AI at Work: Automation, Distributed Cognition, and Cultural Embeddedness

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Abstract
This cross-disciplinary exploration delves into the multiple intersections between Artificial Intelligence (AI), work, and organization, mobilizing different research strands such as STS and Organization Theory, as well as the History of Science and Technology and Cultural Sociology. Matteo Pasquinelli proposes an exploration of theories of automation drawn from political economy and the history of science and technology, investigating their explanatory accounts of technological innovation. As argued by the author, these theories provide important foundations for unveiling the socio-technical genealogy of current forms of AI as well as the specific logic of automation that they follow. Cristina Alaimo continues by illustrating the perspective of distributed social cognition for the study of AI in organizational settings, crucial for abandoning the assumption that intelligence is solely an attribute of individuals or technologies. This second contribution invites an exploration of how, even in organizational environments characterized by the presence of AI, intelligence still appears as a collective capability. Finally, Alessandro Gandini stresses how the encounter between AI and society is primarily a cultural issue, proposing a critical discussion of its main implications. For the author, sociology should approach AI phenomenologically and critically, but it should also take advantage from the innovations that tools such as generative AI might bring.

Keywords
AI; work; organization; digitalization; automation.

Theories of Automation from the Industrial Factory to AI Platforms: An Overview of Political Economy and History of Science and Technology

Matteo Pasquinelli

1. Introduction

What theories of automation have respectively developed in the fields of political economy and history of science and technology (HST) and what is their relationship? This essay undertakes a comparative review of these two fields with the following caveat: the focus is not to rehash the relationship between technology and society *ex-post* and propagate descriptive accounts (such as those studying the "impact" of new media on society), but to investigate causal models and explanatory accounts of technological history *ex-ante*. How does technology progress? Why is it designed in one way rather than another?

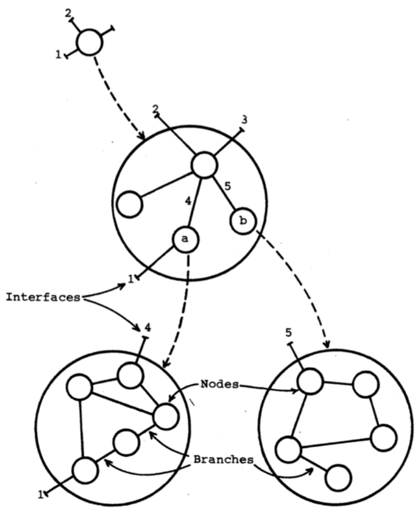

Figure 1.
from Conway, Melvin E. (1968) *How Do Committees Invent?*,
in "Datamation", 14(4), p. 29.

In political economy, a general consensus is found around the following thesis: *technological development is driven by an economy of time (making things faster) as well as of space (organizing things better), which encompass an economy of resources (making things cheaper) and particularly of labour (paying people less)*. This labour component, which is part of a broader social antagonism, is quite crucial. The way in which labour is measured and remunerated, and whether or not workers resist such measure and remuneration, crucially affects technological evolution. In synthesis, within political economy, the matrix of forces driving automation can be viewed from at least three perspectives: capital investments (seeking profit), the design of the division of labour (saving costs), and the standpoint of workers (resisting exploitation). Accordingly, automation theories in political economy can be divided, for reasons of presentation, into three groups: value theories of automation, labour theories of automation, and standpoint theories of automation. As it will be shown below, all these positions are obviously entangled and dialectical. In looking for a convincing explanatory and causal framework of technology development, this essay revisits in particular the labour theory of automation as the missing link between value and standpoint theories and endeavours to shed light on its origins, harking back to the 19th-century political economy.

Value theories of automation conceptualize it predominantly as a dynamic process that is shaped by the imperatives of capital and investment cycles from the outside. This perspective can be traced from Ernest Mandel's seminal work *Late Capitalism* (1972) to Robert Brenner's *The Boom and the Bubble* (2002), whose influence reverberates also in Aaron Benanav's *Automation and the Future of Work* (2020). Within this approach one can include also Ramin Ramtin's *Capital and Automation* (1991) and Neo-Schumpeterian positions popular in Marxist circles (Smith 2004). These theories explain the design of automation as a process that is "selected" *from the outside* by the needs of capital: technological development occurs according to its own logic (e.g., through the application of science to production) and only thereafter capital "selects" (Smith 2004) the most fitting innovations that would accelerate production and secure investment returns.

Labour theories of automation explains automation from the perspective of the material logic of production and the division of labour, or labour process (i.e., from the point of view of labour rather than simply the market). In this lineage, Harry Braverman's *Labour and Monopoly Capital* (1974) is probably the most influential work as it initiated the *labour process theory* and deskilling debate in the Anglo-American world (Smith 2015). Aside considerations about the mechanisation of manual labour, Braverman contributed to rediscover also the project for the *mechanisation of mental labour* in Babbage's "calculating engines" and to stress the influence of political economy on Babbage's early experiments of automated computation. Friedrich Pollock's *Automation* (1956) was another early seminal account stressing the role of information technologies in the industrial assembly line, influencing also the Frankfurt School's views on technology in general (Lenhard 2024).

Standpoint theories of automation see automation as driven by social antagonism and hierarchies of class, gender, and race, i.e., from processes of subjectification that are at the same time processes of resistance. Marx (1867, 552-553) stated that machinery "is the most powerful weapon for suppressing strikes" and that "it would be possible to write a whole history of the inventions made since 1830 for the sole purpose of providing capital with weapons against working-class revolt". The history of machine breakers and technological sabotage run from the 19th century Luddites (Hobsbawm 1952) and Machinery Question (Berg 1980) to the 20th century feminist and hacker movements (Mueller 2021) and recent practices of "algorithmic resistance" in the gig economy (Bonin and Treré 2024). Italian *operaismo*, in particular, has viewed labour struggles as a primary and not secondary actor in capitalism's technological advancements (Panzieri 1961; Tronti 1966). For instance, Alquati (1962; 1963) highlighted the central role of workers at the Olivetti computer factory as producers of "valorising information" in the cybernetic process (Pasquinelli 2015). Similar approaches were observed also in the US, with David Noble's critique of Braverman's deterministic focus on the labour process (1984).

The expression "standpoint theory" comes originally from feminist studies where it emphasises subjectivity as an antagonistic and active force also in knowledge production (Gurung 2020). In this respect, feminist authors, from Ruth Schwartz Cowan (1983) to Astra Taylor (2018), have revealed the ambivalent impact of automation on reproductive labour (a sphere often overlooked in political economy which is primarily focused on productive labour) arguing that it made women work more, not less. At the same time, Shulamith Firestone (1970) and Donna Haraway (1985) stressed the potential for women's emancipation through technology. From a deeper historical perspective, Hilary Rose and Steven Rose (1976), Sandra Harding (1986), Evelyn Fox Keller (1985), and Silvia Federici (2004) have expounded the rise of modern rationality and mechanical mentality in relation to the transformation of women's bodies and the collective body into a docile and productive machine. In other words, they noticed that social relations became an abstract machine before the regime of the industrial factory turn them in actual machines. Ultimately, Neda Atanasoski and Kalindi Vora (2019) have described how the dreams of full automation (which include AI) have been always grounded on the "surrogate humanity" of enslaved, servants, proletarians, and women, that make possible, through their invisibilised labour, the universalistic ideal of the autonomous (white and western) subject. "Automation is a myth" concludes Munn (2020), because it is often used to make all people work more, not less.

2. Automation theory in the 19th century political economy

The idea that organization of labour has to become "mechanical" on its own, before machinery comes to replaces it, is an old fundamental principle of political economy (Aspromourgos 2012; Pasquinelli 2023, 239). Adam Smith was the first to have sketched a *labour theory of automation* in *The Wealth of Nations* (1776) by recognising that new machines are "invented" mostly by imitating the organization of tasks in the workplace: "The invention of all those machines by which labour is so much facilitated and abridged seems to have been originally owing to the division of labour". Also, Hegel's notion of *abstract labour*, as labour that gives form to machinery, was indebted to Adam Smith, who Hegel commented already in his Jena lectures (1805-06). Nevertheless, it fell to Babbage to systematise Adam Smith's insight in a consistent labour theory of automation, that he exposed in this way:

> Perhaps the most important principle on which the economy of a manufacturer depends, is the *division of labour* amongst the persons who perform the work… The division of labour suggests the contrivance of tools and machinery to execute its processes… When each process has been reduced to the use of some simple tool, the union of all these tools, actuated by one moving power, constitutes a machine. (Babbage 1832, pp. 131-136)

What does it mean that "the division of labour suggests the contrivance of tools and machinery to execute its processes"? It means that *the design of the division of labour shapes the inner design of technology*; that labour gives form to automation first, rather than the other way around. Babbage complemented this theory with the *principle of labour calculation* (known as the "Babbage principle") to indicate that the division of labour also allows another key function: the precise computation of labour costs (Babbage 1832, 137).

Interestingly, Babbage maintained these two principles as a cornerstone of his projects of "calculating engines" such as the Difference Engine and Analytical Engine, which are considered prototypes of the modern computer. Babbage was also inspired by the French mathematician Gaspard de Prony who had first the idea of applying Adam Smith's principle of the division of labour to hand calculation and in particular to the calculus of logarithmic tables. Babbage took De Prony's algorithm, known also as "method of difference", and sought to embody its organization into a mechanical artefact. In synthesis, Babbage's design of computation moved from the idea to apply Adam Smith's principle of the division of labour to hand calculation and to mechanise, for the first time, such organization of tasks. The case of Babbage's calculating engines testify that all forms of automation (mechanical as well as informational) may be considered as evolving from the same principles. In the scholarship of the 20th century, this relation between the early project of automated computation and the political economy of labour got somehow forgotten and started to be revisited at least only since Braverman (1974) as mentioned above.

Mimetic theories of automation and variants of the labour theory of automation are actually found in many disciplines. The whole field of robotics and in particular the sub-field of bionics are based on the systematic imitation of the morphology of human and non-human living beings (Freyberg and Hauser 2023). In computer science and programming, the so-called Conway's principle states that the design of a complex artefact such as software mirrors the relations of communication between the parts of the company or organization that contributed to it: "organizations which design systems (in the broad sense used here) are constrained to produce designs which are copies of the communication structures of these organizations" (Conway 1968, 31). In engineering, the Internal Model Principle states that a "regulator must create a model of the dynamic structure of the environment" (Bengtson 1977, 333) meaning that the environment shapes the internal model first. This is, in fact, a typical principle cybernetics and within this lineage of techniques of modelling, one could also include the idea of "internal representation" in artificial neural networks (Clark and Toribio 1994) which remains central in today's AI architectures such as deep learning.

3. Automation theory in the history of science and technology

In the history of science and technology (HST), the problematics of automation has acquired a different dimension than in political economy. One could argue that in political economy the central principle of research is capital accumulation (or labour politics), while in HST the production of new instruments and knowledge. Indeed, one easily perceives that both fields tend to gravitate around their own epistemic centre and give different explanations of technoscientific developments, and yet can the two perspectives illuminate each other? What follows illustrates how HST has incorporated insights and findings from political economy and how the latter could benefit from reciprocating this knowledge transfer.

A theory of automation is implicit in any theory of scientific development as science cannot be separated from its own experimental artefacts and instruments of speculation. The debate on the status of scientific paradigms is vast: here it is framed and illuminated only from the point of concern, that is the role that tools, techniques and technologies of automation play in the history of such paradigms. For a matter of presentation, HST is divided in three main theories: internalist, culturalist, and externalist. Internalist theories often describe techno-scientific development unfolding according to internal principles (see the idea of scientific revolution in Koyré 1939 and paradigm shift in Kuhn 1962); culturalist theories open up technoscience to the influence of the social environment and engage with a constructivist approach (Simondon 1958; Shapin and Schaffer 1985); externalist theories attempt to integrated it within a larger socio-economic dynamic. This is not the place to illustrate the three approaches, as the recent historical epistemology of science and technology has provided exemplary syntheses (Badino et al. 2022; Omodeo 2019; Ienna 2023).

An interesting parallel can be registered at this point between HST and political economy: *internalist theories* in the former appear epistemologically symmetrical to the *value theories of automation* in the latter. Both theories in fact focus on a principle independent from external factors: in internalist HST, science transforms itself regardless of external contingencies, whereas in political economy's value theories, capital finds its own way to accumulate value regardless of technical and scientific achievements. However, at a different level, the two fields seem to have cooperated. The turn to the centrality of labour in political economy has projected new perspectives also in HST and it is through the study of such centrality that HST has absorbed some key notions of political economy in its own.

HST has been marked by the influence of political economy at least since Boris Hessen (1931) foundation paper "The Social and Economic Roots of Newton's Mechanics" in which he recorded the influence of the industrial age technologies on Newton's *Principia*. Another key contribution came from the Polish economists Henryk Grossmann (1935), a figure close to Frankfurt School who analysed "The Social Foundations of the Mechanistic Philosophy and Manufacture". Freudenthal and McLaughlin (2009, 4) encapsulated Hessen and Grossmann's thesis in this way: "Economics is said to present demands, which pose technical problems, which generate scientific problems". The merit of the Hessen-Grossman thesis is that it draws a complex *epistemic scaffolding* of human civilisation in which socio-economic forces shape technical forms, that in their own influence scientific theories in continuous feedback.

The Hessen-Grossman thesis can be considered an elaboration upon a central postulate of historical materialism. Marx (1867/1981, 496-497) famously argued that *the relations of production trigger the development of the means of production*, and not the other way around. Against techno-determinism, Marx intended to clarify that it was not the steam engine to drive capital accumulation in the industrial age but rather a new economic relation between workers and capital (i.e., wage labour) which became hegemonic and required a more powerful source of energy for its expansion that had to be found in steam technology (MacKenzie 1984). Similar interpretations of technological innovations are not rare and found also in the current debates on the Anthropocene. Andreas Malm (2016), for instance, reads the adoption of fossil fuel as a source of energy in place of water similarly due to intensification of labour-capital relations in the industrial age rather than to technological agency per se. However, it is somehow symptomatic that the most accurate interpretations of labour's role in technological development are found in HST rather than in Marxist political economy and, yet, the standpoint of labour still remains a secondary perspective also in the Marxist variants of HST.

On request of the Institute for Social Research in Frankfurt, Franz Borkenau (1932; 1934; 1987) attempted to put labour at the centre of the making of modern science and its "mechanist world-picture" but he did not develop his argument convincingly. His thesis was that the abstract diagram of the division of labour would have given rise to mechanical thinking, directly, with no mediation of technology. Actually, Grossmann was commissioned his 1935 essay precisely to reprimand and amend to Borkenau's simplistic reading. In synthesis, Borkenau imagined a direct relation between labour and science (a *labour theory of science*) overlooking the epistemic mediation of technology, while Grossman framed labour, technology, and science into a more systematic scaffolding (a *machine theory of science*).

The Borkenau controversy is a reminder of a blind spot that is still under-investigated in both HST and political economy: the role of praxis and labour in shaping technoscience. To stress again such shortcoming, recently Jurgen Renn (2020) has suggested to add the *ergosphere* (the sphere of labour cooperation and knowledge production) to the world model that is usually composed by geosphere, biosphere, technosphere plus infosphere and noosphere. Within the debate on the Anthropocene, Pietro Omodeo (2022) has insisted on the level of "geopraxis" to identify the subject of collective action. And similarly, Alexandra Hui, Lissa Roberts, and Seth Rockman have proposed to initiate a *labour history of science* as a dialogue between labour history and science history,

> given the insufficiently recognized and thematized omnipresence of labor in the history of science (not to mention the lack of analytical attention given to science and its practitioners in labor history). (Hui et al. 2023, 820)

As historians of science, Hui, Roberts, and Rockman want to make the point that labour history can provide key insights to HST, but it should be noted that also HST contributed to illuminate economic dynamics, in particular regarding the role of metrics, instruments of measurement, and metrology. Practices and instruments of measurements have been always key to economic exchange, process of valorisation, the institution of money as well as labour management. Metrology has always been a political affair (Kula 1986; Schaffer 2015; Pasquinelli 2022) and the rise of industrial automation can hardly be distinguished from the practices and techniques to quantify and monetize labour.

Under this respect, Norton Wise (1988) has proposed seeing industrial technologies such as the steam engine and the telegraph, as "mediating machines", as epistemic mediators in between the domains of political economy and natural philosophy, between labour and science. Wise has stressed the twofold role of the steam engine in the measurement of labour and the making of the metric unit of work in physics (Wise 1988, 77). Wise's insight points to a common ground between value and labour in theories of automation, according to which technology is not only a *means of production* but, in fact, also an *instrument for measuring production* and labour in particular. As the Babbage principle already expressed, the division of labour (and implicitly any machine) allows the measurement and purchase of the exact quantity of labour and resources that are necessary for production. This perspective can be identified as a *metric theory of automation*, according to which techniques that are used to measure labour suggest also the design of new technologies of automation once the division of labour has reached a mature stage of development (Pasquinelli 2023, 243). The metrology of labour should be used as a prism to pursue a further integration of value theories and labour theories with the standpoint theories of automation (a point that cannot be expanded here).

4. Automation theory at the times of AI

The sociotechnical composition of AI in the early 21st century provides a crucial case study and vantage point of observation, especially given the degree of automation AI has achieved in such epoch. AI is sometimes described as a novel stage of technology that would breaks from the past in terms of scale and capacity (see the myth of Singularity). But is that really so? Let's look at how HST and political economy covers the issue of AI.

HST has never considered AI (as much as its parent discipline cybernetics) as a "science", as it never deployed an experimental method to discover new laws of nature, rather an *analogical method* (or thinking per analogy) which belongs to a pre-scientific mentality. Cyberneticians believed that machines could imitate organisms (including brains), because in their view organisms were like machines. Cybernetics was a branch of electro-mechanical engineering, which was only later arbitrarily termed "computer science". As a matter of fact, the *method of AI* has always been an "imitation game" (Turing 1950) whose object is not nature, but culture – not the universal laws of the human brain to be discovered, but historical social conventions to be recorded. The Turing test came to represent this distinction. Schaffer (2024) has argued that its meaning is to demonstrate that intelligence (whatever in its mechanical or human manifestations) is and can only be an affair of *relational intelligence*, that is an issue of external conventions to follow, rather than internal (biological or logical) rules to execute.

Historians of science tend to agree that modern automated computation (from Babbage's Difference Engine to AI) has historically emerged as a measure and automation of mental labour and specifically hand calculation in the industrial milieu (Daston 1994), rather than as an artefact to simulate intelligence in the abstract. In this regard, Daston (2018) has clarified that the nature of computation (including AI) is a kind of *analytical intelligence* of human organizations and social relations that resonates with Schaffer's interpretation of *relational intelligence* in the Turing test. Internalist and cognitivist approaches in HST (Boden 2006), on the other hand, keep on reading AI as a quest to achieve "machine intelligence" in general by imitating and taking for granted "human intelligence" as an a-historical given. Contra the epistemic reductionism of certain cognitive sciences, HST has been key in clarifying that AI models and models of intelligence are historical and not universal paradigms and that both mirror social hierarchies of head and hand (Schaffer 1994).

A normative paradigm of social intelligence affects, indeed, the design of AI since its inception. The current form of AI, deep learning, originated from Frank Rosenblatt's invention of the first neural network Perceptron in the 1950s (Pasquinelli 2023, 205). The Perceptron imitated the form of biological neural networks only superficially: mathematically speaking it embodied the automation of statistical tools of multidimensional analysis that Rosenblatt, a psychologist by training, inherited from psychometrics. Psychometrics is the discipline that established the infamous cognitive test to measure the "intelligence quotient" (IQ test) and originally aimed to quantify the skills of the population by conducting statistical analyses of such tests. Embedded within the contentious legacy of Alfred Binet, Charles Spearman, and Louis Thurstone, psychometrics emerged as a branch of statistics, which has never been a neutral discipline so much as one concerned with the "measure of man", the institutions of norms of behaviour, and the control of deviations from the norm (Gould 1981). As previous forms of automation emerged from the metrics of labour within the industrial milieu, AI can be said to have emerged from the *psychometrics of labour*, i.e., the measurement and classification of cognitive skills across the population. As I stressed in another context:

> To compare human and machine intelligence implies also a judgement about which human behaviour or social group is more intelligent than another, which workers can be replaced and which cannot. Ultimately, AI is not only a tool for automating labour but also for imposing standards of mechanical intelligence that propagate, more or less invisibly, social hierarchies of knowledge and skill. As with any previous form of automation, AI does not simply replace workers but displaces and restructures them into a new social order. (Pasquinelli 2023, 246)

In short, the current form of AI, machine learning, is the automation of a statistical metric which was originally introduced to quantify cognitive, social, and work-related abilities. This is another case of the labour theory (or metric theory) of automation, as one can see how a technique to measure and organize social relations affects the design of automation itself.

The centrality of the sphere of social relations in the logical constitution of AI, rather than rationality in the abstract, is also demonstrated by its current architecture, that shows a full dependence on massive repositories of personal and collective data (Muldoon et al. 2024). Looking at the current form of AI, machine learning and specifically deep learning (i.e., the type of machine learning based on large artificial neural networks), Science and Technology Studies (STS) have made clear that such systems grow thanks and are indebted to the invisible labour and knowledge of a global multitude of workers and users (Gray and Suri 2019). Here, regarding the political composition of AI, STS prove what HST has discovered regarding its technical genealogy, that is the centrality of the labour form. In short, current AI is a type of automation technology based on the direct imitation of social relations, cultural heritage, and labour at large (both manual and mental) and in this way proving the labour theory of automation that was expounded before.

The centrality of the labour issue in AI brings us finally to consider the perspective of political economy. Although an economic estimate of the current large AI models (ChatGPT, etc.) is still difficult, it cannot be ignored that AI has already constituted powerful monopolies of information processing which can be effective in the partial automation of many jobs (Bommasani et al. 2021). However, Benanav (2020) has warned us that the perception of AI as a cause of technological unemployment may be an optical illusion and actually an effect first of global stagnation rather than automation per se (see also Smith 2020). Benanav moves from the perspective of a value theory of automation to describe AI within the financial trends of the global economy. However, see from the point of view of labour composition, AI systems such as ChatGPT appear similar to the manifestations of platform capitalism and gig economy which are actually expanding and transforming the labour market.

In the last decade, numerous offline and online activities, including small businesses, white-collar professions, care workforce, and a vast delocalised army of workers have been organized through new digital platforms that often established global monopolies in logistics, distribution, and hospitality, among other sectors (Srnicek 2016; Poell et al. 2019). What these platforms represent is not just a business model but a new pervasive form of *algorithmic* *management*, in which bosses are made redundant and replaced by software for monitoring and decision-making (Wood 2021; Woodcock 2021a; 2021b; Armano et al. 2022). The ethnography and sociology of these new forms of labour point to numerous similarities between gig economy and AI platforms: they illuminate AI systems as a new form of monopoly in the logistics and management of a global workforce (Kellogg et al. 2020; Pirina 2022; Bonifacio 2023; Peterlongo 2023). From the point of view of the information flows of the global technosphere, it appears as AI is the ultimate combination of previous processes of data collection and labour management from below rather than the invention of new powerful algorithms from above. Algorithmic management is not an "invention", rather a gradual automation of previous techniques to control and organize the workforce. As those before, also this new process of automation is not seamless, but marked by frictions and conflicts between platforms and workers. Ethnographical and sociological studies of the gig economy have revealed the antagonism that animate such platforms from within, the creative acts of disruption and hacking by workers for better labour condition and against the discriminatory practices that algorithmic management implements every day. For Bonini and Treré (2024), platform workers are continuously engaged in creative acts of "algorithmic resistance" that do not simply disrupt the "algorithmic power", but force it to adapt and innovate from within, as standpoint theories of automation also elucidated in other cases.

5. Conclusions

In conclusion, I argue that the value theory of automation applied to AI is a necessary perspective but not sufficient to explain the current state of affairs by itself. One should integrate a value theory of AI with the perspective of labour to frame AI as a technique, on one hand, for the measurement of labour and, on the other, for the control of social hierarchies, as also standpoint theory would still suggest looking at the previous centuries of technological domination. Regarding the case of AI, the analysis of the division of labour (*labour theory*) and forms of antagonism (*standpoint theory*) should help to illuminate the economic dimension of AI (*value theory*) in a better way and to understand that the valorisation process can be rarely abstracted from the materiality of living labour and social relations and that themselves cannot be removed from the destiny of the value form.

How does the internal design of AI relate to its economic dimension, that is how is its intrinsic labour form interacting with the extrinsic value form? As argued above, AI has not emerged as a specific form of automation that imitates a specific division of labour, but as a general system capable to imitate and model the most diverse forms of manual, mental, and visual labour: it represents the culmination of the labour theory of automation, the automation of the automation principle itself, or the *automation of automation* (Pasquinelli 2023b, 248; see also Steinhoff 2021). This incredible capacity of automation, however, appears to be oriented not to the full replacement of workers, rather to the automation of modular micro-tasks. The worker is not replaced by an AI system but becomes a meta-worker, or a "general worker" (a true cyborg worker, if you like), that provides the human synthesis to a myriad of micro-tasks. Each automated micro-tasks may appear as it helps and empowers the workers but actually it drowns and exhaust their overall energy. The paradox of AI is that it does not replace workers but multiple them: rather than the end of employment, it engenders *under-employment* (Benanav 2020), a precarisation of the labour market in which workers are force to work more and more. In a global tendency of precarisation and stagnation, it appears as *AI will force everyone to work more, not less*. Of course, this destiny is not inevitable. What value, labour, and standpoint theories of automation all suggest is that the technological composition of labour in a given epoch can be changed by changing its social and political composition.

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References

Alquati, Romano (1962) *Composizione organica del capitale e forza-lavoro alla Olivetti – Parte 1*, in “Quaderni Rossi”, 2, pp. 63-98.
Alquati, Romano (1963) *Composizione organica del capitale e forza-lavoro alla Olivetti – Parte 2*, in “Quaderni Rossi”, 3, pp. 119-185.
Armano, Emiliana, Briziarelli, Marco and Risi, Elisabetta (2022) *Digital Platforms and Algorithmic Subjectivities*, London, University of Westminster Press.
Aspromourgos, Tony (2012) *The Machine in Adam Smith’s Economic and Wider Thought*, in “Journal of the History of Economic Thought”, 34(4), pp. 475-490.
Atanasoski, Neda and Vora, Kalindi (2019) *Surrogate humanity: Race, robots, and the politics of technological futures*, Durham, Duke University Press.
Babbage, Charles (1832) *On the Economy of Machinery and Manufactures*, London, Knight.
Badino, Massimiliano, Ienna, Gerardo and Omodeo, Pietro Daniel (2022) *Epistemologia storica: Correnti, temi e problemi*, Roma, Carocci editore.
Benanav, Aaron (2020) *Automation and the future of work*, London, Verso.
Bengtsson, Gunnar (1977) *Output regulation and internal models: A frequency domain approach*, in “Automatica”, 13(4), pp. 333-345.
Berg, Maxine (1980) *The machinery question and the making of political economy: 1815–1848*, Cambridge/New York, Cambridge University Press.
Boden, Margaret A. (2006) *Mind as machine: A history of cognitive science*, Oxford, Oxford University Press.

Bommasani, Rishi, Hudson, Drew A., Adeli, Ehsan et al. (2021) *On the Opportunities and Risks of Foundation Models* [Report], in “arXiv”, 2108.07258v3.

Bonifacio, Francesco (2023) *Fare il rider: Pratiche, saperi e traiettorie di una professione emergente*, Milano, Mimesis Edizioni.

Bonini, Tiziano and Treré, Emiliano (2024) *Algorithms of Resistance: The Everyday Fight against Platform Power*, Cambridge (MA), MIT Press.

Borkenau, Franz (1932) *Zur Soziologie des mechanistischen Weltbildes*, in “Zeitschrift für Sozialforschung”, 1(3), pp. 311-335.

Borkenau, Franz (1934) *Der Übergang vom feudalen zum bürgerlichen Weltbild: Studien zur Geschichte der Philosophie der Manufakturperiode*, Paris, Felix Alcan.

Borkenau, Franz (1987) *The Sociology of the Mechanistic World-Picture*, in “Science in Context”, 1(1), pp. 109-127.

Braverman, Harry (1974) *Labor and Monopoly Capital: The Degradation of Work in the Twentieth Century*, New York, Monthly Review Press.

Brenner, Robert (2002) *The Boom and the Bubble: The U.S. in the World Economy*, London, Verso.

Clark, Andy and Toribio, Josefa (1994) *Doing without Representing?*, in “Synthese”, 101(3), pp. 401-431.

Conway, Melvin E. (1968) *How do Committees Invent?*, in “Datamation”, 14(4), pp. 28-31.

Cowan, Ruth Schwartz (1983) *More Work for Mother: The Ironies of Household Technology from the Open Heart to the Microwave*, New York, Basic Books.

Daston, Lorraine (1994) *Enlightenment Calculations*, in “Critical Inquiry”, 21(1), pp. 182-202.

Daston, Lorraine (2018) *Calculation and the Division of Labor, 1750–1950*, in “Bulletin of the German Historical Institute”, 62(Spring), pp. 9-30.

Federici, Silvia (2004) *Caliban and the Witch: Women, the Body and Primitive Accumulation*, New York, Autonomedia.

Firestone, Shulamith (1970) *The Dialectic of Sex: The Case for Feminist Revolution*, New York, William Morrow.

Freudenthal, Gideon and McLaughlin, Peter (eds.) (2009) *The Social and Economic Roots of the Scientific Revolution*, Dordrecht, Springer Netherlands.

Freyberg, Sascha and Hauser, Helmut (2023) *The morphological paradigm in robotics*, in “Studies in History and Philosophy of Science”, 100 , pp. 1-11.

Gould, Stephen J. (1981) *The Mismeasure of Man*, New York, Norton & Company.

Gray, Mary L. and Suri, Siddharth (2019) *Ghost Work: How to Stop Silicon Valley from Building a New Global Underclass*, Boston, Houghton Mifflin Harcourt.

Grossmann, Henryk (1935) *Die gesellschaftlichen Grundlagen der mechanistischen Philosophie und die Manufaktur*, in “Zeitschrift für Sozialforschung”, 4(2), pp. 161-231.

Gurung, Lina (2020) *Feminist Standpoint Theory: Conceptualization and Utility*, in “Dhaulagiri Journal of Sociology and Anthropology”, 14 , pp. 106-115.

Haraway, Donna (1985) *A Cyborg Manifesto*, in “Socialist Review”, 15(2), pp. 65-107.

Harding, Sandra G. (1986) *The Science Question in Feminism*, Ithaca, Cornell University Press.

Hegel, Georg W. F. (1805[1983]) *Hegel and the Human Spirit: A Translation of the Jena Lectures on the Philosophy of Spirit (1805–6) with Commentary* (Leo Rauch, Translation), Detroit, Wayne State University Press.

Hessen, Boris (1931[2009]) *The Social and Economic Roots of Newton’s* Principia, in Gideon Freudenthal and Peter McLaughlin (eds.), *The Social and Economic Roots of the Scientific Revolution: Texts by Boris Hessen and Henryk Grossmann*, Dordrecht, Springer, pp. 41-101.

Hobsbawm, Eric J. (1952) *The Machine Breakers*, in "Past & Present", 1, pp. 57-70.
Hui, Alexandra, Roberts, Lissa and Rockman, Seth (2023) *Introduction: Launching a Labor History of Science*, in "Isis", 114(4), pp. 817-826.
Ienna, Gerardo (2023) *Genesi e sviluppo dell'épistémologie historique: Fra epistemologia, storia e politica*, Lecce, Pensa Multimedia.
Keller, Evelyn F. (1985) *Reflections on Gender and Science*, New Haven, Yale University Press.
Kellogg, Katherine C., Valentine, Melissa A. and Christin, Angéle (2020) *Algorithms at Work: The New Contested Terrain of Control*, in "Academy of Management Annals", 14(1), pp. 366-410.
Koyré, Alexandre (1939) *Études galiléennes*, Paris, Hermann.
Kuhn, Thomas S. (1962) *The Structure of Scientific Revolutions*, Chicago, University of Chicago Press.
Kula, Witold (1986[2016]) *Measures and Men* (R. Szreter, Translation), Princeton, Princeton University Press.
Lenhard, Philipp (2024, in press) *Friedrich Pollock: The Éminence Grise of the Frankfurt School*, Leida, Brill.
MacKenzie, Donald (1984) *Marx and the Machine*, in "Technology and Culture", 25(3), pp. 473-502.
Malm, Andreas (2016) *Fossil Capital: The Rise of Steam Power and the Roots of Global Warming*, London, Verso.
Mandel, Ernest (1972) *Der Spätkapitalismus*, Berlin, Suhrkamp.
Marx, Karl (1981) *Capital: A Critique of Political Economy* (Ben Fowkes, Translation), London/New York, Penguin Books in association with New Left Review.
Mueller, Gavin (2021) *Breaking Things at Work: The Luddites Are Right About Why You Hate Your Job*, London, Verso.
Muldoon, James, Graham, Mark and Cant, Callum (2024) *Feeding the Machine: The Hidden Human Labour Powering AI*, Edinburgh, Canongate Books.
Munn, Luke (2022) *Automation Is a Myth*, Stanford, Stanford University Press.
Noble, David F. (1984) *Forces of Production: A Social History of Industrial Automation*, Oxford (UK), Oxford University Press.
Omodeo, Pietro D. (2019) *Political epistemology: The problem of ideology in science studies*, Cham, Springer.
Omodeo, Pietro D. (2022) *Geopraxis: A Concept for the Anthropocene*, in "Journal of Interdisciplinary History of Ideas", 11(22), Item 9, pp. 9:1-9:52.
Panzieri, Raniero (1961) *Sull'uso capitalistico delle macchine nel neocapitalismo*, in "Quaderni Rossi", 1(1), pp. 53-72.
Pasquinelli, Matteo (2015) *Italian* Operaismo *and the Information Machine*, in "Theory, Culture & Society", 32(3), pp. 49-68.
Pasquinelli, Matteo (2022) *Labour, Energy, and Information as Historical Configurations*, in "Journal of Interdisciplinary History of Ideas", 11(22), Item 13, pp. 13:1-13:31.
Pasquinelli, Matteo (2023) *The Eye of the Master: A Social History of Artificial Intelligence*, London, Verso.
Peterlongo, Gianmarco (2023) *Nella trama dell'algoritmo: Lavoro e circuiti informali nella gig-economy*, Torino, Rosenberg & Sellier.
Pirina, Giorgio (2022) *Connessioni globali: Una ricerca sul lavoro nel capitalismo delle piattaforme*, Milano, Franco Angeli.
Poell, Thomas, Nieborg, David and van Dijck, José (2019) *Platformisation*, in "Internet Policy Review", 8(4).

Pollock, Friedrich (1956) *Automation: Materialien zur Beurteilung der ökonomischen und sozialen Folgen*, Frankfurt am Main, Europäische Verlagsanstalt.

Ramtin, Ramin (1991) *Capitalism and Automation: Revolution in Technology and Capitalist Breakdown*, London, Pluto Press.

Renn, Jürgen (2020) *The Evolution of Knowledge: Rethinking Science for the Anthropocene*, Princeton, Princeton University Press.

Rose, Steven and Rose, Hilary (eds.) (1976) *The Radicalisation of Science: Ideology of/in the Natural Sciences*, London, Macmillan.

Schaffer, Simon (1994) *Babbage's Intelligence: Calculating Engines and the Factory System*, in "Critical Inquiry", 21(1), pp. 203-227.

Schaffer, Simon (2015) *Ceremonies of Measurement: Rethinking the World History of Science*, in "Annales: Histoire, Sciences Sociales-English Edition", 70(2), pp. 335-360.

Schaffer, Simon (2024) *The hidden history of Alan Turing's famous imitation game* [YouTube video]. Available at: https://www.youtube.com/watch?v=iI0Fb0dwGyM (retrieved May 30, 2024).

Shapin, Steven, Schaffer, Simon and Hobbes, Thomas (1985) *Leviathan and the Air-Pump: Hobbes, Boyle, and the Experimental Life*, Princeton, Princeton University Press.

Simondon, Gilbert (1958[2017]) *On the Mode of Existence of Technical Objects* (Cecile Malaspina and John Rogove, Translation), Minneapolis, Univocal Publishing.

Smith, Adam (1776) *An Inquiry into the Nature and Causes of the Wealth of Nations*, London, Strahan & Cadell.

Smith, Tony (2004) *Technology and History in Capitalism: Marxian and Neo-Schumpeterian Perspectives*, in Riccardo Bellofiore and Nicola Taylor (eds.), *The Constitution of Capital*, London, Palgrave Macmillan, pp. 217-242.

Smith, Chris (2015) *Continuity and Change in Labor Process Analysis Forty Years After* Labor and Monopoly Capital, in "Labor Studies Journal", 40(3), pp. 222-242.

Smith, Jason E. (2020) *Smart Machines and Service Work: Automation in an Age of Stagnation*, London, Reaktion Books.

Srnicek, Nick (2016) *Platform Capitalism*, Cambridge (MA), Polity.

Steinhoff, James (2021) *Automation and Autonomy: Labour, Capital and Machines in the Artificial Intelligence Industry*, Cham, Springer International Publishing.

Taylor, Astra (2018) *The Automation Charade*, in "Logic Magazine", 5.

Tronti, Mario (1966[2019]) *Operai e capitale* (David Broder, Translation), Torino, Einaudi.

Turing, Alan M. (1950) *I.–Computing Machinery and Intelligence*, in "Mind: A Quarterly Review of Psychology and Philosophy", LIX(236), pp. 433-460.

Wise, M. Norton (1988) *Mediating Machines*, in "Science in Context", 2(1), pp. 77-113.

Wood, Alex J. (2021) *Algorithmic Management: Consequences for Work Organisation and Working Conditions*, JRC Working Papers Series on Labour, Education and Technology 2021/07, European Commission.

Woodcock, Jamie (2021a) *Towards a Digital Workerism: Workers' Inquiry, Methods, and Technologies*, in "NanoEthics", 15(1), pp. 87-98.

Woodcock, Jamie (2021b) *The Limits of Algorithmic Management: On Platforms, Data, and Workers*, in "South Atlantic Quarterly", 120(4), pp. 703-713.

The Socio-Cultural Foundations of Intelligence: AI and Organizations

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1. Introduction

Much of the research on the organizational impact of AI is conducted at the level of individual experts or teams interacting with the AI artifact. Even when the recent literature questions the disruptive potential of AI applications on human intelligence, expertise, and knowledge, it rarely investigates how AI enters the complex interplay of action and cognition that underlies human intelligence, expertise, and knowledge in organizational settings.

The advent of Generative AI seems to reinforce this principle of methodological individualism and the perception of individuals as atomized and fenced-off entities rather than as social participants who change and adapt as they continuously interact with one another and the organizational contingencies they confront (March and Simon 1958). Along these lines, the risks and opportunities that GenAI bears for workers or experts are mainly discussed as losses or gains of individual capabilities and investigated as such. In a recent paper, for instance, Brynjolfsson and Raymond (2023) assess the impact of GenAI on jobs by measuring productivity in terms of individual performance per hour. They find that introducing AI in work settings increases productivity by 34% for novice and low skilled workers but much less for experienced workers. A more nuanced yet similar approach is taken by the study on the productivity gains of consultants once ChatGPT is introduced and the "kind" of knowledge AI may augment (Dell'Acqua et al. 2023).

Yet, focusing on augmentation (of knowledge, skills) or productivity issues at the individual or job level presupposes a version of intelligence and how it works thatrisks leaving much unsaid. Current approaches to AI tacitly assume that cognition (i.e., processes of learning, reasoning, decision-making, memory, inference, and so on) effectively happens inside the brains of individual humans or in the "brains" of machines. Consequently, they reduce the study of human-machine interaction in organizational settings to the in-situ observation of a detached individual worker or expert interacting with the outputs of a black-boxed AI artifact. Focusing on human-machine output interaction, specifically in the age of Large Language Models (LLMs) and complex AI applications whose outputs are unstable and whose processes remain relatively unknowable, presents significant limitations with respect to how we assess the impact of artificial intelligence in organizations.

In this essay, I turn to foundational contributions in organization theory, cognitive psychology and sociology that have dealt with social cognition in organizational and social settings. By climbing on the shoulders of a few giants (Bateson 1972; Douglas 1986; Hutchins 1995; March 1994; March and Simon 1958; Nelson and Winter 1982; Simon 1969/1996; Weick 1979), I argue that to study AI we need to turn our attention to where intelligence resides in organizational settings (Nelson and Winter 1982) and how it is disrupted by the diffusion of cognitive technologies of automation. This should entail abandoning the assumption that intelligence is an attribute of individuals and instead examining how organizations condition individual cognition and forms of expertise by 1) structuring social interactions among individuals and 2) providing an ecology of material and immaterial cognitive artifacts through which social interactions occur (Hutchins 1995; Knorr-Cetina 1999; Tomasello 1999). Over the last fifty years, these ecologies of cognitive artifacts have become increasingly translated into data and digital devices and integrated into complex technological infrastructures that have taken over much of the function of organizing (Alaimo and Kallinikos 2024). Today, the boundarylessness of AI artifacts, the invisibility of their cognitive processes, and the lack of cognitive accessibility and accountability of their operations are challenging, once again, the foundations of social cognition in organizational settings.

2. Social intelligence and artificial environments

Intelligence and cognition are hardwired to the cultural, social, and contextual aspects of the environment in which individuals are embedded, without which they would be unable to make sense of the world. Vygotsky was one of the first to advance the concept of the social origins of individual psychological functions (Vygotsky 1978), claiming that every cognitive function appears first as an inter-psychological process and only after as an intra-psychological process. Similarly, the British anthropologist Mary Douglas stated:

> Only collective representations are social facts, and social facts count for more than psychological ones because the individual psyche is constituted by the socially constructed classification. (Douglas 1986, 96-97)

In the introduction of her acclaimed book *How Institutions Think*, she advocated for a theory of institutions that would amend the current unsociological view of human cognition and a cognitive theory to supplement the weakness of institutional analysis (1986, ix).

The idea that organizations and institutions (a cultural unit of analysis that transcends yet encompasses the functional boundaries of organizations, see i.e., Friedland and Alford 1991) are more than the sum of their parts is well accepted. What is still controversial is the idea that individual cognition is closely intertwined with organizations and institutions. Institutions do the thinking that humans alone cannot do. As Mary Douglas put it, “Individuals tend to leave the important decisions to their institutions while busying themselves with tactics and details” (1986, 111). Many may find it challenging to conceive institutions and organizations as the decision-makers. Yet a similar point was raised by March and Simon in 1958 when they advanced the idea of organizations as adaptive cognitive systems (March and Simon 1958; see also March 1994). The complexity and ramified implications of decision-making cannot be handled by individual cognition and must be solved by distributing it across members and entrusting into a variety of cognitive devices. Organizations, in their view, are systems for addressing these issues. Weick and Roberts (1993) went further when they explained coordination in organizations concerned with reliability (such as flight operations, etc.) with the term *collective mind*, by which they mean the distributed mental process and patterns of heedful, interrelated activities that make organizing. In essence, they state that organizations allow agents to understand a system they could not have grasped on their own.

Turning our attention to the organizational settings of cognition and the distributed cognitive structures therein may give us a better idea of the impact of AI on organizations and individuals. Such an outlook provides a more elaborate mirror of the cognitive processes of both individuals and machines and their interaction patterns. The place of intelligence is not in the minds of people or the neural networks of computers (Kittler 1999; Winner 1993) but in social and organizational settings. Nelson and Winter, in 1982, raised the fundamental question, "Where does knowledge reside in organizations?". Their response is that knowledge is neither in the minds of experts nor in the records of organizations, but it mainly emerges from structured interactions embedded in routines (1982). Individual skills matter but only within a broader division of labour and the social rules through which the exercise of human discretion is embedded.

Organizations offer well-trodden cognitive paths that individuals take to handle the contingencies that cannot be foreseen. The patterns of interactions that become structured in organizations have been traditionally studied as facilitating individual cognition. For example, for HR professionals, much of the interaction during job interviews is scripted. This means that HR experts can use these ready-made scripts and engage with the idiosyncrasies and contingencies of individual interviews. Interactions and cognition are tightly coupled and, in social settings, are always structured. They take place within the cultural and cognitive boundaries of organizations or cultural environments, and because of this, they unfold by relying on an acquired mutual impression of intersubjectivity (Garfinkel 1967), maintaining a shared representation of the actions of others and their relations (Weick and Roberts 1993). Interaction in organizational settings is rarely interpreted as one-to-one, as it involves an interaction script, roles, and an organizational environment (Mead 1935; Weick 1995). We know the others as such only because we mobilize existing frames to interpret them (Mead 1935). Humans learn to interact in complex and culturally stratified social environments of their own making. Daft and Weick (1984, 75) explicitly stated: "Only by testing our interpretations back on 'the' environment can we know whether they are reasonable". If action is triggered by perceptual cues that evoke particular identities, frames, and corresponding performance scripts without much deliberate thought, it cannot happen without continuous feedback from the environment, that is, a very complex network of roles, objects, cognitive devices, and routines (Weick 1995).

Can we comprehend how human experts or workers interact with the AI artifact without knowing how their interaction is linked to the environment? In *The Sciences of the Artificial* (1969/1996) Herbert Simon described his observations of an ant finding its way on the beach. The behaviour of the ant is adaptive, complex and irregular, and hard to define. Yet the complexity, Simon observed, is in the surface of the beach, not in the behaviour of the ant. Humans can be quite simple, Simon argued, and the apparent complexity of their behaviour over time is largely a reflection of the complexity of the environment in which they find themselves. Hutchins echoed these ideas of Simon when he affirmed that "humans create their cognitive powers by creating the environments in which they exercise those powers" (Hutchins 1995, 169).

Without looking at how organizations distribute and coordinate cognition across their members and how these arrangements interact with a dynamic environment, we would not be able to productively assess the impacts of AI on the cognitive abilities of individuals and the settings in which these individuals find themselves. If and how AI transforms existing ways of reasoning, learning, and working, it will depend on how much it can facilitate, hinder, or substitute entirely, the coordination of social cognition and action, which is the essence of organizing in a complex environment.

3. Cognitive devices and knowledge artifacts

Much of AI research evolves heavily around the concepts of automation and augmentation. When it is not seen as a substitute for human work, the prevailing idea today is that of augmentation, which leads to a sort of win-win collaboration between humans and AI where the sum of the two will be better than what can be accomplished by humans or AI alone (e.g., Daugherty and Wilson 2018; Fügener et al. 2022; Gal et al. 2020; Grønsund and Aanestad 2020; Lyytinen et al. 2021; Wilson and Daugherty 2018; Zhang et al. 2021). The idea of augmentation is not new; the concept, which assumes that the use of computers and information technology may enhance human abilities, was already in use in 1962 as augmentation of human intellect (Engelbart 1962). By the late seventies, the notion that cognitive artifacts amplify the cognition of users became very diffuse. Yet very few contributions today problematize what is exactly that is augmented (i.e., Baer et al. 2022).

All cognitive devices, including pen and paper or simple calculators, can amplify a human ability if attention is given to the outcome. Writing down things amplifies human memory (Clark and Chalmers 1998), and using calculators augments arithmetic skills. However, as Hutchins reports, Cole and Griffin in 1980 already pointed out how looking at the outcome of technological devices to assess augmentation is simply not enough (Hutchins 2000). It hides the fact that cognitive abilities or skills are rarely augmented by technologies but most often reshuffled and rearranged as cognitive technologies mobilize different functional skills to perform the same tasks. Writing did not augment memory but, for some eminent scholars, changed the cognitive nature of the task and the structure of social cognition (Hutchins 1995; Ong 1982). Simply put, as we interact with our devices, our entire cognitive structure is rewired, and we understand and act upon things and the environment in new ways.

Sociologists and STS scholars have long considered the role of cognitive devices and objects in scientific practice and the process of knowing. Scientists would not be able to work without relying on others and a network of mental and physical devices through which they support common knowledge and understanding. Karin Knorr-Cetina (1999) speaks of a "machinery of knowing" that, in a given field, makes up how and what we know. For Knorr-Cetina, patterned, dynamic sequences of interactions are the ingredients of such machinery of knowing mobilized through material and immaterial objects. In epistemic settings like in organizational settings, individual capabilities tune in and emerge from collective life. Across all these studies mental states or representations are framed as cultural products, not as the idiosyncratic interpretation of individual users but as the residua of a complex and distributed process enacted by a community of practice (Hutchins 1995, 130).

As knowledge and practice are crystalized in the physical structure of artifacts, and in the mental structure of users, ecologies of material and immaterial objects constitute the cultural environment where people interact and forms of organizing emerge and are established.

Any new device, therefore, sits within a complex network of mental and external cognitive structures that can be embedded in knowledge objects such as reports, charts, models, existing digital infrastructures, databases, archives, and so on. Against this background, the notion that devices, objects, or artifacts may augment human capabilities without acknowledging the social nature of those capabilities and how they emerge and evolve in specific chains of practice and across communities of people and networks of objects, seems very limited. A change in one instrument triggers a reshuffling in the whole suite of devices and practice sets to accomplish a task. At the same time, when the nature of practice changes, the role of instruments may also change.

This ecology of epistemic and cognitive devices stands in a meaningful relation of interdependence with organizing. Susan Leigh Star famously demonstrated how the work of epistemic communities is coordinated via cognitive devices. What she called *boundary objects* operate as knowledge brokers across different specializations or different experts (Star 2010; Star and Griesemer 1989). Existing research provides evidence of how individuals from distinct knowledge communities interact with meanings and representations generated by boundary objects to work together (see i.e., Barley et al. 2012). In his illustration of navigation, Hutchins describes the network of mutual computational and representational interdependencies that links devices, practices, and action and forms a cognitive ecology of tools aiding coordination. Mental states are activated by these complex interdependences where one cognitive device may work as the environment for another (Hutchins 1995). In organizations, cognitive ecologies of objects, mental representations, and devices are hardwired to roles, hierarchies, and routines. Cognitive processes may be distributed across individuals performing specific roles (the group of HR professionals, a product team, organizational hierarchies), across several material and immaterial knowledge objects and cognitive devices, and through time (Hutchins 2000; 2014). Workers and employees use many artifacts in their everyday jobs, and disruption caused by new tools or cognitive devices is likely to impact not just existing practices but also existing organizational structures and the division of tasks and roles.

These considerations stand in sharp contrast with the current framing of the impact of AI as augmentation. The focus on outputs and individual skills or capacities (including productivity or efficiency) can hardly explain the complex individual and organizational transformation that takes place as AI changes the distributed toolkits of organizations, rearranges social cognitive functions, and interacts with the environment. There is still a relatively scarce consideration of the transformation of existing cognitive ecologies as the introduction of AI reshuffles interdependencies between practices, subject identities, and existing organizational structures (for an exception, see Waardenburg and Márton 2024).

4. AI, data, and organizations

Digital technologies are not just tools linking means to ends or augmenting individual skills. They are complex systems of meaning tied up to closed chains of formalized reasoning (if-then). One of the earlier accounts of the transformations triggered by cognitive technologies in organizations is given by Zuboff in her *In the Age of Smart Machines* (1988). As work was translated into digital data, or textualized, workers in mills and factories had to forego what they knew about their selves and their jobs, their tools, and ways of doing things, and how they understood their environment, or their *bodily intelligence*, as Zuboff calls it, and try to acquire a novel set of interpretive and intellective skills.

Digital technologies are distributed cognitive processes whose operations remain hidden (Boland et al. 1994). Kallinikos (2010) spoke of technology as a regulative regime as opposed to the perception of technology as an augmentation tool. He advanced the idea that once technological systems are made (through a series of decisions, predilections, and technical facts), they reshape the operations of organizations and institutions. As tasks and procedures are embedded into digital systems, he claimed, the functioning and logics of these systems provide a different direction to social practices from those inscribed in social interaction or routines (see also Kallinikos et al. 2013). The architectural principle of black-boxing functional complexity behind an interface is an example of how technology regulates, as it translates organizational procedures, simplifies, formalizes, and packages them into software. Doing so transforms organizational tasks and operations into something else, making their cultural predilections, cognitive interdependencies, and technical facts invisible. Digital technology reorganizes both the assumptions and the means through which people interact with the environment and one another (Kallinikos 2010, 18. See also Bailey et al. 2012; Bailey et al. 2022; Leonardi 2012).

Against this scholarly tradition, we are urged to reassess what we mean when we discuss the intelligence of machines. A good starting point is to consider that, like humans, AI are not self-contained systems whose intelligence is found inside their "electronic brains". AI works because it is not a bounded device (or a tool) but a complex, distributed, and layered system whose intelligence mostly comes from interacting with its environment. For AI, the environment is made of data. The current wave of AI is built on data and, differently from how previous digital technologies and AI systems operated in organizations, on masses of disparate, heterogeneous, and unbundled data that transcend the confines of organizational operations and particular settings (Alaimo and Kallinikos 2022). Additionally, current AI works with data differently from previous digital systems as it transforms data meant to represent real-life events into sub-conceptual elements (tokenized units) that are no longer comprehensible by humans, experts, or laymen (Cantwell Smith 2019). The features of a face are encoded into data and transformed to the mathematical distance between two points, which is then embedded in a data object template made by hundreds of computational representations. This template is made to stand for faces in face recognition systems. Face recognition applications work not because they encode and recognize features of faces but because they formalize faces as computational representations (Andrejevic and Selwyn 2022).

The boundarylessness of AI artifacts, the invisibility of their cognitive processes, and the lack of cognitive accessibility and accountability of their operations are challenging the rules of social cognition in organizational settings. AI, in this sense, seems to differ from previous digital technology. It does not black-box operational tasks in strings of logical operations embedded in software. These AI systems encode, transform, formalize, and re-package cognitive processes that extend far beyond the confines of organizations (Alaimo and Kallinikos 2022). As individuals and organizations live with, by, and through data-based technologies and devices, they interact with a network of data and data objects that mirror and transform much of social life into data. This is the environment with which AI interacts. A boundless environment that is not confined to established social settings (work, leisure, education, and so on) or organizational tasks and operations (accounting, finance, marketing, and so on). This, of course, completely redraws the rules and process of social cognition and organizing. Navigation today can be supported not only by all the devices that have historically constituted navigation expertise and made the ecology of cognition recounted by Hutchins (1995). New types of data enter the picture, such as weather forecast data, insurance data, and a host of sea sensor data that compute indicators that have been traditionally extraneous to navigation as a distributed cognitive process where each actor knew its role and coordinated with others by relying on shared understanding facilitated by organizations.

The invisibility of AI cognitive processes and the lack of cognitive accessibility and accountability of their operations are further exacerbated by the structure and functioning of current AI technologies. Rather than equating intelligence with the making of inferences from articulated descriptions of a disjoint world, the current wave of AI considers it as an instance of *pattern matching*, teased out of a continuous and dense texture of objects and events in constant change. Such processes of cognition develop below or beyond appearances and entail sub-conceptual, lower-level operations that provide essential support to the higher-level functions that render the world recognizable and intelligible (Cantwell Smith 2019). What defines the current wave of AI is their modelling of lower-level, sub-conceptual processes that bear upon and sustain the perception, recognition, and understanding of the world. The datafied social environment is transformed and processed in ways that evade human cognition and inspection. Data are becoming invisible to the human eye: they are tokenized, embedded, and vectorized. Social life events are still datafied and encoded in long chains of transformations that black-box data together with their cultural assumptions and social interdependencies. Yet, these links and interdependencies are impossible to reverse engineer. Facial recognition systems black box a complex ecology of data that encode, for instance, not only the computational definition and digital understanding of what faces are, but also the civil rights of face beholders, how much political power a face recognition system vendor should have, and so on (Polito and Alaimo 2023).

5. Conclusions

There have been historical and scientific reasons why mainstream economics, cognitive science, and computer science have discounted the social nature of cognition, the role of culture in facilitating human reasoning, and other socio-cultural dimensions without which cognition does not happen in the first place. The task of social science, including organization studies and STS, is to re-establish the primacy of cognitive artifacts, social structures, and their cultural environment for the social study of AI (Alaimo and Kallinikos 2024). Being human is not only a situated property of agents but a sociotechnical process that unravels in time and necessitates institutional support, the efforts of others, and an ecology of devices.

In this essay, I have drawn from several social science fields to retrace the links between intelligence and organizations. Intelligence is neither in the brains of individuals nor in the electronic circuits of machines. Asking where intelligence resides in organizations means studying how it emerges in institutionalized social interactions, how it is maintained by an ecology of cognitive devices, and how it adapts to the challenges of complex environments. This is a fundamental prerequisite for studying the impact of AI on laymen, experts, and organizations.

The boundarylessness of AI artifacts, the invisibility of their cognitive processes, and the lack of cognitive accessibility and accountability of their operations are challenging the rules of social cognition in organizational settings. To rise to this challenge, social scientists need to do justice to the socio-cultural embedment of cognition and how it is reframed by the developments that are linked to AI. Organizations today are often fully digitalized environments where work is primarily performed by, with, and through data (Alaimo and Kallinikos 2024). Accordingly, a possible research avenue would be to lay out how this data work happens across organizations and how it is linked to the reframing of cognition and intelligence through AI.

References

Alaimo, Cristina and Kallinikos, Jannis (2022) *Organizations Decentered: Data Objects, Technology and Knowledge*, in "Organization Science", 33(1), pp. 19-37.

Alaimo, Cristina and Kallinikos, Jannis (2024) *Data Rules: Reinventing the Market Economy*, Cambridge (MA), MIT Press.

Andrejevic, Mark and Selwyn, Neil (2022) *Facial Recognition*, Hoboken, John Wiley & Sons.

Baer, Ines, Waardenburg, Lauren and Huysman, Marleen (2022) *What Are We Augmenting? A Multidisciplinary Analysis of AI-based Augmentation for the Future of Work*, in "ICIS 2022 Proceedings", 6.

Bailey, Diane E., Faraj, Samer, Hinds, Pamela J., Leonardi, Paul M. and von Krogh, Georg (2022) *We Are All Theorists of Technology Now: A Relational Perspective on Emerging Technology and Organizing*, in "Organization Science", 33(1), pp. 1-18.

Bailey, Diane E., Leonardi, Paul M. and Barley, Stephen R. (2012) *The Lure of the Virtual*, in "Organization Science", 23(5), pp. 1485-1504.

Barley, William C., Leonardi, Paul M. and Bailey, Diane E. (2012) *Engineering Objects for Collaboration: Strategies of Ambiguity and Clarity at Knowledge Boundaries*, in "Human Communication Research", 38(3), pp. 280-308.

Bateson, Gregory (1972/2000) *Steps to an Ecology of Mind: Collected Essays in Anthropology, Psychiatry, Evolution, and Epistemology*, Chicago, University of Chicago Press.

Boland Jr, Richard J., Tenkasi, Ramkrishnan V. and Te'eni, Dov (1994) *Designing Information Technology to Support Distributed Cognition*, in "Organization Science", 5(3), pp. 456-475.

Brynjolfsson, Erik, Li, Danielle and Raymond, Lindsey R. (2023) *Generative AI at Work* [Working Paper n. w31161], in "National Bureau of Economic Research".

Cantwell Smith, Brian (2019) *The Promise of Artificial Intelligence: Reckoning and Judgment*, Cambridge (MA), MIT Press.

Clark, Andy and Chalmers, David (1998) *The Extended Mind*, in "Analysis", 58(1), pp. 7-19.

Daft, Richard L. and Weick, Karl E. (1984) *Toward a Model of Organizations as Interpretation Systems*, in "Academy of Management Review", 9(2), pp. 284-295.

Daugherty, Paul R. and Wilson, H. James (2018) *Human + Machine: Reimagining Work in the Age of AI*, Harvard, Harvard Business Press.

Dell'Acqua, Francesco, McFowland, Edward, Mollick, Ethan R., Lifshitz-Assaf, Hila, Kellogg, Katherine, Rajendran, Sanjog et al. (2023) *Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality* [Working Paper n. 24-013], in "Harvard Business School: Technology & Operations Management Unit Working Paper Series".

Douglas, Mary (1986) *How Institutions Think*, Syracuse (NY), Syracuse University Press.

Engelbart, Douglas (1962, October) *Augmenting Human Intellect: A Conceptual Framework* [Summary Report AFOSR-3223], Stanford Research Institute. Available at: https://www.dougengelbart.org/content/view/138/ (retrieved February 7, 2024).

Friedland, Roger and Alford, Robert R. (1991) *Bringing Society Back In: Symbols, Practices, and Institutional Contradictions*, in Walter W. Powell and Paul J. DiMaggio (eds.), *The New Institutionalism in Organizational Analysis*, Chicago, University of Chicago Press, pp. 232-263.

Fügener, Anna, Grahl, Jonas, Gupta, Alok and Ketter, Wolfgang (2022) *Cognitive Challenges in Human–Artificial Intelligence Collaboration: Investigating the Path Toward Productive Delegation*, in "Information Systems Research", 33(2), pp. 678-696.

Gal, Uri, Jensen, Tina B. and Stein, Mari-Klara (2020) *Breaking the Vicious Cycle of Algorithmic Management: A Virtue Ethics Approach to People Analytics*, in "Information and Organization", 30(2), 100301.

Garfinkel, Harold (1967) *Studies in Ethnomethodology*, Cambridge (UK), Polity Press.

Grønsund, Tor and Aanestad, Margunn (2020) *Augmenting the Algorithm: Emerging Human-in-the-loop Work Configurations*, in "The Journal of Strategic Information Systems", 29(2), 101614.

Hutchins, Edwin (1995) *Cognition in the Wild*, Cambridge (MA), MIT Press.

Hutchins, Edwin (2000) *Distributed Cognition*, in "International Encyclopedia of the Social and Behavioral Sciences", 138(1), pp. 1-10.

Hutchins, Edwin (2014) *The Cultural Ecosystem of Human Cognition*, in "Philosophical Psychology", 27(1), pp. 34-49.

Kallinikos, Jannis (2010) *Governing Through Technology: Information Artefacts and Social Practice*, London, Palgrave Macmillan.

Kallinikos, Jannis, Hasselbladh, Hans and Marton, Attila (2013) *Governing Social Practice: Technology and Institutional Change*, in "Theory and Society", 42(4), pp. 395-421.

Kittler, Friedrich A. (1999) *Gramophone, Film, Typewriter*, Stanford, Stanford University Press.

Knorr Cetina, Karin (1999) *Epistemic Cultures. How the Sciences Make Knowledge*, Cambridge (MA), Harvard University Press.

Leonardi, Paul M. (2012) *Car Crashes Without Cars: Lessons About Simulation Technology and Organizational Change from Automotive Design*, Cambridge (MA), MIT Press.

Lyytinen, Kalle, Nickerson, Jeffrey V. and King, John L. (2021) *Metahuman systems = humans + machines that learn*, in "Journal of Information Technology", 36(4), pp. 427-445.

March, James G. (1994) *A Primer on Decision Making: How Decisions Happen*, New York, Simon & Schuster.

March, James G. and Simon, Herbert A. (1958) *Organizations*, Hoboken, John Wiley & Sons.

Mead, George H. (1935) *Mind, Self & Society*, Chicago, University of Chicago Press.

Nelson, Richard and Winter, Sidney (1982) *An Evolutionary Theory of Economic Change*, Cambridge (MA), Harvard University Press.

Ong, Walter J. (1982) *Orality and Literacy*, London, Routledge.

Polito, Carolina and Alaimo, Cristina (2023) *The Politics of Biometric Technologies: Borders Control and the Making of Data Citizens in Africa*, in "ECIS 2023 Research-in-Progress Papers", 78.

Simon, Herbert A. (1969/1996) *The Sciences of the Artificial*, Cambridge (MA), MIT Press.

Star, Susan Leigh (2010) *This is Not a Boundary Object: Reflections on the Origin of a Concept*, in "Science, Technology, & Human Values", 35(5), pp. 601-617.

Star, Susan Leigh and Griesemer, James R. (1989) *Institutional Ecology, "Translations" and Boundary Objects: Amateurs and Professionals in Berkeley's Museum of Vertebrate Zoology, 1907–39*, in "Social Studies of Science", 19(3), pp. 387-420.

Tomasello, Michael (1999) *The Cultural Origins of Human Cognition*, Cambridge (MA), Harvard University Press.

Vygotsky, Lev S. (1978) *Mind in Society: Development of Higher Psychological Processes*, Cambridge (MA), Harvard University Press.

Waardenburg, Lauren and Márton, Attila (2024) *It Takes a Village: The Ecology of Explaining AI*, in Ioanna Constantiou, Mayur P. Joshi and Marta Stelmaszak (eds.), *Research Handbook on Artificial Intelligence and Decision Making in Organizations*, Cheltenham, Edward Elgar Publishing, pp. 214-225.

Weick, Karl E. (1979) *The Social Psychology of Organizing*, New York, Random House.

Weick, Karl E. (1995) *Sensemaking in Organizations*, Thousand Oaks, SAGE.

Weick, Karl E. and Roberts, Karlene H. (1993) *Collective Mind in Organizations: Heedful Interrelating on Flight Decks*, in "Administrative Science Quarterly", pp. 357-381.

Wilson, H. James and Daugherty, Paul R. (2018) *Collaborative Intelligence: Humans and AI are Joining Forces*, in "Harvard Business Review", 96(4), pp. 114-123.

Winner, Langdon (1993) *Upon Opening the Black Box and Finding it Empty: Social Constructivism and the Philosophy of Technology*, in "Science, Technology, & Human Values", 18(3), pp. 362-378.

Zhang, Zhu, Yoo, Youngjin, Lyytinen, Kalle and Lindberg, Aaron (2021) *The Unknowability of Autonomous Tools and the Liminal Experience of Their Use*, in "Information Systems Research", 32(4), pp. 1192-1213.

Zuboff, Shoshana (1988) *In the Age of the Smart Machine: The Future of Work and Power*, New York, Basic Books.

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"Functioning Automatic, Dancing Mechanic": A Reflection on AI in Culture and Society

Alessandro Gandini

1. Introduction

The year 2023 was marked by one of the most impactful labour strikes in the history of the media industries. Members of the Writers Guild of America (WGA) abstained from work for about 5 months, during which a significant number of multi-million screen productions were halted. Besides issues of pay, one of the key aspects in this negotiation was the emergent role played by artificial intelligence in the creative writing process.

In particular, the popularization of so-called generative AI – which is based on machine learning processes that offer users a rapid response to a query, obtained from probabilistic inference upon a pre-trained set of data – is expected to "disrupt" the creative (and many other) industries, exacerbating the risks of disenfranchisement and obsolescence of a variety of jobs. In response to these concerns, screen writers (supported by actors) moved to strike and ultimately agreed upon a deal which grants them that AI cannot be used to write scripts, or to edit scripts that have been written by a writer. At the same time, studios cannot consider AI-generated content as "source material" that writers may be asked to adapt or rework, for lower pay. In turn, when writers do adapt or rework output from text-based generative AI applications such as Chat GPT, this will continue to be considered original screenplay (The Guardian 2023).

Besides this landmark event, 2023 might be considered as the year generative AI made it out into the world to become part of the everyday activity of many ordinary folks. In particular, a variety of knowledge workers from different sectors, together with students (yes, students) and virtually anyone with a cognitive task to complete, turned to Chat GPT and similar tools for specific activities, or simply to test the new toy that everyone was talking about. Perhaps unsurprisingly, academics also experimented with generative AI, for better – that is, to experiment its potential advantages in data science methodology, cfr. De Kok 2024 – or worse – that is, using it as a co-author in journal publications, which led to skyrocketing numbers of paper retraction (Retraction Watch 2023). This comes together with rising concerns for academic integrity in schools at all levels; the essay as an instrument for evaluation of student competence in the humanities and the social sciences is suddenly at risk of obsolescence while exams are making an unexpected return to the scene (Clark 2024).

This essay discusses the cultural implications of the diffusion of everyday forms of AI, and questions the role of sociology within this process. Following the popularization of this new technology we have witnessed pretty much the usual response that, as a society, we tend to produce when faced with the arrival of a perceivably significant technological innovation. This consists in a binary discourse that positions, on one side, those who hail the new technology as a somewhat revolutionary one, predicting it will solve a plethora of societal issues – a tendency that Evgenij Morozov labels "technological solutionism" (2013). On the other side we find those who warn against the new technology as a mounting threat, perhaps accompanying these concerns with a tingle of prohibitionist nostalgia, which often translates in explicit calls for the "banning" of said new technology – or at least the imposition of severe boundaries of use that would render it almost useless, and henceforth lead to its abandonment.

As every social scientist knows, however, none of these positions really hold. What we know instead (since Karl Marx's *Fragments on Machinery* (2005[1858/1939]), indeed!) is that *any* technology is a social actor that gets embedded in social processes. Generative AI technology such as Chat GPT or Midjourney makes no exception and yet, in the perception of both academics and ordinary folks alike, this time feels different: there is a widespread sense of "before and after" that accompanies the popularization of generative AI.

While this is partly the fault of science fiction, which has depicted a set of dystopian imaginaries of artificial intelligence as a threat for society, ranging from mass unemployment to human extinction (Gandini 2020), yet, as they say, there is more to the picture (no pun intended) than meets the eye. How can sociology respond to this new challenge?

I will argue that we should abandon the notion of the "digital society" since this has now become, in fact, society, and take proper stock of this evolution. In doing so, we should also rethink the attempt at developing a "digital sociology", in that this has become, ultimately, sociology. In turn, we should make good use of our sociological imagination, firmly maintaining our primary focus onto the study of the embeddedness of technology within the social and its related implications.

2. From big data, to algorithms, to AI

In recent years we have experienced the diffusion of various forms of artificial intelligence in our everyday lives. Before generative AI, this has been largely synonymous with algorithms, and the role that these digital affordances have come to play in many of our ordinary activities. Whenever we book a flight, read the news, purchase a product for it to be delivered to our doorstep, or assess a potential partner, algorithms of different kind are the largely invisible, but somewhat inescapable infrastructure that enables these processes. Whether we like it or not, algorithmic systems today have become a non-human social actor we all deal with at some point; and yet, we know little to nothing about them, how they work, how they are constructed. Nonetheless, we tend humanize them, negotiating our agency (within and beyond digital platforms) against them (Gandini et al. 2023).

In principle, algorithms should be seen as computational operations. Working on large sets of data, algorithms "learn" patterns in said data, in an apparently neutral and objective manner, offering us a response to a query, or providing us with a set of recommended content. Yet, their objectivity and neutrality are indeed just apparent. A large body of research underlines that algorithms are the byproduct of the optimization of predictive statistical performances (Enni and Herrie 2021). This favours the unreflexive and uncritical implementation of these tools in a variety of domains, which results in the risk of reproducing existing societal biases and discriminations (Veale and Binns 2017). Pivotal research has highlighted, for instance, the inequality and bias surrounding the experimentation of facial recognition systems (Eubanks 2018), as well as the forms of algorithmic surveillance (Amoore 2020) and racism (Noble 2018) bound to the introduction of these tools in several public service settings. An equally rich stream of research has addressed the remarkable controversies underpinning the role that algorithms play in online spaces, from their role in content moderation (Roberts 2019; Gillespie 2017; Gorwa et al. 2020) to their potential to foster circulation of misinformation and junk news, with related concerns regarding the formation of public opinion (Tufekci 2018).

In the last year or so, as said, we have seen a new evolution in this trajectory, embodied by so-called generative AI. This new technology has been approached with the same array of theoretical and empirical tools that was until then employed for the study of algorithms, and has become a new strand within the broader, emergent field of critical algorithm studies (cfr. Lomborg and Kapsch 2020). Generative AI is a form of artificial intelligence that is capable of generating text, images, videos, or other data, typically in the form of prompts, operating on large language models. What pumps generative AI are, specifically, machine learning algorithms. These consist of "computers that learn from experience" (Airoldi 2021), that is, they work to determine probabilistic inference from a given set of data; upon this inference, they produce an answer, in the form of a text or image. From the perspective of cultural sociology, the chief aspect to consider in this discussion is that this process is an eminently cultural one. This is nothing new in principle, if we think for instance at recommendation algorithms within digital music streaming platforms, that infer the musical taste of users and produce a set of recommendations based on a user's previous activity (Seaver 2022). However, Airoldi (2021) flags up that if we conceive of machine learning algorithms as instruments that learn from human-generated data and autonomously manipulate human language, knowledge and relationships, then these are more than just a machine. Instead, in doing so they become social agents that develop what Bourdieu (1984) would describe as a habitus – a *machine* habitus, specifically (Airoldi 2021). While a significant number of studies have examined the knowledge, skills and prejudices reproduced by machines, Airoldi continues, this has somewhat obscured the role that culture plays at the root of this process. Culture is more than just a mass of data or patterns, Airoldi argues: it operates in the very same code of machine learning systems, tacitly guiding their predictions. Once translated into machine-readable data, culture enters the code of algorithms and AI systems, affecting existing forms of techno-social reproduction.

This process directly ties to the ways in which artificial intelligence systems operate from a technical standpoint. Kate Crawford and Vladan Joler (2018) argue that three central elements are constitutive of the extractive process that enables a large-scale artificial intelligence system to operate: material resources, human labor, and data.

This starts with the chemical and geological elements that make the components of these machines: "Each object in the extended network of an AI system, from network routers to batteries to microphones, is built using elements that required billions of years to be produced" (p. VIII), they argue. Therefore, they continue:

> Looking from the perspective of deep time, we are extracting Earth's history to serve a split second of technological time, in order to build devices than are often designed to be used for no more than a few years. (*ibid*.)

The second key element in this process is human labor. Drawing from digital labour theory and particularly the work of Christian Fuchs (2014), Crawford and Joler describe AI systems as exploitative insofar as they appropriate of the invisible, unpaid and oftentimes forcible activity of individual human beings in training and cleaning datasets, producing user-generated content, and more, to feed the large datasets at the core of these tools. Put differently, the idea that AI systems do not rely on human labour is a mere illusion. The example of the Mechanical Turk illustrates this aspect quite clearly: this was a chess-playing automaton created in 1770 by a Hungarian inventor, Wolfgang von Kempelen, which presented itself in the form of a life-sized human head and torso, dressed in Ottoman robes and a turban. This was, however, a trick: despite the size of the inside of the machine was deemed to fit only a small child or an amputee, it is widely believed that this was actually operated by a skilled human being. It is no coincidence that, some 250 years later, Amazon turned back to the Turk to brand one of its soon-to-be most successful applications: a digital microwork platform. Toying with the idea of the "thinking machine", Amazon presented its

Mechanical Turk as "artificial artificial intelligence" (Stephens 2023), perhaps unknowingly revealing the worst kept secret of 21st century tech: large-scale digital applications ultimately depend on large-scale underpaid human labor to exist.

The third element needed by AI to operate, again following Crawford and Joler (2018), is data. At a basic level, this can be understood as the body of knowledge upon which algorithmic and AI systems develop their elaborations. Yet, as Dencik et al. (2016) underline, data are also imbued with certain values of society; while data scientists tend to view human behavior as representable through data points, the coming to light of this data is not neutral either.

Thus, Dencik et al. (2016) call for a rejection of the mainstream "datacentric" and deterministic approach to data, in favour of a strive for "data justice". This is centred upon who owns the data, what social groups are favoured or excluded by way of their use, what forms of inequality arise from their integration in a variety of processes, and ultimately how democratic is data production in present day societies.

Extending this understanding to more recent forms of AI, Natale and Depounti (2024, 89) employ the effective metaphor of the "mirror" to describe the critical relationship between data and generative AI. If data are the fabric of generative AI elaborations, then the outputs of the latter are a mirror of how the former are produced, managed, curated, and integrated into the system. This, they argue, represents "a leap forward" in the extractive process that "turns sociality into something that can be owned, patented, and brought to use by developers and companies" (cfr. also Esposito 2022). In turn, this newly calls under question the original notion of the Internet as a commons that is at the heart of much of the Autonomist Marxist literature on digital media, starting with Tiziana Terranova's influential essay on free labour (2000). The process by which algorithms, first, and generative AI more recently, extract and appropriate of the mass of social and networked data that exists on the Web for purposes of economic accumulation is now fully in the hands of a small number of corporate platforms, which run what is essentially a financialised, oligopolistic economy. Revising her own work over the years, in her latest book *After The Internet* (2024) Terranova argues that the consequence of this state of things is that the Internet as we know it "is no more", since little is left of Richard Stallman's motto "free as in free speech, not free beer" (Lessig 2006).

Instead, today we are enmeshed within a socio-cultural and economic setting whereby the winner-takes-all has been the platform model, which represents the best-to-date optimisation infrastructure for the affirmation of the Internet as a knowledge-extractivist endeavour. I have argued elsewhere (Caliandro et al. 2024) that, in relation to cultural production (Poell et al. 2021), the process of platformisation intertwines with user commodification logics through three distinctive features: *concentration*, that is, platforms concentrate users in a single online social environment for the purposes of behavioral prediction and targeted advertising (what has been referred to as "surveillance capitalism", Zuboff 2019); *fragmentation*, that is, platforms represent an ideal infrastructure for the production of organized, coordinated and standardized digital publics (Boyd 2010) made of consumers who are made subject of classification and categorization based on the data they produce; and *contingency*, that is, platforms foster the production of ephemeral, multimodal content that generates attention around a specific issue or focus of interest, and then fades just as quickly (take TikTok challenges, or memetic waves, as an example). It may be argued that generative AI introduces a fourth dimension to this process, that of *automation*. Extending the role that recommendation algorithms play on social media platforms, generative AI algorithms rework the knowledge produced by users on the web into an automated response, selling back to users – the same producers of those data points – an output in the form of (presumptive) new knowledge.

3. Job automation?

This element of automation of knowledge production leads us back to jobs, especially those in the knowledge and creative economy. The most common outputs generated by Chat GPT and similar generative AI applications are prompts that can be employed in relation to a variety of knowledge work-related tasks. Need to identify a set of key elements to highlight in a project presentation? Chat GPT will assemble an answer for you in seconds. Need to summarise a long book in 5 sentences? Chat GPT can also do that efficiently – that is, if it does not fall into "hallucinations", i.e., make things up, which allegedly happens quite often (cfr. The New York Times 2023). Want to write a piece of code, or an Excel formula? Chat GPT, you might have guessed, has the solution to your problem.

This has raised questions concerning the continued existence of some of the jobs currently held by a number of professional figures in the digital economy, who possess specific technical and creative skillsets in relation to knowledge production. We have seen how the screenwriters' strike in the US entailed a specific claim against the devaluation of their creative labour as a result of the diffusion of generative AI. A recent report by ILO (Gmyrek et al. 2023) employs the same GPT-4 model that runs Chat GPT to estimate the potential exposure of GPT-related tasks to risks of automation, foreseeing that clerical jobs are bound to be subject to significant risk, since generative AI platforms are able to replicate and replace many of the activities that these entail. For higher-skilled knowledge work, instead, the analysis suggests what is described as an "augmentation" potential, leading to greater productivity, rather than a mere threat of automation. Put differently: while certain jobs may ultimately be outsourced completely to generative AI, the role of the human is predicted to evolve into that of an "AI supervisor", which initiates and oversees a number of AI-executed tasks.

To an extent, this signals a departure from previous academic and grey literature that warned against the prospect of mass job automation (and henceforth elimination) as a result of the large-scale diffusion of artificial intelligence. In a well-known contribution of this sort, Frey and Osborne (2013) predicted that more than half of the (back then) current occupations would be at risk of automation, especially repetitive, routine and low-skill jobs. Top of this list was assembly work: this was also linked to the rise of robotics in manufacturing and a result of the enthusiastic expectations around so-called Industry 4.0, which promised to replace and automate most of physical labour in this setting (Pfeiffer 2016).

However, as Gmyrek et al. (2023) also underline, more recent literature has suggested that machine learning systems are actually more efficient at improving performance for non-routine jobs (Brynjolfsson et al. 2018), thanks to their capacity to quickly perform complex cognitive tasks, such as analysing text, drafting documents and messages, searching through repositories or the Web for information (Gmyrek et al. 2023, 43). The same Frey and Osborne

(2023) recently reassessed their predictions, sustaining that AI is more likely to replace tasks requiring social intelligence, which they considered to be non-automatable at first:

> (a)s a rule of thumb, the more transactional a relationship becomes, the more prone it is to automation. Going forward, we expect many occupations that don't entail in-person communication – like telemarketers, travel agents, and call centre operators – to vanish. (*ibid.*, 4-5)

Nonetheless, they continue: "[...] without major leaps, longstanding relationships – benefiting from in-person interaction – will remain in the realm of humans", as generative AI's inclination to "hallucinations" makes its use a potential reputational risk for all work that requires the development of a bond of trust and a long-standing relational exchange.

Overall, it may be argued this is just another reiteration of the same concerns that have characterized the introduction of technology in the workplace for about a century. Arguably, fears of job automation (encapsulated in the phrase "robots will take our jobs") have been regular and recursive in culture and society for some time now. In the 1920s, the *New York Times* featured a book review titled *Will Machines Devour Man*, accompanied by an illustration of a man eaten by a sausage grinder. Both Albert Einstein and John Maynard Keynes warned about "technological unemployment". Each decade of the 20th century has been marked by a call against the risk of job automation (cfr. Anslow 2016; Gandini 2020). The rapid-paced technological advancement of the last 20 years has newly revived this discourse. Yet, once again, while it is likely that many jobs will be reconfigured, reshaped or even eliminated because of AI, history teaches us that others will contextually be created. Ultimately, our concern as sociologist must remain focused, just like Marx, upon the ways in which technology gets integrated in the social, contributing to reshape or reconfigure relations of production. It is in the becoming productive of social relations and in the changing conditions under which this takes place that resides the kernel of the understanding of AI in the years to come.

4. Conclusion: AI and the "sociological imagination"

This essay has traced the emergence of the most recent forms of artificial intelligence in society and culture, proposing a critical discussion of its main implications. It has argued that, despite the fuzz surrounding in particular generative AI, *any* technology remains a social actor that gets embedded in social processes. It is the understanding of this embeddedness that, as sociologists, we should ultimately pay attention to. However, it would be too simplistic to argue that our discipline must only stay true to its epistemology and core values in order to rise up to the challenge posed by artificial intelligence. As Airoldi (2021) argues, the encounter between AI and the human is primarily a cultural issue, and it is essential we put the human back into the equation so as to avoid falling into the "empiricist" trap that is integral to this technology. It has been argued that a revival of the constructivist approach which has animated much of the 1980s and 1990s science and technology studies, combined with a present-day feminist intersectional approach, may help significantly in addressing the more deterministic tensions towards AI (Huyskes 2024). But this might, and likely will not, be sufficient.

Building on C. Wright Mills's well-known concept of the "sociological imagination" (2000 [1959]), Hepp (2022) has argued that (digital) media sociology is best placed to overcome what Mills described as the tension between the individual and society in sociological thinking. To do so, Hepp continues, (digital) media sociology should evolve into a "cross-sectional" discipline, that is, one that transcends thematic boundaries in the sociological field (i.e., economic sociology, labour sociology) to address the role of digital media across different domains of society. While it is undoubted that developments in technology affect all domains of life today, I would argue this is an interesting but perhaps too humble proposition.

A decade ago or so, much of the academic debate at the crossroads between sociology, media and communication studies, and digital methods, revolved around the idea of developing a new sub-discipline called "digital sociology". This was designed to be a move away from a media-centred perspective in the study of digital media, in favour of an actor-centred understanding of the ways in which different kinds of technologies were being entrenched in the social (Marres 2017). Some years later, on the back of a global pandemic that has significantly accelerated the process of integration of digital technologies into the social, arguably the prefix "digital" has somewhat become redundant to this proposition. To put it bluntly: there is no such thing as a digital society anymore, in that the digital society is, in fact, society. And, as a consequence, there is no such thing as "digital sociology", in that this has become, ultimately, sociology. To some extent, this may be seen as the full realization of Niklas Luhmann's (1995) theory of social systems as systems of communication. Generative AI, for one, can be seen an excellent example of an operationally closed autopoietic system, in Luhmannian terms. Albeit Luhmann's work is not without its critics (cfr. Viskovatoff 1997), yet it was arguably prescient in its capacity to locate communication as the centrepiece of the study of social life – inasmuch as, today, social media and platforms of different kinds have repurposed a significant portion of our everyday sociality within their ring-fenced boundaries.

In other words, to metaphorically put it in the words of electronic music legends Kraftwerk, it may be argued that sociology in the rise of AI should "function automatic" and "dance mechanic". On the one hand, it should approach technological advancement phenomenologically and critically, epistemologically building upon the actor-centred perspective that animated the call for a "digital sociology" but also aiming at taking advantage from the potentially significant methodological innovations that tools such as generative AI might bring. On the other hand, however, it should refrain from transforming this tension into empirical fetishism, maintaining its chief focus onto the study of the embeddeddness of technology within the social and the comprehensive investigation of its related implications.

References

Airoldi, Massimo (2021) *Machine Habitus: Toward a Sociology of Algorithms*, London, John Wiley & Sons.

Amoore, Louise (2020) *Cloud Ethics: Algorithms and the Attributes of Ourselves and Others*, Durham (US), Duke University Press.

Anslow, Louis (2016, May 16) *Robots have been about to take all the jobs for more than 200 years*. Medium. Available at: https://medium.com/timeline/robots-have-been-about-to-take-all-the-jobs-for-more-than-200-years-5c9c08a2f41d (retrieved July 24, 2019).

Bourdieu, Pierre (1984) *Distinction: A Social Critique of the Judgement of Taste*, London, Routledge.

Boyd, Danah (2010) *Social Network Sites as Networked Publics: Affordances, Dynamics, and Implications*, in Zizi Papacharissi (ed.), *A Networked Self: Identity, Community, and Culture on Social Network Sites*, New York, Routledge, pp. 47-66.

Brynjolfsson, Erik, Mitchell, Tom and Rock, Daniel (2018) *What Can Machines Learn, and What Does It Mean for Occupations and the Economy?*, in "AEA Papers and Proceedings", 108, pp. 43-47.

Caliandro, Alessandro, Gandini, Alessandro, Bainotti, Lucia and Anselmi, Guido (2024) *The platformization of consumer culture: A theoretical framework*, in "Marketing Theory", 24(1), pp. 3-21.

Clark, Pilita (2024, April 13) *ChatGPT essay cheats are a menace to us all*. Financial Times. Available at: https://www.ft.com/content/cde75f58-20b9-460c-89fb-e64fe06e24b9 (retrieved April 26, 2024).

Crawford, Kate and Joler, Vladan (2018, September 7) *Anatomy of an AI System: The Amazon Echo As An Anatomical Map of Human Labor, Data and Planetary Resources*. AI Now Institute and Share Lab. Available at: https://anatomyof.ai/ (retrieved April 26, 2024).

De Kok, Ties (2024) *ChatGPT for Textual Analysis? How to use Generative LLMs in Accounting Research*, in "SSRN". Available at: http://dx.doi.org/10.2139/ssrn.4429658 (retrieved June 28, 2024).

Dencik, Lina, Hintz, Arne and Cable, Jonathan (2016) *Towards data justice? The ambiguity of anti-surveillance resistance in political activism*, in "Big Data & Society", 3(2).

Enni, Simon A. and Herrie, Maja B. (2021) *Turning biases into hypotheses through method: A logic of scientific discovery for machine learning*, in "Big Data & Society, 8(1).

Esposito, Elena (2022) *Artificial Communication*, Cambridge (MA), MIT Press.

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

Frey, Carl B. and Osborne, Micheal (2013) *The Future of Employment* [Working Paper], in "Oxford Martin Programme on Technology and Employment".

Frey, Carl B. and Osborne, Micheal (2023) *Generative AI and the Future of Work: A Reappraisal*, in "Brown Journal of World Affairs", 30(1).

Fuchs, Christian (2014) *Digital Labour and Karl Marx*, London, Routledge.

Gandini, Alessandro (2020) *Zeitgeist Nostalgia: On Populism, Work and the "Good Life"*, London, John Hunt Publishing.

Gandini, Alessandro, Gerosa, Alessandro, Giuffrè, Luca and Keeling, Silvia (2023) *Subjectivity and algorithmic imaginaries: The algorithmic other*, in "Subjectivity", 30(4), pp. 417-434.

Gillespie, Tarleton (2017) *Governance of and by platforms*, in Jean Burgess, Alice E. Marwick and Thomas Poell (eds.), *The SAGE Handbook of Social Media*, London, SAGE, pp. 254-278.

Gmyrek, Pawel, Berg, Janine and Bescond, David (2023) *Generative AI and jobs: A global analysis of potential effects on job quantity and quality* [ILO Working Paper n. 96], in "International Labour Organization".

Gorwa, Robert, Binns, Reuben and Katzenbach, Christian (2020) *Algorithmic content moderation: Technical and political challenges in the automation of platform governance*, in "Big Data & Society", 7(1).

Hepp, Andreas (2022) *Agency, social relations, and order: Media sociology's shift into the digital*, in "Communications", 47(3), pp. 470-493.

Huyskes, Diletta (2024) *Tecnologia della rivoluzione*, Roma, Saggiatore.

Lessig, Lawrence (2006, September 1) *Free, as in Beer*. Wired. Available at: https://www.wired.com/2006/09/free-as-in-beer/ (retrieved April 26, 2024).

Lomborg, Stine and Kapsch, Patrick H. (2020) *Decoding algorithms*, in "Media, Culture & Society", 42(5), pp. 745-761.

Luhmann, Niklas (1995) *Social systems*, Redwood City, Stanford University Press.

Marres, Noortje (2017) *Digital Sociology: The Reinvention of Social Research*, London, John Wiley & Sons.

Marx, Karl (2005[1858/1939]) *Grundrisse: Foundations of the critique of political economy*, London, Penguin Books in association with New Left Review.

Mills, C. Wright (2000[1959]) *The Sociological Imagination*, Oxford (UK), Oxford University Press.

Morozov, Evgeni (2013) *To Save Everything, Click Here: The Folly of Technological Solutionism*, New York, PublicAffairs.

Natale, Simone and Depounti, Iliana (2024) *Artificial Sociality*, in "Human-machine Communication Journal", 7(5), pp. 83-98.

Noble, Safia U. (2018) *Algorithms of Oppression*, New York, New York University Press.

Pfeiffer, Sabine (2016) *Robots, Industry 4.0 and Humans, or Why Assembly Work Is More than Routine Work*, in "Societies", 6(2), 16.

Poell, Thomas, Nieborg, David B. and Duffy, Brooke E. (2021) *Platforms and Cultural Production*, London, John Wiley & Sons.

Retraction Watch (2023, October 6) *Signs of undeclared ChatGPT use in papers mounting*. Retraction Watch. Available at: https://retractionwatch.com/2023/10/06/signs-of-undeclared-chatgpt-use-in-papers-mounting/ (retrieved April 26, 2024).

Roberts, Sarah (2019) *Behind the screen: Content Moderation in the Shadows of Social Media*, Yale, Yale University Press.

Seaver, Nick (2022) *Computing Taste: Algorithms and the Makers of Music Recommendation*, Chicago, University of Chicago Press.

Stephens, Elizabeth (2023) *The mechanical Turk: A short history of "artificial artificial intelligence"*, in "Cultural Studies", 37(1), pp. 65-87.

Terranova, Tiziana (2000) *Free Labor: Producing Culture for the Digital Economy*, in "Social Text", 18(2), pp. 33-58.

Terranova, Tiziana (2024) *After the Internet*, Cambridge (MA), MIT Press.

The Guardian (2023) *How Hollywood writers triumphed over AI – and why it matters*. The Guardian. Available at: https://www.theguardian.com/culture/2023/oct/01/hollywood-writers-strike-artificial-intelligence (retrieved April 26, 2024).

The New York Times (2023) *Chatbots May "Hallucinate" More Often Than Many Realize. The New York Times*. Available at: https://www.nytimes.com/2023/11/06/technology/chatbots-hallucination-rates.html (retrieved April 26, 2024).

Tufekci, Zeynep (2018, March 10) *YouTube, the Great Radicalizer*. The New York Times. Available at: https://www.nytimes.com/2018/03/10/opinion/sunday/youtube-politics-radical.html (retrieved April 26, 2024).

Veale, Michael and Binns, Reuben (2017) *Fairer machine learning in the real world: Mitigating discrimination without collecting sensitive data*, in "Big Data & Society", 4(2).

Viskovatoff, Alex (1999) *Foundations of Niklas Luhmann's Theory of Social Systems*, in "Philosophy of the Social Sciences", 29(4), pp. 481-516.

Zuboff, Shoshana (2019) *The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power*, London, Profile Books.