Focus – *peer-reviewed*
https://doi.org/10.60923/issn.1971-8853/23907
Sociologica. V.20 N.2 (2026)
ISSN 1971-8853

A Sociological Eye on AI. Key Concepts, Analytical Dimensions, and Methodological Tensions

Marco Solaroli* [a] Emma Garzonio [b]

[a] Department of the Arts, University of Bologna (Italy)
[b] Department of Philosophy, Communication and Performing Arts, Roma Tre University (Italy)

Submitted: January 21, 2026 – Accepted: June 8, 2026 – Published: August 6, 2026

Abstract

Between 2024 and 2026, a variety of position papers and special issues in the field of social sciences have started addressing the social, epistemological, and cultural impact of generative AI. Such emerging literature looks vast, heterogeneous, fragmented, and expectably still at a pre-paradigmatic stage. Without the ambition of addressing such a fast-growing body of work in a fully systematic way, this paper reviews a significant variety of recent publications to identify major trends and some common ground aimed at bridge-building among different intra-disciplinary research strands, while remaining open to inter-disciplinary dialogue. It proposes a framework based on a few key concepts (AI as agency, communication, and memory), analytical dimensions (AI as object, practice, and method), and methodological tensions (macro-micro, quanti-quali, distant-close). In doing so, it contributes to the ongoing construction of a shared toolkit to investigate how various social and cultural domains have been affected by the recent development and increasing adoption of generative AI.

Keywords: Artificial Intelligence (AI); Artificial agency; Artificial communication; Artificial memory; Generative Artificial Intelligence (GenAI); Sociology of AI.

Acknowledgements

This paper is the result of a shared research project and intellectual exchange in which both authors were equally involved. We acknowledge that Marco Solaroli wrote paragraphs 1 and 2, Emma Garzonio wrote paragraphs 3 and 4, while paragraph 5 was written jointly.

* marco.solaroli@unibo.it

1 Introduction

Between 2024 and 2026, the social sciences have witnessed a rapid proliferation of position papers, special issues, and monographs addressing the societal implications of generative artificial intelligence (GenAI). This emerging literature is vast, heterogeneous, and fragmented, reflecting a field still in a pre-paradigmatic phase. Contributions span sociology, STS, media and communication studies, memory studies, and beyond, often developing in parallel rather than in sustained dialogue.

A quick glance at some of the titles can easily confirm the intellectual momentum. Sociologists started asking "What is sociological about AI?" (Davis & Sloane, 2025) or "Can generative AI improve social science?" (Bail, 2024), trying to define "A sociology of Artificial Intelligence" (Joyce & Cruz, 2024) and "The promises and perils of AI for sociology" (Au & Fong, 2025), including methodological efforts of "Repurposing generative AI for social research" (Pilati et al., 2024) or "Integrating Generative Artificial Intelligence into Social Science Research" (Davidson & Karell, 2025; Davidson, 2024). At the same time, scholars working on media, culture, and communication started "Situating AI", developing "Global media approaches to artificial intelligence" (Arora & Natale, 2025), identifying major "challenges for media and communication" in the age of AI (Poell, 2025; Danziger et al., 2025), while analysing new forms of mediatization and human-machine communication cultures (Hepp et al., 2024; Natale & Ji, 2025), thus "Decoding artificial sociality" (Depounti & Natale, 2025). Similarly, sociologists and scholars working on memory started mapping the new dynamics of the AI-memory nexus (Hoskins, 2024 & 2026), "Demystifying artificial intelligence" (Merrill et al., 2025) by investigating new technological mediation of mnemotechnic values (Matei, 2024), including "stochastic remembering" (Smit et al., 2024), thus asking whether AI is set to become the future of collective memory (Gensburger & Clavert, 2024).

This paper positions itself as a literature review aimed at identifying common ground across these strands. It proposes a framework organized around a few key interrelated concepts (*AI as agency, communication, and memory*), analytical dimensions (*AI as object, practice, and method*), and methodological tensions (*macro-micro, quanti-quali, distant-close*). In so doing, it aims to contribute to the ongoing construction of a shared toolkit for future social-scientific research on (and with) generative AI.

As it is today widely known, generative AI is conceivable as a subset of machine learning (ML) and automated computational techniques that employ deep neural network technologies based on transformer architectures to create novel, synthetic content across various modalities (e.g., text, images, sound, code), on the basis of large training datasets, statistical models, and user prompts (Omena et al., 2024; Pilati et al., 2024; Fazi, 2024). Evolving from machine learning tools designed primarily for pattern recognition — that is, identifying latent structures in text, images, or other unstructured data — to socio-technical systems capable of generating new, multimodal content, generative AI can be argued to represent a deeply impactful societal innovation as well as a theoretical and methodological turning point for the social sciences. In this context, public debate around AI predictably continues to oscillate between utopian and dystopian narratives. As with previous technological innovations, generative AI is often naively and reductively framed either as an unprecedented opportunity or a serious threat. Alongside these dichotomies, a substantial body of scholarly research has focused on specific issues of AI bias, accuracy, authenticity, authorship, and evidentiary power (Baert et al., 2025; Elliott, 2022; Bender et al., 2021; Nadeem et al., 2022; Motoki et al., 2023; Schneider & Hagendorff, 2025). Some of this work on AI and bias — that will be addressed in greater detail in the next pages — has been relevant to understanding possible distortions and symbolically violent effects of the social diffusion of GenAI. However, it soon became clear that a restricted focus on bias risks what Lindgren (2023) has called a "bias bias": the tendency to treat racism, sexism, or epistemic injustice as technical glitches amenable to correction, rather than as manifestations of deep-seated social structures, histories, and power relations.

To intellectually move beyond bias and simplistic dichotomies, it would be necessary to elaborate a conceptual vocabulary capable of grasping what generative AI meaningfully does in social life, not only what it fails to do normatively. Drawing on Everett Hughes' (1971) famous conceptualization, developing a sociological eye on AI implies deliberately foregrounding perspective, rather than prediction or prescription. It implies being attentive to relations rather than isolated entities, to processes rather than outcomes, and to power, inequality, and temporality as constitutive dimensions of the social uses of technologies. Applied to generative AI, this perspective shifts the focus away from technical performance or normative deficits alone and toward the social (re)configurations, communicative practices, and memory infrastructures through which AI is deployed and made meaningful. In this sense, developing a sociological eye can help recognize and trace how AI becomes entangled with social action, cultural production, and collective remembering, and how such entanglements, in turn, reshape the conditions under which social life is constructed, narrated, and remembered.

In what follows, the paper offers a literature review that first suggests how social sciences can productively conceptualize AI through three interrelated lenses — AI as agency, communication, and memory — which foreground relational, distributed, and socio-technical dynamics, cut across disciplinary boundaries, and enable theoretical and methodological reflexivity. This first part integrates the sociological analysis of the GenAI turn within a broader reconstruction of digital innovation, with particular attention to the role of algorithms. In its second part, the paper then explores the literature on AI as, on the one hand, practice and object (that is, as sociotechnical phenomena that reshape social relations, cultural products, and meaning-making processes) and, on the other hand, research method (in terms of innovative tools capable of amplifying the analytical and interpretive reach of the sociological inquiry). It shows how AI can offer powerful tools to automate, scale, and augment core research practices, while also demanding critical reflection on their epistemological and ethical implications. In other words, the second part of the paper argues that social science can analytically engage with GenAI in two major ways. Sociology *of* AI understands technology as embedded in socio-economic systems and takes it as an object of research. Understanding AI as part of an ongoing historical process of domestication (and re-domestication) of technological practices and objects helps situate it within a longer trajectory of methods and epistemologies (e.g. Neff & Nagy, 2025; Eubanks, 2018; Noble, 2018; Burrell & Fourcade, 2021). Sociology *with* AI instead indicates that the field of social science is also integrating AI into its methodological toolbox (Pilati et al., 2024; Pronzato & Risi, 2025; Tubaro, 2025). From this perspective, the understanding of AI as a driver of innovation (Law & McCall, 2024), particularly within computational social science, implies the use of machine learning and LLMs to revisit enduring sociological questions (Edelmann et al., 2020; Salganik, 2017; Nelson, 2020; Molina & Garip, 2019). A diachronic reconstruction of the application of AI-based tools as research methods, and of the use of generative artifacts as research objects, highlights the fluidity between these two dimensions: rather than clearly delimited domains, AI as method and AI as object can overlap and interact in empirical research.

In the final section of the paper, a typology is proposed to visualize the various dimensions explored in the second part of the literature review, while the conclusions focus on a few underdeveloped analytical dimensions as well as opportunities for future research.

2 Generative AI as Agency, Communication, Memory

Based on the existing literature, this paper proposes agency, communication, and memory as three analytically distinct yet tightly correlated concepts for making sense of generative artificial intelligence in the social sciences. This framework conceives generative AI as *a dynamic and relational form of distributed, socio-technical agency that operates through communication with artificial partners and is grounded in algorithmically selected, recombinatory memory*.

First and most visibly, generative AI systems enact *agency* as a capacity to intervene in social processes, redistribute action, and shape outcomes within human-machine assemblages. This agency is inherently relational, distributed, and asymmetrical, emerging from interactions between models, data, designers, institutions, users, and broader political economies of media technologies. Moreover, such an agency operates primarily through communication. Generative AI systems are communicative technologies designed to produce socially intelligible outputs (e.g., texts, images, sounds) that respond to prompts, adaptively align to users' sociocultural expectations, and increasingly play a role in meaning-making processes. In doing so, and following previously identified constitutive dynamics of digital culture, they appear to increasingly blur and, at the same time, enrich simplistic distinctions between producer and consumer, medium and actor, automation and interaction — while asking for new conceptualizations of mediatization. Finally, the communicative agency of GenAI is inseparable from its mnemonic agency. Generative AI relies on vast, datafied human knowledge, stored, weighted, and algorithmically activated. At the same time, it increasingly works as an actively mediating mnemonic actor, contributing to the production, stabilization, or transformation of collective and cultural memory. AI thus operates not only on memory, but as a mnemotechnic infrastructure that reshapes how societies remember and forget. Taken together, these three concepts can allow scholars to move beyond reductive framings and instead analyze how generative AI reconfigures action, meaning, and temporality across social domains. Let us address these three concepts in greater detail.

The concept of agency has been foundational in a variety of theoretical traditions and research strands in the social sciences over the last decades, and today it appears to be gaining increasing centrality as well as complexity in scholarly debates about generative AI. As it is widely known, major sociological frameworks — e.g. structuration, practice, actor-network theory — have conceptualized agency not as an attribute of isolated actors but as a relational, temporally embedded process of capability construction, negotiation, and enactment, which involves projectivity and practical evaluation, and is significantly shaped by social and cultural structures, resources, dispositions, and interactions — conceived as constraints as well as opportunities. In an influential systematization of sociological theories of agency, Emirbayer and Mische (1998) defined it as

> the temporally constructed engagement by actors of different structural environments — the temporal-relational contexts of action — which, through the interplay of habit, imagination, and judgment, both reproduces and transforms those structures in interactive response to the problems posed by changing historical situations (p. 970).

They identified its constitutive elements in a chordal triad composed by iterational, projective, and practical-evaluative dimensions. On this basis, agency can thus be conceptualized as a temporally embedded process of social engagement informed by the past (in its iterational or habitual dimension) and oriented (projected) toward the future as well as the present — as a practical-evaluative and reflexive capacity to contextualize past habits and future projections within the contingencies, structural constraints, and opportunities of the moment. Such an approach to agency might arguably turn out to be still beneficial for contemporary theoretical interpretations of AI, which are trying to redefine and overcome reductively dichotomous approaches to social and machine agency (Borch, 2023). In the digital age, in fact, different emphasis has been attributed to the role played by humans and non-human actors, gradually focusing on their relationally co-constitutive entanglements and imbrications, recognizing the difficulty of disentangling the social from the material as well as the increasing pervasiveness and significance of technology. In this context, over the last two years, the rapid spread of generative artificial intelligence has invited a more theoretically nuanced and internally articulated reconceptualization of AI agency that could account for its increasingly diffused role in sociotechnical systems. From this perspective, having a presumably unprecedented "potential to compromise significantly notions of human agency", GenAI might "affect how sociologists conceptualize agency-related questions and might further undermine assumptions of the primacy of the social within the discipline" (Baert et al., 2025, p. 4; see also Cowley, 2025; Venturini, 2023).

In this vein, more than artificial intelligence, GenAI is increasingly theorized as artificial agency, in an interdisciplinary fashion among sociology, STS, media studies, and philosophy. This intellectual move implies discerning its continuities as well as novel specificities. Following calls to differentiate the actions of AI from those of both traditional information systems and humans (Dattathrani & De', 2023), artificial agency has been defined as "a novel form of agency emerging from the interplay of programmed objectives and learned behaviours [...] a computational, goal-driven form of agency defined by human purposes" (Floridi, 2025a, p. 30). Rather than asking whether AI possesses agency in a human-like sense, contemporary scholarship thus increasingly focuses on how AI reconfigures agency within socio-technical systems. These new configurations of agency are neither fully human-controlled nor autonomous, instead they emerge from complex assemblages of humans and machines (Schulz-Schaeffer, 2025). GenAI systems intervene in decision-making, knowledge production, cultural creation, and remembrance, obviously without intentionality or consciousness, yet with tangible social and performative effects. GenAI agency can thus be conceived as (unevenly) distributed, relational, contingent, and temporally embedded within social and material arrangements (including training datasets, labour regimes, and environmental resources), as well as within professional cultures and ideologies of the knowledge class of software engineers championing algorithmic management (Stark, 2022; Stark & Vanden Broeck, 2024), which, as a whole, shape what GenAI systems can do and whose interests they ultimate serve. In this sense, GenAI agency is conceivable as a multi-dimensional configuration that can redistribute power, authority, responsibility, and accountability in different ways. This theoretical reconfiguration of agency has significant implications for social sciences. Only empirically tracing how AI agency is co-constructed, enacted, constrained, and contested across contexts and within hybrid socio-technical fields will it become possible to theoretically redefine it in greater details, in its various possible kinds, "styles", and degrees (Symons & Abumusab, 2024; Lee, 2025), and in its multiple and interrelated conceptual declinations — including mnemonic agency, visual agency, and epistemic agency (e.g. Punziano, 2025; Barisione, 2026).

The question of agency is brought to the fore in the strand of literature on GenAI as *communication*. This perspective conceives GenAI primarily as a form of communication, or even sociality (Depounti & Natale, 2025). In so doing, it pursues a research strand significantly shaped by previous work on "artificial communication", particularly by Esposito (2022), which addressed algorithmic technologies as communicative partners capable of adjusting to users' sociocultural expectations thanks to the accumulation of datafied human knowledge. As a matter of fact, GenAI can exist and operate only thanks to the massive production, sharing, and accumulation of web users' content and online interactional exchanges, which constitute its underpinnings, in the form of datasets used to train Large Language Models. As Natale & Ji (2025, p. 1065) aptly synthesized, "Generative AI quite literally has been built out of communication". Along similar theoretical lines, drawing on Luhmann's theory of social systems as systems of communication (one of the major references in Esposito's work), GenAI "can be seen as an excellent example of an operationally closed autopoietic system" (Pasquinelli et al., 2024, p. 129).

From this perspective, GenAI is fundamentally conceived as a technological form of communication, designed to produce outputs that are socially intelligible, context-sensitive, and responsive to human prompts — thus simulating, and stimulating, interactions. This generative communicative orientation marks a qualitative shift in research on mediatization and human-machine communication (Hepp et al., 2024; Natale & Guzman, 2022). GenAI systems increasingly participate in meaning-making processes, producing narratives, explanations, and potentially affective responses, while interactions with GenAI systems are increasingly assigned social and cultural meanings. In other words, GenAI technologies, especially advanced AI chatbots, can be quite easily perceived as social actors, even similarly to traditional participants in a mediated social interaction — thus extending even further the degree and effect of algorithmic agency. On this basis, following previous work on "machine habitus" (Airoldi, 2021), influenced by Bourdieu's conceptual framework, recent sociological research has explored the sociocultural roots of GenAI communication, focusing on the taste, class, and habitus of generative AI chatbots (Rama & Airoldi, 2025).

The perspective of GenAI as communication also raises relevant and complex questions about authorship, authority, authenticity, as well as evidentiary and epistemic power. Baert et al. (2025) identify agency and authorship as interconnected themes in contemporary sociological debates on GenAI. Notwithstanding well-established research traditions in sociology of culture, communication, and journalism studies stressing how authorship is never purely individual but emerges from networks of actors, conventions, and technologies within social and cultural fields, GenAI radicalizes this insight by making machinic participation explicit and scalable. As a result, traditional markers of authorship, authenticity, and authority become apparently destabilized. Asking what counts as a credible source, an original contribution, or reliable evidence when communication is co-produced by humans and machines is not a new question, but it needs to find new answers in the GenAI age. This question becomes particularly salient in the context of knowledge controversies, that is, moments in which new actors, methods, and norms unsettle established epistemic practices. The spread of GenAI represents such a controversy across various domains of knowledge production, introducing large language models, probabilistic outputs, and promises of efficiency into taken-for-granted epistemic routines and institutional settings. This unsettling can be uncomfortable (see Pasquale, 2020), but it can also create opportunities for social and institutional reflexivity and innovation (Baert et al., 2025). Addressing issues of epistemic power as well as social trust in GenAI also contributes to analyse its spread as a social and cultural process, significantly based on users' shifting expectations, beyond legitimate yet merely technical accounts of explainability and transparency — such as "Explainable AI" (XAI) — aimed at revealing parameters or weights, and making explicit why algorithms and AI technically work the way they do (Gutierrez Lopez & Halford, 2025; Esposito, 2022).

The perspective on GenAI as communication also highlights its implications in terms of inequality and power. Recent critical research has shown how GenAI can amplify dominant voices while marginalizing others, reinforcing existing and powerful hierarchies of inequality and (in)visibility (Tubaro et al., 2020; Joyce & Cruz, 2024; Baert et al., 2025). However, it could be argued that, both theoretically and empirically, these dynamics can hardly be addressed by reductively focusing on bias alone. They should instead be traced back, at least, to wider political economies of media (Poell, 2025). As it becomes increasingly clear, conceiving GenAI as communication implies redefining its agency as unevenly distributed, shaped, inter alia, by infrastructures, corporate actors, training data, labor regimes, and regulatory environments. With similar intentions, Natale & Ji (2025) further developed this perspective through the conceptual framework of the "power geometries of AI". Such a framework contributes to emphasizing how GenAI creates a new layer of power dynamics across global contexts, and to cautioning against the attribution of agency disconnected from such power geographies.

Finally, as it becomes clear, the communicative agency of GenAI is inseparable from its mnemonic agency. GenAI systems rely on vast accumulations of past data, making *memory* a foundational dimension of their operation. At the same time, GenAI increasingly mediates access to the past, shaping how individuals and collectivities remember, forget, reinterpret, and literally (re)generate historical events. Conceiving GenAI as memory implies recognizing how it can allow the automated execution of memory-making tasks, including communicatively shaped search and algorithmically selected information retrieval. In other words, "[i]n a thoroughly mediatized, digitalized, and datafied society, concerns relating to AI-controlled access to information are also essentially concerns about AI-controlled access to memory" (Merrill, 2023, p. 173). Over the last two years, the sociological and interdisciplinary analysis of the GenAI-memory nexus has constituted a particularly vibrant research area. The literature seems to largely share the assumption that GenAI plays a new and increasingly relevant role in memory-building. A few quotes from recent works confirm such assumption: "There is a general consensus that the spread of artificial intelligence is redefining collective remembering and forgetting" (Matei, 2024, p. 4); "AI's evolution has drastically reshaped our relationship with collective memory" (Schuh, 2024, p. 231); GenAI has taken "a technological leap forward as a new kind of infrastructure of memory" (Gensburger & Clavert, 2024, p. 196); "Generative AI changes what memory is and what memory does, pushing it beyond the realm of individual, human, influence, and control, yet at the same time offering new modes of expression, conversation, creativity, and ways of overcoming forgetting" (Hoskins, 2024, p. 1).

In this context, various efforts have been devoted to specifying both continuities and discontinuities with previous conceptions of memory and mnemonic agency. From "algorithmic memory" (Esposito, 2017) to "robotic collective memory" (Shur-Ofry & Pessach, 2020) and "cyborgian memory" (Merrill, 2023), theoretical frameworks of memory over the last decade have shifted from a focus on social media platforms' algorithmic logics of datafication and practices of memory-building to the gradually increasing relevance of distributed mnemonic assemblages, in which fragments of the past can be woven together within datasets used also for Large Language Models training. In this shifting perspective, GenAI is investigated within the configurations of actors involved in the appraisal of the past and the power relations that structure these configurations. Conceived as an actor imbued with mnemonic agency, actively participating in mnemonic assemblages, GenAI is argued to significantly characterize human memory through operations that shape the conditions of remembrance (Richardson-Walden & Makhortykh, 2024). Hoskins (2024) describes the emergence of a new AI memory ecology, in which GenAI systems increasingly produce both the context and the content of memory itself. This is made possible particularly by the systemic integration of GenAI models in widely used platforms and search engines (Esposito, 2026), positioning GenAI among primary public mediating actors for information retrieval and memory-shaping, and gradually configuring it as a large mnemotechnic infrastructure (Schuh, 2024; Gensburger & Clavert, 2024; Matei, 2024; Hoskins, 2026). From this perspective, the new role played by GenAI in collective memory can be identified in "AI working at scales beyond our perception, AI's logical and probabilistic rather than cultural or ethical valuing of data, and its modular treatment of data instead of human preference for narrativization" (Richardson-Walden & Makhortykh, 2024, p. 334). Focusing on the past as modular data points — and to GenAI agency in identifying, connecting, and re-arranging them, even in new patterns and contexts — highlights various challenges and critical issues. To explore them, it is useful to recall that the field of memory studies has long overcome a conception of memory as a stable storage and static entity, instead framing remembering as an active process, in which the past is reconstructed, reenvisioned, and even revised, in the present, and shaped by situated socio-technical conditions, contexts, and frameworks. In other words, every time individuals and social groups remember the past, they do so relatively anew; and every time a GenAI computational task is carried out, it is carried out relatively anew, notwithstanding the seemingly consistent generated outputs (Merrill, 2023; Hoskins, 2024 & 2026). This suggests relevant theoretical tensions and connections, based on the assumption that, beyond the possible uses and meanings related to its embedding into online search engines, artificial memory involves elaboration and transformation, rather than merely information access and retrieval. In other words, GenAI does not simply reproduce the past; it can recombine, recontextualize, and invent it through probabilistic inference. Ideology and affect are increasingly intertwined with logical and statistical principles in the construction of public collective memory. As Smit et al. (2024) show — focusing on actors such as designers, expert users, and non-expert users involved in the production and use of ChatGPT – chatbots introduce a new form of "stochastic remembering", based on the probabilistic distribution of words in their training datasets.

This reconfiguration can have significant implications for the future of memory. If GenAI is changing the nature of collective memory in a process that turns history "from media representation to algorithmic performativity", based on a redefinition of mnemotechnic values, defined as "technologically-mediated criteria against which a type of knowledge about the past is appropriated as meaningful, socially acceptable, and intelligible" (Matei, 2024, p. 3), then concerns can quite expectably be newly raised about the emergence of hegemonic memory regimes and the consolidation of dominant perspectives, as well as about issues of authorship, accuracy, authenticity, and authority. At the same time, the GenAI-memory nexus can also become a source of critical enrichment for new productive forms and practices of collective memory-building based on affective engagement and contextual interpretation, aimed at deepening understanding of the past and giving remembering new hope (Richardson-Walden & Makhortykh, 2024; Hoskins, 2024). Recent examples suggest a very wide spectrum of possibilities, ranging from design studios using GenAI and working with displaced and immigrant communities to recreate photographs lost when families moved (or even of experiences that were never visually documented) in the form of blurred, glitched images imbued with emotional (rather than documentary) value (Hoskins, 2024), to projects using GenAI to support professional documentary photographers' authorship and legacy, preserving and enhancing the intellectual and mnemonic value of their visual archives.[1] The role that this overall reconfiguration could play in the social and cultural production of collective memory and shared understandings of history, shaping how future generations might learn about and relate to the past, will be at the center of research addressing GenAI — as *object*, *practice*, and *method*.

3 Generative AI as Object and Practice

Considering GenAI as an *object* of study means observing and interpreting how it is developed, implemented, used, and integrated within social and cultural contexts. The investigation of generative AI systems can be articulated across different levels of analysis. At the *production* level, analysis examines the social, cultural, and economic contexts shaping the design of generative systems, including the values and assumptions embedded in technical choices. *Implementation* focuses on how GenAI is introduced within organizations and institutions, transforming work practices and generating negotiation or resistance. The *use* level investigates how different social groups interact with GenAI, including intended, unintended, and subversive practices. The *meaning-making* level addresses public discourse, media narratives, and symbolic frames through which GenAI is interpreted. Finally, the *impact and output* levels consider the broader social, political, and epistemic consequences of generative systems, as well as the analysis of AI-generated outputs as meaningful cultural artifacts (Pilati, 2025). Studying AI-as-object across these analytical levels allows to show how AI (in its code, design, and uses) is inherently shaped by social contexts and values, and how it is co-produced with and through social processes in arenas ranging from medicine, criminal justice, the future of work, sexual practices, or public policy (Joyce & Cruz, 2024).

From this perspective, a major strand of research has addressed the relation between GenAI-as-object and bias. Bourdieu's notion of habitus has proved to offer a convincing metaphor to grasp relevant dynamics of such a relation. Just as, in social life, habitus shapes social practice through socially and culturally embedded dispositions, machine learning models can be argued to develop a form of *machine habitus* (Airoldi, 2021), that is, a way of "seeing the world", shaped by the data on which they are trained. More sophisticated architectures, such as word embeddings, extend this logic: they reproduce the cultural and cognitive schemas rooted in the textual worlds they process (Arseniev-Koehler & Foster, 2022). From this perspective, large generative models are not neutral entities, rather, they embed the worldviews, biases, and power structures present in the data on which they are trained. Their capacity to generate content is thus strictly linked with the reproduction of the dominant meanings and hierarchies inscribed in those data sources. This has led critics to argue that by drawing on massive, internet-based datasets, LLMs tend to amplify hegemonic viewpoints and perpetuate existing biases and stereotypes (Bender et al., 2021; Nadeem et al., 2022). These biases are not merely technical errors to be corrected but reveal the epistemological and political foundations upon which AI is built. In other words, it can be argued that AI systems function as political registers that encode power relations through their architecture and the data they rely on (Crawford, 2021), and representational bias emerges in the tendency of datasets to overrepresent certain populations and to underrepresent or stereotypically portray other groups (Esposito, 2022; Noble, 2018).

1. For a valuable example, see "Expanding the Archive with Kira Pollack and Christopher Morris": https://theviifoundation.org/resource/expanding-the-archive-with-kira-pollack-and-christopher-morris/.

Although bias-detection analyses are widespread in studies of AI-generated images, the ability of large generative models to write about virtually any topic, in any style, and while adopting any voice or positionality also raises questions about cultural appropriation, authority, and authenticity. In the field of political communication and discourse analysis, several studies have examined the political orientation and potential political bias of texts generated by platform-based proprietary models such as OpenAI's ChatGPT (Feng et al., 2023; Motoki et al., 2023; Condorelli et al., 2024). A focus has been on comparing the model's responses in its primary training language (English) with those produced in minority or less-represented languages (e.g., Garzonio et al., 2024). This line of inquiry typically relies on a comparative analytical approach to identify systematic differences in how the model answers across languages. Researchers commonly prompt the model to express scalar judgments (e.g., from "strongly agree" to "strongly disagree") using both "neutral" prompts (such as propositions taken from the Political Compass) and more directive prompts designed to test the model's susceptibility to polarization (for example, asking it to respond *as if* it were a left-wing or right-wing voter). Such studies also investigate how the model's outputs may drift or diverge depending on the language used, revealing potential asymmetries tied to training data coverage. In response to misalignments and bias, alignment techniques have been developed by computer scientists (Lyman et al., 2025), that rely on human feedback to guide models toward responses deemed more "socially responsible" or "normatively desirable" (Ouyang et al., 2022). Yet, such interventions also raise deeper questions about whose norms and values are being encoded, and, ultimately, about how power and culture continue to shape the very foundations of "intelligent" systems.

The study of bias and intrinsic distortion in deep learning models, both in their training and in the generation of outputs, constitutes a well-established and continuously expanding area of sociological research on algorithms and GenAI systems. Critical algorithm studies address several key issues related to studying AI as both an object and a practice: beyond the reproduction and amplification of stereotypes and the pervasive presence of bias, scholars highlight the ethical concerns surrounding the invisible human labor in data annotation, often carried out under exploitative conditions, which forms the infrastructural backbone of AI systems. Other critical areas of inquiry include platform surveillance and oligopolistic control; the environmental impact and forms of digital coloniality embedded in global AI supply chains; questions of governance and regulation (Ofosu-Ampong, 2024); and the ongoing reconfiguration of cognitive and creative labor, with profound implications for the cultural and media industries (e.g., Lee, 2024).

Research on *visual* GenAI, in particular, has confirmed that, just like LLMs, multimodal and vision-language models acquire a structured way of seeing the world through pretraining data, which can embed and reproduce systematic biases. Studies in computer vision have demonstrated persistent demographic misclassification that disproportionately affects marginalized groups (Buolamwini & Gebru, 2018), while audits of image generators reveal the reproduction of visual stereotypes and the amplification of existing social hierarchies in generated outputs (Bianchi et al., 2023). More recent research has also evaluated how widely used diffusion models readily generate sexual, violent, and sensitive images when prompted, and the generated outputs reveal significant and problematic representational distortions while highlighting the absence of effective safety mechanisms or refusal behaviors in such models (Schneider & Hagendorff, 2025). These issues are especially relevant given the rapid evolution of visual generative models, from early GANs to diffusion-based and multimodal architectures that now dominate the field,[2] and the repercussions related to the possibility of producing visual cultural products (almost) autonomously (Laba, 2024).

Sociological research using VLLMs and AI-based image generators has expanded rapidly, creating new opportunities to investigate both visual culture and socio-technical dynamics. Many studies have employed VLLMs for different research purposes: from identifying protest imagery on social media, to mapping neighbourhood or macro region characteristics through street-level, or satellite photos (Law & Roberto, 2025), to analysing visual patterns in political communication, to large-scale image annotation, for which VLLMs are used to produce descriptive and interpretive captions that link visual content to social meanings (Arminio et al., 2025).

In journalism and political communication, increasing empirical research has been carried out about the relationship between the adoption of AI and the spread of purposeful disinformation, even in the form of AI-generated images diffused by political actors (e.g. Farooq & De Vreese, 2025; Grub & Humprecht, 2025; Novelli et al., 2025; Pilati & Venturini, 2025).

If compared with the research on GenAI as an object, the literature on GenAI as a *practice* appears much less developed. It is, however, possible to categorize the practices of AI generation into a few major modalities — i.e., textual, visual, and sonic. Conceptually developed vis-à-vis Moretti (2013)'s influential approach to (computational) distant reading, "distant writing" describes a new literary practice in which authors design narratives rather than write them directly, relying on LLMs to generate the text. Through prompting strategies and iterations, human authors retain creative control while delegating execution to the model. Unlike distant reading, which analyses large corpora of existing texts, distant writing uses computational tools to produce new narrative works. Authorship is thus reconfigured: the writer becomes an architect of narrative possibilities, defining constraints, goals, and stylistic choices, while the resulting texts are outcomes of human-AI collaboration (Floridi, 2025b). It's the technical infrastructure of generative writing that shapes where and how authorship is located, as different writing architectures imply different chains of action. The concept of "causal authorship" (Bajohr, 2024) captures these configurations by focusing on who acts, through which tools, and at which stage of text production, defining different possible "degrees of distance" between the human author and the generated text. Recent empirical research, especially in the UK, has explored the impact of GenAI in the professional field of literature, analyzing the gradual adoption, resistance, and discursive framing of the GenAI practice of distant writing (Collett, 2025).

Similar to the "distant writing" framework (referring to writing practices carried out also through communication with GenAI chatbots), "distant imaging" refers to the practice of iteratively producing AI co-generated visuals, in which the image-maker comes to be conceivable as a narrative designer or "meta-author". The actual production of the artifact is delegated to AI systems, but humans define the constraints, requirements, and prompts that originate results while also editing, curating, and refining the output (Letiche et al., 2025).

2. Diffusion models, popularized by breakthroughs such as DALL·E 2 and Stable Diffusion, generate images through denoising: they learn to reverse a process that gradually adds noise to an image, enabling the reconstruction of high-fidelity visuals from random noise and providing fine-grained control over attributes, composition, and style (Rombach et al., 2022). More recent multimodal systems align text and image representations, enabling prompts to specify complex visual semantics. This trajectory culminates in Vision-Language Large Models (VLLMs), including systems such as Sora, Imagen-2, and LLaVA, which integrate language and vision within a single framework and support widely used tools like Midjourney, DALL·E 3, Adobe Firefly, and Stable Diffusion (Laba, 2024).

Finally, if in the "distant listening" approach to sound, computing can "distill the many-layered four-dimensional space of the text in performance (i.e., embodied within the performance network of interpretations with the listener in time and space) into a two-dimensional script called 'code' " (Clement, 2020), distant sounding as a practice of cultural production refers to the use of multimodal GenAI systems to produce sound, such as music, voices, or soundscapes. Multimodality substitutes "the lack of granular observation based on proximity in terms of space" (*ibidem*), and distant sounding places synthesis over perception: the sound of auditory artifacts is generated from statistical patterns learned from large audio corpora, as novel sonic forms that extend beyond more traditional, situated sound-making.

4 Generative AI as a Method

The adoption of GenAI in the social sciences may be interpreted as an epistemological and methodological turn. The core mechanics behind generative AI, in fact, are not entirely new to social scientists. The introduction of big data and computational techniques has long been established as a new paradigm for the social sciences, marked by the rise of large-scale quantitative approaches (Salganik, 2017) and the development of natively digital methods for analyzing online traces (Rogers, 2013). The generative turn we are currently witnessing represents a further qualitative shift, as it brings into social research not only new analytical tools but entities capable of producing knowledge in a semi-autonomous manner.

As early as 2013, researchers at Google introduced the *word2vec* architecture, a word-embedding technique that encodes lexical items as vectors in a high-dimensional space. This approach was designed to address a key limitation of many machine learning algorithms, which cannot process raw text directly and instead require numerical inputs to perform given tasks — say classification, or regression (Johnson et al., 2024). Those internal vector representations, known as embeddings, can capture the semantic relationships between words in large text corpora (Mikolov et al., 2013). Building on this foundation, sociologists have employed word embeddings to explore various dimensions of culture, meaning, and discourse (e.g., Karell & Sachs, 2023; Kozlowski et al., 2019; Stoltz & Taylor, 2019), demonstrating how computational models of language can be used to map social and cultural structures (Davidson, 2024). These developments reflect the ongoing advances across multiple areas of AI, particularly deep learning and natural language processing (NLP): contemporary generative models rely on complex neural architectures trained on massive corpora of textual and multimodal data, enabling them to learn linguistic structures, communicative patterns, and cultural conventions.

Along one of sociology's most debated methodological divides — the qualitative/quantitative axis — technologies of social computation have increasingly shown the ability to blur these distinctions (Venturini & Latour, 2010). Rather than fitting neatly into either tradition, computational, and AI-based methods often combine quantitative scale with qualitative interpretation, supporting more hybrid forms of sociological inquiry.

Over the years, the application of deep generative models and GenAI has held significant promise across various research domains, from text analysis to experimentation and simulation (Bail, 2024; Evans, 2022; Grossmann et al., 2023), encompassing a wide range of methodological traditions, including computational, qualitative, and experimental approaches. Researchers still find innovative ways to integrate GenAI as a methodology into a wide range of social science applications: generative models can impute missing survey data (Kim & Lee, 2023), assist in conducting online semi-structured interviews (Chopra & Haaland, 2023), and generate more realistic simulations and agent-based models (Park et al., 2023). The ability of GenAI to handle multimodal data makes it extremely valuable for studying large digital and online corpora, expanding the use of computational methods in the analysis of cultural products (Bail, 2014), while examining the representations embedded within these models can produce new insights into culture and cognition, building on earlier research with word embeddings (Arseniev-Koehler & Foster, 2022; Kozlowski et al., 2019). The ability of large generative models to function as "text wizards and scholarly editors" (Venturini & Rogers, 2025), bias detectors, and text annotators is now well established and widely discussed in sociological and digital-methods literature.

GenAI's ability to mimic human behavior offers valuable tools for social science research: it can automate and diversify experimental stimuli, making study design more efficient and scalable. Groups of AI agents can simulate collective behaviors or large-scale human populations, allowing new ways to study group dynamics that are otherwise costly or impractical (Allamong et al., 2023; Törnberg et al., 2023). Numerous studies have used LLMs to generate "synthetic participants", virtual agents that can act as survey respondents in early stages of research instrument validation, as the pre-testing of questionnaires and interview guides (Olivos & Liu, 2024; Kim et al., 2024) or attitude scales (Salah et al., 2024).

GenAI can serve as a methodological enhancer that strengthens and extends established research methods — e.g., text classification, data annotation, and labeling — while enabling new research modes, such as conversational and image-based analysis. In the realm of quantitative methodology, GenAI systems deeply change how researchers approach data analysis, interpretation, and visualization (Perkins & Roe, 2024).

A first domain of application concerns visual analytics and pattern detection: GenAI models can process large datasets, identify recurring structures, and even generate data visualizations (Niederer & Colombo, 2024) that support researchers in interpreting and presenting their findings, assisting computational sociologists in the classification of both textual and visual materials (Davidson, 2024). The combination of computational techniques and interpretive analysis for studying large-scale patterns aligns with *distant* analytical and methodological approaches (see Tab. 1) such as distant reading, distant viewing, and distant listening,[3] and the contribution of LLM-based tools helps extend their scope and efficiency. Doing research "at a distance" generally involves the collection and selection of data, which is then remade, often with the assistance of computational processes, into one or more abstract visual models (Mueller, 2009). Distant reading, for instance, which refers to the use of computational and AI-based techniques to analyse large corpora of texts at scale — identifying patterns, themes, styles, or discursive structures that are not accessible through close reading alone — deliberately varies the level of detail at which we ordinarily read texts, and it's the models that bring to light patterns that would have been difficult to apprehend because of the very broad scope of the materials being considered (Moretti, 2013). LLMs extend this tradition by enabling semantic clustering, automated annotation, summarization, and comparative analysis across languages and genres.

Applying such an approach in the realm of visual culture, computational methods can help detect recurring visual motifs, stylistic regularities, or representational biases across extremely

3. Distant listening (Clement, 2013) involves the use of computational tools to analyze large-scale audio data, such as speech, music, or soundscapes, by extracting patterns related to tone, rhythm, affect, or semantic content. Here, AI supports comparative analysis of sonic cultures across time, space, and platforms: its outputs are typically visual representations, such as waveforms or spectrograms, which allow researchers to observe, compare, and interpret different kinds of sonic structures.

vast image collections that would be unmanageable through close analysis alone. Distant viewing (Arnold & Tilton, 2019) is a methodological framework intended for analyzing large collections of visual materials, emphasizing the interpretive work involved in computational image analysis (see also Azar et al., 2021). It requires constructing a representational system, such as a metadata schema, that translates visual elements into analyzable categories, and then using algorithms to extract information from images at scale. Distant viewing becomes an interpretive practice that makes large-scale visual analysis possible with computer vision to detect recurring visual patterns, iconographies, and representational trends at the broadest level. Vision-language models extend this approach by linking visual features to language, allowing images to be described, compared, and grouped through natural-language concepts. Recent research has combined object detection, OCR, and multimodal embeddings to extract, annotate, and index illustrations and captions from digitized periodicals, making vast archives accessible for large-scale visual analysis by creating a multimodal dataset and retrieval tool (Smits et al., 2025). In this way, LLMs and multimodal systems act as a bridge between scale and interpretation, that is, between computational pattern detection and interpretive analysis, allowing researchers to move back and forth between large-scale visual regularities and close readings.

Text classification and data annotation are two other most immediate applications of LLMs in computational sociology (Edelmann et al., 2020) as well as methodological domains most widely and cross-disciplinarily discussed in the literature (Vallejo Vera & Driggers, 2025; Calderon et al., 2025). LLMs automate the categorization of large text corpora (such as news articles or social media posts, see Molina & Garip, 2019) and their pretraining on vast datasets enables strong performance and adaptability,[4] maximizing efficiency and often matching or surpassing human crowd workers at lower cost (Gilardi et al., 2023). These models are highly versatile and can support a wide range of text-as-data tasks, from familiar procedures such as sentiment analysis and topic modeling to more project-specific annotation challenges. Unlike earlier computational approaches, LLMs do not rely solely on the syntactic features of text; instead, they draw on contextual knowledge and inference. Their ease of use (they are capable of annotation based on prompts, instructions written in natural language) and relatively low cost have driven a rapid surge in adoption, suggesting a potential paradigm shift in text-as-data research, as they allow even researchers with limited computational expertise to conduct sophisticated large-scale analyses. Yet the field's rapid expansion and the absence of shared standards and established practices have raised concerns about the quality and validity of research. As a result, some have proposed a systematization of LLMs applications as annotators and recommended guidelines and best practices (Törnberg, 2024) to ensure the reliable, reproducible, and ethical use of LLMs, particularly to counter the risks posed by misleading applications of these models as annotators, given their susceptibility to bias, misinterpretation, and inconsistency. Among the solutions proposed, the combination of human and LLM annotators is often recommended to benefit from their strengths while mitigating their limitations (Ziems et al., 2024), an approach aligned with the growing body of research on "humans in the loop" (Schroeder et al., 2025).

Another area of application concerns the integration of GenAI with statistical software, which allows operations such as data cleaning and preprocessing (Pronzato & Risi, 2025), the identification of anomalies, and the suggestion of suitable statistical models based on the char-

4. Through techniques like zero-shot learning (the ability of a model to perform tasks without task-specific training examples), few-shot learning (adapting to new tasks from a very small number of examples provided in the prompt), and fine-tuning (the targeted retraining of a pretrained model on domain-specific data to improve performance and alignment for particular tasks) (Manning, 2022; Wei et al., 2022).

acteristics of the dataset (Perkins & Roe, 2024). A third domain relates to natural-language interaction, whereby researchers can instruct GenAI models to execute statistical procedures through plain-language queries. While conventional machine learning distinguishes between supervised (deductive) and unsupervised (inductive) models, such as text classification and topic modeling (Molina & Garip, 2019), LLMs typically blur this divide, as a single model can serve multiple analytical purposes: BERT (Bidirectional Encoder Representations from Transformers) variants,[5] for example, have been fine-tuned for classification, used inductively for topic discovery, and studied as probabilistic models of language (Devlin et al., 2019; Bonikowski et al., 2022; Egger & Yu, 2022; Vicinanza et al., 2023). Notably, LLMs can be instructed via natural language prompts, making it possible for social scientists to develop tailored analytical tools without needing specialized coding expertise. This interactive use of models supports rapid experimentation and broadens access to computational methods, potentially accelerating innovation in sociological research (Evans & Aceves, 2016) and contributing to a "democratization of advanced statistical techniques" (Perkins & Roe, 2024, p. 8), since researchers with diverse backgrounds are allowed to conduct statistical analyses by interacting directly with a GenAI system.

The rise of commercial and open-source GenAI platforms based on LLMs has also introduced new ways of producing synthetic textual and visual data. One of the most debated applications of GenAI in social science research is the use of LLMs as surrogates for human populations (Grossmann et al., 2023; Davidson & Karell, 2025), which Argyle et al. (2023) call *silicon sampling*. The generated data are intended to "mimic" content that individuals might produce on social media or in surveys and interviews (Choenni et al., 2023), bypassing situations in which access to specific data types is restricted. Synthetic data can play multiple roles — from data augmentation and prototyping to direct analysis — where LLMs act as proxies for real human subjects (Rossi et al., 2024). In this respect, LLMs function not only as analytical tools but also as systems for data creation.

Nevertheless, while such models may represent an appealing opportunity for social science research, given their ease of use and fluency in producing language in response to researchers' crafted prompts, the use of such data to generate insights about people still demands serious critical reflection. LLMs can indeed produce human-like data, but the utility of such synthetic data depends on factors such as the fidelity and representativeness of training data, model biases, and the propensity of these systems to hallucinate or reproduce social stereotypes. Assessing the fidelity of generated outputs is still a major challenge: unlike traditional synthetic data, whose quality can be assessed by comparing them directly to the real datasets they mimic, LLM-generated data pose problems due to the opacity of models and their training data. Along with fidelity issues, instability and lack of internal consistency have been detected by various research (Johnson & Hajisharif, 2024; Atil et al., 2024), and results can vary not only across different models but even within the same model when repeating the same task (Rossi et al., 2024). More broadly, such uses of GenAI still raise important concerns about the risks of misinterpretation within quantitative research, reinforcing the need to maintain statistical literacy and sociological expertise to contextualize model outputs. These reflections again illustrate how GenAI

5. Building on the Transformer architecture — introduced in 2017 and based on attention mechanisms that model relationships between elements in a sequence — BERT (2018) marked a turning point in natural language understanding by enabling words to be interpreted in relation to both their preceding and following context. With GPT-3 (2020), large-scale pretraining on massive text corpora enabled highly flexible and coherent language production. This pretraining-fine-tuning paradigm has since become standard for models such as PaLM, Claude, LLaMA, and later versions of GPT (Pilati, 2025, p. 22).

systems can be framed as assistants that facilitate or streamline research processes (Pronzato & Risi, 2025) and, in some cases, may shape or reduce the range of choices available to the researcher.

Beyond methodological innovation, in fact, GenAI also plays its role in the research practice itself, acting as a "virtual research assistant", supporting the teaching of coding and analytical skills, and even generating new research questions. Framing LLMs-based systems as assistants implies contextualizing them as supportive tools that aid the research process rather than technologies through which research is substantively developed (Pronzato & Risi, 2025). A section of the existing literature focuses on this "utilitarian" approach to generative and conversational AI, highlighting the many ways in which AI-based tools can support researchers across the various stages of the research process. A concrete example of this operational approach is given by the "AI Methodology Map" developed by Omena et al. (2024): a pedagogical resource, including an interactive toolkit and teaching resource designed to help researchers use GenAI in digital-methods research. It combines digital methods theory, visual thinking, and interdisciplinary practice into a single framework to help organize and guide concrete research choices when working with GenAI tools. A similar practice-oriented approach is shown in recent works that reconstruct the development of AI-powered technologies and their use in the field of social sciences: AI tools cut across multiple overarching domains of expertise and can be deployed in a wide array of contexts, spanning both professional and everyday activities (Matrella et al., 2025). The domains of content creation and editing (e.g., content generation, copywriting, image and video editing, storytelling, summarization, transcription), analysis and research (e.g., digital data analysis, research support, search engines, spreadsheet processing), and development and innovation (e.g., code assistance, AI application building) comprehend distinct functions that can be mobilized at different stages of the research process. These include assistance in citation, communication, data analysis, and data extraction (Matrella et al., 2025, p. 150).

Finally, in the field of visual culture, as a method today, visual GenAI can enable new forms of visual analysis and experimentation, particularly through practices of prompting, where prompt *engineering*, *design*, and *tuning*[6] become analytical operations (Niederer & Colombo, 2024; Venturini & Rogers, 2025). By systematically varying prompts, sociologists can explore how models associate social categories, styles, and meanings, using the model's responses as a lens onto dominant visual imaginaries. This approach resonates with the tradition of cultural analytics (Manovich, 2020), which combines computational techniques and interpretive analysis to study large-scale visual patterns, and again with *distant* approaches to research.

Recent sociological literature has also highlighted the potential of LLMs to revitalize computational methods in qualitative research by integrating computational rigor with a certain interpretive depth (Davidson & Karell, 2025). Previous techniques, such as topic modeling or supervised learning, tend to perform best on large, homogeneous text corpora but often fail to capture the complexity of qualitative materials, such as interviews or field notes. Since LLMs encode a richer and more context-sensitive representation of language, they can process multi-

6. Prompt engineering involves systematically structuring and testing prompts to control content, style, and constraints: it "is about mastering the art of prompting to generate awe-inducing images" (Niederer & Colombo, 2024, p. 115); prompt design and tuning, on the other hand, concern the iterative refinement of prompts to explore variations, stabilize results, and analytically probe how models translate linguistic cues into visual representations. With techniques of prompt design, the researchers seek to compose prompts as queries, to explore output bias, AI aesthetics, machine critique, content moderation, or practices of participatory research (*ibidem*).

layered, dialogic data without long preprocessing phases, preserving the contextual richness to be explored in qualitative analysis. A major innovation in this context is conversational computational content analysis (Davidson, 2024), which enables researchers to engage in interactive dialogue with models, such as the current GPT-5, to summarize, identify, and interrogate themes within qualitative data (Hayes, 2023).

The potential of LLM-based GenAI systems to identify recurring patterns has undoubtedly attracted attention, and several scholars are experimenting with GenAI in qualitative research and coding (Dunivin, 2025; Than et al., 2025). Recent advances suggest promising applications for generating inductive coding results, as well as for streamlining tasks such as transcribing audio and video recordings, conducting coding phases, analyzing field notes and analytical memos, grouping codes, and even suggesting interpretive directions. More recent research has highlighted the added value of transcription tools such as Whisper AI, which integrate automatic tagging alongside transcription: these systems can automatically identify speaker changes, segment the text into thematic units, and highlight significant passages based on predefined keywords or linguistic patterns, pre-structuring the data in ways that facilitate the subsequent phases of coding and analysis. In the steps following the transcription of textual data, qualitative analysis can be further supported by LLMs-enhanced interactive work environments that help researchers to manage, organize, and navigate large corpora of data more efficiently. These tools offer advanced functionalities for indexing, retrieving, synthesizing, and comparing qualitative data, effectively integrating traditional qualitative analysis with sophisticated NLP capabilities. Finally, GenAI (particularly LLMs such as GPT, Claude, or Llama) offers new opportunities to support and enrich the processes of thematic detection and systematic coding of qualitative data, complementing the interpretive work traditionally carried out by research teams. Such models deploy different computational approaches, including latent semantic analysis (identifying clusters of meaning within text), discourse anomaly detection, sentiment and stance analysis, and conceptual network mapping (tracing relationships between concepts within the corpus and visualizing how different themes intersect and influence one another). Unlike traditional computational approaches to text analysis — which are often based on frequency counts or lexical co-occurrences — contemporary language models can capture semantic and contextual nuances.

This kind of hybridization based on the research interaction between researchers and machines raises fundamental questions about the very nature of AI-mediated research, the authenticity of experience, the subjectivity of interpretation, and ultimately the construction of meaning (Esposito, 2022); however, it has not been immune also to skepticism, resistance and critique — at least, as far as reflexive qualitative research is concerned (Jowsey et al., 2025).

Despite its clear methodological promise, generative AI also introduces major challenges in terms of interpretability, transparency, reproducibility, reliability, and ethics (Bail, 2024). The immense scale that supports its performance also makes these systems highly opaque, making it far more difficult to understand how they generate output than in conventional statistical or machine learning models (Molina & Garip, 2019; Davidson, 2019). The emerging field of mechanistic interpretability seeks to reverse-engineer these architectures by tracing how specific parameters or clusters of parameters respond to inputs and produce outputs (Olsson et al., 2022), but this research remains in its early stages. The fact that many of the most advanced GenAI models are developed and maintained by private corporations that disclose little about their training data makes it hardly practicable to assess how pretraining content shapes model behavior and outputs (Bommasani et al., 2023). Moreover, the stochastic nature of these systems means that identical prompts can generate different results, and frequent, undisclosed updates can further alter responses. While computational methods are often praised for their replicability compared to more interpretive approaches (Nelson, 2020), reproducibility remains a persistent challenge in machine learning contexts (Liu & Salganik, 2019), and is even magnified in the case of GenAI.

Finally, on the basis of the literature reviewed above, it becomes clear that considering AI as both method and practice or object at-a-distance can imply focusing on a diverse range of methodological choices and empirical contexts. Given the rapid pace of socio-technological change and scholarly production, the typology proposed here should be conceived as an initial attempt to catch an evolving scenario. It is therefore graphically represented so as to include existing observable cases as well as an emerging and not yet fully established set of practices (Tab. 1).

Table 1. The AI at-a-distance typology

	Textual	**Visual**	**Sonic**
AI as method	Distant reading	Distant seeing	Distant listening
AI as practice/object	Distant writing	Distant imaging	Distant sounding

5 Conclusions

This essay has reconstructed some of the major strands in a rapidly expanding body of social science research on generative AI, proposing a framework that brings together key concepts (AI as agency, communication, and memory), analytical dimensions (AI as object, practice, and method), and, transversally, methodological tensions (macro-micro, quali-quanti, distant-close). To conclude this overview, drawing on the idea of considering GenAI as an "anticipatory infrastructure" for future research (Pink, 2025), we would like to suggest the need to move beyond a series of dichotomous oppositions that currently structure much of the literature. These tensions were relatively expectable and even analytically productive in the early stages. Yet, it could be argued that they might risk limiting both empirical insight and theoretical development in future research.

The first dichotomy, frequently found in public discourse as well as in selected strands of scholarly research, is between critical risks and enabled opportunities. Such discursive opposition often emerges publicly after a major technological innovation enters market and society. In the case of GenAI, the critical scholarly focus is most frequently oriented toward the possible emergence of hegemonic memory regimes, the consolidation of mainstream perspectives, and the diffusion of biased AI-generated (visual) content, as well as related issues of authorship and veracity. Analogous critical attitudes also address ethical and methodological questions of transparency, or research replicability. The second dichotomy can be argued to deal with, in the phrasing made famous by C.W. Mills (1959), grand theorizing and abstracted empiricism. Since GenAI is a relatively recent topic that seems to be perceived with increasing urgency in a variety of disciplinary fields, it inevitably lends itself to different approaches with different sound foundations, theoretically as much as empirically. The final two relevant dichotomies concern the tensions between macro- and micro- levels of analysis, as well as between distant and close methodological approaches. At the macro level, critical political economy approaches highlight how corporate interests, intellectual property regimes, and platform capitalism shape the conditions under which AI agency operates; at the micro level, for example, studies of domestication and re-domestication show how users negotiate AI agency in everyday practices, attributing competence and even affective presence to chatbots. However, macro-level analyses of political economy, supranational governance, and big cultural change develop in parallel to — and without significant, yet potentially beneficial, reciprocal relations with — micro-level analyses of social practices of use, negotiation, and framing. Similarly, distant methods, such as large-scale computational text analysis, can benefit from integration with close, interpretive approaches that attend to situated agency and meaning-making. Rather than choosing sides, future research stands to gain from methodological and analytical designs that explicitly connect these levels and scales, focusing on the role potentially played in both by generative AI, and eventually problematizing the epistemological and methodological assumptions of traditionally established dichotomies within social science — a theoretical line increasingly pursued by recent works (Cammaerts, 2026; Venturini, 2026; see also Krause, 2013).

In this respect, greater attention to the meso-level — such as organizations and institutions — is still very rare and appears especially promising. These arenas mediate between individual actors and societal structures and are key sites where generative AI is currently being implemented, regulated, and normalized. Focusing on meso-level dynamics and strategies could shed light on the ways in which authority, expertise, and legitimacy are being redistributed in the generative AI age, and how shifting institutional logics can shape and be reshaped by the adoption and regulation of these systems. Only a few contributions have already productively adopted existing theoretical models, such as Bourdieu's field theory (e.g., Atkinson, 2025; Roland et al., 2025), to begin investigating such dynamics. From this perspective, a fertile empirical domain is offered by memory institutions. Recent research has addressed case studies through which to analyze how the resources and legitimacy of powerful institutional actors who establish and preserve mnemonic frames can be invested toward an ethically reflexive use of Gen AI, and, at the same time, how a productive combination of distant and close analysis of their institutional archives can shed light on the future of memory, (distant) witnessing and testimony — e.g., of the Holocaust (Presner, 2016 & 2024; Makhortykh et al., 2023). From the domain of institutional memory, such research thus also explores how GenAI can contribute to redefining notions and values of accountability and authority.

As AI technologies, practices, and meanings continue to evolve, enabling new forms of creativity, coordination, and control, and increasingly reshaping everyday social life, the challenge for social science is to productively inhabit these emerging tensions, looking for integrative and reflexive approaches. Advancing research that bridges levels of analysis, combines methodological traditions, opens spaces of possibility for intellectual discovery and original theorizing, and does not avoid taking a critical stance will be crucial for understanding the social spread and effects of GenAI and for favoring informed and responsible engagement with these transformations.

References

Airoldi, M. (2021). *Machine Habitus: Toward a Sociology of Algorithms*. Cambridge: Polity.

Allamong, M., Trexler, A., Alqabandi, F., LaChapelle, T., Bail, C.A., Hillygus, D.S., & Volfovsky, A. (2023). Outnumbered Online: The Consequences of Partisan Imbalance in Online Political Discussions. *Open Science Framework Preprints*. https://doi.org/10.31219/osf.io/tygec

Arora, P., & Natale, S. (2025). Situating AI: Global Media Approaches to Artificial Intelligence. *Media, Culture & Society*, *47*(5), 1007–1011. https://doi.org/10.1177/01634437251341702

Argyle, L.P., Busby, E.C., Fulda, N., Rytting, C., & Wingate, D. (2023). Out of One, Many: Using Language Models to Simulate Human Samples. *Political Analysis*, *31*(3), 337–351. https://doi.org/10.1017/pan.2023.2

Arminio, L., Magnani, M., Piqueras, M., Rossi, L., & Segerberg, A. (2025). Leveraging VLLMs for Visual Clustering: Image-to-Text Mapping Shows Increased Semantic Capabilities and Interpretability. *Social Science Computer Review*, *44*(3), 572–591. https://doi.org/10.1177/08944393251376703

Arnold, T., & Tilton, L. (2019). Distant Viewing: Analyzing Large Visual Corpora. *Digital Scholarship in the Humanities*, *34*(1), 3–16. https://doi.org/10.1093/llc/fqz013

Arseniev-Koehler, A., & Foster, J.G. (2022). Machine Learning as a Model for Cultural Learning: Teaching an Algorithm What it Means to be Fat. *Sociological Methods and Research*, *51*(4), 1484–1539. https://doi.org/10.48550/arXiv.2003.12133

Atil, B., Chittams, A., Fu, L., Ture, F., Xu, L., & Baldwin, B. (2024). LLM Stability: A Detailed Analysis with Some Surprises. https://doi.org/10.48550/arXiv.2408.04667

Atkinson, W. (2025). Artificial Intelligence as a Strategy in the British Economic Field. *British Journal of Sociology*, *76*(4), 814–827. https://doi.org/10.1111/1468-4446.13218

Au, A., & Fong, E. (2025). The Promises and Perils of AI for Sociology. *Sociology*, *59*(6), 1129–1134. https://doi.org/10.1177/00380385251357523

Azar, M., Cox, G., & Impett, L. (2021). Introduction: Ways of Machine Seeing. *AI and Society, 36*, 1093–1104. https://doi.org/10.1007/s00146-020-01124-6

Baert, P., Dorschel, R., Hall, M., Higgins, I., McPherson, E., & Philip, S. (2025). Dialogues Towards Sociologies of Generative AI. *Social Science Computer Review*, *44*(1), 59–79. https://doi.org/10.1177/08944393251370354

Bail, C.A. (2014). The Cultural Environment: Measuring Culture with Big Data. *Theory and Society*, *43*(3-4), 465–482. https://doi.org/10.1007/s11186-014-9216-5

Bail, C.A. (2024). Can Generative AI Improve Social Science? *Proceedings of the National Academy of Sciences of the United States of America*, *121*(21), e2314021121. https://doi.org/10.1073/pnas.2314021121

Bajohr, H. (2024). Writing at a Distance: Notes on Authorship and Artificial Intelligence. *German Studies Review*, *47*(2), 315–337. https://dx.doi.org/10.1353/gsr.2024.a927862

Barisione, M. (2026). Charismatic Machines: On the Epistemic Power of Generative AI within Platform Convergence. *New Media & Society,* online first. https://doi.org/10.1177/14614448261441417

Bender, E.M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? *FAccT '21: ACM (Association for*

Computing Machinery) Conference on Fairness, Accountability, and Transparency, March 2021. https://doi.org/10.1145/3442188.3445922

Bianchi, F., Kalluri, P., Durmus, E., Ladhak, F., Cheng, M., Nozza, D., Hashimoto, T., Jurafsky, D., Zou, J., Caliskan, A. (2023). Easily Accessible Text-to-Image Generation Amplifies Demographic Stereotypes at Large Scale. FAccT '23: *ACM (Association for Computing Machinery) Conference on Fairness, Accountability, and Transparency*, June 2023, Chicago (IL). https://doi.org/10.48550/arXiv.2211.03759

Bommasani, R., Klyman, K., Longpre, S., Kapoor, S., Maslej, N., Xiong, B., Zhang, D., Liang, P. (2023). *The Foundation Model Transparency Index*. https://doi.org/10.48550/arXiv.2310.12941

Bonikowski, B., & Nelson, L.K. (2022). From Ends to Means: The Promise of Computational Text Analysis for Theoretically Driven Sociological Research. *Sociological Methods and Research*, *51*(4), 1469–1483. https://doi.org/10.1177/00491241221123088

Borch, C. (2023). Machine Learning and Postcolonial Critique: Homologous Challenges to Sociological Notions of Human Agency. *Sociology*, *57*(6), 1450–1466. https://doi.org/10.1177/00380385221146877

Buolamwini, J., & Gebru, T. (2018). Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification. *Proceedings of Machine Learning Research*, *81*, 77–91.

Burrell, J., & Fourcade, M. (2021). The Society of Algorithms. *Annual Review of Sociology*, *47*, 213–237. https://doi.org/10.1146/annurev-soc-090820-020800

Calderon, N., Reichart, R., & Dror, R. (2025). The Alternative Annotator Test for LLM-as-a-Judge: How to Statistically Justify Replacing Human Annotators with LLMs. In W. Che, J. Nabende, E. Shutova, & M.T. Pilehvar (Eds.), *Annual Meeting of the Association for Computational Linguistics*, August 2025, Vienna. https://doi.org/10.48550/arXiv.2501.10970

Cammaerts, B. (2026). *Dichotomies in Media and Communication Theory*. London: Routledge.

Choenni, S., Busker, T., & Bargh, M.S. (2023). Generating Synthetic Data from Large Language Models. *International Conference on Innovations in Information Technology*, November 2023, Al Ain. IEEE Computer Society, 2023. https://doi.org/10.1109/IIT59782.2023.10366424

Chopra, F., & Haaland, I. (2023). Conducting Qualitative Interviews with AI. *CESifo Working Paper No. 10666*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4583756

Clement, T.E. (2013). Distant Listening or Playing Visualisations Pleasantly with the Eyes and Ears. *Digital Studies/Le champ numérique*, *3*(2). https://doi.org/10.16995/dscn.236

Clement, T.E. (2020). Distant Listening and Resonance. *ESC: English Studies in Canada*, *46*(2), 279–284. https://doi.org/10.1353/esc.2020.a903548

Collett, C. (2025). *The Impact of Generative AI on the Novel.* Minderoo Centre for Technology and Democracy. https://www.crassh.cam.ac.uk/research/publications/the-impact-of-generative-ai-on-the-novel/

Condorelli, V., Beluzzi, F., & Anselmi, G. (2024). Assessing ChatGPT Political Bias in Italian Language: A Systematic Approach. *Comunicazione Politica*, *25*(3), 409–428. https://doi.org/10.3270/115248

Cowley, S. (2025). Doing Agency: How Agents Adapt in Wide Systems. *AI & Society*, *40*, 1–3. https://doi.org/10.1007/s00146-024-02176-8

Crawford, K. (2021). *The Atlas of AI: Power, Politics, and the Planetary Costs of Artificial Intelligence*. New Haven, CT: Yale University Press.

Danziger, R., Levy-Landesberg, H., Yadlin, A., Ramati, I., Lidor, I., & Manor, I. (2026). Not Entirely Artificial, Not That Intelligent. AI and Communication Research: A Conversation on Hype, Contexts, and Practices (Part 1). *International Journal of Communication*, *20*. https://doi.org/10.65476/8tntk984

Dattathrani, S., & De', R. (2023). The Concept of Agency in the Era of Artificial Intelligence: Dimensions and Degrees. *Information Systems Frontiers*, *25*, 29–54. https://doi.org/10.1007/s10796-022-10336-8

Davidson, T. (2019). Black-box Models and Sociological Explanations: Predicting High School Grade Point Average Using Neural Networks. *Socius. Sociological Research for a Dynamic World*, *5*. https://doi.org/10.1177/2378023118817702

Davidson, T. (2024). Start Generating: Harnessing Generative Artificial Intelligence for Sociological Research. *Socius. Sociological Research for a Dynamic World*, *10*. https://doi.org/10.1177/23780231241259651

Davidson, T., & Karell, D. (2025). Integrating Generative Artificial Intelligence into Social Science Research: Measurement, Prompting, and Simulation. *Sociological Methods and Research*, *54*(3), 775–793. https://doi.org/10.1177/00491241251339184

Davis, J.L., & Sloane, M. (2025). AI's Sociological Era. *Social Science Computer Review*, *44*(1), 3–9. https://doi.org/10.1177/08944393251394690

Depounti, I., & Natale, S. (2025). Decoding Artificial Sociality: Technologies, Dynamics, Implications. *New Media & Society*, *27*(10), 5457–5470. https://doi.org/10.1177/14614448251359217

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In J. Burstein, C. Doran, & T. Solorio (Eds.), *Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, June 2019, Minneapolis (MN). https://doi.org/10.18653/v1/N19-1423

Dunivin, Z.O. (2025). Scaling Hermeneutics: A Guide to Qualitative Coding with LLMs for Reflexive Content Analysis. *EPJ Data Science*, *14*(28). https://doi.org/10.1140/epjds/s13688-025-00548-8

Edelmann, A., Wolff, T., Montagne, D., & Bail, C.A. (2020). Computational Social Science and Sociology. *Annual Review of Sociology*, *46*(1), 61–81. https://doi.org/10.1146/annurev-soc-121919-054621

Egger, R., & Yu, J. (2022). A Topic Modeling Comparison between LDA, NMF, Top2Vec, and BERTopic to Demystify Twitter Posts. *Frontiers in Sociology*, *7*. https://doi.org/10.3389/fsoc.2022.886498

Elliott, A. (2022). *Making Sense of AI: Our Algorithmic World*. Cambridge: Polity.

Emirbayer, M., & Mische, A. (1998). What Is Agency? *American Journal of Sociology*, *103*(4), 962–1023. https://doi.org/10.1086/231294

Esposito, E. (2017). Algorithmic Memory and the Right to be Forgotten on the Web. *Big Data & Society*, *4*(1). https://doi.org/10.1177/2053951717703996

Esposito, E. (2022). *Artificial Communication: How Algorithms Produce Social Intelligence*. Cambridge, MA: MIT Press.

Esposito, E. (2026). Answer Engines and Other Communication Partners. *Communication Theory*, *36*(2), 86–94. https://doi.org/10.1093/ct/qtaf036

Eubanks, V. (2018*). Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor*. New York, NY: Picador.

Evans, J.A. (2022). From Text Signals to Simulations: A Review and Complement to Text as Data by Grimmer, Roberts & Stewart (PUP 2022). *Sociological Methods and Research*, *51*(4), 1868–1885. https://doi.org/10.1177/00491241221123086

Evans, J.A., & Aceves, P. (2016). Machine Translation: Mining Text for Social Theory. *Annual Review of Sociology*, *42*(1), 21–50. https://doi.org/10.1146/annurev-soc-081715-074206

Farooq, A., & de Vreese, C. (2025). (Generative) AI and Disinformation: Introduction. *International Journal of Communication*, *19*, 3559–3576.

Fazi, M.B. (2024). The Computational Search for Unity: Synthesis in Generative AI. *Journal of Continental Philosophy*, *5*(1), 31–56. https://doi.org/10.5840/jcp202411652

Feng, S., Park, C.Y., Liu, Y., & Tsvetkov, Y. From Pretraining Data to Language Models to Downstream Tasks: Tracking the Trails of Political Biases Leading to Unfair NLP Models. In A. Rogers, J. Boyd-Graber & N. Okazaki (Eds.), *Annual Meeting of the Association for Computational Linguistics*, July 2023, Toronto. https://aclanthology.org/2023.acl-long.656/

Floridi, L. (2025a). AI as Agency without Intelligence: On Artificial Intelligence as a New Form of Artificial Agency and the Multiple Realisability of Agency Thesis. *Philosophy and Technology*, *38*(30). https://doi.org/10.1007/s13347-025-00858-9

Floridi, L. (2025b). Distant Writing: Literary Production in the Age of Artificial Intelligence. *Minds and Machines*, *35*(30). https://doi.org/10.1007/s11023-025-09732-1

Garzonio, E., Huang, C., & Liberatore, T. (2024). *Concept or Language: What is Lost in AI Image Generation? It's Giving AI: Exploring and Investigating Generative AI Aesthetics*. August 5. https://www.digitalmethods.net/Dmi/WinterSchool2024ItsGivingAI

Gensburger, S., & Clavert, F. (2024). Is Artificial Intelligence the Future of Collective Memory? *Memory Studies Review*, *1*(2), 195–208. https://doi.org/10.1163/29498902-202400019

Gilardi, F., Alizadeh, M., & Kubli, M. (2023). ChatGPT Outperforms Crowd Workers for Text-annotation Tasks. *Proceedings of the National Academy of Sciences*, *120*(30). https://doi.org/10.1073/pnas.2305016120

Grossmann, I., Feinberg, M., Parker, D.C., Christakis, N.A., Tetlock, P.E., & Cunningham, W.A. (2023). AI and the Transformation of Social Science Research. *Science*, *380*(6650), 1108–1109. https://doi.org/10.1126/science.adi1778

Grub, M.F., & Humprecht, E. (2025). Defining the Role(s) of AI in Disinformation Research: A Systematic Review. *International Journal of Communication*, *19*, 3577–3601.

Gutierrez Lopez, M., & Halford, S. (2025). Explaining Machine Learning Practice: Findings from an Engaged Science and Technology Studies Project. *Information, Communication & Society*, *28*(4), 616–632. https://doi.org/10.1080/1369118X.2024.2400130

Hayes, A.S. (2023). "Conversing" with Qualitative Data: Enhancing Qualitative Sociological Research through Large Language Models (LLMs). *Open Science Framework Preprints*. https://osf.io/preprints/socarxiv/yms8p

Hepp, A., Bolin, G., Guzman, A., & Loosen, W. (2024). Mediatization and Human-Machine Communication: Trajectories, Discussions, Perspectives. *Human-Machine Communication*, *7*, 7–21. https://doi.org/10.30658/hmc.7.1

Hoskins, A. (2024). AI and Memory. *Memory, Mind and Media*, *3*, e18. https://doi.org/10.1017/mem.2024.16

Hoskins, A. (2026). AI and Collective Memory. *Current Opinion in Psychology*, *67*. https://doi.org/10.1016/j.copsyc.2025.102156

Hughes, E.C. (1971). *The Sociological Eye. Selected Papers*. Chicago, IL: Aldine-Atherton.

Johnson, S.J., Murty, M.R., & Navakanth, I. (2024). A Detailed Review on Word Embedding Techniques with Emphasis on Word2vec. *Multimed Tools Appl*, *83*, 37979–38007. https://doi.org/10.1007/s11042-023-17007-z

Johnson, E., & Hajisharif, S. (2024). The Intersectional Hallucinations of Synthetic Data. *AI & Society*, *40*, 1575–1577. https://doi.org/10.1007/s00146-024-02017-8

Jowsey, T., Braun, V., Clarke, V., Lupton, D., & Fine, M. (2025). *We Reject the Use of Generative Artificial Intelligence for Reflexive Qualitative Research*. https://ssrn.com/abstract=5676462

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

Karell, D., & Sachs, J. (2023). How Symbols Influence Social Media Discourse: An Embedding Regression Analysis of Trump's Return to Twitter. *Socius. Sociological Research for a Dynamic World*, 9. https://doi.org/10.1177/23780231231212108

Kim, J., & Lee, B. (2023). AI-augmented Surveys: Leveraging Large Language Models for Opinion Prediction in Nationally Representative Surveys. https://doi.org/10.48550/arXiv.2305.09620

Kim, S., Jeong, J., Han, J.S., et al. (2024). LLM-Twin: A Generated-persona Approach for Survey Pre-testing. https://doi.org/10.48550/arXiv.2412.03162

Kozlowski, A.C., Taddy, M., & Evans, J.A. (2019). The Geometry of Culture: Analyzing the Meanings of Class through Word Embeddings. *American Sociological Review*, *84*(5), 905–949. https://doi.org/10.1177/0003122419877135

Krause, M. (2013). Recombining Micro/Macro: The Grammar of Theoretical Innovation. *European Journal of Social Theory*, *16*(2), 139–152. https://doi.org/10.1177/1368431012459696

Laba, N. (2024). Engine for the Imagination? Visual Generative Media and the Issue of Representation. *Media, Culture & Society*, *46*(8), 1599–1620. https://doi.org/10.1177/01634437241259950

Law, T., & McCall, L. (2024). Artificial Intelligence Policymaking: An Agenda for Sociological Research. *Socius. Sociological Research for a Dynamic World,* 10. https://doi.org/10.1177/23780231241261596

Law, T., & Roberto, E. (2025). Generative Multimodal Models for Social Science: An Application with Satellite and Streetscape Imagery. *Sociological Methods and Research*, 54(3), 889–932. https://doi.org/10.1177/00491241251339673

Lee, F. (2025). Reassembling Agency: Epistemic Practices in the Age of Artificial Intelligence. *Sociologisk Forskning*, *62*(1–2), 43–58. https://doi.org/10.37062/sf.62.27824

Lee, H.-K. (2024). Reflecting on Cultural Labour in the Time of AI. *Media, Culture & Society*, *46*(6), 1312–1323. https://doi.org/10.1177/01634437241254320

Letiche, T., Lissack, M., & Letiche, H. (2025). *Distant Imaging: A Six-Phase Framework for AI Co-Creation in Marketing Education*. https://doi.org/10.2139/ssrn.5570898

Lindgren, S. (2023). *Critical Theory of AI*. Cambridge: Polity.

Liu, D.M., & Salganik, M.J. (2019). Successes and Struggles with Computational Reproducibility: Lessons from the Fragile Families Challenge. *Socius. Sociological Research for a Dynamic World*, 5. https://doi.org/10.1177/2378023119849803

Lyman, A., Hepner, B., Argyle, L.P., Busby, E.C., Gubler, J.R., & Wingate, D. (2025). Balancing Large Language Model Alignment and Algorithmic Fidelity in Social Science Research. *Sociological Methods and Research*, *54*(3), 1110–1155. https://doi.org/10.1177/00491241251342008

Makhortykh, M., Zucker, E.M., Simon, D.J., Bultmann, D., & Ulloa, R. (2023). Shall Androids Dream of Genocides? How Generative AI Can Change the Future of Memorialization of Mass Atrocities. *Discover Artificial Intelligence*, *3*(28). https://doi.org/10.1007/s44163-023-00072-6

Matei, Ș. (2024). Generative Artificial Intelligence and Collective Remembering: The Technological Mediation of Mnemotechnic Values. *Journal of Human-Technology Relations*, *2*(1), pp. 1–22. https://doi.org/10.59490/jhtr.2024.2.7405

Manning, C.D. (2022). Human Language Understanding and Reasoning. *Daedalus*, *151*(2), 127–138. https://doi.org/10.1162/daed_a_01905

Manovich, L. (2020). *Cultural Analytics*. Cambridge, MA: MIT Press.

Matrella, A., Cavagnuolo, M., & Capozza, V. (2025). The Use of Artificial Intelligence within Social Research: A Classification Proposal. *The Lab's Quarterly*, *27*(3). https://doi.org/10.13131/unipi/7c8y-gg23

Merrill, S. (2023). Artificial Intelligence and Social Memory: Towards the Cyborgian Remembrance of an Advancing Mnemo-Technic. In S. Lindgren (Ed.), *Handbook of Critical Studies of Artificial Intelligence* (pp. 173–186). Cheltenham: Edward Elgar.

Merrill, S., Makhortykh, M., Mandolessi, S., Richardson-Walden, V.G., Smit, R., & Wang, Q. (2025). Handling the Hype: Demystifying Artificial Intelligence for Memory Studies. *Memory, Mind and Media*, *4*(18). https://doi.org/10.1017/mem.2025.10018

Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). Efficient Estimation of Word Representations in Vector Space. https://doi.org/10.48550/arXiv.1301.3781

Mills, C.W. (1959). *The Sociological Imagination*. Oxford: Oxford University Press.

Molina, M., & Garip, F. (2019). Machine Learning for Sociology. *Annual Review of Sociology*, *45*, 27–45. https://doi.org/10.1146/annurev-soc-073117-041106

Moretti, F. (2013). *Distant Reading*. London: Verso.

Motoki, F., Neto, V.P., & Rodrigues, V. (2023). More Human than Human: Measuring ChatGPT Political Bias. *Public Choice*, *198*, 3–23. https://doi.org/10.1007/s11127-023-01097-2

Mueller, D.N. (2009). *Clouds, Graphs, and Maps: Distant Reading and Disciplinary Imagination* [Doctoral dissertation, Syracuse University]. https://surface.syr.edu/wp_etd/19/

Nadeem, A., Marjanovic, O., & Abedin, B. (2022). Gender Bias in AI-based Decision-Making Systems: A Systematic Literature Review. *Australasian Journal of Information Systems*, *26*, 1–34. https://doi.org/10.3127/ajis.v26i0.3835

Natale, S., & Guzman, A.L. (2022). Reclaiming the Human in Machine Cultures: Introduction. *Media, Culture & Society*, *44*(4), 627–637. https://doi.org/10.1177/01634437221099614

Natale, S., & Ji, D. (2025). Human-Machine Communication Cultures: Introduction. *Global Media and China*, *10*(4), 417–424. https://doi.org/10.1177/20594364251353382

Neff, G., & Nagy, P. (2025). The Quasi-Domestication of Social Chatbots: The Case of Replika. *New Media & Society*, *27*(10), 5508–5524. https://doi.org/10.1177/14614448251359218

Nelson, L.K. (2020). Computational Grounded Theory: A Methodological Framework. *Sociological Methods and Research*, *49*(1), 3–42. https://doi.org/10.1177/0049124117729703

Niederer, S., & Colombo, C. (2024). *Visual Methods for Digital Research*. Cambridge: Polity.

Novelli, E., Ruggiero, C., & Solaroli, M. (2025). Visual Political Communication of Competing Leadership: Italy's 2024 European Election Campaign on Social Media. *Media and Communication*, *13*. https://doi.org/10.17645/mac.10751

Noble, S.U. (2018). *Algorithms of Oppression: How Search Engines Reinforce Racism*. New York, NY: New York University Press.

Ofosu-Ampong, K. (2024). Artificial Intelligence Research: A Review on Dominant Themes, Methods, Frameworks and Future Research Directions. *Telematics and Informatics Reports*, *14*. https://doi.org/10.1016/j.teler.2024.100127

Olivos, F., & Liu, M. (2024). ChatGPTest: Opportunities and Cautionary Tales of Utilizing AI for Questionnaire Pretesting. *Field Methods*, *37*(4), 277–290. https://doi.org/10.1177/1525822X2412805

Olsson, C., Elhage, N., Nanda, N., Joseph, N., DasSarma, N., Henighan, T., Mann, B., Askell, A., Bai, Y., Chen, A., Conerly, T., Drain, D., Ganguli, D., Hatfield-Dodds, Z., Hernandez, D., Johnston, S., Jones, A., Kernion, J., Lovitt, L., Ndousse, K., Amodei, D., Brown, T., Clark, J., Kaplan, J., McCandlish, S., Olah, C. (2022). *In-context Learning and Induction Heads. Transformer Circuits Thread*, March 8. https://transformer-circuits.pub/2022/in-context-learning-and-induction-heads/

Omena, J.J., Autuori, A., Leite Vasconcelos, E., Subet, M., & Botta, M. (2024). AI Methodology Map: Practical and Theoretical Approach to Engage with GenAI for Digital Methods Research. *Sociologica*, *18*(2), 109–144. https://doi.org/10.6092/issn.1971-8853/19566

Ouyang, L., Wu, J., Jiang, X., Almeida, D., Wainwright, C.L., Mishkin, P., Zhang, C., Agarwal, S., Slama, K., Ray, A., Schulman, J., Hilton, J., Kelton, F., Miller, L., Simens, M., Askell, A., Welinder, P., Christiano, P., Leike, J., & Lowe, R. (2022). Training Language Models to Follow Instructions with Human Feedback. https://doi.org/10.48550/arXiv.2203.02155

Park, J.S., O'Brien, J.C., Cai, C.J., Morris, M.R., Liang, P., & Bernstein, M.S. (2023). Generative Agents: Interactive Simulacra of Human Behavior. In S. Follmer, J. Han, J. Steimle, N. Henry Riche (Eds.), *UIST'23: Annual ACM (Association for Computing Machinery) Symposium on User Interface Software and Technology*, October 2023, San Francisco (CA). https://doi.org/10.48550/arXiv.2304.03442

Pasquale, F. (2020). *New Laws of Robotics: Defending Human Expertise in the Age of AI*. Cambridge, MA: Harvard University Press.

Pasquinelli, M., Alaimo, C., & Gandini, A. (2024). AI at Work: Automation, Distributed Cognition, and Cultural Embeddedness. *Tecnoscienza – Italian Journal of Science and Technology Studies*, *15*(1), 99–131. https://doi.org/10.6092/issn.2038-3460/20010

Perkins, M., & Roe, J. (2024). Generative AI Tools in Academic Research: Applications and Implications for Qualitative and Quantitative Research Methodologies. https://doi.org/10.48550/arXiv.2408.06872

Pilati, F., Munk, A.K., & Venturini, T. (2024). Generative AI for Social Research: Going Native with Artificial Intelligence. *Sociologica*, *18*(2), 1–8. https://doi.org/10.6092/issn.1971-8853/20378

Pilati, F. (2025). *Sociologia Digitale 2.0. Intelligenza artificiale generativa come oggetto e strumento della ricerca sociale.* Milano: Ledizioni.

Pilati, F., & Venturini, T. (2025). The Use of Artificial Intelligence in Counter-Disinformation: A World Wide (Web) Mapping. *Frontiers in Political Science*, *7*. https://doi.org/10.3389/fpos.2025.1517726

Pink, S. (2025). Artificial Intelligence and the Futures Turn: An Anticipatory Infrastructure for Qualitative Methods. *Qualitative Research in Psychology*, 1–20. https://doi.org/10.1080/14780887.2025.2570167

Poell, T. (2025). Three Challenges for Media and Communication Studies in the Age of AI. *Global Media and China*, *10*(4), 526–533. https://doi.org/10.1177/20594364251400619

Presner, T. (2016). The Ethics of the Algorithm: Close and Distance Listening in the Shoah Foundation Visual History Archive. In C. Fogu, W. Kansteiner, & T. Presner (Eds.), *Probing the Ethics of Holocaust Culture* (pp. 175–202). Cambridge, MA: Harvard University Press.

Presner, T. (2024). *Ethics of the Algorithm. Digital Humanities and Holocaust Memory*. Princeton, NJ: Princeton University Press.

Pronzato, R., & Risi, E. (2025). Research on and through Generative AI? An Inevitable Entanglement. *The Lab's Quarterly*, *27*(3). https://doi.org/10.13131/unipi/7b2k-yp40

Punziano, G. (2025). Adaptive Epistemology: Embracing Generative AI as a Paradigm Shift in Social Science. *Societies*, *15*(7), 205. https://doi.org/10.3390/soc15070205

Rama, I., & Airoldi, M. (2025). The Sociocultural Roots of Artificial Conversations: The Taste, Class and Habitus of Generative AI Chatbots. *New Media & Society*, *27*(10), 5546–5567. https://doi.org/10.1177/14614448251338273

Richardson-Walden, V. G., & Makhortykh, M. (2024). Imagining Human-AI Memory Symbiosis: How Re-Remembering the History of Artificial Intelligence Can Inform the Future of Collective Memory. *Memory Studies Review*, *1*(2), 323–342. https://doi.org/10.1163/29498902-202400016

Rogers, R. (2013). *Digital Methods*. Cambridge, MA: MIT Press.

Roland, E., So, R., & Long, H. (2025). The Social AI Author: Modeling Creativity and Distinction in Simulated Cultural Fields. *AI & Society*, *41*, 4333–4347. https://doi.org/10.1007/s00146-025-02790-0

Rombach, R., Blattmann, A., Lorenz, D., Esser, P., & Ommer, B. (2021). High-resolution Image Synthesis with Latent Diffusion Models. *CVPR: Conference on Computer Vision and Pattern Recognition*, June 2021, New Orleans (LA), IEEE/CVF, 2022. https://doi.org/10.48550/arXiv.2112.10752

Rossi, L., Harrison, K., & Shklovski, I. (2024). The Problems of LLM-generated Data in Social Science Research. *Sociologica*, *18*(2), 145–168. https://doi.org/10.6092/issn.1971-8853/19576

Salah, M., Abdelfattah, F., Al Halbusi, H., Jassem, S., Mohammed, M., Ismail, M.M., & Al Balghouni, A. (2024). Can Generative AI Craft Scale Items? A Mixed-Method Study on AI's Capability to Adapt and Create New Scales with Recommendations for Best Practices. *Social Sciences & Humanities Open*, *12*. https://doi.org/10.1016/j.ssaho.2025.101698

Salganik, M.J. (2017). *Bit by Bit: Social Research in the Digital Age*. Princeton, NJ: Princeton University Press.

Schneider, M., & Hagendorff, T. (2025). Investigating Toxicity and Bias in Stable Diffusion Text-to-Image Models. *Scientific Reports*, *15*. https://doi.org/10.1038/s41598-025-12032-4

Schroeder, H., Roy, D., & Kabbara, J. (2025). Just Put a Human in the Loop? Investigating LLM-Assisted Annotation for Subjective Tasks. In W. Che, J. Nabende, E. Shutova, & M.T. Pilehvar (Eds.), *Annual Meeting of the Association for Computational Linguistics*, August 2025, Vienna. https://doi.org/10.18653/v1/2025.findings-acl.1323

Schuh, J. (2024). AI as Artificial Memory: A Global Reconfiguration of Our Collective Memory Practices? *Memory Studies Review*, *1*(2), 231–255. https://doi.org/10.1163/29498902-202400012

Schulz-Schaeffer, I. (2025). Why Generative AI is Different from Designed Technology Regarding Task-relatedness, User Interaction, and Agency. *Big Data & Society*, *12*(3). https://doi.org/10.1177/20539517251367452

Shur-Ofry, M., & Pessach, G. (2020). Robotic Collective Memory. *Washington University Law Review*, *97*(3), 975–1005. https://doi.org/10.2139/ssrn.3364008

Smit, R., Smits, T., & Merrill, S. (2024). Stochastic Remembering and Distributed Mnemonic Agency. Recalling Twentieth Century Activists with ChatGPT, *Memory Studies Review*, *1*(2), 209–230. https://doi.org/10.1163/29498902-202400015

Smits, T., Warner, B., Fyfe, P., & Lee, B.C.G. (2025). A Fully-Searchable Multimodal Dataset of the Illustrated London News, 1842–1890. *Journal of Open Humanities Data*, *11*(1). https://doi.org/10.5334/johd.284

Stark, D. (2022). Questioning Humans versus Machines: Artificial Intelligence in Class Conflict. *Administrative Science Quarterly*, *67*(3), 42–46. https://doi.org/10.1177/00018392221095682

Stark, D., & Vanden Broeck, P. (2024). Principles of Algorithmic Management. *Organization Theory*, *5*(2). https://doi.org/10.1177/26317877241257213

Stoltz, D.S., & Taylor, M.A. (2019). Concept Mover's Distance: Measuring Concept Engagement via Word Embeddings in Texts. *Journal of Computational Social Science*, *2*, 293–313. https://doi.org/10.1007/s42001-019-00048-6

Symons, J., & Abumusab, S. (2024). Social Agency for Artifacts: Chatbots and the Ethics of Artificial Intelligence. *Digital Society*, *3*(2). https://doi.org/10.1007/s44206-023-00086-8

Than, N., Fan, L., Law, T., Nelson, L.K., & McCall, L. (2025). Updating "the Future of Coding": Qualitative Coding with Generative Large Language Models. *Sociological Methods and Research*, *54*(3), 849–888. https://doi.org/10.1177/00491241251339188

Törnberg, P. (2023). How to Use LLMs for Text Analysis. https://doi.org/10.48550/arXiv.2307.13106

Törnberg, P. (2024). Best Practices for Text Annotation with Large Language Models. *Sociologica*, *18*(2), 67–85. https://doi.org/10.6092/issn.1971-8853/19461

Tubaro, P. (2025). Sociology of AI, Sociology with AI (1). *Data Big and Small*, November 16. https://databigandsmall.com/2025/11/16/sociology-of-ai-sociology-with-ai-1/

Tubaro, P., Casilli, A.A., & Coville, M. (2020). The Trainer, the Verifier, the Imitator: Three Ways in Which Human Platform Workers Support Artificial Intelligence. *Big Data & Society*, *7*(1). https://doi.org/10.1177/2053951720919776

Vallejo Vera, S., & Driggers, H. (2025). Bias in LLMs as Annotators: The Effect of Party Cues on Labelling Decisions by Large Language Models. *Humanities and Social Sciences Communications*, *12*. https://doi.org/10.48550/arXiv.2408.15895

Venturini, T. (2023). Bruno Latour and Artificial Intelligence. *Tecnoscienza – Italian Journal of Science and Technology Studies*, *14*(2), 101–114. https://doi.org/10.6092/issn.2038-3460/18359

Venturini, T. (2026). The Vanishing Micro/Macro Divide and the Politics of Computational Interactionism. In A. Koed Madsen & A.K. Munk (Eds.), *Handbook of Digital and Computational SSH*. Cheltenham: Edward Elgar.

Venturini, T., & Latour, B. (2010). The Social Fabric: Digital Traces and Quali-quantitative Methods. In *Proceedings of Future en Seine 2009* (pp. 87–101). Paris: Editions Future en Seine.

Venturini, T., & Rogers, R. (2025). *Digital Methods: A Short Introduction*. Cambridge: Polity.

Vicinanza, P., Goldberg, A., & Srivastava, S.B. (2023). A Deep-learning Model of Prescient Ideas Demonstrates that They Emerge from the Periphery. *PNAS Nexus*, *2*(1). https://doi.org/10.1093/pnasnexus/pgac275

Wei, J., Bosma, M., Zhao, V.Y., Guu, K., Yu, A.W., Lester, B., Du, N., Dai, A.M., & Le, Q.V. (2022). Finetuned Language Models are Zero-shot Learners. https://doi.org/10.48550/arXiv.2109.01652

Ziems, C., Held, W., Shaikh, O., Chen, J., Zhang, Z., & Yang, D. (2024). Can Large Language Models Transform Computational Social Science? *Computational Linguistics*, *50*(1), 237–291. https://doi.org/10.1162/coli_a_00502

Marco Solaroli – Department of the Arts, University of Bologna (Italy)
https://orcid.org/0000-0001-5433-1540 | marco.solaroli@unibo.it
https://www.unibo.it/faculty/marco.solaroli
Marco Solaroli is an Associate Professor of Sociology of Culture and Communication in the Department of the Arts at the University of Bologna. He studies cultural production, innovation, valuation, and consecration in relation to the digital transformation of media and culture. His current research projects deal with news photography and global crises; social media images and political power; generative AI and visual memory.

Emma Garzonio – Department of Philosophy, Communication and Performing Arts, Roma Tre University (Italy)
https://orcid.org/0000-0001-7047-9289
https://phd.uniroma1.it/web/EMMA-GARZONIO_nT1419310_IT.aspx
Emma Garzonio is a Research fellow in the Department of Philosophy, Communication and Performing Arts at Roma Tre University (Italy). Her research interests focus on the sociology of media, political communication, AI, and digital visual culture.