an endless horizons, AI fits more neatly into the post-digital era in which no significant change to the existing social order is to be expected. At a superficial level, this reappraisal of rhetoric could help to steer AI development in line with existing traditions of de-escalation, such as decomputerization and degrowth, although the nuances of this proposal merit closer consideration (since algorithmic silence could also be abused). Those who address the environmental toll of machine learning systems, however, have made similar calls for decomputerization[151, 152]. Such acts of relief color the edges of what could become a powerful deindustrial revolution: a transformation equal in magnitude to the fabled AI Revolution but led, instead, by communities rather than corporate needs.

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References

[1] Y. Katz, Manufacturing an artificial intelligence revolution, *SSRN Electronic Journal*, doi: 10.2139/ssrn. 3078224.

[2] J. S. Brennan, A. Schulz, P. N. Howard, and R. K. Nielsen, Industry, experts, or industry experts? Academic sourcing in news coverage of AI', Reuters Institute for the Study of Journalism, https://reutersinstitute.politics. ox.ac.uk/sites/default/files/2019-12/Brennen_Academic_ Sourcing_in_News_Coverage_of_AI_FINAL.pdf, 2019.

[3] J. Penn, Inventingintelligence: On the history of complex information processing and artificial intelligence in the United States in the Mid-Twentieth Century, PhD Dissertation, University of Cambridge, Cambridge, UK, 2020.

[4] M. I. Ganesh and S. Lohmüller, #5 Spectres of AI, *Spheres: Journal for Digital Cultures*, https://spheres-journal.org/contribution/5-spectres-of-ai/, 2019.

[5] S. Cave and K. Dihal, Ancient dreams of intelligent machines: 3, 000 years of robots, *Nature*, vol. 559, no. 7715, pp. 473–475, 2018.

[6] S. Cave, C. Craig, K. Dihal, S. Dillon, J. Montgomery, B. Singler, and L. Taylor, Portrayals and perceptions of AI and why they matter, The Royal Society, https://royalsociety.org/-/media/policy/projects/ai-narratives/AI-narratives-workshop-findings.pdf, 2018.

[7] S. Cave, K. Dihal, and S. Dillon, eds., *AI Narratives: A History of Imaginative Thinking About Intelligent Machines*. New York, NY, USA: Oxford University Press, 2020.

[8] J. Dinerstein, Technology and its discontents: On the verge of the posthuman, *American Quarterly*, vol. 58, no. 3, pp. 569–595, 2006.

[9] P. Mirowski, *Machine Dreams: Economics Becomes a Cyborg Science*. Cambridge, UK: Cambridge University Press, 2002.

[10] R. Scott, Blade Runner, Movie, Jun. 25, 1982.

[11] M. Hicks, *Programmed Inequality: How Britain Discarded Women Technologists and Lost Its Edge in Computing*. Cambridge, MA, USA: MIT Press, 2017.

[12] J. Penn, Programmed inequality: How Britain discarded women technologists and lost its edge in computing, H-Sci-Med-Tech, no. H-Net Reviews, http://www.h-net.org/reviews/showrev.php?id=52804, 2019.

[13] C. Hauskeller and C. Hick, *Captivating Technology: Race, Carceral Technoscience, and Liberatory Imagination in Everyday Life*. Durham, UK: Duke University Press, 2019.
[14] R. Benjamin, *Race After Technology: Abolitionist Tools For The New Jim Code*. Cambridge, UK: Polity, 2019.
[15] V. Eubanks, *Automating Inequality: How High-Tech Tools Profile, Police, and Punish The Poor, First Edition*. New York, NY, USA: St. Martin's Press, 2017.
[16] M. Broussard, *Artificial Unintelligence: How Computers Misunderstand The World*. Cambridge, MA, USA: The MIT Press, 2018.
[17] C. D'Ignazio and L. F. Klein, *Data Feminism*. Cambridge, MA, USA: The MIT Press, 2020.
[18] J. Buolamwini and T. Gebru, Gender shades: Intersectional accuracy disparities in commercial gender classification, *Proceedings of the 1st Conference on Fairness*, *Accountability and Transparency*, vol. 81, pp. 77–91, 2018.
[19] O. Keyes, The misgendering machines: Trans/HCI implications of automatic gender recognition, *Proceedings of the ACM on Human-Computer Interaction*, vol. 2, no. 88, pp. 1–22, 2018.
[20] K. M. Miltner, Girls who coded: Gender in twentieth century U. K. and U. S. computing, *Science, Technology, & Human Values*, doi: 10.1177/0162243918770287.
[21] S. M. Ali, A brief introduction to decolonial computing, *XRDS*: *Crossroads*, *The ACM Magazine for Students*, vol. 22, no. 4, pp. 16–21, 2016.
[22] B. Green, The contestation of tech ethics: A sociotechnical approach to technology ethics in practice, *Journal of Social Computing*, doi: 10.23919/JSC.2021.0018.
[23] D. McDermott, Artificial intelligence meets natural stupidity, *ACM SIGART Bulletin*, no. 57, pp. 4–9, 1976.
[24] M. M. Malik, A hierarchy of limitations in machine learning: Data biases and the social sciences, presented at the Ministry of Science, Innovation, Technology and University of Spain, Virtual, 2020.
[25] Z. C. Lipton and J. Steinhardt, Troubling trends in machine learning scholarship, *Queue*, vol. 17, no. 1, pp. 45–77, 2019.
[26] S. C. Garvey, The "general problem solver" doesn't exist: Mortimer taube & the art of AI criticism, presented at the Society for the History of Technology, St. Louis, MO, USA, 2018.
[27] H. L. Dreyfus, *What Computers Can't Do: A Critique of Artificial Reason, 1st ed*. New York, NY, USA: Harper & Row, 1972.
[28] H. L. Dreyfus, *What Computers Still Can't Do: A Critique of Artificial Reason*. Cambridge, MA, USA: MIT Press, 1992.
[29] H. L. Dreyfus, Why heideggerian AI failed and how fixing it would require making it more heideggeria, in *The Mechanical Mind in History*, P. Husbands, O. Holland, and M. Wheeler, eds. Cambridge, MA, USA: MIT Press, 2008, pp. 331–372.
[30] A. Agrawal, J. Gans, and A. Goldfarb, *Prediction Machines: The Simple Economics of Artificial Intelligence*. Boston, MA, USA: Harvard Business Review Press, 2018.
[31] D. Gayo-Avello, "I wanted to predict elections with Twitter and all I got was this lousy paper" — A balanced survey on election prediction using Twitter data, arXiv preprint arXiv: 1204.6441, 2019.
[32] M. Mitchell, B. Agüera y Arca, and A. Todorov, Do algorithms reveal sexual orientation or just expose our stereotypes?https://medium.com/@blaisea/do-algorithms-reveal-sexual-orientation-or-just-expose-our-stereotypes-d998fafdf477, 2019.
[33] M. Malik, Can algorithms themselves be biased, https://medium.com/berkman-klein-center/can-algorithms-themselves-be-biased-cffecbf2302c, 2019.
[34] J. C. Scott, *Seeing Like a State: How Certain Schemes to Improve the Human Condition Have Failed*. New Haven, CT, USA: Yale University Press, 2008.
[35] G. C. Bowker and S. L. Star, *Sorting Things Out: Classification and Its Consequences*. Cambridge, MA, USA: MIT Press, 1999.
[36] N. Ensmenger, Chess, cars, and cognition: How problem choice shapes a discipline, Pavilion Room, Hughes Hall, Cambridge,http://lcfi.ac.uk/events/origin-myths-artificial-intelligence-histories-tec/, 2018.
[37] K. Crawford, R. Dobbe, T. Dryer, G. Fried, B. Green, E. Kaziunas, A. Kak, V. Mathur, E. McElroy, A. N. Sánchez, et al., AI now 2019 report, AI Now Institute, New York, https://ainowinstitute.org/AI_Now_2019_Report.html, 2019.
[38] E. Antonova, Y. Chaudhary, S. Dick, and S. McDonald, Next leaders: Bold visions for the future of AI, presented at the CogX 2019, London, https://www.youtube.com/watch?v=9ifNuQCdvJI, 2019.
[39] S. Schaffer, Babbage's intelligence: Calculating engines and the factory system, *Critical Inquiry*, vol. 21, no. 1, pp. 203–227, 1994.
[40] M. W. Marshall, "Automation" today and in 1662, *American Speech*, vol. 32, no. 2, pp. 149–151, 1957.
[41] A. Taylor, The automation charade, *Logic Magazine*, https://logicmag.io/05-the-automation-charade/, 2018.
[42] M. L. Gray and S. Suri, *Ghost Work: How to Stop Silicon Valley From Building A New Global Underclass*. Boston, MA, USA: Houghton Mifflin Harcourt, 2019.
[43] D. Weil, *The Fissured Workplace: Why Work Became so Bad For So Many And What Can Be Done To Improve It*. Cambridge, MA, USA: Harvard University Press, 2014.
[44] J. Woodcock and M. Graham, *The Gig Economy: A Critical Introduction*. Cambridge, UK: Polity, 2020.
[45] J. Koebler and J. Cox, The impossible job: Inside Facebook's struggle to moderate two billion people, *Motherboard Vice*, https://perma.cc/389C-Y2FN, 2019.
[46] 2018 employer information report, consolidated report - Type 2, Facebook, Inc., 1 Hacker Way, CW14861, https://diversity.fb.com/wp-content/images/2018-Consolidated-EEO-1-Part-1.pdf, 2019.
[47] C. Newton, The trauma floor: The secret lives of Facebook moderators in America, *The Verge*,

https://perma.cc/SJ3V-N6PP, 2019.
[48] P. Olson, Image-recognition technology may not be as secure as we think, *The Wall Street Journal*, https://perma.cc/Z9T2-2S5Z, 2019.
[49] LinkedIn: YouTube LLC, https://www.linkedin.com/company/youtube/about/, 2019.
[50] S. Levin, Google to hire thousands of moderators after outcry over YouTube abuse videos, *The Guardian*, Dec. 05, 2017.
[51] Number of monthly logged-in YouTube viewers worldwide as of May 2019 (in billions), Statistica. com, https://www.statista.com/statistics/859829/logged-in-youtube-viewers-worldwide/, 2019.
[52] DefinedCrowd triples team and keeps hiring, *GlobalNewsWire*, https://www.globenewswire.com/news-release/2019/02/26/1742790/0/en/DefinedCrowd-triples-team-and-keeps-hiring.html, 2019.
[53] Neevo. ai, https://www.neevo.ai/, 2019.
[54] Economic news release; Table B-1. Employees on nonfarm payrolls by industry sector and selected industry detail, *Bureau of Labor Statistics*, https://www.bls.gov/news.release/empsit.t17.htm, 2019.
[55] Data engineering, preparation, and labeling for AI 2019, *Cognilytica*, https://www.cognilytica.com/2019/03/06/report-data-engineering-preparation-and-labeling-for-ai-2019/, 2019.
[56] M. Murgia, AI's new workforce: The data-labelling industry spreads globally, *Financial Times*, https://www.ft.com/content/56dde36c-aa40-11e9-984c-fac8325aaa04, 2019.
[57] Data-labelling startups want to help improve corporate AI, *The Economist*, https://www.economist.com/business/2019/10/17/data-labelling-startups-want-to-help-improve-corporate-ai, 2019.
[58] A. Sage, California Senate passes bill to tighten "gig" worker rule, *Reuters*, San Francisco, https://www.reuters.com/article/us-employment-california/california-senate-passes-bill-to-tighten-gig-worker-rule-idUSKCN1VW0M7, 2020.
[59] E. Torpey, You're a what? Social media specialist, *Career Outlook*, *Bureau of Labor Statistics*, https://www.bls.gov/careeroutlook/2016/youre-a-what/social-media-specialist.htm?view_full, 2016.
[60] Industry and occupation indexes, *Census.gov*, https://www.census.gov/topics/employment/industry-occupation/guidance/indexes.html, 2019.
[61] S. T. Roberts, *Behind The Screen: Content Moderation in the Shadows of Social Media*. New Haven, CT, USA: Yale University Press, 2019.
[62] S. C. Kuek, Paradi-Guilford, Cecilia Maria, T. Fayomi, S. Imaizumi, and P. Ipeirotis, The Global Opportunity in Online Outsourcing (English), Washington, D. C. : World Bank Group, http://documents.worldbank.org/curated/en/138371468000900555/The-global-opportunity-in-online-outsourcing, 2015.
[63] W. Cunningham, The WyCash portfolio management system, *Addendum to the proceedings on Object-oriented programming systems, languages, and applications (Addendum) - OOPSLA '92*, doi: 10.1145/157709.157715.
[64] A. Chatzigeorgiou, A. Ampatzoglou, A. Ampatzoglou, and T. Amanatidis, Estimating the breaking point for technical debt, in *Proc. 2015 IEEE 7th International Workshop on Managing Technical Debt (MTD)*, Bremen, Germany, 2015, pp. 53–56.
[65] Z. Li, P. Avgeriou, and P. Liang, A systematic mapping study on technical debt and its management, *Journal of Systems and Software*, vol. 101, pp. 193–220, 2015.
[66] C. Seaman and Y. Guo, Measuring and monitoring technical debt, *Advances in Computers*, vol. 82, pp. 25–46, 2011.
[67] B. Curtis, J. Sappidi, and A. Szynkarski, Estimating the size, cost, and types of Technical Debt, presented at 2012 Third International Workshop on Managing Technical Debt (MTD), Zurich, Switzerland, 2012.
[68] N. Brown, Y. Cai, Y. Guo, R. Kazman, M. Kim, P. Kruchten, E. Lim, A. MacCormack, R. Nord, I. Ozkaya, et al., Managing technical debt in software-reliant systems, in *Proc. the FSE/SDP workshop on Future of software engineering research - FoSER'10*, Santa Fe, NM, USA, 2010, pp. 47–51.
[69] P. Kruchten, R. L. Nord, and I. Ozkaya, Technical debt: From metaphor to theory and practice, *IEEE Software*, vol. 29, no. 6, pp. 18–21, 2012.
[70] D. Sculley, G. Holt, D. Golovin, E. Davydov, T. Phillips, D. Ebner, V. Chaudhary, M. Young, J. Crespo, and D. Dennison, Hidden technical debt in machine learning systems, *Advances in Neural Information Processing Systems*, https://proceedings.neurips.cc/paper/2015/file/86df7dcfd896fcaf2674f757a2463eba-Paper.pdf, 2015.
[71] H. Foidl, M. Felderer, and S. Biffl, Technical debt in data-intensive software systems, arXiv preprint arXiv: 1905.13455, 2019.
[72] Protocol Service of the European Commission, http://ec.europa.eu/dgs/secretariat_general/corps/index.cfm?go=protocol.protoco, 2019.
[73] S. Applin, Autonomous vehicle ethics: Stock or custom? *IEEE Consumer Electronics Magazine*, vol. 6, no. 3, pp. 108–110, 2017.
[74] J. Zittrain, The hidden costs of automated thinking, *The New Yorker*, https://www.newyorker.com/tech/annals-of-technology/the-hidden-costs-of-automated-thinking, 2019.
[75] C. Anderson, The end of theory: The data deluge makes the scientific method obsolete, *Wired*, https://www.wired.com/2008/06/pb-theory/, 2008.
[76] D. Weinberger, Our machines now have knowledge we'll never understand, *Wired*, https://www.wired.com/story/our-machines-now-have-knowledge-well-never-understand/, 2017.
[77] M. Kochen, How well do we acknowledge intellectual debts? *Journal of Documentation*, vol. 43, no. 1, pp. 54–64, 1987.
[78] M. L. Jones, How we became instrumentalists (again): Data positivism since World War II', *Historical Studies in the Natural Sciences*, vol. 48, no. 5, pp. 673–684,

2018.
[79] B. Green, *Smart Enough City: Putting Technology in Its Place to Reclaim Our Urban Future*. Boston, MA, USA: MIT Press, 2019.
[80] Human-Centered Artificial Intelligence, Stanford University, 2019 AI index: Ground the conversation about AI in data, https://aiindex.org/, 2019.
[81] L. Floridi, Translating principles into practices of digital ethics: Five risks of being unethical, *Philosophy & Technology*, vol. 32, no. 2, pp. 185–193, 2019.
[82] J. Fjeld, H. Hilligoss, N. Achten, and A. Nagy, Principled artificial intelligence: Mapping consensus in ethical and rights-based approaches to principles for AI, *Berkman Klein Center Research Publication*, vol. 2020, no. 1, p. 39, 2020..
[83] D. S. Murray, The precarious new faculty majority: Communication and instruction research and contingent labor in higher education, *Communication Education*, vol. 68, no. 2, pp. 235–245, 2019.
[84] University and College Union, Counting the costs of casualisation in higher education, https://www.ucu.org.uk/media/10336/Counting-the-costs-of-casualisation-in-higher-education-Jun-19/pdf/ucu_casualisation_in_HE_survey_report_Jun19.pdf, 2019.
[85] U. Huws, *Labor in The Global Digital Economy: The Cybertariat Comes of Age*. New York, NY, USA: Monthly Review Press, 2014.
[86] L. Nakamura, Don't hate the player, hate the game: The racialization of labor in World of Warcraft', *Critical Studies in Media Communication*, vol. 26, no. 2, pp. 128–144, 2009.
[87] L. Nakamura, The unwanted labour of social media: Women of colour call out culture as venture community management, *New Formations*, vol. 86, no. 86, pp. 106–112, 2015.
[88] S. A. Applin and M. D. Fischer, New technologies and mixed-use convergence: How humans and algorithms are adapting to each other, presented at 2015 IEEE International Symposium on Technology and Society (ISTAS), Dublin, Ireland, 2015.
[89] A. Darlo and H. Brignull, Dark patterns, https://www.darkpatterns.org/, 2020.
[90] M. C. Elish, Moral crumple zones: Cautionary tales in human-robot interaction (WeRobot 2016), *SSRN Electronic Journal*, doi: 10.2139/ssrn.2757236.
[91] A. Mateescu and M. C. Elish, AI in context: The labor of integrating new technologie, https://datasociety.net/wp-content/uploads/2019/01/DataandSociety_AIinContext.pdf, 2019.
[92] N. Couldry and U. A. Mejias, *The Costs of Connection: How Data Is Colonizing Human Life and Appropriating It for Capitalism*. Redwood City, CA, USA: Stanford University Press, 2019.
[93] R. S. Cowan, More Work for Mother: *The Ironies of Household; Technology from the Open Hearth to the Microwave, Nachdr*. New York, NY, USA: Basic Books, 2011.
[94] P. Peña and J. Varon, Consent to our Data Bodies: Lessons from feminist theories to enforce data protection, https://codingrights.org/docs/ConsentToOurDataBodies.pdf, 2019.
[95] M. Pasquinelli and V. Joler, The nooscope manifested: Artificial intelligence as instrument of knowledge extractivism, KIM HfG Karlsruhe and Share Lab, http://nooscope.ai, 2020.
[96] K. Crawford and V. Joler, Anatomy of an AI system: The Amazon Echo as an anatomical map of human labor, data and planetary resources, AI Now Institute and Share Lab, https://anatomyof.ai, 2018.
[97] S. Dick and D. Volmar, DLL hell: Software dependencies, failure, and the maintenance of Microsoft Windows, *IEEE Annals Hist. Comput.*, vol. 40, no. 4, pp. 28–51, 2018.
[98] M. V. Wilkes, *Memoirs of A Computer Pioneer*. Cambridge, MA, USA: MIT Press, 1985.
[99] N. Ensmenger, *The Computer Boys Take Over: Computers, Programmers, and the Politics of Tecnical Expertise*. Cambridge, MA, USA: MIT Press, 2010.
[100] Employment by detailed occupation, U. S. Bureau of Labor Statistics | Office of Occupational Statistics and Employment Projections, Washington, DC, Table 1.2 Employment by detailed occupation, 2016 and projected 2026 (Numbers in thousands), https://www.bls.gov/emp/tables/emp-by-detailed-occupation.htm, 2019.
[101] P. G. Neumann, The risks digest: Forum on risks to the public in computers and related systems, http://catless.ncl.ac.uk/Risks/, 2019.
[102] T. Huckle, Collection of software bugs, https://www5.in.tum.de/~huckle/bugse.html, 2019.
[103] SIGCIS 2019 - Exception error: Fatal, illegal, unknown, https://www.sigcis.org/node/621, 2019.
[104] M. A. Makary and M. Daniel, Medical error—the third leading cause of death in the US, *BMJ*, doi: 10.1136/bmj.i2139.
[105] K. G. Shojania and M. Dixon-Woods, Estimating deaths due to medical error: The ongoing controversy and why it matters: Table 1', *BMJ Quality & Safety*, doi: 10.1136/bmjqs-2016-006144.
[106] M. Thomas and H. Thimbleb, Computer bugs in hospitals: A new killer−professor Martyn Thomas CBE and professor Harold Thimbleb, Gresham College, London, https://www.youtube.com/watch?v=seyaYL2ou14, 2018.
[107] M. Thomas and H. Thimbleb, Computer bugs in hospitals: An unnoticed killer, http://www.harold.thimbleby.net/killer.pdf, 2019.
[108] National Institute of Standards and Technology, Program Office Strategic Planning and Economic Analysis Group, The economic impacts of inadequate infrastructure for software testing, https://www.nist.gov/sites/default/files/documents/director/planning/report02-3.pdf, 2002.
[109] J. Williams, *Stand Out of Our Light: Freedom and Resistance in the Attention Economy*. Cambridge, UK: Cambridge University Press, 2018.
[110] R. Benjamin and J. McNealy, A new Jim code, https://cyber.harvard.edu/sites/default/files/2019-10/2019_09_24_RuhaBenjamin_Transcript.pdf, 2019.

[111] B. Cooper, The racial politics of time, presented at the TEDWomen, https://www.ted.com/talks/brittney_cooper_the_racial_politics_of_time/transcript, 2016.
[112] J. Halberstam, *In A Queer Time and Place: Transgender Bodies, Subcultural Lives*. New York, NY, USA: New York University Press, 2005.
[113] Western States Center, *Dismantling Racism*: *A Resource Book for Social Change Groups*, Anti-Racism Digital Library, https://sacred.omeka.net/items/show/221, 2022.
[114] J. Von Neumann, Can we survive technology? *Fortune*, no. 15, Jun. 1955.
[115] M. Minsky, Steps toward artificial intelligence, *Proceedings of the IRE*, vol. 49, no. 1, pp. 8–30, 1961.
[116] H. T. Larson, The computer issue, *Proceedings of the IRE*, vol. 49, no. 1, pp. 4–7, 1961.
[117] L. Daston, Enlightenment calculations, *Critical Inquiry*, vol. 21, no. 1, pp. 182–202, 1994.
[118] M. D. Sahlins, *Stone Age Economics*. New Brunswick, NJ, USA: Transaction Publishers, 2011.
[119] U. A. Mejias, *Off the Network: Disrupting the Digital World*. Minneapolis, MN, USA: University of Minnesota Press, 2013.
[120] Z. Lissa, Aesthetic functions of silence and rests in music, *The Journal of Aesthetics and Art Criticism*, vol. 22, no. 4, p. 443, 1964.
[121] E. Nelson, Walking to the future in the steps of our ancestors: Haudenosaunee traditional ecological knowledge and queer time in the climate change era, *New Geographies*, vol. 09, no. Posthuman, pp. 133–138, 2017.
[122] A. L. Stoler, *Imperial Debris: On Ruins and Ruination*. Durham, UK: Duke University Press, 2013.
[123] M. Liboiron, M. Tironi, and N. Calvillo, Toxic politics: Acting in a permanently polluted world, *Social Studies of Science*, vol. 48, no. 3, pp. 331–349, 2018.
[124] M. Richtel and T. Shanker, In new military, data overload can be deadly, *The New York Times*, https://www.nytimes.com/2011/01/17/technology/17brain.html, 2011.
[125] A. Young, Too much information: Ineffective intelligence collection, *Harvard International Review*, Aug. 18, 2019.
[126] M. G. D. C. Katoch, Leadership challenges in the information age, *Journal of the United Service Institution of India*, https://usiofindia.org/publication/usi-journal/leadership-challenges-in-the-information-age/, 2015.
[127] M. J. L. Campo, Information dominance or information overload? Unintended consequences of "every soldier and platform a sensor", Naval War College, https://apps.dtic.mil/dtic/tr/fulltext/u2/a525256.pdf, 2010.
[128] T. Dryer, Designing certainty: The rise of algorithmic computing in an age of anxiety 1920−1970, https://escholarship.org/uc/item/4d02g6x3, 2019.
[129] J. Stilgoe, R. Owen, and P. Macnaghten, Developing a framework for responsible innovation, *Research Policy*, vol. 42, no. 9, pp. 1568–1580, 2013.
[130] E. Gordon and G. Mugar, *Meaningful Inefficiencies: Designing for Public Value in an Age of Digital Expediency*. New York, NY, USA: Oxford University Press, 2020.
[131] L. Downey and J. Simons, Charismatic moments, in *A Political Economy and Justice*, D. Allen, Y. Benkler, and R. Henderson, eds. Chicago, IL, USA: Chicago University Press, 2022.
[132] C. Lanius, Fact check: Your demand for statistical proof is racist, *Cyborgology*, https://thesocietypages.org/cyborgology/2015/01/12/fact-check-your-demand-for-statistical-proof-is-racist/, 2015.
[133] K. Hill, Imagine being on trial. With exonerating evidence trapped on your phone. *The New York Times*, https://www.nytimes.com/2019/11/22/business/law-enforcement-public-defender-technology-gap.html?auth=login-email&login=email, 2019.
[134] D. Harwell, AI will solve Facebook's most vexing problems, Mark Zuckerberg says. Just don't ask when or how, *The Washington Post*, https://www.washingtonpost.com/news/the-switch/wp/2018/04/11/ai-will-solve-facebooks-most-vexing-problems-mark-zuckerberg-says-just-dont-ask-when-or-how/?utm_term=.8c71a2d658f6, 2018.
[135] R. A. Oppel Jr. and J. K. Patel, Onelawyer, 194 felony cases, and no time, *The New York Times*, https://www.nytimes.com/interactive/2019/01/31/us/public-defender-case-loads.html, 2019.
[136] E. J. Topol, *Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again, First edition*. New York, NY, USA: Basic Books, 2019.
[137] I. Joshi, Waiting for deep medicine, *The Lancet*, vol. 393, no. 10177, pp. 1193–1194, 2019.
[138] Z. Tufekci, Why Zuckerberg's 14-year apology tour hasn't fixed Facebook, *Wired*, https://www.wired.com/story/why-zuckerberg-15-year-apology-tour-hasnt-fixed-facebook/, 2018.
[139] C. Garvey, Broken promises and empty threats: The evolution of AI in the USA, 1956−1996, *Tech's Stories*, doi: 10.15763/jou.ts.2018.03.16.02.
[140] D. C. Brock, Our censors, ourselves: Commercial content moderation, *Los Angeles Review of Books*, https://lareviewofbooks.org/article/our-censors-ourselves-commercial-content-moderation/, 2019.
[141] K. Cascone, The aesthetics of failure: "Post-digital" tendencies in contemporary computer music, *Computer Music Journal*, vol. 24, no. 4, pp. 12–18, 2000.
[142] S. M. Ali, Fugitive decolonial luddism – A hauntology, Presentation, Digital Ethics Lab, Oxford Internet Institute, Dec. 10, 2019.
[143] D. Ribes, A. S. Hoffman, S. C. Slota, and G. C. Bowker, The logic of domains, *Social Studies of Science*, vol. 49, no. 3, pp. 281–309, 2019.
[144] S. Kelkar, Reinventing expertise in the age of platforms: The case of data science, presented at the BIDS Data Science, https://www.youtube.com/watch?v=-Ba2Gq13dBI, 2019.
[145] D. Forsythe and D. J. Hess, *Studying Those Who Study Us: An Anthropologist in the World of Artificial Intelligence*. Redwood City, CA, USA: Stanford University Press, 2001.
[146] S. Viljoen, The promise and limits of lawfulness:

Inequality, law, and the techlash, *Journal of Social Computing*, doi: 10.23919/JSC.2021.0025.
[147] E. Tuck and M. McKenzie, *Place in Research: Theory, Methodology, and Methods*. New York, NY, USA: Routledge, 2016.
[148] E. Tuck and M. McKenzie, Relational validity and the “where” of inquiry: Place and land in qualitative research, *Qualitative Inquiry*, vol. 21, no. 7, pp. 633–638, 2015.
[149] E. Tuck and K. W. Yang, Decolonization is not a metaphor, *Decolonization: Indigeneity, Education & Society*, vol. 1, no. 1, pp. 1–40, 2012.
[150] A. C. Clarke, *Profiles of The Future: An Inquiry into the Limits of the Possible*. London, UK: Indigo, 2000.
[151] E. Strubell, A. Ganesh, and A. McCallum, Energy and policy considerations for deep learning in NLP, arXiv preprint arXiv: 1906.02243, 2019.
[152] B. Tarnoff, To decarbonize we must decomputerize: why we need a Luddite revolution, *The Guardian*, https://www.theguardian.com/technology/2019/sep/17/tech-climate-change-luddites-data, 2019.

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