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# From Research Tool to Epistemic Actor: Artificial Intelligence as Co-Producer of Social Knowledge

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**Abstract**

This contribution examines the role of artificial intelligence technologies in the co-construction of social reality, with specific attention to AI-generated data as emergent agents of knowledge production. Building on perspectives from science and technology studies and recent debates on algomorphic sociology, the contribution conceptualizes generative AI systems not as research instruments, but as active participants in epistemic processes. The analysis argues that AI-generated data exhibit a performative character: they do not simply represent social phenomena but actively contribute to their stabilization, classification, and circulation. This performativity fosters a shift from researcher-centered interpretation toward hybrid configurations in which meaning emerges through human–machine assemblages. Through a theoretical synthesis of recent methodological and epistemological reflections, the contribution highlights a transition from anthropocentric models of knowledge production to post-anthropocentric, relational frameworks in which agency, cognition, and sense-making are distributed across sociotechnical networks. The contribution concludes by outlining the implications of this shift for the future of digital social research and also for reflexivity, methodological design, and the ethics of social research, advocating a critical and adaptive stance toward AI as a co-producer of knowledge rather than a subordinate analytical tool.

**Keywords:** AI; social research; social knowledge; methodology

## 1. Introduction

The entry of Generative Artificial Intelligence (GenAI) into the field of social research does not merely represent the adoption of a new family of computational tools. Rather, it signals a deeper transformation, one that simultaneously affects the ontological, epistemological, and methodological dimensions of the social sciences. What is changing, in our opinion, is not only the way researchers collect, process, and interpret information, but the framework within which the objects and processes of social research are defined [1–4].

From this perspective, Generative Artificial Intelligence cannot be understood solely as a technical innovation. It should be interpreted as an active component of a broader sociotechnical reconfiguration of knowledge [5], in which platforms, language models, digital infrastructures, big data [6,7], prompting practices, and research environments all participate in the construction of sociological knowledge.

Human–machine assemblages are not, of course, specific to Generative Artificial Intelligence; technologies have long participated in the organization of human action,

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perception, and knowledge. What changes with generative systems is the degree and mode of their participation in epistemic work. GenAI does not merely mediate access to information or automate predefined operations: through iterative interaction, it produces semantically organized and context-responsive outputs that intercede in classification, synthesis, hypothesis generation, and the formulation of interpretations. The novelty therefore lies not in the existence of human–machine relations as such, but in the incorporation of generative models into the internal chain through which social-scientific evidence is produced and made intelligible.

The literature on this topic indicates that social research is entering a transitional phase rather than a fully consolidated paradigm [8]. In the post-digital age, in fact, traditional paradigms are no longer sufficient to describe forms of knowledge production that have become structurally hybrid, emergent, and reflexive [9]. Moreover, every methodological use of generative systems points back to their conditions of production, the logics governing their operation, and the regimes of visibility that shape their outputs [1]. Finally, algorithmic systems must therefore be examined as emergent co-actors endowed with relational forms of agency [10] capable of influencing subjectivities, interactions, and structures of power [11].

Recent sociological and methodological debate reinforces this point. For example, Davidson [12] has shown that generative AI should be situated within sociological research not only as a tool for text production, but as a methodological environment that can intervene across qualitative, computational, and experimental designs. In a similar way, Davidson and Karell [13] argue that the incorporation of generative AI into social science research requires explicit attention to measurement, prompting, and simulation, since each of these dimensions affects how evidence is produced, stabilized, and made comparable. These contributions are important because they suggest that the problem is not simply whether AI can assist research, but under what conditions its outputs can be treated as analytically meaningful within sociological inquiry.

At the same time, this transformation should not be assumed to be homogeneous across the discipline. Alvero et al. [14] suggest that the epistemic shift is still uneven and contested: methodological experimentation coexists with skepticism, limited delegation of interpretive authority, and persistent concerns about validity, accountability, and professional control.

Starting from these premises, this article advances an analytical argument according to which GenAI, and in particular the data it produces, should be understood not merely as an object or tool of social research, but as an emergent agent of epistemic production. AI-generated data should not be read as simple representations of already-given social phenomena; rather, they contribute to stabilizing, classifying, ordering, and rendering those phenomena socially intelligible according to specific model-dependent logics. Their character is therefore performative, insofar as they participate in the institution of social reality. Social research methodology is consequently confronted with a double task: to analyze the social construction of these technologies and to redesign its own procedures because generative systems intervene directly in the production of knowledge.

The original contribution of the article is therefore organized around a three-dimensional analytical framework. First, GenAI is treated as a sociotechnical assemblage whose outputs condense data infrastructures, labor, institutional interests, platform logics, and cultural imaginaries. Second, AI-generated data are conceptualized as performative data because they classify, textualize, and circulate representations of the social. Third, the article derives methodological rules for incorporating such outputs into empirical research without conflating machine fluency with scientific validity.

In this article, the term post-anthropocentric does not imply an equivalence between human and machine agency, nor the displacement of the researcher. Rather, it refers to an analytical decentering of the human as the exclusive locus of epistemic agency, recognizing that classification, synthesis, and meaning-making are distributed across researchers, models, datasets, interfaces, infrastructures, and institutional settings. This definition structures the argument developed in the following sections: the sociotechnical assemblage perspective specifies the distributed conditions of knowledge production; the notion of performative data identifies the epistemic effects of machine-generated outputs; and the methodological discussion reaffirms human accountability through documentation, validation, triangulation, and reflexivity.

This framework also implies a transformation in the epistemic position of the researcher. The researcher can no longer be represented as an external observer who independently collects data and subsequently assigns meaning to them. When generative systems participate in classification, synthesis, textualization, and interpretation, knowledge emerges through a distributed process involving researchers, models, datasets, interfaces, and institutional conditions. The researcher therefore becomes a reflexive co-producer of knowledge: not one agent among others in an undifferentiated sense, but the actor responsible for designing, contextualizing, validating, and critically assessing the sociotechnical mediations through which evidence is produced.

## 2. From the Social Construction of Reality to the Social Construction of Technology

In our view, an unquestionably fundamental starting point for addressing Generative Artificial Intelligence sociologically is social constructivism. In Berger and Luckmann, social reality is the product of historical processes of externalization, objectivation, and internalization [15]. Institutions are not natural facts, but sedimented configurations of meaning that impose themselves upon actors as objective reality. When transposed to the field of Artificial Intelligence, this thesis allows us to avoid any naturalization of technology: AI systems are not, in themselves, autonomous or necessary entities, but rather the outcome of social processes of problem definition, solution stabilization, normative sedimentation, and cultural legitimation.

Generative Artificial Intelligence thus appears as a technical institution in the process of consolidation. Discursively, it is constructed as a promise of efficiency, creativity, personalization, and cognitive support; materially, as an infrastructure of computation, data, human labor, and capital; symbolically, as a form of "intelligence" capable of accompanying, or even replacing, human practices of writing, analysis, and decision-making [16].

What presents itself as neutral automatism is instead the result of historically situated choices, moral economies, and relations of power [17]. This reading is consistent with what emerges in some works [1,2], who respectively insist on the socio-technical nature of generative platforms and on the embeddedness of artifacts within their epistemic and ideological horizon.

The constructivist perspective gains further depth when integrated with science and technology studies [18]. These theoretical traditions insist that technologies should not be treated as variables external to society, but rather as the outcomes of controversies, translations, assemblages, and forms of co-evolution between the human and the non-human. Reference to Latour [19–21], Callon and Law [22], as well as to Winner [23], Suchman [24], Pickering [25], and Jasanoff [26], allows Artificial Intelligence to be read as part of heterogeneous networks in which materials, codes, institutions, imaginaries, regulations, and practices are intertwined. From this perspective, artifacts are never mere means: they carry with them a politics, an embedded normativity, and a specific regime of action.

Classical formulations of the social construction of technology, together with Latour's work [19], foreground the way technical artifacts contribute to shaping social orders rather than merely serving them. GenAI is therefore located within a double movement: it is socially constructed, yet it also participates in constructing the social reality that researchers subsequently observe and analyze.

A further implication of this constructivist argument concerns the infrastructural form through which epistemic power is increasingly exercised. As Ozturkcan [27] argues in her discussion of «zero-click AI», contemporary generative systems do not simply mediate access to knowledge, but they reorganize credibility, visibility, provenance, and authorship by returning synthesized answers directly within platform interfaces. In this sense, the question is not only whether AI acts within epistemic processes, but also how platformized generative systems become digital knowledge infrastructures that redistribute attribution and shape what can be recognized as relevant, legitimate, and citable knowledge.

## 3. Generative AI as a Sociotechnical Assemblage

Within the theoretical framework just outlined, one of the most interesting contributions is that reconstructed by Pronzato and Risi [1], who shows in their analysis that the apparently simple and dialogical surface of Generative Artificial Intelligence platforms actually conceals highly complex processes: massive datasets, models trained on large corpora, often invisible human labor, monopolized cloud infrastructures, filtering rules, extractive economies, and corporate narratives. In this sense, the conversational interface tends to produce an effect of naturalization, whereby the user has the impression of interacting with a coherent, fluid, and almost intentional "assistant". Yet this immediacy is, in reality, the result of strong socio-technical mediation. Indeed, the artifact takes the form of an interactive relation only after a long chain of labor, data extraction, and technical translation has been concealed.

This point refers directly to Crawford [28] and to the critique of the political, environmental, and planetary costs of Artificial Intelligence, but also to Pasquinelli and Joler [29], who define AI as an instrument of «knowledge extractivism». Drawing on these claims, it becomes necessary to emphasize that generative technologies do not produce content out of nothing; rather, they rework, compress, and reuse pre-existing material according to probabilistic and infra-systemic logics that depend on vast processes of extraction and ordering. From a strictly sociological standpoint, this implies that any generated output is already the condensation of social relations, inequalities, linguistic hierarchies, and cultural selections [30–32].

On these grounds, Airoldi's reflection and his notion of «machine habitus» [33] become central, since they allow us to think of algorithms not as simple applications of rules, but as systems that incorporate operational dispositions [34,35], hierarchies of relevance, statistical expectations, and sedimented forms of classification. From this perspective, the generative system is not neutral with respect to the content it produces; rather, content derives from the dynamic encounter between the adaptive model and the context of the data. In continuity with the perspective of Berger and Luckmann, it follows that the research relationship with Generative Artificial Intelligence never concerns a mere tool, but rather a configuration of technically encoded and socially constructed dispositions.

Interaction with such systems, moreover, is itself always socially mediated. References to Lomborg and Kapsch [36], Bonini and Trerè [37], Bucher [38,39], and Ytre-Arne and Moe [40] show how users develop moral economies and algorithmic imaginaries that guide practices of appropriation. In this sense, Artificial Intelligence does not enter everyday life as a transparent object, but as an interpreted, negotiated, and evaluated artifact [41–45][1].

## 4. From Platform Society to the Post-Digital Condition

The expression "post-digital" does not refer to the overcoming of the digital, but rather to its full integration into the infrastructures of social life [46], to the point that the separation between online and offline, technology and society, the human and the digital environment becomes increasingly implausible [47].

In this context, social research no longer operates upon stable and separate objects, but rather within mediated, fluid, and opaque worlds in which data, devices, platforms, and subjects co-evolve. In this regard, Couldry and Hepp speak of the «mediated construction of reality» [48], Van Dijck, Poell, and de Waal of the «platform society» [49], and Srnicek of «platform capitalism» [50]. In any case, all of these references converge in describing a social order in which the power to organize access, visibility, and participation is increasingly entrusted to proprietary digital infrastructures.

Within this framework, Generative Artificial Intelligence represents a further threshold. If platforms previously organized primarily the distribution, ranking, and recommendation of content, generative systems intervene directly in textual, visual, and discursive production. Their methodological centrality is therefore more pronounced, because they do not merely return digital traces; they generate new discursive material that may enter the research process as data, evidence, coding support, or interpretive suggestion.

The epistemological question consequently becomes unavoidable: when the system produces the text that the researcher analyzes, synthesizes, or uses as an aid to coding, what are the conditions of validity of that material? Where does the researcher's interpretive work end, and where does machine-mediated pre-interpretation begin?

To address these methodological questions, it is useful to refer to Rogers's notion of «natively digital data» [51], developed to indicate data that originate within digital environments and bear the imprint of the platforms through which they circulate. However, although this notion is undoubtedly useful, in the present author's view contemporary reflection must take a further step.

At this point, however, it becomes necessary to specify more analytically what is meant by AI-generated data. The category should include at least four distinct forms: (1) outputs directly generated by the model in response to a prompt; (2) classifications, labels, or summaries produced by the model on previously collected empirical materials; (3) synthetic data generated for simulation, augmentation, or testing purposes; (4) multimodal outputs that combine textual, visual, and other semiotic formats. Recent work has shown that these forms cannot be treated as epistemologically equivalent, because they involve different degrees of mediation, reproducibility, and inferential risk [13–42,46–52]. For social research, the consequence is that the methodological status of generated material must be specified each time, rather than assumed in generic terms.

AI-generated data, in this sense, are not merely natively digital: they are generative data, that is, data produced through probabilistic processes that do not simply record traces but synthesize, combine, and reformulate pre-existing material according to criteria internal to the algorithmic model. This gives rise to a specific epistemic quality, because such data are already analytically processed, already oriented, already filtered through a "grammar" embedded in the system.

This shift is decisive for social research methodology. The researcher is no longer dealing only with evidence collected from the social world, but also with materials that stand halfway between data, inference, and writing. The classical separation between observation, analysis, and interpretation is therefore weakened, because generated data are at once a technical output, a form of pre-analysis, an interpretive suggestion, and a classificatory device, within a context of growing "adaptive epistemology" [9].

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## 5. AI-Generated Data and Epistemic Performativity

Digital sociology [53] had already called into question the idea of data as simple registration. Boyd and Crawford [7], Marres [54], Halford and Savage [55], Ruppert et al. [56], Savage and Burrows [57], in fact, had shown that digital traces are selective, partial, situated, and performative.

Generative Artificial Intelligence radicalizes this issue. AI-generated data are not merely residues of social action captured by an infrastructure; they are produced by systems that actively intervene in the ordering of material, semantic synthesis, and generation of plausible formulations. They therefore do not simply describe the social, but contribute to producing a specific intelligibility of the social.

Recent scholarship has extended this performative understanding from digital traces to AI-generated outputs [58]. In this perspective, performativity does not imply that the model acts autonomously or intentionally. Rather, it refers to the capacity of generated outputs to enter subsequent chains of interpretation and action: they select and organize semantic associations, stabilize categories through linguistically persuasive formulations, and circulate representations that may subsequently be reused as evidence, labels, hypotheses, or interpretive frameworks. AI-generated data are therefore performative insofar as they contribute to configuring the objects, categories, and relations that social research subsequently observes and analyzes.

To make this contribution more analytically distinguishable, the performativity of generative data [59] appears to manifest itself in at least three ways:

(1) at the classificatory level, because the system proposes categories, groupings, thematic clusters, and semantic relations that orient the subsequent work of analysis;
(2) at the discursive level, insofar as the output is returned in an ordered linguistic form that tends to naturalize its own argumentative structure;
(3) at the circulatory level, because generated content is easily reusable, translatable, and shareable, and therefore tends to stabilize itself as a credible representation of the phenomenon under analysis.

The three mechanisms should be understood as an analytical framework rather than as a typology of separate effects. In empirical practice, classificatory, discursive, and circulatory performativity often operate together: a model classifies material, expresses that classification in persuasive language, and enables the resulting formulation to circulate as an apparently stabilized interpretation. This is precisely why the epistemic status of AI-generated data must be defined before they are incorporated into sociological analysis.

The point of discursive level, in particular, has become evident in recent studies on LLM-based annotation and text classification. Lin and Zhang [60], for example, show that the adoption of large language models in annotation tasks may improve speed and scale, but simultaneously introduces problems of validity, reliability, replicability, and transparency that cannot be resolved by the apparent fluency of the output alone. For this reason, the distinction between heuristic assistance and delegated interpretation must remain explicit: a model may function as a coding assistant, as a generator of candidate labels, or as a provisional classifier, yet each of these uses implies different thresholds of epistemic control.

At the circulatory level, instead, recent reflection on factuality further strengthens the point. Dierickx et al. [61], for example, approaching generative AI through the lens of «fact-checking», argue that GenAI reshapes factuality by producing what they call emergent facts: outputs whose credibility depends less on direct source transparency than on synthetic plausibility, interface authority, and downstream verification practices. For social research, this is highly relevant because it shows that generated material may circulate as cognitively stabilized knowledge even when its evidentiary provenance remains opaque or only partially reconstructable.

Within this framework, a fundamental methodological implication emerges, because the researcher may be induced to take as analysis what is, in reality, a probabilistic synthesis made persuasive by its discursive form. It is therefore necessary to distinguish between heuristic power and scientific validity. A generative system may be useful for identifying interpretive pathways, coding alternatives, comparative hypotheses, and classificatory schemes, but this does not grant it the status of a reliable interpreter. Its output must be treated as a contribution to the construction of analysis, not as the conclusive outcome of analysis itself.

## 6. Implications for Social Research Methodology

The discussion developed so far leads to a more operational question: how can social researchers incorporate generative systems without weakening validity, reflexivity, and accountability? The answer is not a generic recommendation to use or avoid AI, but a set of methodological conditions under which AI-generated material can be treated as epistemically relevant.

The following two scenarios illustrate how the proposed framework can be translated into concrete research designs. They are only two examples of the methodological decisions that must be made explicit when GenAI is incorporated into social research.

Scenario 1: survey design. A researcher asks GenAI to draft items measuring trust in automated decision systems. The epistemic risk is that items may reproduce common cultural framings of AI rather than the construct intended by the researcher. The required control procedure is to subject generated items to theoretical review, cognitive pretesting, and conventional validation procedures.

Scenario 2: literature synthesis. A researcher uses GenAI to map debates on algorithmic governance before constructing a theoretical argument. The epistemic risk is that the system may privilege visible or highly cited literature while obscuring provenance and exclusions. The required control procedure is to verify sources manually, reconstruct the search strategy, and distinguish heuristic mapping from systematic review.

These scenarios clarify that methodological control does not depend on excluding AI from research, but on specifying its position in the chain of evidence. This repositioning also changes the researcher's role within the research process. Rather than exercising interpretive authority only at the final stage of analysis, the researcher must intervene reflexively throughout the human–machine interaction: in defining the task, constructing and revising prompts, selecting or rejecting outputs, verifying sources and classifications, documenting model-related decisions, and comparing machine-generated formulations with empirical and theoretical materials. Co-production therefore does not imply the delegation of epistemic responsibility. On the contrary, it expands the researcher's responsibility from the interpretation of data to the governance of the sociotechnical conditions under which data, categories, and inferences are generated. In each case, the decisive question is whether the generated output is treated as data, as analytic support, as simulation, or as an object of sociological analysis. Different uses require different standards of disclosure, validation, and triangulation.

The discussion developed in the paper also leads us to consider a wide range of methodological implications for social research, in both quantitative and qualitative terms.

Abdurahman et al. [62] argue that research using LLMs[2] should be evaluated in terms of task appropriateness, model instability, prompt sensitivity, and reporting transparency. From this perspective, validity can no longer be reduced to correspondence between indicator and phenomenon, but must also include the conditions under which the model was queried, the degree of output variability across iterations, and the procedures

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adopted to verify or contest machine-generated inferences. Validity, in other words, becomes inseparable from the documentation of sociotechnical mediation.

An analogous concern emerges in qualitative research. Jones [63] notes that existing reporting standards were developed before the current wave of generative AI and therefore do not adequately capture the hidden decision points introduced by prompting, output selection, and iterative interaction with black-box systems. His proposal of a «disclosure heuristic» centred on the research team, participant interaction, study design, data practices, and data analysis is particularly relevant here, because it offers a concrete way of translating reflexivity into reporting practice. Alongside this, Messner et al. [64] warn that the accelerated use of AI in qualitative data analysis may generate epistemological incongruences whenever interpretive depth is replaced by procedural fluency. Taken together, these contributions suggest that triangulation must be accompanied by systematic disclosure of how the machine entered the analytic chain.

This problem also extends beyond reporting standards narrowly understood. Bareither and Griessl [65], on the basis of an ethnographic study in the qualitative social sciences and humanities, argue that GenAI gives rise to hybrid epistemic practices and to a condition of epistemic messiness in which epistemic relations are simultaneously strengthened and weakened. Their contribution is useful because it shows that the integration of generative systems does not only affect validity and transparency at the technical level, but also transforms academic routines, trust relations, perceptions of deskilling, and the normative boundaries of what counts as good scholarly practice.

In this scenario, in our opinion, other three methodological implications require explicit development.

The first one concerns research design. In the presence of generative systems, the methodological protocol can no longer be limited to defining the sample, data collection techniques, analytical procedures, and theoretical frameworks. It must also describe the generative environment used: model, version, access modality, prompting logic, iteration criteria, temperature or equivalent parameters when available, output selection procedures, and the relationship between original and generated material. The use of AI should therefore enter the definition of research design, not only its execution phase[3].

The second implication concerns validity. In classical paradigms, validity was often conceived in terms of correspondence, internal coherence, theoretical saturation, and replicability [66]. Today, an additional level must be added: validity as sociotechnical mediation. Researchers must account for how the system contributed to producing the data or inference, clarifying how the machine oriented categories, summaries, labels, or textual forms. Transparency therefore concerns not only the researcher, but the interaction between researcher and algorithmic system: prompts, modifications, output selection criteria, and verification procedures must be documented.

The third implication, as already mentioned, concerns triangulation [67]. In a context where generative data are intrinsically performative, triangulation is no longer merely a strategy of reinforcement, but a necessity of epistemic control. Generative Artificial Intelligence outputs should be systematically compared with heterogeneous sources such as original empirical documentation, human coding, conventional statistical procedures, and theoretical analysis. This brings adaptive epistemology closer to the tradition of mixed-methods [68–70], but in a new form: not simply the integration of qualitative and quantitative techniques, but the integration of sources, cognitive agents, and levels of mediation.

In this sense, the posture of «critical optimism» proposed by Amaturo and Aragona [4] remains useful. The authors, in fact, invite us to avoid both enthusiastic determinism and methodological catastrophism: digital methods must be experimented with, but critically integrated with the consolidated repertoires of social research, especially in an era marked by the strong pervasiveness of Artificial Intelligence tools.

## 7. Conclusions: Toward a Critical and Adaptive Methodology of Social Research with AI

Building on the methodological and operational proposals discussed above, the article formulates “six operational principles” for a critical and adaptive methodology of social research with AI. These principles translate the proposed framework into practical requirements:

(1) principle of explicitation: the use of Generative Artificial Intelligence (GenAI) must be described as an integral part of the research design, specifying where it intervenes in the empirical and analytical chain;
(2) principle of documentation: prompts, model settings, iterations, selections, verifications, and rejected outputs should be preserved and, when ethically and legally possible, made open to scrutiny within the scientific community;
(3) principle of triangulation: generative output should not be assumed to be self-sufficient, but compared with original empirical materials, human interpretation, and alternative analytical procedures;
(4) principle of reflexivity: the researcher must interrogate not only their own categories, but also the epistemic infrastructures that make the output possible;
(5) principle of ethical responsibility: bias, opacity, and asymmetries of power must be considered constitutive elements of the knowledge process;
(6) principle of methodological integration: Generative Artificial Intelligence can have high heuristic value when inserted into mixed and critically controlled research designs, and not when it replaces human interpretive work.

Recent sociological interventions also suggest, in this framework, that this transformation should be located within a broader redefinition of sociology’s object and vocation. More specifically, the ethical use of GenAI in social research requires explicit safeguards concerning privacy and confidentiality, informed consent, authorship and intellectual property, algorithmic bias, and accountability for machine-assisted outputs and decisions. Baert et al. [71] call for «plural sociologies of generative AI» capable of addressing evidence, authorship, inequality, intellectual property, labour, and identity as interconnected dimensions of the same sociotechnical formation. Likewise, Davis and Sloane [72] propose that contemporary sociology has entered an «AI’s sociological era», that is, a phase in which AI must be treated simultaneously as infrastructure, cultural form, epistemic problem, and domain of stratification. These perspectives reinforce the line of reasoning by showing that the question of AI in social research is not exhausted by methodological innovation, but concerns the reorganization of evidentiary power and of sociology’s own critical gaze.

So, the final question is, in our view, not whether sociology should use Generative Artificial Intelligence, but how it can do so without subordinating its critical autonomy to the dominant technical form. Adaptive epistemology [9], algomorphic sociology [2], and critical optimism [4] converge on one fundamental point: social research must inhabit sociotechnical transformation without being absorbed by it. This requires recognizing AI as a co-producer of knowledge while preserving the specifically sociological work of contextualization, historicization, comparison, and critique.

Within this framework, Generative Artificial Intelligence makes visible a transformation already underway in social research [73]: the end of the illusion that data are entities simply collected and that tools are merely neutral supports of observation. Contemporary sociological knowledge is now co-produced within sociotechnical assemblages in which platforms, models, interfaces, human subjects, prompting practices, and institutional regimes jointly participate in defining what can be observed, classified, and interpreted. GenAI radicalizes this condition, since it does not merely mediate the relationship with the real, but directly generates discursive material that enters into the research process.

For this reason, AI-generated data must be understood as "performative data" that do not merely represent social phenomena, but contributes to their cognitive stabilization and social circulation. In this context, the figure of the researchers also changes: they are no longer configured as the sovereign interpreter of empirical materials, but as a reflexive node within networks of knowledge co-production.

The task of social research methodology, in conclusion, is not to delegate interpretation to the machine, but to build procedures capable of rendering visible, debatable, and controllable the mediations through which the machine participates in interpretation. So, AI should therefore be conceptualized as a co-producer of social knowledge rather than as a subordinate analytical tool, but only within research designs that preserve sociological reflexivity, empirical control, and critical autonomy.

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## Notes

1. This reflection on Domestication of digital technologies is situated within a line of research focused on mobile communication devices, which results are published in some papers and books [43–45].
2. Large Language Models (LLMs) are advanced AI systems based on neural networks trained on massive text datasets to understand, generate, and summarize human language.
3. This applies both to qualitative and quantitative research: in quantitative research, AI can contribute to the generation of synthetic data, the construction of items, the preliminary exploration of patterns, or the simulation of responses, whereas in qualitative research it can support coding, comparison, interview synthesis, and discourse analysis. In both cases, however, the critical issue does not lie in mere technical feasibility, but rather in clarifying the conditions under which such operations produce reliable and scientifically meaningful knowledge.

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