Journal of Economy Culture and Society,
JECS 2025, (71): 1–20

https://doi.org/10.26650/JECS2024-1467424

Submitted: 11.04.2024
Revision Requested: 13.10.2024
Last Revision Received: 26.10.2024
Accepted: 02.11.2024
Published Online 19.03.2025

Journal of Economy Culture and Society

Research Article

Open Access

Opening the Black Box of AI: A Sociological Study of AI as a Network

Borabay Erbay [1] & Kelly Joyce [2]

[1] İzmir University of Economics, Department of Sociology, İzmir, Türkiye
[2] Professor, Drexel University, Department of Sociology, Philadelphia, USA

Abstract This study provides a sociological understanding of the production of AI, which is underexplored in the sociology of AI. To achieve this, the study focuses on the AI development process. Utilizing Actor-Network Theory (ANT), this study demonstrates how the development of AI creates a network consisting of both human and nonhuman actors. The sociological literature focuses on how AI is adopted in various social contexts, identifying the social effects of its introduction and use. We investigate AI itself, showing the values and politics that constitute AI sociotechnical systems in the United States. Based on interviews with software engineers residing in Northeastern USA who work on AI and music platforms, the study highlights how humans and nonhuman actors and social forces such as capitalism and imperialism co-produce AI systems. Engineers' technicality-bound worldview plays a crucial role in their interpretation of AI and the drive for efficiency and profit are foundational values that justify including nonhuman actors such as generative AI platforms and datasets as participants in AI networks. This ultimately results in the production of AI sociotechnical systems that recreate values central to capitalism and imperialism.

Keywords Sociology · Actor-Network Theory · Artificial Intelligence · Science and Technology Studies (STS) · Software Engineering

Author Note This article is derived from the corresponding author's PhD thesis supported by TÜBİTAK 2214-A International Research Fellowship Programme for PhD Students.

Citation: Erbay, B. & Joyce, K. (2025). Opening the black box of AI: A sociological study of AI as a network. *Journal of Economy Culture and Society*, (71), 1-20. https://doi.org/10.26650/JECS2024-1467424

Corresponding author: Borabay Erbay borabay.erbay@ieu.edu.tr

Opening the Black Box of AI: A Sociological Study of AI as a Network

The advancements in both hardware and software technologies and continuous digitalization in societies around the world have led to an unprecedented progress in the field of artificial intelligence (AI). As a result of this progress, we now experience an AI-bound world, with AI use bringing significant transformations and challenges in different social spheres (Perc et al., 2019; Joyce & Cruz 2024). One of the most visible and significant impacts of AI can be observed in the labor market, where automation driven by AI is reshaping traditional employment structures (Ford, 2015; Ozer et al., 2024). As AI systems are adopted, they frequently displace and change human labor (Acemoglu et al., 2022; Ozer & Perc, 2024).

Within sociology, there is a growing body of literature that investigates the societal impact of AI adoption, examining if the technology use exacerbates inequalities. Scholarship within the sociology of AI has created important knowledge that shows societal impact in fields such as work, law, security and entertainment. It also demonstrates how humans, as reflexive actors, both accept and reject the AI output. Critical analysis of the values and politics embedded in the design and content of AI platforms, however, tends to be ignored in this literature. This is not surprising. Questioning AI is not easy for non-tech experts since it is perceived as a 'black box'. When a technology is "black boxed" its inner workings are unclear or taken for granted and its main value is that it is perceived to work in a correct and efficient way (Latour, 2000). These traits associated with AI rise not solely from the complexity of algorithms and the extensive, distributed knowledge and expertise needed to understand how they operate but also from how scientists themselves talk about AI and the massive amounts of data they process every second; the more complex algorithms get, the more opaque or black boxed they get (Pasquale, 2015; Burrell, 2016). This opacity shrouds AI systems in a myth, which promotes exaggerated expectations for their future impact (Natale & Ballatore, 2020; 2023). It also creates a perception of AI as a technological force that possesses a human-like intelligence and autonomy, obscuring the actual 'reality' of AI. This misinterpretation results in a lack of understanding of the human labor, decisions, and values involved and results in ascribing a human-like nature to AI, in the end forming a "black box society" that is governed by algorithms seemingly incomprehensible to humans (Pasquale, 2015). Expanding the sociology of AI to examine the design of AI platforms challenges the black boxing of AI, demonstrating which values are embedded in the design and content of AI.

In this paper, we aim to provide sociological insight into the AI development process by identifying the values and politics embedded in AI sociotechnical systems. To achieve this, we use a science and technology studies (STS) approach to study AI as a network consisting of humans, nonhumans, beliefs and ideologies. Built on the foundational idea that technology possesses a social and political character (Winner, 1980; Verbeek, 2005) with a certain form of agency embedded in it, interacting directly with humans in constituting society (Callon, 1986; Verbeek, 2005; Latour, 1994; 2000), STS calls for analyzing technology as a sociotechnical system, challenging the rooted technology/society dichotomy in classical and mainstream sociology. This view asserts that technology is not isolated from the social and political environment; on the contrary, it inherently possesses a social and political nature—indeed, technology and society co-produce each other (Jasanoff, 2002). Drawing on insights from the semi-structured interviews with software engineers who work in the field of music AI, we draw on Actor-Network Theory (ANT) to show how human and nonhuman actors co-constitute (Latour, 2005) AI networks together. Building on sociological criticisms of ANT's neglect of power and social contexts (Fine, 2005; Gille, 2010; White, 2013), we advance ANT in a way that can answer macro-sociological questions such as how major social forces like capitalism and imperialism are embedded in the actors and actions that constitute the AI network.

The essay is structured as follows: We begin with a literature review on the sociology of AI to highlight both contributions and gaps. We then discuss how STS can help sociologists understand AI as a dynamic, ever-changing network. This review and discussion provides the paper's framework. Next, we provide a methodological outline for the paper, which involved in-depth interviews conducted with software engineers who work on AI and music platforms and who reside and work in the Northeastern USA. In the findings section, we highlight how the technical-rational worldview of engineering affects how software engineers interpret generative AI, such as ChatGPT, and datasets. After examining how engineers comprehend AI in a strictly technical sense, we discuss AI as a network in the frame of ANT, highlighting how humans and nonhuman actors (generative AI and datasets) interact with each other in AI development. These interactions are shaped by major social forces, ideologies and beliefs, leading to the creation of a technology that recreates values central to capitalism and imperialism.

Theorizing AI: How STS Can Help Sociology Unlock the Black Box of AI?

The United States holds a leading position in the development of AI, both economically and culturally, largely due to the influence of Silicon Valley. This has led researchers globally to examine and analyze the relationship between AI development and the prevailing ideology of Silicon Valley (Lee, 2018; Gray & Suri, 2019; Sadowski, 2020). The constitution of AI in the USA is shaped by the influence of Silicon Valley's neoliberal ideology, which emphasizes technological innovation as a central driver of economic growth and societal advancement. This ideology, deeply embedded in US science and technology policy, has shaped AI development through the entanglement of academic science, industry, and government. The transformation of American universities into engines of economic growth (Berman, 2012) AI, like other technological fields, emerged within this market-oriented framework, reflecting the values of efficiency, entrepreneurship, and market-driven solutions that characterize Silicon Valley (Cohen, 2019; Sadowski, 2020).

Berman's analysis of how universities increasingly aligned their research with market needs reveals the shift toward a market-based model of academic science, where the commercial potential of technologies like AI became the driving force behind research. AI development within this space mirrors this transformation, as research is no longer driven solely by scientific curiosity but by its potential for economic return. The commercialization of research translates scientific inquiry into products shaped by venture capital and market imperatives (Kleinman, 2003; Jeske, 2022). In AI, this has led to the commodification of AI systems, where corporate interests and investment have defined not only the direction of research but also the very framing of AI as a solution to societal challenges and a way for AI practitioners to make money through patents and technology transfer.

The political economy of AI reveals how innovation, though framed as neutral, is deeply tied to commercial interests. As academic research becomes increasingly entangled with industry and the desire to be entrepreneurial, the boundaries between public knowledge and science blur, leading to a blind faith in technology stemming from the technochauvanistic approach of engineering (Broussard, 2018). Thus, AI becomes part of a larger sociotechnical system that reflects and perpetuates the neoliberal values of competition, growth, and profit. In other words, the constitution of AI in the US is not merely a technical process but a sociopolitical one, shaped by Silicon Valley's ideology (Cohen, 2019). This process has profound social and political implications, as AI becomes a mechanism for reproducing capitalist values and maintaining global technological dominance (Lee, 2018; Sadowski, 2020). Rather than existing as a neutral tool, AI serves to reinforce systems of power and inequality, perpetuating the very structures that define the neoliberal and technical worldview embedded in its creation.

The ever-growing literature in the sociology of AI, which is a relatively new subfield of sociology, studies how AI impacts society and how people use AI-in-practice. Similar to early sociological studies of the Internet and its reinforcing effects on social inequalities (called the digital divide) (DiMaggio et al., 2004; Selwyn, 2004; Van Dijk, 2005; 2006), the sociology of AI investigates the relationship between AI, power and social inequalities (Noble, 2018; Benjamin, 2019), identifying how AI systems discriminate people among class (O'Neil, 2016; Dyer-Witheford et al., 2019; Eubanks, 2018; Katz, 2020), gender (Benjamin; 2019; Hashemi & Hall, 2020), race and ethnicity (Benjamin, 2019; Hanna et al., 2019; Obermeyer eanst al., 2019). The effects of this digital discrimination are widely analyzed in the sociology of AI as well since classifying and labeling people by class, gender, race and ethnicity has historically been used as a means for the centralization of power around the ruling elite. More and more gigabytes of data have been extracted and monetized through algorithmic processes every day, creating a form of digital capitalism that serves both as a tool for exploitation and surveillance at the same time (Zuboff, 2019; Sadowski, 2020). Brayne (2020), for example, has shown how data-driven tech companies practice their power on police departments through monopolization of big data in the USA. The sociology of AI has built a far-reaching corpus of studies on the triangle of AI, inequalities and power due to the extensive works of many scholars around the world (Zajko, 2022; Liu, 2021).

In addition to reinforcing present inequalities and situating power, the sociology of AI investigates how AI might change or have already transformed work. This scholarship varies from critical analysis of predictions about robots taking over human jobs, the consequences of automation throughout the job market and the predictive after effects of this dystopian process (Rhee, 2018; Vicsek, 2020; James & Whelan, 2021) to how algorithms change and reconfigure labor as capitalistic values of efficiency and profit maximization demands (Shestakofsky, 2017; Kellog et al., 2020), how algorithms govern work environment detrimental to workers, like forcing workers to keep pace with algorithmic systems in work to maximize efficiency and productivity (Crawford, 2021; Newlands, 2021).Using ethnographic methods, scholarship has critically examined how workers use (or do not use) AI platforms, demonstrating the rich ways people interact with AI systems at work (Brayne and Engele, 2021; Brayne, 2020; Christin, 2020; Ticona and Mateescu, 2018; Sachs, 2019; Shestakofsy and Kelkar, 2020; Shestakofsky, 2017). Although organizations may hope that AI use leads to the triumph of Silicon Valley ideology over all (Sadowsky, 2020), this scholarship shows that humans are reflective actors who make decisions about when and where to use AI output and that AI use usually does not replace human labor but rather reconfigures what counts as work.

This body of work recognizes AI as central to their analysis. How AI became capable of creating social change is mostly addressed through reference to algorithms, which can be defined as the main components that guide AI systems to desired outcomes (Lupton, 2015; Sheikh et al., 2023) and their power to shape various social spheres. Sociologists and social theorists consider algorithms as entities that control and sort datasets, possessing distinct contexts, allowing AI to make judgments and perform certain actions based on these contexts (Beer, 2013; 2017). Algorithms act as "filter bubbles", technological things that decide what Internet users will encounter based on information such as location, clicking behavior, and search history (Pariser, 2011, 2013). This process results in algorithms sorting, filtering and suggesting what people should listen (Airoldi et al., 2016; Karakayali et al., 2018), what news they should read (Bucher, 2012; Rieder, 2017), who they should meet, flirt and fall in love with (Slater, 2013) and so on. Through algorithmic power, the asymmetric power relations in societies are reproduced. Life itself becomes algorithmic. In the end, algorithms become the deciding parts of the codes that make up the AI systems, gaining a social and political character in this process (Beer, 2013; 2017; Airoldi, 2022).

Although making substantial contributions, the aforementioned studies do *not* turn the sociological lens onto the making of AI itself. What remains to be answered are questions such as how is AI created? Which social interactions occur in this process, for example, who builds these systems and for whom (Joyce et al., 2021)? Which social forces are salient? What is the intersection of AI platforms with these powers (Burrell & Fourcade, 2020)? Social scientific research on AI focuses on a *pre-conceptualized* machine intelligence, identifying its use and societal impact, rather than shifting the lens to investigate the ecosystem of humans and nonhumans constituting AI (Jaton, 2020; Kajava & Shawney, 2023). This, can be said in a sociological sense, is *black boxing redux*. As Pasquale states, opaque algorithms and AI systems are conceptualized as black boxes throughout society, uncomprehensible for non-experts of specific scientific fields, thus becoming technical entities residing in their own domain, far from society (Pasquale, 2015). In this sense, *black boxing redux* is what happens in previous sociological studies of AI because the question of the values embedded in AI processes is not adequately explored. Sociologists bracket the AI system, focusing on its effects rather than its construction. In this paper, we focus on the sociological dimensions of AI itself. Rather than highlighting the effects of AI use on society, we investigate the very values and politics that co-produce AI, music, and creativity. We do this by drawing on science and technology studies theories and methods.

Science and technology studies (STS) unlock the black box of AI because it offers an approach that focuses on the technology itself as the object of study. Emerging in the 1970s in diverse sites, STS calls for social sciences to exceed the dichotomy between technological and social, emphasizing the sociotechnical nature of technology (Sismondo, 2010). Built on the works of scholars like Haraway (1991), Akrich (1992), Latour (1993; 1994; 2000; 2005), Callon (1984; 1997), Law (Callon & Law, 1997), and Woolgar (Woolgar, 1985; Latour & Woolgar, 1979), STS calls for a departure from conventional sociological studies of a technology's impact to studying how values and politics comprise the design and use of a technology. Using STS demonstrates how AI is a sociotechnical system, consisting of humans, non-human actors, data and algorithms (Jaton, 2020; Roberge & Castelle, 2021; Joyce et. al, 2021; Kajawa & Shawney, 2023). In other words, STS takes AI into the center of analysis, rather than comprehending it as a means in human-to-human relations in wider social contexts. It offers a toolbox for sociology by reformulating the question from how AI is embedded in social to how social is embedded in AI, thus offering insights into the values and politics that constitute particular AI systems.

We use Actor-Network Theory (ANT) as the main theoretical lens. As famously noted by Latour, what we call society is a network consisting of networks which are populated by humans and nonhumans alike (Latour, 1993; 2005). Taking an ANT approach means identifying the human and non-human actors that bring a particular technology or scientific claim into being. Debates on ANT are not fully settled to this day as scholars question and criticize its methodological and theoretical shortcomings. Such criticisms focus on how ANT assumes humans are rational actors and how ANT overlooks the unique aspects of human agency in favor of nonhumans, thus, reducing social phenomena to interactions between actors and neglecting the broader social contexts and power relations indispensable for societies to operate (Fine, 2005; Gille, 2010; White, 2013).

Bearing these criticisms in mind, we advance ANT by combining its unique focus on human and nonhuman actors with a sociological analysis of the broader social forces that impact actors in the creation of AI music-related platforms. In doing so, we combine the rich insights of sociology with STS's emphasis on the technology itself as the object of analysis. In doing so, we challenge *black boxing redux*. We theorize AI as a network consisting of people, algorithms, data, beliefs, ideologies and techniques to provide a sociological understanding of the values and politics that co-constitue the AI platforms related to music.

Data and Method

This study aims to illuminate the embedded social, political and economic power relations that shape AI development. In alignment with the aim of this study, we focus on the developers of AI and algorithms, in particular to music composition algorithms that are written, coded and deployed by AI practitioners. As mentioned above, we offer an understanding of AI as a network consisting of software/computer engineers, algorithms, data and programming languages (softwares). Findings indicate that the development of AI is a multifaceted process consisting of complex layers of interactions between humans and nonhumans, who are both bearers and at the same time, consequences of certain values, beliefs and ideologies embedded within them. In this context, qualitative methods, which are useful to describe and understand how social interactions constitute phenomena (Marvasti, 2003) forms the basis of the research.

A purposive sampling method was employed to recruit participants with expertise in AI development for music, ensuring that the data collected was rich in relevant insights. The research includes in-depth interviews with 20 software/computer engineers with at least a Master's degree in the field, all residing in the USA, supplemented by fieldwork at AI music conferences and workshops. To obtain in-depth qualitative data, engineers specifically involved in designing music composition algorithms were selected as participants. No gender or age quotas were applied. 14 of the 20 participants identified as men and 6 of the 20 participants identified as women, representing the asymmetric gender diversity of the field (Chang, 2019; Campero, 2021). 5 of 20 participants worked in the private sector and 15 of them were academics. The primary data collection tool used in this study was semi-structured interviews, chosen specifically for the method's suitability in achieving the project's descriptive and exploratory objectives. The interview guide includes questions categorized into four key topics: the characteristics of software/computer engineering education, the conceptualization of AI and algorithms, AI development in action, and the intersection of AI and music. The interview guide was used with all interviews. The interviews had a duration of 45-60 minutes and were conducted in person. Before the interviews, all participants were given advanced information about the research and were provided with an informed consent form. Audio recordings were conducted during the interviews. Detailed notes were taken during interviews with participants who did not provide consent for audio recording. Ethics committee approval was obtained before the research. Interviews were coded for reoccurring themes and saturation of reoccurring themes was reached.

In the next section, we describe how engineers imagine AI and how they understand the process of creating code for an AI system. Throughout the interviews, engineers repeatedly highlighted AI and the decisions they made in terms of the choice of training data as a technical matter with little understanding or interest in the socio-political dimensions of their work. Analysis of interview data also reveals the key human and nonhuman actors in the creation of AI platforms.

Findings

Imagining AI: Exploring the Perspective of AI Practitioners

Across all of our interviews, engineers imagined and conceptualized AI as a highly technical system. When discussing their choices when creating an AI system, participants repeatedly referred to a desire to increase accuracy and efficiency—two key values of engineering. Algorithms and training data, the main parts that bring AI into being are understood through the lens of the technical, accuracy, and efficiency. Participants do not see their decisions (or the impact of their decisions) as social.

When asked to describe the terms AI, algorithms and data in their own terms, without using textbook definitions, engineers—usually after a long pause while the respondent considers the question, and after the common phrase of “this is actually a great question, I have never defined it in my own words” - tend to give an explanation that highlights AI as an accurate, efficient machine. One respondent exemplifies this when he explains, “It is actually a system that approximates human behavior in the most accurate way. It has algorithms, based on certain mathematical models which charts the way for the system to follow and data, which is the source that these algorithms process and probabilitate th outcomes” (P3, Academic). Another respondent likened AI to a car, “The thing about AI is, it is actually a category of computational systems having a goal to mimic humans. You have your algorithms as the engine of AI and the data, that is the fuel for your engine. Think of AI as a car, when fuel is not efficiently processed by the engine, you are left in a desparate situation. Either you cannot complete your travel from your point of departure to your arrival, or you do it in an undesired way, the cost of your travel might exceed your money or you might end up there late. You lost money, you lost time. (…) It is the same thing with ML projects, you need to efficiently process the data to have the most accurate outcome” (P6, Company owner). Here again, we see the entanglement of the technical with accuracy and efficiency.

Accuracy is often intertwined with efficiency, as it is commonly referred together with mathematical and statistical models that call for a certain degree of expertise in natural sciences, which has a foundational effect on the perception of precision and efficiency in the world of engineering (Noble, 1977; Lucciarrelli, 1994; Newberry, 2015). In a sense, efficiency lays the groundwork for accuracy in AI systems. Participants overwhelmingly noted that when it is efficient and accurately meets the need, AI is working correctly. Efficiency, the main value of classical engineering (Faulkner, 2015; Newberry, 2015), is reproduced in software engineering as well.

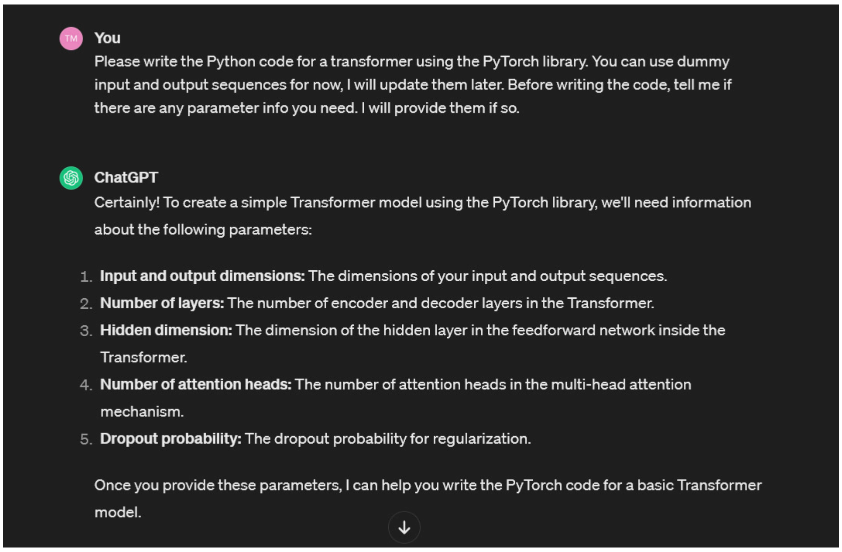
When asked what algorithmic bias is, 14 of 20 participants emphasized the technical and its connection to accuracy. One participant noted, for example, “I mean, [algorithmic bias] is simply a deviation, the algorithm doing things in a way that you don’t expect it to do. It deviates from your way, you know? Resulting in an undesirable outcome that might take longer to get or with reduced accuracy, something like that” (P10, Private Sector). When asked if they provided a technical or social description of algorithmic bias and why that description came to their mind, the same participant answered right away, with a clear, one-word answer followed by an interesting question: “Technical. (…) What is [algorithmic] bias in sociology? You guys know how to code?!” (P10, Private Sector). For our participants, the people who write, code and develop algorithms, algorithmic bias is a systematic deviation, a set of errors and loops that hinders the efficiency of the outcomes of algorithmic data processing (Danks & London, 2017; Fazelpour & Danks, 2021)

Key findings indicate that the perception of engineers on AI is heavily shaped by a technical-rational worldview, underlining efficiency as both the main value in engineering and the main goal to be achieved in AI systems. In this regard, the findings align with previous research on engineers, which show that the drive for efficiency is an indispensible part of engineering identities built on a technical/social dichotomy (Hughes, 1986; Bucciarelli, 1994; Newberry, 2015). In practical terms, incorporation of this dichotomic nature of engineering subtly dictates software engineers to conceptualize AI as a technically mediated, accurate and efficient technology for data processing, often overlooking the social aspects that constitute this technology, in the end, juxtaposing them with the technical aspects of AI rather than the social aspects as tech experts with a limited understanding of the social aspects. The following section will present how engineers perceive generative AI and datasets in their own work.

Sidekick or an Unlikely Hero? Engineers' Interpretation of Generative AI Platforms in Their Works

AI development can be broken down into two phases: algorithm coding and training. In order to understand the initial coding phase, participants were asked to provide a chronological explanation on how they code and train algorithms in their work. 15 out of 20 participants stated that, at the very beginning of AI development, they use generative AI software to generate code for a specific project. For the engineers that we interviewed, generative AI, in particular ChatGPT, was an important member of their team. They often began the coding process by consulting ChatGPT and then would go back and forth with ChatGPT as they continued to refine the code. A participant exemplified this pattern when he explained, "First thing I do. Hmm... First, I go and ask ChatGPT how to write the code in the [coding] language that I am using, have myself a solid ground to work on." (P1, Academic).

Figure 1
Engineer Employing ChatGPT as a knowledge source (P13, Academic)

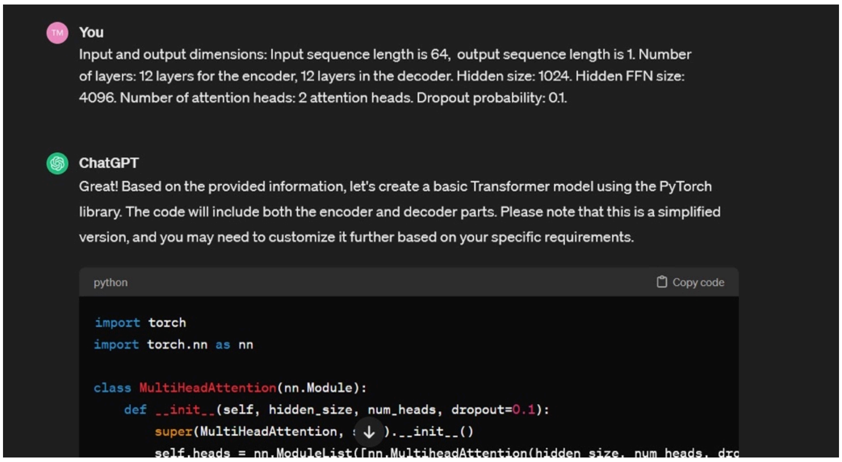


When asked why they used ChatGPT, participants often explained that "it is a time saver" as they often referred to market needs on being time and labor efficient as a must. A participant exemplifies this pattern when she notes, "You know, actually nobody codes from scratch anymore. It saves you so much time using ChatGPT and Copilot. In our company, we use ChatGPT as a tool to sketch ideas and Copilot to write codes fast and complete. Sometimes it will take days or even weeks to find an error in your code and correct it. If you do it on your own, you have to go through thousands of lines [of codes], map them and detect errors.

This is a fast-growing industry; you actually race against time in completing a project. [Using AI] is a must in this business, if I am to be honest” (P6, Company owner).

Figure 2

Engineer providing details for ChatGPT to make it write the code (P13, Academic)



All participants (20 out of 20) reported using ChatGPT to sort out errors in the code. Again, the reason for using ChatGPT was related to achieving maximum time efficiency. Exemplifying this response among participants, one noted, “More often than not, the code has some errors and flaws in it (...) In a large scale project, you have maybe tens of thousands of lines of code written to get your algorithm to work. It is literally impossible to go back, find the error, correct it and try giving it a go again, because there will always be errors. If you try to do it on your own you will need the whole time in the world!” (P13, Academic).

Engineers tend to not question what values are embedded in ChatGPT and other generative AI platforms. When asked if they know how ChatGPT works and what effects it might have on their projects, all participants reported that they do not know how ChatGPT works. As one participant stated, “No one knows how ChatGPT works. You can only assume it. OpenAI does not disclose [the technicalities of] its models and the truth is, even if they went all-open, it is too complex to understand how a system that big works. (...) But the most important thing is that: their models are trained on certain data before they are out and they are not open on which data it is and how they collected it” (P4, Academic).

Throughout the interviews, it is observed that the drive for achieving maximum efficiency has become the major value for engineers’ perception of the technologies they both create and use. As the previous section has highlighted, the effect of the efficiency-driven character of engineering identities has a constitutional effect on how engineers perceive AI. Their perceptions of the use of generative AI platforms in their works show a different aspect of efficiency fetishism. Engineers employ ChatGPT in their works to meet the market demands, which they conceptualize as a highly competitive one. ChatGPT gives them a tool, or a source of knowledge, to efficiently complete their works in a time and labor efficient way that the field itself demands. At the intersection of efficiency-based engineering identities (Newberry, 2015; Faulkner, 2015) and the alienating effect of the tech-driven pursuit of efficiency constituting the market/field (Braverman; 1974; Marx, 1992/1867), participants’ view of ChatGPT detaches the platform from its social aspects, reducing it to a mere technology used for efficiently handling business. The social is overlooked in favor of efficiency once more.

Fuel for the Machine: How Do Engineers Interpret Datasets in Their Work?

The second phase of AI development involves using datasets to train algorithms to identify patterns. To understand the training phase and how engineers perceive datasets, they were asked to explain what data is and how they use it in their work. When thinking about the training data, the participants emphasized approximation and consistency. As one participant noted, data is a cluster of knowledge that needs to be processed with correct technical approaches:

“Data is basically approximating what we do not know. To make sense of it, you use certain ML methods to process the data and the algorithms start to learn and discriminate between what data holds. Your model must meet the data [it processes], that is the main point of AI development; finding the right approach to data” (P1, Academic).

Participants were asked if they use their own data or ready datasets provided by certain communities or corporations. In all cases, participants stated that they do not use their own data but instead used datasets from other sources. When asked which datasets they mainly use in their music AI works, answers provided by the vast majority of participants show that datasets utilized as the main source of training data by engineers who aim to develop music composition algorithms actually resemble a monopoly in the field of music AI:

“LAKH and Wikifonia” (P2, Academic).

“LAKH, mainly. Wikifonia is also good” (P11, Private Sector).

“LAKH and sometimes Music21” (P4, Academic).

The most mentioned dataset emerged as LAKH. It has a description on its website as “the Lakh MIDI dataset is a collection of 176.581 unique MIDI files, 45.129 of which have been matched and aligned to entries in the Million Song Dataset”. Basically, this dataset has approximately 180.000 sound entries and almost 46.000 of them are aligned to Million Song Dataset, featuring the metadata of a million contemporary songs. As mentioned above, this resembles a monopoly; one dataset dominating the field of music AI.

When participants were asked if they have an opinion on why certain datasets are dominating the field of music AI, none of the participants provided a clear answer as it is seen that they interpret having premade datasets as a conventional way of doing work, providing consistent data for their AI models. This situation is exemplified in terms of consistency by the engineers, leaning on qualities assessed with technology once more. In other words, the technical-rational worldview of engineering is again at play in conceptualizing and using training data in AI. When asked why they build AI models on other people’s data sets, the majority of participants pointed out to the consistency they are trying to achieve, using terms “input” and “output” mostly. For participants, the goal is to generate consistent models that would take data as input and provide ‘meaningful’ outputs. A participant illustrates this point of view when he explained, “Think it as this: you have your input, which is data and your end goal is having meaningful outputs based on this input, like estimations. You might think this as the human mind; this is coffee, what’s meaningful for me is the taste of coffee, not its color, right? This is why you start by deciding on your data. If you wish to have an opinion on coffee, you need to learn what coffee tastes like in order to determine which one is best for you. If you try to estimate coffee by its color, it won’t do anything good, right?” (P16, Academic).

When pressed to think about how inequalities are built into training data, participants reported that algorithms without bias is a non-achievable ideal since it is impossible to have unbiased data to train algorithms and AI systems. Moreover, even if there is an AI system running on algorithms free of bias, the system will not reflect the actual world, making it both less accurate and less useful. As one participant explained, “Unbiased AI systems or algorithms in terms of that is not achievable. Why, you ask? It is simple because the training data is biased. It is human data. So, humans are biased, right? We cannot expect to have unbiased data from humans. In theory, first, you’ll need the data of all people who are actually present in the world. Second, you’ll need maybe thousands of months, maybe years to label these data accordingly. Third, there is no computer that can actually process that amount of data, maybe with quantum computers in the future, but not today. Also, what is the point of that? If we can do that, we do not need AI” (P7, Academic).

After being asked if they know who made the datasets they use in their work and the origin of the sounds in the datasets, all participants reported that they did not know who made their dataset, the dataset’s origin, if musicians were involved in the creation of the dataset and if there were any copyright issues. Not only did they not know about these issues, they were also not major concerns. Exemplifying this perspective, one participant noted, “it is open source, anyone can contribute to it. Can be a musician or not, it is based on a digital form of sound so it is not actually sound. (...) Copyright is a hard thing, a big issue in music AI. You cannot use licensed content in your work. But people always find a way [to short circuit licensing issues] (laughs)” (P6, Company owner).

For participants, training data is a cluster (or many clusters) of information, which provides the basis for AI—it needs to be processed using correct technical tools and approaches to achieve consistent outcomes. The technicality imbued worldview of engineering seems to have a crucial effect on how engineers perceive data, as in engineers’ minds, it is detached from its social and political aspects and reduced to a technological tool to achieve the best possible outcomes with maximum consistency and efficiency. Although participants recognize the politics of data sets when pressed, they consider this issue as outside their purview. In the next section, we will present an analysis of AI as a network consisting of humans and nonhumans, showing how they co-constitute AI together with certain ideologies embedded in.

Understanding AI through Actor Network Theory (ANT)

Through the analysis of the interview data and fieldwork notes, an understanding of the actors in the AI network emerges. In a sociological sense, working with generative AI can be understood as the first step of the process of AI being formed as a network. Generative AI platforms, in particular ChatGPT, are employed as sources of knowledge by participants in their networks. As described in ANT, nonhuman actors (actants) in a network gain agency through their capacity to manipulate and change human action (Latour, 1993; 2005). In the context of AI, agency in a network is defined by its capacity to connect the other actors together (Jaton, 2020). AI intervention does not stop there, though. Employed at the beginning, generative AI becomes a participant in the project as it is used by participants to correct mistakes and debug the algorithm. In the process, through a set of interactions back and forth, generative AI becomes a participant of the network; human and machine agency working together, lines blurring, with a new, sociotechnical hybrid formed (Latour, 1993, 2000; 2005).

As ANT provides the necessary conceptual framework and tools to depict how this hybrid network, one comprised of human and nonhuman actors, is formed, a key sociological question remains unanswered since it does not question if nonhumans in networks have a social and political character embedded in them or how these actors politically shape the network (Fine, 2005; Gille, 2010; White, 2013). To advance ANT, both human and nonhuman actors that form the network should be addressed in terms of the following questions. How does the interaction between engineers and generative AI affect the process of AI development? How are social forces embedded in the network and who (as human and nonhuman) brings what to the network? Capitalism is a central context that shapes the development of AI (Gray & Suri, 2019; Crawford, 2021; Ozer et al. 2024). Efficiency, which is analyzed as a central theme and one of the founding values of capitalism (Marx, 1992/1867), is crucial to this context.

Studies on generative AI have shown that many questions still need to be answered in terms of what values are embedded in these technologies. Based on an extensive literature review, some scholars have observed seven controversies and risks generative AI technologies, including a) no regulation in AI market, b) lack of quality control and algorithmic bias, c c) job displacement, d d) personal data violation and surveillance e) social manipulation and weakening ethics, f f) widening socio-economic inequalities, and g) AI-related technostress (Wach et al., 2023). Based on our observations, these controversies and risks incorporated in generative AI systems are not unknown to engineers as none of the participants have answered the question if there is a possibility of achieving unbiased algorithms. As mentioned above, engineers are aware of algorithmic bias, but they conceptualize it in a different way than sociologists, underlining the technicalities intrinsic to the field. This conceptualization, combined with the drive for efficiency, makes engineers employ generative AI in their network as a source of knowledge, or even a teammate without an extensive consideration of its social and political characteristics with capitalist values embedded in them.

Consequently, generative AI becomes an actor in AI development. It can be considered as a mediating actant in terms of ANT, manipulating and altering human action on the course, resulting in a process that differs from what would have happened without their intervention (Latour, 1993; 2005). Engineers employ generative AI to save time and achieve maximum efficiency, with AI gaining agency in terms of amplifying human action with its speed. The final product will not be the same if there was no intervention from generative AI as it acts as a source of knowledge to engineers, charting the way for AI development. In this sense, the lines between human and machine are blurred, thus creating a sociotechnical hybrid (Latour, 2000; 2005; Jaton, 2020). At the intersection of capitalist values such as meeting market demands, exploitation of labor and data violence, the sacrification of ethics for the need to achieve maximum efficiency and profit embedded within both human and nonhuman actors, the network becomes a co-process of humans and nonhumans, operated by the capitalist drive of efficiency acting as the foundational value. In this sense, engineers adopting the worldview of engineering become the deacons of capitalism (Noble, 1977) embedded in technological efficiency and neutrality (Faulkner, 2015; Newberry, 2015). One crucial part of AI must be addressed in terms of these to fully understand this network, that is, training data, the fuel for the AI engine.

The AI network continues to expand by including training data to feed the algorithms after the initial coding phase. There are two main algorithm training approaches in ML methods. The first is reinforcement learning, in which algorithms train under human supervision, and the second is profoundly named as deep learning, which employs large numbers of labeled data inducted into AI algorithms to make them learn on their own (Sheikh et al., 2023). Besides technicalities, data can be assessed as the part that determines what an AI algorithm will learn. In sociology, data is widely considered as how high-tech empires built on exploitation of labor of many people making little or no money for labeling volumes of data used in training algorithms (Fuchs, 2010; Gray & Suri, 2019; Mühlhoff; 2020) and how cultural bias is transmitted into AI systems (Katz, 2020; Airoldi, 2022).

In terms of ANT, data becomes yet another non-human actor in the network, playing its role in shaping the network. The dataset functions as a comprehensive repository of musical compositions that shape the algorithm's advancement and influence the algorithm's understanding of music theory and structure, as well as its ability to generate compositions. Incorporating these datasets into the development process requires balancing the interests of the software engineer, the algorithm, and the dataset. The engineer needs to assess the dataset's appropriateness for their goals, adjust the algorithm to efficiently learn from the dataset, and the dataset's composition impacts the direction and emphasis of the development work. The use of datasets for algorithmic training significantly affects the originality and distinctiveness of the music it generates; thus, it gains agency in terms of ANT (Latour, 1993; 2005). It exerts an influence on the creative process by assimilating specific musical information and prejudices into the algorithm, thereby affecting the final outcome to reflect the characteristics of the dataset. The network continues to expand with the addition of a new nonhuman actor. Engineer, ChatGPT and datasets are now seem to be merged in one another, creating the final form of the hybrid AI network (Latour, 2005).

As we navigate our way through the complex relationships and interactions constituting AI-in-practice, the conceptual and methodological toolset of ANT made it possible to depict the actor network of AI development. Here we advance ANT by situating human and non-human actors like engineers, generative AI and datasets within social forces such as the ideologies of capitalism; the drive for efficiency, rationality and technicality to bring the unseen into light. The research indicates that capitalism is not the only power structure at play in the network. There is one more power structure embedded in the final product, the music composition algorithm itself: Western imperialism.

The conceptualization of data as a neutral tool by participants poses a question that can be briefly formulated as follows: What kind of music do they compose? Is it biased? To answer that question, participants were first asked what kind of music their algorithms compose or transcribe best. All participants gave the answer as Western music, none of them mentioned an AI algorithm composing Eastern music as their work. As vastly explored in the sociology of music, music has been utilized by colonial forces and the capitalist elite to institutionalize Western imperialism (Gilroy, 1995; Turino, 2000) and capitalism (Adorno, 1988; 2001/1944) in societies, using instruments, music schools, musicians and the music itself as a form of art.

In order to elucidate how these two major social forces are embedded in the network of music AI, the participants were asked if it is possible to compose non-Western music (like Turkish, Persian, Chinese, Indian music, representing the middle or far East) using their algorithms. The main themes once more emerge as efficiency and consistency of data and algorithm produce together, showing the intertwinement of capitalism and Western imperialism in the network of AI:

"Of course it won't work correctly because it is not based on that music. [By that] I mean the data. To compose good Eastern music, you must train your model on Eastern music data. It will be irrelevant I think, a bad song." (P3, Academic).

This returns us to the question of data and the effects of the social and political character embedded within it. According to the participants, most datasets comprise sound files representing Western popular music and related subgenres as data; in other words, the abovementioned monopoly over data imbues it with Western music, incorporating Western imperialism within. Thus, imperialism becomes the political character of data, which is transmitted to the AI network by one of the actors shaping it. The question, then, becomes as this: why is there not a reliable source of data for non-Western music? Yet again, the intersection between major social forces and actors of AI network are at interplay as answers provided by participants make two themes emerge resting on embedded capitalism and imperialism both in human and nonhuman, first being standardization:

“Well, microtonal music is difficult to annotate as data, the commas make it hard [to label and process as data]. There are many notes in Eastern music. Some people need to dedicate real labor to this. This is the main reason [of lack of non-Western music data] I think.” (P2, Academic).

Findings indicate that the main reason for Western music being the dominant mode of music in music AI is closely linked with the rationalization of music. Openness to standardization, which rests upon order, predictability and stability in Western music harmonies and tonalities, makes Western music a rationalized institution, giving way for it to be the dominant mode of music both in the East and the West, instilling capitalist bureaucratization and imperialist power structures into music (Weber, 1958/1921). This sociological feature of Western music is carried into the digital world through music composition AI algorithms, reproducing imperialism in a digitalized and subtle mode.

The second theme, closely interlinked with the standardization of music composed by AI, can be described as getting aligned with capitalist interests. When participants asked to what is their end goal with their AI algorithms and if these technologies are capable of creating artistic music, the answers are surprisingly diverse, yet resembling each other. Engineers tend to classify artistic music as a humane form of music, reflecting human creativity. What music AI composes is classified as background or elevator music, which is a form of commercial music used as jingles in stores, TV series, or background music of any kind. The end goal seems simple: selling big. One participant who is a PhD student working as a teaching assistant in a university describes his goal as follows:

“Well, I do not get paid enough in my job. There is no money in the music business, though. My endgame is selling my product to big companies, this is how you get paid. Streaming services, for instance, they pay good money for jingles, or stores, malls, the background music. This is where the money is at” (P4, Academic).

The same goes for private businesses as well:

“Our aim is to help people create music, yes. But music AI is not at a level that can actually generate good, artistic music. It is used for background music mostly; the music you listen while shopping or an opening jingle for a TV series, maybe some atmospheric music in movies” (P10, Company owner).

According to engineers, AI is not capable of producing artistic music, which suggests that “music” and “musicians” may remain largely unaffected by automation. However, questions remain about the implications for studio musicians—the often unseen contributors who create background music typically designed to enhance an atmosphere or mood without drawing focus away from the main activity or setting, such as in restaurants, stores, or films and the musicians whose music has been annotated as training data to feed AI systems. This raises issues about capitalism’s role in the AI landscape, with AI expanding labor market transformations creating new social challenges and amplifying inequalities (Ozer et al., 2024; Acemoglu et al., 2022) to benefit corporate interests. These challenges, besides the macrostructural economic changes, mainly stem from the conceptualization of AI technologies by AI practitioners. As mentioned above, engineers tend to perceive data purely as a technical resource, often overlooking the complex ethical considerations of stakeholders. When asked if they were aware of the ethical concerns associated with the datasets used to train AI models, such as issues of consent and compensation for musicians, the responses were often vague and ambivalent. One engineer stated, for example, "I do not know, to be honest. I see where you’re coming from—data privacy is a concern, yes… In short, yes, it is not possible to get consent from everyone, and maybe there are some people—musicians—who might feel upset about it" (P1, Academic). Engineers’ focus on the technical aspects of technologies helps produce a lack of attention to and knowledge about how to navigate the ethical aspects of AI.

Moreover, the issue of compensating musicians whose work is used as training data for music AI also appears unresolved. When asked if musicians were compensated for their contributions to training data, responses often signaled acceptance of the lack of paid work. One participant remarked, "Well, of course, not everyone's getting paid. That part is true. But no one is getting paid, man. I told you before, there is no money in the music business. Who's going to pay the musicians? Me? I don't get paid either!" (P4, Academic). In this context, musicians are increasingly becoming a source of low-cost or unpaid labor in the AI industry, a shift that exemplifies broader transformations in labor that exacerbate inequalities within the job market (Ozer & Perc, 2024). This dynamic mirrors what Gray and Suri (2019) describe as "ghost work"—the often invisible, undervalued labor force that supports AI systems, largely unrecognized and undercompensated for their contributions.

Ultimately, music AI emerges as a highly standardized product of an AI network, co-produced by engineers, generative AI models, and datasets—all of which carry embedded social and political power dynamics in the form of values and beliefs. Primarily generating Western-centric popular music, music AI sociotechnical systems reflect and reproduce existing power asymmetries, subtly reinforcing the Western influence in the digitalized music landscape. This network of human and non-human collaborators is imbued with capitalist values, including efficiency, technicality, and profit maximization. In this context, the drive for maximum efficiency often supersedes ethical considerations, relegating musicians to the invisible labor force, or "ghost work," which constitute music AI.

Conclusion

In this paper, we investigated the production of AI as a sociotechnical system. To understand how AI is developed and how it gains its social and political character, we utilized ANT as our theoretical framework, suggesting that AI can not be understood solely based on technical or social viewpoints. Using ANT's concepts of hybridity and networks shows how AI is developed as a network through the interconnected work of both human and nonhuman actors. To advance ANT in a way that can answer macro sociological questions, we examined the social forces that co-produce the interactions of human and nonhuman actors and the development of AI platforms.

Adopting this viewpoint showed that AI algorithmic bias is not solely based on engineers' cultural and political dispositions. Instead, bias is produced through a complex set of interactions between social contexts (e.g., capitalism and imperialism) and human and nonhuman actors. In the processes of writing/coding and training algorithms, nonhuman actors such as generative AI and datasets play a crucial role, mediating the process we named as AI network. Engineers, who have adopted the main values of capitalism such as achieving maximum efficiency, reliability and profit, and promote technological neutrality, utilize ChatGPT as a source of knowledge in the process of AI development. This use in turn affects their modes of thought and practices, creating a hybrid network in which human and machine agencies become inextractable throughout continuous interactions. With ChatGPT, which is also a black box to engineers, the AI network not only gains its first nonhuman actor but throughout all these interactions the values and ideologies of capitalism are introduced into the network, altering the network's course of action to prioritize the desire to achieve maximum efficiency and profit. With the introduction of homogeneous datasets, the network expands not only by being a hybrid entity with increased complexity but also by bringing imperialism into the network as an embedded social force. The end result: whether intentional or not, the music composition algorithm equals the values, courses of action, and social and political characters of capitalism, imperialism, and the interactions of human and nonhuman actors.

This study contributes to the sociology of AI literature by providing a framework for sociologists to open the black box redux of AI. To help imagine more just AI sociotechnical systems, it is crucial to challenge the technological/social dichotomy and identify the values and politics embedded in the choices that comprise the content and design of AI systems. Thus, this paper is also a call for sociologists to engage with STS more and bring sociotechnical systems into question using sociological methods. It is our hope that this paper will serve the community of sociology as a steppingstone to explore AI as a network within different social contexts other than the US.

Ethics Committee Approval	Ethics approval was obtained from Aydın Adnan Menderes University Social and Human Sciences Scientific Research Publication Ethics Board (Date: 01.12.2023, Decision: 09/18).
Informed Consent	Consent was obtained from the participants' parents.
Peer Review	Externally peer-reviewed.
Author Contributions	Conception/Design of Study- B.E., K.J.; Data Acquisition- B.E.; Data Analysis/Interpretation- B.E., K.J.; Drafting Manuscript- B.E.; Critical Revision of Manuscript- K.J.; Final Approval and Accountability- B.E., K.J.
Conflict of Interest	The authors have no conflict of interest to declare.
Grant Support	The authors declared that this study has received no financial support.

Author Details

Borabay Erbay (Research Assistant)
[1] İzmir University of Economics, Department of Sociology, İzmir, Türkiye
0000-0002-5744-1638 borabay.erbay@ieu.edu.tr

Kelly Joyce (Professor)
[2] Professor, Drexel University, Department of Sociology, Philadelphia, USA
0000-0002-2822-1548

References

Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2022). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics*, *40*(1), 293-340.

Adorno, T. W. (1988). *Introduction to the sociology of music.* Seabury.Adorno, T. W. (2001). *The culture industry: Selected essays on mass culture* (J. M. Bernstein, Ed.). Routledge. (Original work published 1944).

Airoldi, M. (2022). *Machine habitus: Toward a sociology of algorithms.* Polity Press.

Airoldi, M., Beraldo, D. & Gandini, A. (2016). Follow the algorithm: An exploratory investigation of music on YouTube, *Poetics*, *57*. 1-13. https://doi.org/10.1016/j.poetic.2016.05.001

Akrich, M. (1992). The description of technical objects. In Bijker, W. E., and Law, J. (Eds.), *Shaping technology-building society: Studies in sociotechnical change*, MIT Press.

Angèle, C. (2017). Algorithms in practice: Comparing web journalism and criminal justice. *Big Data & Society,* 4(2). 1–14. https://doi.org/10.1177/2053951717718855

Angèle, C. (2020). *Metrics at work: Journalism and the contested meaning of algorithms*. Princeton University Press.

Barocas, S., & Selbst, A. D. (2016). Big data's disparate impact. *California Law Review*, *104*(3). 671-732. https://www.jstor.org/stable/24758720

Beer, D. (2013). *Popular culture and new media: The politics of circulation.* Palgrave Macmillan.

Beer, D. (2017). The social power of algorithms. *Information, Communication & Society,* 20*(1).* 1-13. https://doi.org/10.1080/1369118X.2016.1216147

Berman, E. P. (2012). *Creating the market university: How academic science became an economic engine*. Princeton University Press.

Braverman, H. (1974). *Labor and monopoly capital: The degradation of work in the twentieth century*. Monthly Review Press.

Brayne, S. (2020). *Predict and surveil: Data, discretion, and the future of policing*. Oxford University Press.

Broussard, M. (2018). *Artificial unintelligence: How computers misunderstand the world.* MIT Press.

Buchanan, B. G. (2005). A (very) brief history of artificial intelligence. *AI Magazine, 26(4).* 53-60. https://doi.org/10.1609/aimag.v26i4.1848

Bucher, T. (2012). Want to be on top? Algorithmic power and the threat of invisibility on Facebook. *New Media & Society*, *14*. 1164–1180. https://doi.org/10.1177/146144481244015

Burrell, J. & Fourcade, M. (2021). The society of algorithms. *Annual Review of Sociology,* 47. 213-217. https://doi.org/10.1146/annurev-soc-090820-020800

Callon, M. (1984). Some elements of a sociology of translation: domestication of the scallops and the fishermen of St Brieuc bay. *The Sociological Review*, *32*(1), 196-233.https://doi.org/10.1111/j.1467-954X.1984.tb00113.

Callon, M. (1986). The sociology of an actor-network: The case of the electric vehicle. In Callon, M., Law, J., Rip, A. (Eds.), *Mapping the dynamics of science and technology*. Palgrave Macmillan.

Callon, M., Law, J. & Rip, A. (1986). Putting texts in their place. In Callon, M., Law, J. & Rip, A. (Eds.), *Mapping the dynamics of science and technology,* Palgrave-Macmillan.

Campero, S. (2021). Hiring and intra-occupational gender segregation in software engineering. *American Sociological Review*, *86*(1), 60-92. https://doi.org/10.1177/0003122420971805

Chang, E. 2019. *Brotopia: breaking up the boys' club of Silicon Valley*. Penguin Books.

Cohen, N. (2019). *The know-it-alls: The rise of Silicon Valley as a political powerhouse and social wrecking ball*. The New Press.

Crawford, K. (2021). *Atlas of AI*. Yale University Press.

Crawford, K., & Paglen, T. (2021). Excavating AI: The politics of images in machine learning training sets. *AI & Soc*, *36*. 1105–1116. https://doi.org/10.1007/s00146-021-01162-8

Danks, D., & London, A. J. (2017). Algorithmic bias in autonomous systems. In C. Sierra (Ed.), *Proceedings of the 26th International Joint Conference on Artificial Intelligence,* 4691-4697.

DiMaggio, P., Hargittai, E., Celeste, C., & Shafer, S. (2004). Digital inequality: From unequal access to differentiated use. In K. M. Neckerman (Ed.), *Social inequality*. New York:Russel Sage Foundation Press.

Dyer-Witheford, N., Kjosen, A. M. & Steinhoff, J. (2019). *Inhuman power: Artificial intelligence and the future of capitalism.* London:Pluto Press.

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

Faulkner, W. (2015). 'Nuts and bolts and people': Gender troubled engineering identities. In Christensen, S., Didier, C., Jamison, A., Meganck, M., Mitcham, C., Newberry, B. (Eds.), *Engineering identities, epistemologies and values: Engineering education and practice in context, volume 2* (pp. 23-40). Cham:Springer Press.

Fazelpour, S., & Danks, D. (2021). Algorithmic bias: Senses, sources, solutions. *Philosophy Compass*, *16*(8). 1-16. https://doi.org/10.1111/phc3.12760

Fine, B. (2005). From actor-network theory to political economy. *Capitalism, Nature, Socialism, 16*(4). 91-108. "https://doi.org/10.1080/10455750500376057

Ford, M. (2015). *Rise of the robots: Technology and the threat of mass unemploymen*t. Basic Books.

Forsythe, D. E. (1993). Engineering knowledge: The construction of knowledge in artificial intelligence. *Social Studies of Science, 23*(3), 445-477. https://doi.org/10.1177/030631279302300300

Fuchs, C. (2010). Labour in informational capitalism and on the Internet. *The Information Society, 26*(3). 176-196. https://doi.org/10.1080/01972241003712215

Gille, Z. (2010). Actor networks, modes of production, and waste regimes: Reassembling the macro-social. *Environment and Planning, 42*. 1049-1064. https://doi.org/10.1068/a42122

Gilroy, P. (1995). *The black Atlantic: Modernity and double consciousness*. Harvard University Press.

Gray, M. L. & Suri, S. (2019). *Ghost work: How to stop silicon valley from building a new global underclass.* Harper Business.

Goldberg, D. E. (2006). *The entrepreneurial engineer*. Wiley Press.

Hanna, A., Denton, E., Smart, A., & Smith-Loud, J. (2019). Towards a critical race methodology in algorithmic fairness. *Proceedings of Conference on Fairness, Accountability, and Transparency.* https://doi.org/10.48550/arXiv.1912.03593

Hashemi, M., & Hall, M. (2020). Criminal tendency detection from facial images and the gender bias effect. *Journal of Big Data, 7*(2), 1–16. doi: 10.1186/s40537-019-0282-4

Hughes, T. (1986). The seamless web: Technology, science, etcetera, etcetera. *Social Studies of Science*, 16*(2)*, 281–292. https://doi.org/10.1177/0306312786016002004

James, A., & Whelan, A. (2021). 'Ethical' artificial intelligence in the welfare state: Discourse and discrepancy in Australian social services. *Critical Social Policy,* 42, 1–42. https://doi.org/10.1177/026101832098546

Jasanoff, S. (2002). New Modernities: Reimagining Science, Technology and Development. *Environmental Values*, *11*(3), 253–276. https://www.jstor.org/stable/30301896

Jaton, F. (2020). *The constitution of algorithms: Ground-truthing, programming, formulating.* Cambridge: MIT Press.

Jeske, M. (2022). *Organs and humans on chips: Translation, biomedical models, and the political economy of innovation* (Doctoral dissertation, University of California, San Francisco).

Johnson, G.M. (2021). Algorithmic bias: on the implicit biases of social technology. *Synthese*, *198*, 9941–9961. doi:10.1007/s11229-020-02696-y

Joyce, K., & Cruz, T. M. (2024). A Sociology of Artificial Intelligence: Inequalities, Power, and Data Justice. *Socius*, *10*. https://doi.org/10.1177/23780231241275393

Joyce, K., Smith-Doerr, L., Alegria, S., Bell, S., Cruz, T., Hoffman, S. G., Noble, S. U., & Shestakofsky, B. (2021). Toward a sociology of artificial intelligence: A call for research on inequalities and structural change. *Socius*, 7. 1-11. https://doi.org/10.1177/23780231219995

Kajava, K. & Sawhney, N. (2023). Language of algorithms: Agency, metaphors and deliberations in AI discourses. In S. Lindgren (Ed.), *Handbook of critical studies of artificial intelligence.* Edward Elgar Publishing.

Karakayali, N., Kostem, B. and, & Galip, I. (2018). Recommendation systems as technologies of the self: Algorithmic control and the formation of music taste. *Theory, Culture & Society*, *35*(2), 3-24. https://doi.org/10.1177/02632764177223

Katz, Y. (2020). *Artificial whiteness: Politics and ideology in artificial intelligence.* Columbia University Press.

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *The Academy of Management Annals, 14*(1), 366–410. https://doi.org/10.5465/annals.2018.0174

Kitchin, R. (2014). *The data revolution: Big data, open data, data infrastructures and their consequences*. SAGE.

Kleinman, D. L. (2003). Impure cultures: *University biology and the world of commerce*. University of Wisconsin Press.

Latour, B. (1993). *We have never been modern.* Harvard University Press.

Latour, B. (1994). On technological mediation: Philosophy, sociology, genealogy, *Common Knowledge, 3*(2), 29-64. https://sciencespo.hal.science/hal-02057233

Latour, B. (2000). *Pandora's hope: Essays on the reality of science studies.* Harvard University Press.

Latour, B. (2005). *Reassembling the social: An introduction to actor-network theory*. Oxford University Press.

Latour, B. & Woolgar, S. (1986). *Laboratory life: The construction of scientific facts.* Princeton University Press.

Lee, K. (2018). *AI superpowers: China, Silicon Valley and the new world order.* Houghton Mifflin.

Liu, Z. (2021). Sociological perspectives on artificial intelligence: A typological reading. *Sociology Compass, 15*(1). https://doi.org/10.1111/soc4.12851

Lupton, D. (2015). *Digital sociology.* Routledge Press.Marx, K. (1992). *Capital: Volume 1* (B. Fowkes, Ed..). Penguin Books. (Original work published 1867).

Marvasti, A. B. (2003). *Qualitative research in sociology.* Thousand Oaks:SAGE.

Mateescu, A. & Ticona, J. (2020). Invisible work, visible workers: Visibility regimes in online platforms for domestic work. In D. Acevedo (Ed.), *Beyond the algorithm: Qualitative insights for regulating gig work*. Cambridge University Press.

Meyer, A., Barr, E., Bird, C. & Zimmermann, T. (2021). Today Was a Good Day: The Daily Life of Software Developers. *IEEE Transactions on Software Engineering, 47*(5), 863-880. https://doi.ieeecomputersociety.org/10.1109/TSE.2019.2904957

Mühlhoff, R. (2020). Human-aided artificial intelligence: Or, how to run large computations in human brains? Toward a media sociology of machine learning. *New Media & Society, 22*(10), 1868–1884. doi: 10.1177/146144481988533

Natale, S., & Ballatore, A. (2020). Imagining the thinking machine: Technological myths and the rise of artificial intelligence. *Convergence*, *26*(1), 3-18.https://doi.org/10.1177/1354856517715164

Natale, S., & Ballatore, A. (2023). Technological failures, controversies and the myth of AI. In S. Lindgren (Ed.), *Handbook of critical studies of artificial intelligence.* Edward Elgar Publishing.

Newberry, B. (2015a). Efficiency animals: Efficiency as an engineering value. In Christensen, S., Didier, C., Jamison, A., Meganck, M., Mitcham, C., Newberry, B. (Eds.), *Engineering identities, epistemologies and values: Engineering education and practice in context, volume 2* (pp. 199-215). Springer Press.

Noble, D. F. (1977). *America by design: Science, technology and the rise of corporate capitalism.* Alfred A. Knopf Publishing.

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

O'Neil, C. (2016). *Weapons of math destruction: How big data increases inequality and threatens democracy*. Crown.

Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science,* 366(6464), 447–453. https://doi.org/10.1126/science.aax2342

Ozer, M., Perc, M., & Suna H.E. (2024). Artificial intelligence bias and the amplification of inequalities in the labor market. *Journal of Economy Culture and Society*, 69, 159–168. doi:10.26650/JECS2023-14150855

Ozer, M. & Perc, M. (2024). Human complementation must aid automation to mitigate unemployment effects due to AI technologies in labor market. *Reflektif Journal of Social Sciences, 5(*2). 503-514.https://doi.org/10.47613/reflektif.2024.176

Pariser, E. (2011). *The filter bubble: How the new personalized web is changing what we read and how we think*. Penguin Press.

Parisi, L. (2013). *Contagious architecture: Computation, aesthetics, and space*. MIT Press.

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

Perc, M., Ozer, M., & Hojnik, J. (2019). Social and juristic challenges of artificial intelligence. *Palgrave Communications*, *5*(61). doi:10.1057/s41599-019-0278-xhttps://doi.org/10.1057/s41599-019-0278-x

Rhee, J. (2018). *The robotic imaginary: The human and the price of dehumanized labor*. University of Minnesota Press.

Roberge, J., & Castelle, M. (2021). Toward an end-to-end sociology of 21st-century machine learning. In J. Roberge & M. Castelle (Eds.),. *The cultural life of machine learning: An incursion into critical AI studies* (pp. 1–29). Springer International Publishing.

Russell, S. & Norvig, P. (2020). *Artificial intelligence: A modern approach.* Pearson Press.

Sachs, S. E. (2019). The Algorithm at work? Explanation and repair in the enactment of similarity in art data. *Information, Communication & Society, 23*(11). 1689–1705. https://doi.org/10.1080/1369118X.2019.1612933

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

Selwyn, N. (2004). Reconsidering political and popular understandings of the digital divide. *New Media & Society, 6*(3), 341–362. https://doi.org/10.1177/146144480404251

Sheikh, H., Prins, C. & Schrijvers, E. (2023). *Mission AI: The new system technology.* Springer Press.

Shestakofsky, B. (2017). Working algorithms: Software automation and the future of work. *Work and Occupations,* 44(4), 376–462. https://doi.org/10.1177/0730888417726119

Shestakofsy B. & Kelkar. (2020). Making Platforms Work: Relationship Labor and the Management of Publics. *Theory & Society, 49*, 863–96. https://doi.org/10.1007/s11186-020-09407-z

Sismondo, S. (2010). *An introduction to science and technology studies.* Blackwell.

Slater, M. (2013). *Love in the time of algorithms: What technology does to meeting and mating.* Current Publishing.

Ticona, J. Mateescu, A. (2018). Trusted strangers: Cultural entrepreneurship on domestic work platforms in the on-demand economy. *New Media & Society, 20*(11). 4384–4404. https://doi.org/10.1177/1461444818773727

Turino, T. (2000). *Nationalists, cosmopolitans, and popular music in Zimbabwe*. University of Chicago Press.

Van Dijk, J. A. G. M. (2005). *The deepening divide: Inequality in the information society*. SAGE.

Van Dijk, J. A. G. M. (2006). Digital divide research, achievements and shortcomings. *Poetics, 34*(4–5), 221–235. https://doi.org/10.1016/j.poetic.2006.05.004

Verbeek, P. (2005). *What things do: Philosophical reflections on technology, agency and design.* Pennsylvania University Press.

Vicsek, L. (2020). Artificial intelligence and the future of work: Lessons from the sociology of expectations. *International Journal of Sociology & Social Policy, 41*(7/8), 842–861. doi: 10.1108/IJSSP-05-2020-0174

Wach, K., Duong, C.D., Ejdys, J., Kazlauskaitė, R., Korzynski, P., Mazurek, G., Paliszkiewicz, J., & Ziemba, E. (2023). The dark side of generative artificial intelligence: A critical analysis of the controversies and risks of ChatGPT. *Entrepreneurial Business and Economics Review, 11*(2), 7-30. https://doi.org/10.15678/EBER.2023.110201

Weber, M. (1958). *The rational and social foundations of music* (D. Martindale, J. Riedel, & G. Neuwirth, Trans. & Eds.). Southern Illinois University Press. (Original work published 1921).

White, H. (2013). Materiality, form and context: Marx contra Latour. *Victorian Studies, 55*(4). 667-682. https://doi.org/10.2979/victorianstudies.55.4.667

Winner, L. (1980). Do artifacts have politics?. *Daedalus, 109*(1). 121-136. https://www.jstor.org/stable/20024652

Woolgar, S. (1985). Why not a sociology of machines? The case of sociology and artificial intelligence. *Sociology, 19*(4). 557-572. https://www.jstor.org/stable/42853468

Zajko, M. (2022). Artificial intelligence, algorithms, and social inequality: Sociological contributions to contemporary debates. *Sociology Compass, 16*(3). https://doi.org/10.1111/soc4.12962

Zuboff, S. (2019). *The age of surveillance capitalism: The fight for a human future at the new frontier of power.* PublicAffairs.