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Sociological perspectives on artificial intelligence: A typological reading

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Abstract

Interest in applying sociological tools to analysing the social nature, antecedents and consequences of artificial intelligence (AI) has been rekindled in recent years. However, for researchers new to this field of enquiry, navigating the expansive literature can be challenging. This paper presents a practical way to help these researchers to think about, search and read the literature more effectively. It divides the literature into three categories. Research in each category is informed by one analytic perspective and analyses one "type" of AI. Research informed by the "scientific AI" perspective analyses "AI" as a science or scientific research field. Research underlain by the "technical AI" perspective studies "AI" as a meta-technology and analyses its various applications and subtechnologies. Research informed by the "cultural AI" perspective views AI development as a social phenomenon and examines its interactions with the wider social, cultural, economic and political conditions in which it develops and by which it is shaped. These analytic perspectives reflect the evolution of "AI" from chiefly a scientific research subject during the twentieth century to a widely commercialised innovation in recent decades and increasingly to a distinctive socio-cultural phenomenon today.

KEYWORDS
artificial intelligence, digital technology, sociology, typology

1 | INTRODUCTION

Interest in applying sociological tools to analysing the social nature, antecedents and consequences of artificial intelligence (AI) has been rekindled in recent years as a result of the widespread use of AI technologies in a broad variety of social domains, ranging from education to security, from retail to healthcare, from transport to law enforcement. However, for researchers new to this field of enquiry, a field that may be called "the sociology of AI", it can be challenging to navigate the existing literature to find a point of entry into the field.

For one thing, the existing literature under the banner of the "sociology of AI" can appear to be diffuse and dated. Searching for "artificial intelligence; sociology" on Google Scholar (GS), a "superset" of the academic literature databases Web of Science and Scopus (Martín-Martín, Orduna-Malea, Thelwall, & Delgado López-Cózar, 2018, p. 1751), can return a remarkably heterogeneous body of results. Some studies analyse the implications of AI for social processes and relations. Others discuss the use of AI techniques in sociological research. Still others appear in the search results because they happen to list "artificial intelligence" and "sociology" as keywords, and yet do not analyse "artificial intelligence" in sociological terms. Moreover, in a GS search conducted on 20 May 2020, 80% of the studies shown on the first results page (results sorted by relevance) were published between 1980 and 2000, and all before 2003. In comparison, 70% of the most relevant results from a search for "artificial intelligence; economics" was research published in the past decade.

However, a change in search strategy can result in very different outcomes. If we refine the search by adding to the original search phrase––"artificial intelligence; sociology"––terms alluding to specific AI techniques or applications––for example "robots", "algorithms", "self-driving cars", "facial recognition", "machine learning" and so forth––we will discover a whole range of recent publications about specific AI products or subtechnologies.

From diffuse and dated to abundant and dynamic, navigating the diverse literature in the sociology of AI can be challenging for researchers new to this field. Knowing what literature to find and how to find it is as important as knowing what it is about. The purpose of this paper is to provide a practical way to help these researchers to navigate the literature more effectively. It suggests that we can better think about, search and read the existing literature in the sociology of AI by dividing it into three categories. Research in each category is informed by one analytic perspective and analyses one particular "type", or conception, of AI. Research informed by the "scientific AI" perspective analyses "AI" as a science or scientific research field. Research underlain by the "technical AI" perspective studies "AI" as a meta-technology and analyses its various applications and subtechnologies. Research informed by the "cultural AI" perspective views AI development as a social phenomenon and examines its interactions with the wider social, cultural, economic and political conditions in which it develops and by which it is shaped.

The paper proceeds as follows. First, I differentiate four principal senses in which "AI" is discussed across scientific and non-scientific contexts. I argue that the diverse understandings of "AI" give rise to the "scientific AI", "technical AI" and "cultural AI" analytic perspectives that underlie the sociological literature on AI. Next, I discuss the main research strands, key work and important findings by which these categories may be elaborated. Finally, I conclude by suggesting that these analytic perspectives demonstrate shifts over the past decades in our understanding of what constitutes "AI" and what "AI" entails. In particular, they reflect the evolution of "AI" from chiefly a scientific research subject during the twentieth century to a widely commercialised innovation in the first 2 decades of the 21st century and to a distinctive socio-cultural phenomenon as it is increasingly viewed today.

The paper reviews research that applies sociological concepts and theories to analysing "AI" in its diverse senses and the associated artefacts, practices, processes and phenomena. The work discussed below was found according to this criterion through two methods. First, multiple searches were conducted on Google Scholar, Web of Science and Scopus using the search phrase "artificial intelligence; sociology" combined with a variety of restrictive terms such as those indicated above to identify an initial collection of publications. Then, following these studies' references, I was able to discover more research that employs sociological frameworks to analyse AI. This resulted in a large volume of studies. Since the size of the literature is beyond the capacity of a review paper, I focus my attention on identifying the main research strands and discussing the key work in the literature, rather than offering a comprehensive survey of it. In selecting the work to be reviewed, I did give attention to a body of research published in the 1980s and 1990s. I believe it is important to include this work in this review, despite its age, because it laid important foundations for contemporary sociological discussions of AI.

1.1 | Four senses of AI

It is widely agreed that the term "artificial intelligence" was first coined in 1955 by the computer scientists John McCarthy, Marvin Minsky, Nathaniel Rochester and Claude Shannon. They use the term to describe the capability of machines to "use language, form abstractions and concepts, [to] solve kinds of problems now reserved for humans" (McCarthy, Minsky, Rochester, & Shannon, 1955, p. 1). Later, McCarthy (2007, p. 1) gives a simpler definition, describing AI as "the science and engineering of making intelligent machines". When AI is understood along these lines, it is perceived to be a *science*, or, a *system of scientific knowledge and practices*, that aims to make machines do things that humans can do. The term "AI", therefore, is sometimes used interchangeably with the terms "machine intelligence" and "intelligent machines".

Distinctions have been made between strong (or general) and weak (or narrow) AI. Whereas strong AI (or artificial general intelligence [AGI]) is found in machines capable of performing *any* intellectual and cognitive tasks that a human can perform, weak AI can only accomplish tasks in a *human-like* way. In other words, the difference lies in "whether machines can be truly intelligent or simply able to act 'as if' they are intelligent" (Kaplan, 2016, p. 68). Although most AI scientists nowadays agree that AGI is unlikely to be achieved in the near future, narrow AI has made significant progress over the past few decades, thanks to advances in two techniques: machine learning (ML) and deep learning (DL). Current AI development is so reliant on ML and DL that the terms are often used as synonyms of AI, especially in the media and other public discourse.

The term "AI" is also used to refer to the *scientific research field* or *community* that is devoted to the production and dissemination of AI knowledge and expertise. In this sense, it is a branch of computer science and interlinked with disciplines such as mathematics, neuroscience, psychology, linguistics and philosophy. The scientific AI research field consists of AI researchers working in universities, research institutes and government- or corporation-funded laboratories. As with other scientific fields, the products of the AI field––AI knowledge and practices––are socially constructed and shaped by power relations between agents and groups of agents that exist and act in this field (Bourdieu, 1975).

Scientifically, core to many AI systems are algorithms, sets of mathematical instructions given to computer programs for them to perform certain tasks. Because of the centrality of algorithms to AI systems, many sociologists have discussed AI in terms of these artefacts. Meanwhile, the commercialisation of AI in recent decades has seen the term "AI" enter the lexicon of citizens and scholars alike via a range of popular AI applications and subtechnologies, such as smart home assistants, virtual reality and facial recognition. As a result, "AI" has been discussed as a *metatechnology* and analysed in terms of its various subtechnologies and applications.

Lastly, the recent revival of AI has occurred in the middle of what is known as "the digital revolution". Many view AI development as a distinctive technological, and socio-cultural, *phenomenon*, which constitutes an integral part of the digital revolution. They have discussed AI alongside discussions of other digital technologies, such as big data, the Internet of Things, 5G, cloud computing, and blockchain, to assess the broader social, economic, cultural and political effects of these technologies.

These four senses in which "AI" has been discussed across scientific and nonscientific contexts underlie the three principal analytic perspectives identified in the sociological literature on AI. Each of these perspectives examines "AI" in one or two of these senses.

1. The "scientific AI" analytic perspective focuses on the core scientific features of AI as a science or a scientific research field.
2. The "technical AI" analytic perspective treats AI as a metatechnology and analyses the social ramifications of various AI applications and subtechnologies.
3. The "cultural AI" analytic perspective is concerned less with the scientific or technical dimensions of AI and more with AI development's wider social, cultural, economic and political effects, particularly in the context of the digital revolution.

1.2 | Scientific AI

Most 1980s and 1990s sociological discussions of AI treat it as a system of scientific knowledge and expertise which seeks to make machines do things that humans can do. These studies are informed by what I term the "scientific AI" analytic perspective. Some of them address the question of how AI research is conducted by *social* actors (AI researchers) in *social* environments (universities, research institutes, corporate research labs, etc.) and therefore is a *socially constructed* enterprise. Others explore the *socially constituting* role of AI systems. Still others examine AI's implications for the nature of human knowledge and for the human–machine relation more broadly. This body of research is influenced by intellectual traditions from the sociology of science, the sociology of knowledge, science and technology studies (STS) and human–computer interaction, among others.

Viewing science as an assemblage of subjective knowledge rather than objective facts, Bloomfield (1987) argues that AI research is conditioned by various social and cultural factors. Understanding it thus requires an examination of what these conditioning factors are and how they work to shape AI research and development. He argues that these exogenous factors affect AI research through "thought styles", sets of socially constituted "beliefs and convictions" prevalent in a scientific field (Bloomfield, 1987, p. 98), and that analysing the dominant "thought style" shared by most AI researchers provides a key to understanding the social logic of AI research. As an example, Bloomfield examines AI development in the US after World War II and illustrates that the direction and outcomes of AI research during this period were shaped by three dominant "thought styles", namely, expectation of imminent breakthroughs, faith in the universality of computer programs and technological determinism.

Similarly, Fleck (1987) explores why AI research is not a purely scientific process but is shaped by power struggles within the AI field itself and between AI as a rising scientific research field and the social and scientific establishments challenged by it. Also using AI development in the post-1945 US and UK as an example, Fleck shows that within the AI field, key figures such as McCarthy, Minsky, Simon and Newell in the US and Michie in the UK had almost complete control over issues such as directions of the field's development and key appointments in the field. However, outside the AI field, their authority would be eclipsed by researchers in more established disciplines, such as computer science and mathematics, when bidding for research funding. AI research was, therefore, as much shaped by scientific endeavours as by competition between AI and other disciplines over research resources or, in a Bourdieusian sense, by power struggles between these scientific fields within the larger economic and political fields.

Like Bloomfield and Fleck, Forsythe (1993a, 1993b) analyses the influence of "nontechnical factors" (Forsythe, 1993a, p. 460) on AI research, focusing on how AI systems embody and reproduce their developers' cultural values. She maintains that, wittingly or unwittingly, AI developers bring pre-existing values, beliefs and assumptions into what they design. AI systems are therefore anything but objective and value free. Supposedly "scientific" systems can be deeply subjective and value-laden and serve to (re)affirm and reinforce values and beliefs homogeneous with those of their developers. Forsythe's findings are not news today. There has been much discussion about how AI systems routinely deliver biased and/or discriminatory results (Obermeyer, Powers, Vogeli, & Mullainathan, 2019; Sap, Card, Gabriel, Choi, & Smith, 2019). Given that Forsythe's research was published almost 30 years ago, its importance lies less in its specific findings and more in the fact that it makes us ask, "Why do these problems, exposed nearly 3 decades ago, still persist today?"

For some sociologists, AI is not only a socially constituted enterprise, but also socially constituting in the sense that when implemented in a social environment an AI system can assume social roles, enact social practices and form social relations. An important task of sociologists of AI is hence to examine how AI systems "penetrate and transform social institutions" (Schwartz, 1989, p. 180) and in the process "[redefine] social life" (Schwartz, 1989, p. 199).

In a widely cited paper, Woolgar (1985) suggests that one way of elucidating the social nature of AI is by rejecting the idea that there is an intrinsic distinction between humans and machines in their social capacities. For Woolgar (1985, p. 565), this idea is not based on any convincing sociological grounding but is constructed by scientific and commercial AI circles to advance the "marketability" of their research and business, and rejecting this idea would pave the way for discussion of the social nature of AI systems. On this basis, Woolgar goes on to call for the development of a sociology of machines to analyse how AI systems function like human social actors to form social relations and construct social realities. This viewpoint is reminiscent of actor–network theory and suggests that the early sociological work on AI perceived it primarily as a technoscientific development.

A third thread in the "scientific AI" literature tackles more pointedly the question of AI's implications for human society and the human–machine relation. Bloomfield (1988) draws on the sociology of knowledge to discuss AI's impact on the nature of knowledge. The sum of knowledge had always been conceived of as created by human intellectual activities, but intelligent machines were now increasingly contributing to it. Instead of casting a verdict on the quality of AI-generated knowledge compared with human-generated knowledge, Bloomfield suggests that AI developers can better their systems' ability to generate knowledge by assimilating social science and humanities research on the nature of knowledge and the process of knowledge production.

Other researchers are more sceptical of AI's allegedly human-like ability. A common concern is AI systems' social inadequacy. Collins (1990, 2018), for instance, tackles the question of "Can machines be as intelligent as human beings?" and contends that although smart machines can demonstrate impressive capabilities to execute mechanical tasks such as pattern identification, they lack the ability to "see" and "understand" contexts, a core quality of human intelligence. Smart machines thus can never be said to possess genuine human intelligence. Similarly, Suchman (1987, 2007, 2011) rejects the idea that robots can be programmed to behave like humans, on the grounds that whereas humans "study" social settings before acting, robots "act" mechanically as a result of prescribed programs. Robots are incapable of modifying either their programs or their resultant actions to take into account situational changes and thus will never be able to behave in ways akin to how humans would behave in the same situations.

Despite their diverse concerns, the above studies all analyse "AI" either as a scientific research field or as a system of scientific knowledge. This indicates that the early sociological intervention in AI mainly considered it in terms of its scientific quality, as opposed to its other attributes. This analysis, on one hand, transcends the material details of its object of study and on the other hand is underlain and constrained by such materiality. What also is worth noting is that although the debate about AI's intelligence from a sociological perspective continues to this day, interest in exploring how AI research is affected by nonscientific factors, and the consequences of this, seems to have declined since the 1990s. However, questions like how corporations are playing an increasingly important role in funding and shaping AI research, how this influence has encountered resistance from the AI community (Belfield, 2020; Lardieri, 2018; Wong, 2019), and the implications of this power struggle for AI research clearly deserve more attention from sociologists. They deserve more attention not only from sociologists of AI and science but also from sociologists of work and labour, of political economy, of culture and activism and so forth.

1.3 | Technical AI

Compared with the early sociological work on AI, which analysed it as a science or scientific research field, most recent studies take AI's various applications as objects of study.

As one of the earliest AI applications, automation in the workplace has been widely discussed by sociologists since its inception. An early consensus was that different kinds of work were subject to the impact of automation to differing degrees and that, whereas the more mechanical work was more vulnerable to replacement by AI, work requiring more sophisticated human inputs was relatively safe in the face of automation (Churcher, 1991; Gurstein, 1985).

Recent advances in AI and the application of automation in more diverse professions have led many to reconsider the question of AI's impact on work and employment. Some bleak observations have been made (Brynjolfsson & McAfee, 2014; for a helpful review, see; Wajcman, 2017), including predictions such as that up to 47% of today's jobs will be replaced by AI (Frey & Osborne, 2013). Many sociologists, however, have drawn different conclusions. Some criticise that owing to their epistemological flaw of technological determinism, the pessimistic accounts fail to take into account the political-economic and socio-cultural complexity of automation's impact on the workplace and that their conclusions are therefore one-sided and untenable (Boyd & Holton, 2017; Clark & Gevorkyan, 2020; Spencer, 2017). Others offer empirical accounts of the ways in which automation affects workers and work. For instance, Petterson (2019) analyses the use of AI in "knowledge work", work that requires sophisticated problem-solving capabilities, and contends that AI will not threaten human "knowledge workers", for it lacks the human expert's ability to deploy tacit knowledge to assess and resolve problems. McClure (2018) explores how workers' agency affects their job security in the age of robotics and AI. He suggests that workers with a more positive attitude towards AI tend to have higher job security and increased employability because they are more willing to embrace and adapt to the new AI-present workplace order. In contrast, workers who fear AI are more likely to suffer precisely because their fear will prevent them learning new skills to better coexist with AI.

Other kinds of automation have also been examined by sociologists. Research on self-driving cars has suggested that to make these smart vehicles fit for purpose––to safely drive on real-world roads––requires not only better ML techniques but also better "social learning" on the part of all parties involved in making and governing the technology (Stilgoe, 2018, p. 25). For Stilgoe (2018), only through regulating autonomous driving by taking into account the technology's social deficiencies, risks and challenges, as well as its technological virtues, can we develop self-driving systems that are fit both technically and socially. In a slightly different light, Marres (2020a, 2020b) maintains that such an element of social learning must be incorporated in the design and experimentation phases of the relevant systems. In showing how and why AI development can benefit from social science research, these studies highlight the role of social sciences not only in analysing AI as an object of study but also in informing its technical details and specificities. A more theoretical account of the social impact of autonomous driving is given by Bissell, Birtchnell, Elliott, and Hsu (2020) from a mobilities studies perspective. They argue that by invoking new mobility experiences for some groups of people and not others, and by triggering new social infrastructure and institutions to facilitate it, autonomous driving would transform labour relations, widen social inequality and shift existing social systems and institutions. Although insightful in many ways, this discussion is rather more "speculative" than empirical and "in-depth" (Bissell et al., 2020, p. 118), and more substantive research is required to test its wide-ranging predictions.

Some researchers examine the use of automated systems for military purposes from a sociological perspective (Crogan, 2016, 2019; Elliott, 2019a; Suchman & Weber, 2016). A common concern has been to what extent "automated" systems should be trusted to make high-stake decisions such as targeting and firing. Underlying this concern is a distinction in social science traditions between *automation* and *autonomy*. Whereas the former indicates a machine's ability to follow prescribed instructions without external forms of human involvement, the latter is normally associated with rational decision-making within certain social, cultural, historical and ethical contexts. However, sophisticated and "smart" they may be, automated weapons are not generally deemed to have "autonomy", and thus to apply them in warfare as though they could be held accountable for their "decisions" would have severe legal, social, political, ethical and moral consequences.

One way in which automation is shifting practices in the financial market, or economic life more broadly, is through the application of high-frequency trading (HFT; Beverungen, 2019). MacKenzie (2017, 2018a, 2018b, 2019) explores extensively the workings of this technology from a sociological perspective, focusing on detailing the material, interactive and political-economic features of HFT and HFT algorithms. HFT uses complex algorithmic computer programs to automatically transact large volumes of orders at very high speeds independently of human traders' instructions on specific orders. On the surface, HFT appears to exemplify those high technologies that revolutionise human life by replacing human experts. Yet, as Mackenzie shows, HFT functions–that is makes "decisions" to "make" and "take" orders (MacKenzie, 2018a, p. 1678)––in a complex web not only of symbolic data and algorithms but also of real humans, institutions and their interactions. By demonstrating that fundamentally determining the workings of HFT is "the interaction of people, organizations, algorithms, and machines", rather than some "black box" technology, Mackenzie highlights the social embeddedness of new technologies including AI.

A group of scholars examine the rise of automated surveillance from a sociological perspective. Most AI-powered smart surveillance technologies rely on recognition technologies of various kinds; much of the discussion thus focuses on assessing the technologies' implications for issues such as privacy, transparency and social control. For instance, scrutinising the ethical dimension of the various AI-powered emotion detection technologies, such as facial recognition, eye tracking and sentimental analysis, McStay (2018) warns that these technologies are subject to misuse by commercial and political entities to advance their private interests at the expense of public good. In a similar vein, many studies explore the use of automated surveillance technologies in public or semipublic spaces, including in schools (Andrejevic & Selwyn, 2020; Dewan, Murshed, & Lin, 2019; Monahan & Torres, 2010), public transport (McClain, 2018) and public service (Taylor, 2016; Young, Katell, & Krafft, 2019). Together these studies draw attention to the question of how automated surveillance has both benefits and risks for society as a whole and should be managed with caution.

Apart from examining various AI applications, some sociologists have analysed AI in terms of algorithms, the underpinning components of most AI systems. This work joins a large body of research on algorithms by scholars from media studies, journalism, STS, anthropology, geography, law and other disciplines, which constitutes a multidisciplinary research field––algorithm studies (Lee & Larsen, 2019; Seaver, 2019). It is beyond the scope of this paper to review the literature in this field. Moreover, the size and scope of the literature mean that to accomplish such a review would require a division of labour (see, e.g., Mittelstadt, Allo, Taddeo, Wachter, & Floridi's 2016 review of research on the ethics of algorithms). Bearing this in mind, I shall conclude this section by highlighting several studies that in my view are the most relevant to the purposes of this paper. These empirical studies all analyse AI/algorithms in terms of the gap between their significant social power, on one hand, and yet unsatisfactory social effects, on the other. Albeit not an exhaustive list, these studies are exemplary of the common concerns and theses of the wider debate.

Algorithms are deemed powerful social 'institutions' because they are widely utilised in a range of social sorting, profiling, recommendation and decision-making processes upon whose results salient social and legal actions are taken (Beer, 2017). However, algorithms are "inevitably" biased (Mittelstadt, Allo, Taddeo, Wachter, & Floridi, 2016, p. 7). For one thing, algorithm development is not a neutral process but one that retains and reproduces the values and biases of the developers (Bechmann & Bowker, 2019; Broussard, 2018). For another, mitigating mechanisms are not always technically available or effective, or else are available but are, for various reasons, ignored by the algorithms' users. As a result, when applied in socially consequential settings without adequate mitigating measures, algorithmic decision-making tools can do more harm than good, at least from a critical sociological perspective. For example, examining the use of algorithmic tools in public services, including housing, Eubanks (2017) contends that these tools serve to "[automate] inequality" in that they routinely make biased and discriminatory decisions that subject the poor and underprivileged to even direr circumstances. This claim is echoed by Noble's (2018) description of how search engines can be persistently discriminatory and misleading. Although in a technical sense the search algorithms only "reflect" the racist realities online and offline, for Noble, in being technically "neutral" but socially insensitive, these algorithms serve to reinforce racism in society and are therefore morally and politically problematic. Examining another important online tool, Facebook, Bucher illustrates that through advanced ranking and sorting algorithms, platforms like Facebook not only surveil and police users' online activities (Bucher, 2012) but also can shape users' sociality and affect their emotional life (Bucher, 2018). Given emotion's proven influence on behaviour, including political behaviour such as voting, Bucher warns that the corporations that make, deploy and profit from these algorithms are granted far more social and political power than they are able––and willing––to handle ethically.

1.4 | Cultural AI

In the "scientific AI" and "technical AI" research reviewed above, the images of "AI" evoked are tangible or intangible AI techniques, systems or products, or the research work that creates them. It analyses the social dimensions of AI's technoscientific features––their social nature and ramifications––and tries to make sense of AI products and research from a sociological perspective. In contrast, research in what I term the "cultural AI" category is less concerned with specific AI artefacts or research activities. Instead, it (a) views AI development as a social phenomenon; (b) takes this phenomenon as its object of study; and (c) analyses its interactions with the wider social, cultural, economic and political conditions in which it occurs and by which it is affected. The images of "AI" evoked in this research are AI-triggered new trends, processes, actions and relations in a diversity of social settings.

At the dawn of personal computers, thinkers like Turkle (1984) explored how computers affect human cognition and sociality. Turkle found that our tendency to define and describe AI in terms of human features and using human terms (e.g., computers as "electronic brains") can result in our defining and describing humans in terms of computer features and using computer analogies. As a consequence, the proliferation of AI can have a colonising effect on human society by causing humans to think and behave like computers. Along this line, Berman (1989, 1992) argues that AI can be not only colonising but also dehumanising. Influenced by Marxism, he maintains that discussing human capabilities using computer-inspired metaphors (e.g., human brains as "information processors") helps to justify the alienating social and economic conditions in capitalist societies, while popular AI narratives such as "augmented productivity" serve to threaten workers and encourage their "acquiescence in the power of the scientific, economic and political elites who control computer technology" (Berman, 1992, p. 112). The popularisation of AI and an AI culture can thereby help to widen and deepen the unequal power relations in society rather than to abate them. More recently, Mühlhoff (2020) has examined the extraction of human-generated data in DL. By revealing that DL routinely uses the often "involuntary" input of user-generated data for algorithm training, he elucidates how advances in AI are "structurally dependent on" the exploitation of human capacities and free human labour (Mühlhoff, 2020, p. 1868). All these studies show that AI development brings about both benefits and challenges to society and that the social challenges of AI are not always easy to identify and address. The AI community and the social scientist must work together if the technology is to be made more socially beneficial and sustainable.

Some other researchers draw upon perspectives from cultural sociology, media and cultural studies and social construction of technology to analyse the cultural construction of AI (Eynon & Young, 2021; Natale & Ballatore, 2020; Šabanović, 2014). Their focus is on how different groups leverage different cultural resources and traditions to develop AI narratives that help to advance their differing agendas. Eynon and Young (2021, p. 4) have examined how academics, industry practitioners and policymakers frame educational AI and identify that these groups have "diverging interpretations of AI" and tend to define and characterise AI in ways that benefit the work and goals of their respective fields. These stakeholders do not just happen to have different understandings of AI; rather, by strategically "framing" it, they seek to influence how educational AI is used, funded, regulated and commercialised in the long term. Similarly, Šabanović (2014) has investigated the cultural factors behind Japan's robot culture. Šabanović (2014, p. 342) shows that, by incorporating popular images and treasured cultural values and traditions into their designing, Japanese roboticists cunningly establish and derive “epistemological grounding and social justification” for their robots by eliciting cultural consent. This strategy of leveraging cultural resources to trigger wider social interest in and acceptance of AI is also observed by Natale and Ballatore (2020), who have examined the rise and development of AI from the 1950s to the 1970s and diagnose that framing the novel technology in terms of some kind of “technological myth” helped to popularise AI. These studies illustrate the importance of effective cultural framing for AI development. In a sense, cultural framing is a form of social intervention in AI design. These studies thus shed light on how social researchers, users, regulators and other relevant parties can help to create socially beneficial AI by shaping AI developers' perception of what makes socially “popular” AI and by influencing the “social” design of AI through active cultural framing and deframing of AI.

Researchers in economics, political science, and law have examined the development of AI by relating it to the digital revolution. Elliott's (2019b) book *The Culture of AI* exemplifies sociology's attempt to explore the broader and longer term social impacts of AI in the digital age. Without dwelling too much on the technical details of AI, the book surveys several social domains that are undergoing transformation prompted by AI technologies. This includes the self and identity; the (de)globalisation of the global economy; social interaction; mobility; and politics and policy. The main merit of the book is that it places the sociological analysis of AI within the wider context of the digital revolution. It thus moves the sociological study of AI from making sense of AI development from a sociological perspective to reconsidering the existing sociological concerns, concepts, theories and practices from the angle of how these are (to be) shifted by AI and digitisation. By connecting the sociological study of AI with sociology's classical concerns and subfields, the book indicates new directions not only for further analysis of AI in sociology but also for reimagining sociology in terms of AI development in the digital era. However, as with any book that attempts to cover a broad topic within a limited number of pages, this book has its shortcomings. First, the text is more descriptive than analytical. While the chapters provide an excellent overview of the important ways in which digital technologies, including AI, affect social life, they lack analytical depth. Moreover, the book makes many bold and yet ambiguous and untenable statements, such as that “AI is not an advancement of technology, but rather the metamorphosis of all technology” (Elliott, 2019b, p. xix). Claims like this can be misleading. Despite these shortcomings, however, the book is a timely and important contribution to the sociology of AI.

Compared with “scientific AI” and “technical AI” research, “cultural AI” research is still a budding field. Whereas much research in the first two categories is conducted within the subdisciplinary confines of the sociology of science and STS––the established social science subfields for studying science and technology––the “cultural AI” analytic perspective opens spaces for sociologists in other sociology subfields to research AI's impact on issues of concern to their fields. The sociology of AI should contain the sociology of science and STS research on AI, but it should not be limited to that. Rather, it should be a research field in its own right, involving contributions by scholars from across the full spectrum of sociology to debate AI's relations with and impacts on all major concerns of the discipline.

2 | CONCLUSION

An increasing number of sociologists are examining, or wanting to examine, the social production, distribution and consumption of AI. Some sociologists write about this within the sociology of science or STS, the fields that have generated most existing work on the topic. Others are drawn to the topic because AI development is affecting issues at stake to their fields of study; however, for them, it is not always easy to navigate the literature and connect their research interests in AI to the existing debate. The purpose of this paper was to devise a way to help these researchers navigate these waters more effectively. By first determining which conception of AI they have an interest in studying––as a science or scientific research field, as a technology, or as a socio-cultural phenomenon–– researchers will be better able to think about, search for and read the studies that are the most relevant to their needs.

Despite this purpose, the typology presented here is not merely utilitarian or purely conceptual. Rather, the three analytic perspectives reflect some substantive shifts in "AI" itself and in our understanding of it over time. The "scientific AI" perspective, which is most evident in research conducted in the 1980s and 1990s, corresponds with the mainstream view of AI as a novel scientific invention during the 20th century. The "technical AI" perspective, most prominent in studies published in the 2000s and 2010s, reflects the wider application and commercialisation of AI technologies during these decades. In contrast, the "cultural AI" perspective, which is observed more and more in current discussions of AI, reflects the growing social and cultural embeddedness of AI which we are increasingly experiencing today. The typology will thus not only help researchers to better navigate the literature but also serve as a reference for considering the social evolution of AI.[1]

The typology emerged from my reading of the existing sociological research on AI. Although I consider it an effective tool with which to approach and navigate the literature, it does not follow that AI can only be sociologically conceptualised in terms of these three categories and must be analysed as either a science or scientific research field, or a meta-technology or a socio-cultural phenomenon. There is no reason why "AI" cannot be conceptualised and examined in other senses and from other perspectives–– for instance, as a concept, as a mode of social interaction, as a business circle or as "narrative" (Cave, Dihal, & Dillon, 2020). Eventually, the sociology of AI should aim to examine AI development in all dimensions in which AI technologies interact with social actors, affect social relations, shift social structures and remake social realities––including in ways we may not have the capacity to fully imagine and grasp today.

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ENDNOTE

[1] Despite this temporality, the typology should not be understood as a chronological one. Not only does new research keep emerging that would fall within the 'scientific AI' and 'technical AI' categories, but the 'cultural AI' perspective can be traced back to the 1980s, as Turkle's (1984) and Berman's (1989) work attests. The distinction between the three perspectives is analytic rather than temporal.

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