

ARTIFICIAL INTELLIGENCE AND SOCIOLOGY: TOWARD A SOCIOLOGICAL APPROACH TO UNDERSTANDING INTELLIGENT TECHNOLOGIES, INTELLIGENCE ARTIFICIELLE ET SOCIOLOGIE : VERS UNE APPROCHE SOCIOLOGIQUE POUR COMPRENDRE LES TECHNOLOGIES INTELLIGENTES

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ABSTRACT

Artificial intelligence (AI) is often described as a technical capacity to automate prediction, classification, generation, and decision-making. A sociological perspective, however, asks how these capacities are embedded in institutions, social relations, economic interests, cultural meanings, and unequal distributions of power. This article develops a conceptual framework for studying intelligent technologies as socio-technical arrangements rather than autonomous tools. It combines insights from classical sociology, the sociology of technology, critical data studies, and AI ethics to examine five connected processes: datafication, algorithmic classification, institutional delegation, labour reorganisation, and the production of trust and legitimacy.

The article argues that AI does not simply enter a pre-existing society; its design and use reorganise social practices while being shaped by existing hierarchies, infrastructures, and norms. The consequences are therefore neither inherently emancipatory nor inevitably oppressive. They depend on data quality, institutional accountability, user participation, ownership structures, and the capacity of affected communities to contest automated outcomes. A comparative analytical table and a proposed research model identify variables suitable for empirical investigation. The discussion also highlights the relevance of a sociological approach in Arabic-speaking societies, where language representation, uneven digital access, public-sector transformation, and imported technological systems deserve particular attention. The article concludes with research and policy priorities for socially accountable AI, including participatory impact assessment, algorithmic transparency, independent evaluation, and sustained public digital literacy.

Keywords: artificial intelligence; sociology; algorithmic governance; datafication; social inequality; digital society

Résumé:

L'intelligence artificielle (IA) est souvent présentée comme une capacité technique d'automatisation de la prédiction, de la classification, de la génération de contenus et de la prise de décision. Une approche sociologique

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interroge toutefois l'inscription de ces capacités dans les institutions, les relations sociales, les intérêts économiques, les significations culturelles et les inégalités de pouvoir. Cet article propose un cadre conceptuel qui considère les technologies intelligentes comme des dispositifs sociotechniques plutôt que comme de simples outils autonomes. Il mobilise la sociologie classique, la sociologie des techniques, les études critiques des données et l'éthique de l'IA afin d'analyser cinq processus liés : la mise en données, la classification algorithmique, la délégation institutionnelle, la réorganisation du travail et la production de la confiance et de la légitimité.

L'argument central est que l'IA ne s'intègre pas dans une société immuable : sa conception et ses usages transforment les pratiques sociales tout en étant façonnés par les hiérarchies, les infrastructures et les normes existantes. Ses effets ne sont donc ni nécessairement émancipateurs ni automatiquement oppressifs. Ils dépendent notamment de la qualité des données, de la responsabilité institutionnelle, de la participation des usagers et de la possibilité de contester les décisions automatisées. L'article propose un tableau analytique et un modèle de recherche empirique, en soulignant l'importance des langues, des inégalités d'accès au numérique et de la transformation des services publics dans les sociétés arabophones. Il conclut par des priorités de recherche et d'action publique en faveur d'une IA socialement responsable.

Mots-clés: intelligence artificielle ; sociologie ; gouvernance algorithmique ; mise en données ; inégalités sociales ; société numérique

1. INTRODUCTION

Artificial intelligence has moved from specialist laboratories into ordinary social environments. Recommendation systems shape what people see; automated tools support recruitment and credit assessment; generative systems assist writing and translation; and public institutions increasingly explore data-driven services. These developments are not only technical innovations. They also alter how people encounter institutions, how organisations distribute opportunities, how expertise is recognised, and how social categories are reproduced. The central sociological question is therefore not simply what AI can do, but what happens when its capabilities become embedded in everyday relations and institutional routines.

A sociological approach treats intelligent technologies as products of collective choices, organisational priorities, historical inequalities, and cultural assumptions. Algorithms are built from data generated under particular social conditions; their outputs are interpreted by people and institutions; and their consequences vary across groups. Critical work on surveillance capitalism and data colonialism shows how data extraction may become a source of economic power, while ethical frameworks stress human dignity, fairness, transparency, and accountability. The challenge is to connect these macro-level structures with the lived experiences of workers, students, citizens, and communities.

1.1 Background and rationale

The rapid spread of AI has created a gap between technical adoption and social understanding. Public discussion frequently oscillates between technological optimism—where AI is expected to improve productivity and access—and technological determinism—where social change appears unavoidable. Sociology offers a third path: investigate the institutions, interests, practices, and power relations through which technologies are designed, adopted, resisted, and normalised. This approach also makes it possible to examine differences between contexts instead of assuming that findings from highly digitised economies apply universally.

1.2 Significance of the study

The study is significant in three ways. Theoretically, it connects classical sociological concerns—social order, authority, inequality, labour, and interaction—to contemporary algorithmic systems. Analytically, it proposes a framework that links design choices to institutional practices and social outcomes. Practically, it identifies questions that public agencies, universities, employers, and civil-society organisations can use when evaluating AI deployments. Its relevance is particularly clear in settings where digital services are expanding while data governance, local-language resources, public understanding, and independent evaluation may develop unevenly.

1.3 Research problem

How can sociology explain the ways in which artificial intelligence reshapes social relations, institutions, and inequalities, while also recognising that AI systems are themselves shaped by existing social structures?

1.4 Sub-questions

- Which sociological concepts best explain the relationship between AI systems and social structure?
- Through what mechanisms can AI reproduce, intensify, or sometimes reduce social inequalities?
- How do algorithmic systems transform authority, professional judgement, labour, and everyday interaction?
- What methodological approaches can make AI's social effects observable and contestable?
- What principles should guide socially accountable AI in public and private institutions?

1.5 Objectives

- To conceptualise AI as a socio-technical arrangement rather than a neutral instrument.
- To synthesise sociological perspectives relevant to datafication, classification, labour, power, and trust.
- To identify mechanisms linking algorithmic design to unequal social outcomes.
- To propose an analytical model and a set of empirical questions for future research.
- To formulate recommendations for accountable and context-sensitive AI governance.

1.6 Methodology

Descriptive method: The descriptive method is used to map key concepts and social settings in which AI is deployed, including education, employment, public administration, language, and digital platforms.

Analytical method: The analytical method is used to separate the AI lifecycle into data collection, classification, deployment, human interpretation, and review. Each stage is examined for assumptions, power relations, possible benefits, and risks.

Comparative method: The comparative method is used conceptually to contrast technical-performance criteria with social criteria such as fairness, accountability, autonomy, representation, and legitimacy. The article does not claim a statistical comparison between countries or institutions.

Critical document and discourse analysis: A critical reading of selected academic and policy documents is used to identify recurring concepts, normative assumptions, and proposed safeguards. The analysis focuses on how documents define trustworthy AI, responsibility, transparency, and social harm.

Synthesis procedure and limitations: The sources are grouped thematically, then synthesised into the process model and the analytical dimensions presented in Figure 1 and Table 1. This is a narrative, theory-guided synthesis rather than a systematic review: no exhaustive database search, preregistered protocol, or formal risk-of-bias scoring was conducted. The conclusions should therefore be treated as a conceptual framework to be tested empirically.

This article uses a qualitative, interpretive, and theory-guided review of selected sociological and interdisciplinary literature. It is a conceptual article, not a report of original fieldwork. The analysis compares theoretical propositions and policy frameworks, then organises them into a process model linking inputs, institutional mediation, and outcomes. The sources include critical data studies, sociology of technology, and international AI ethics guidance. Since the Arabic-language literature is unevenly indexed and some editions are difficult to verify online, any Arabic-language reference should be checked against the exact edition consulted before formal submission.

1.7 Structure of the article

The article is organised into three main sections. Section One establishes the sociological foundations for analysing AI. Section Two examines the social mechanisms and consequences of intelligent technologies. Section Three develops an empirical framework and discusses governance, context, and future research. The conclusion summarises the argument, presents four findings and four recommendations, and identifies future research directions.

2. SOCIOLOGICAL FOUNDATIONS FOR UNDERSTANDING AI

2.1 From technical artefact to socio-technical arrangement

A technical artefact does not operate in isolation. It requires infrastructures, labour, standards, organisational rules, and users who interpret its outputs. The term socio-technical arrangement captures this interdependence. A recruitment model, for example, is not merely code: it depends on decisions about which applicants count as

successful, which historical records are used, which errors are acceptable, and who can challenge a result. The apparent objectivity of a numerical score can conceal these normative choices.¹

The sociology of technology rejects the idea that technological development follows a single inevitable path. Technologies emerge through negotiation among designers, institutions, markets, regulators, and users. Once adopted, they can stabilise particular routines and make alternatives more difficult. AI should thus be studied across its lifecycle: problem definition, data collection, model development, procurement, deployment, monitoring, and retirement. Each stage contains social decisions and unequal capacities to influence them.²

2.2 Classical sociological questions in an algorithmic age

Durkheim's concern with social facts encourages researchers to examine how AI becomes external to individuals and constrains their choices through institutional rules. Weber's analysis of rationalisation illuminates the attraction of calculable, standardised decisions, while also directing attention to the authority of bureaucratic systems and the tension between formal efficiency and substantive judgement. Marxian approaches draw attention to ownership, labour control, commodification, and the distribution of economic gains. These traditions do not provide ready-made answers to every AI problem, but they identify enduring questions: who controls resources, whose knowledge is treated as valid, and how are decisions justified?³

Symbolic interactionism adds a micro-level perspective. People do not merely receive algorithmic classifications; they interpret them, negotiate them, and adapt their conduct in response. A worker may change behaviour to satisfy a performance dashboard, a student may write for a recommendation system, and a citizen may treat an automated answer as more authoritative than a human explanation. Such responses can create feedback loops: the system influences behaviour, and the resulting behaviour becomes new data for the system.

2.3 Power, classification, and the production of social categories

Classification is a core social process. Institutions categorise people as eligible or ineligible, high or low risk, suitable or unsuitable, visible or irrelevant. AI can accelerate classification and apply it at scale, but it does not eliminate the politics of categories. Training data may encode past discrimination, while proxy variables can reproduce social distinctions even when sensitive attributes are excluded. The result may be a system that appears formally neutral while distributing burdens unevenly.⁴

The sociological task is to ask how categories are constructed, what assumptions sustain them, who benefits from their use, and whether affected people can contest them. Researchers should distinguish disparate outcomes from the mechanisms producing them. Unequal outcomes may arise from historical data, unequal measurement, inaccessible appeals, organisational incentives, or the uneven ability of groups to correct their records. This broader account prevents the analysis from reducing social harm to a narrow technical defect.⁵

2.4 Datafication and surveillance

Datafication converts aspects of life into measurable records: clicks, location traces, learning activity, work rhythms, purchases, and social interactions. These records can support useful services, but they can also create asymmetries between those who collect data and those who are observed. Zuboff (2019) describes surveillance capitalism as an economic logic in which personal experience becomes a source of behavioural data and prediction. Couldry and Mejias (2019) extend the analysis through the concept of data colonialism, highlighting how everyday life can be appropriated as a resource.⁶

From a sociological perspective, surveillance is not limited to secret observation. It can become routine through convenience, institutional dependence, or the expectation that digital participation requires data disclosure. People may consent without meaningful understanding, or they may lack realistic alternatives. The issue is therefore not simply whether data collection occurs, but whether it is proportionate, transparent, contestable, and governed in the public interest.

2.5 AI as an institutionally embedded form of rationalisation

Organisations often adopt AI to increase speed, consistency, and scale. Yet efficiency is not a neutral objective: institutions decide which outcomes to optimise and which costs to ignore. A system that reduces processing time may increase appeal burdens; a school tool that predicts performance may narrow expectations; an employer dashboard may make measurable tasks more visible than care, collaboration, or tacit expertise. Sociological evaluation must therefore compare stated goals with the distribution of benefits and burdens.⁷

The distinction between automation and augmentation is also socially consequential. Automation transfers some tasks to a system, whereas augmentation changes the relationship between human judgement and computational recommendations. In practice, the two overlap. Workers may formally retain decision authority while being pressured to follow machine outputs. This phenomenon—sometimes described as automation bias—can weaken accountability if responsibility is unclear. Institutions should specify when human review is meaningful, what expertise reviewers need, and how disagreement with the system is documented.

3. SOCIAL MECHANISMS AND CONSEQUENCES OF INTELLIGENT TECHNOLOGIES

3.1 Inequality, bias, and unequal exposure to risk

AI systems can reproduce inequality through at least four pathways. First, data may underrepresent groups whose lives are less frequently recorded or whose records are unreliable. Second, labels may reflect biased historical decisions. Third, design objectives may privilege institutional convenience over the needs of marginalised users. Fourth, the ability to understand and challenge an outcome is unequally distributed. These pathways can interact, so a technically accurate model may still contribute to an unjust institutional process.⁸

Sociological analysis should avoid treating social groups as internally uniform. Age, gender, class, disability, geography, language, and migration status can intersect to shape exposure to automated decisions. Digital inequality is not only a question of access to devices or broadband; it also includes differences in skills, confidence, language resources, time, and institutional support. People may be connected but unable to influence how digital systems classify them.⁹

At the same time, AI may improve access when carefully designed: translation tools can reduce some language barriers, assistive technologies can support people with disabilities, and decision-support systems may help identify service gaps. The question is not whether AI is good or bad in the abstract. It is which groups benefit, under what conditions, with what safeguards, and compared with which alternative.

3.2 Labour, professional identity, and workplace control

AI changes work through task substitution, task augmentation, monitoring, and the reorganisation of skills. Public debate often focuses on the number of jobs that may disappear, but sociological analysis also examines job quality, autonomy, bargaining power, professional identity, and the distribution of productivity gains. Workers may be expected to manage more cases, respond faster, or accept algorithmic assessments without receiving corresponding increases in pay, training, or decision authority.¹⁰

Professional expertise is particularly affected when institutions treat algorithmic outputs as objective benchmarks. Teachers, doctors, lawyers, public administrators, and researchers may be asked to justify decisions that diverge from a model. This can support reflective practice if systems are transparent and contestable; it can also create deskilling if professional judgement is routinely subordinated. A responsible approach requires worker participation, retraining, clear responsibility, and evaluation of psychosocial effects.¹¹

3.3 Education, knowledge, and the authority of expertise

In education, AI can assist feedback, translation, accessibility, and personalised learning. It can also encourage surveillance of students, reproduce language and cultural biases, or blur the distinction between learning and the production of acceptable outputs. A sociological analysis asks how AI changes relationships among students, teachers, institutions, and knowledge. It examines whether tools widen participation or reinforce advantages held by learners who already possess stronger digital resources.¹²

Generative AI also challenges conventional markers of authorship and expertise. The availability of fluent text can make weakly supported claims appear credible. Educational institutions should therefore teach verification, source evaluation, disclosure of AI assistance, and the limits of automated systems. Rather than treating AI literacy as prompt-writing alone, curricula should include the social history of data, privacy, bias, ownership, and the politics of knowledge production.

3.4 Public administration, citizenship, and algorithmic governance

When public agencies use AI to allocate benefits, detect fraud, prioritise inspections, or answer citizen enquiries, technological design becomes a question of public authority. Administrative decisions affect rights and access to essential services, so efficiency cannot be the only criterion. Citizens need understandable explanations, accessible

appeal procedures, and a clear route to a responsible human authority. Public agencies should also assess whether automated services exclude people who lack stable connectivity, digital skills, or access to supported languages.¹³

Algorithmic governance can shift power away from visible public deliberation toward procurement contracts, technical standards, and data infrastructures. If a public institution cannot explain a vendor's system, its formal responsibility may be weakened in practice. Transparency should therefore cover not only model descriptions but also procurement, data provenance, intended use, known limitations, incident reporting, and the process for suspension or withdrawal.¹⁴

3.5 Culture, language, and social representation

AI systems learn from available digital material, which is unevenly distributed across languages and cultural settings. Languages with extensive digitised corpora and strong commercial incentives may receive better support than languages with fewer resources or greater dialectal diversity. This imbalance can affect translation quality, speech recognition, educational applications, and the visibility of cultural knowledge. Arabic-speaking contexts are internally diverse: Modern Standard Arabic, regional dialects, Amazigh languages, and multilingual practices cannot be reduced to a single linguistic category.¹⁵

The issue is not merely technical coverage. Language determines who can participate, which forms of expression are recognised, and what knowledge is represented as authoritative. Locally grounded datasets, community review, and culturally sensitive evaluation can reduce some problems, but they require investment and governance. Sociologists can contribute by documenting how people adapt systems, where automated language tools fail, and which forms of knowledge remain underrepresented.

3.6 Trust, legitimacy, and human agency

Trust in AI is often discussed as a user attitude, but sociologically it is also an institutional achievement. People are more likely to regard systems as legitimate when procedures are understandable, errors can be corrected, responsibilities are clear, and affected groups have meaningful influence. Trust should not be confused with uncritical acceptance. A healthy system enables informed reliance as well as justified refusal.¹⁶

Human agency is preserved not by inserting a nominal human at the end of an automated pipeline, but by ensuring that people have time, competence, authority, and information to challenge outputs. A reviewer who must process hundreds of recommendations under severe time pressure may have little practical freedom to disagree. Organisational design is therefore central to the meaning of human oversight.¹⁷

3.7 Environmental and infrastructural dimensions

AI depends on physical infrastructures: data centres, electricity, water, minerals, devices, and global supply chains. Its social costs and benefits are unevenly distributed geographically. Some communities receive improved services while others bear extraction, energy demand, or electronic waste. A full sociological account connects digital systems to environmental justice and to the labour conditions behind hardware and data services. Environmental evaluation should consider the scale of a system, its lifecycle, and whether a less resource-intensive method could achieve the same social purpose.¹⁸

4. AN INTEGRATED SOCIOLOGICAL FRAMEWORK FOR AI RESEARCH

4.1 A process model: from social context to social outcomes

The framework proposed here treats AI as a sequence of socially mediated processes rather than a self-contained model. Contextual inequalities and institutional goals shape data collection and system design. Organisations then deploy systems within rules and routines, and people respond through acceptance, adaptation, avoidance, or resistance. These responses generate new data and feedback, potentially reinforcing or correcting the original system. Outcomes should be assessed across distribution, autonomy, accountability, and legitimacy.¹⁹

Figure 1: A sociological process model for analysing AI. Source: Author's conceptual synthesis.

2. ANALYTICAL DIMENSIONS AND OPERATIONAL QUESTIONS

The model can guide case studies in education, employment, public administration, health, and digital platforms. Researchers should specify the unit of analysis—individual interaction, organisation, policy system, or infrastructure—and identify whose experience is being measured. They should also distinguish technical

SOCIAL INPUTS	MEDIATING PROCESSES	SOCIAL OUTCOMES
Existing inequalities Institutional goals Data availability Ownership and regulation	Datafication Algorithmic classification Organisational adoption Human interpretation and appeal	Access and exclusion Autonomy and control Trust and legitimacy Feedback and resistance

performance from social performance: accuracy alone cannot establish fairness, legitimacy, or public value.²⁰

Table 1: Suggested dimensions for empirical sociological assessment. Source: Author’s synthesis.

Dimension	Core question	Possible indicators
Distribution	Who receives benefits and burdens?	Access rates; error rates by group; appeal outcomes
Agency	Can people understand and challenge outputs?	Explanation quality; override rates; time to appeal
Accountability	Who is responsible for failures?	Named owner; audit trail; incident response
Labour	How does AI alter work?	Task change; autonomy; workload; training access
Representation	Whose language and knowledge are included?	Coverage by language; dialect performance; community review
Legitimacy	Do procedures merit public confidence?	User understanding; complaint resolution; perceived procedural fairness
Sustainability	What material costs support the system?	Energy use; lifecycle impact; system necessity

4.3 Research methods: beyond technical audits

No single method captures the full social life of AI. Interviews can reveal how workers and citizens interpret automated decisions; ethnography can show how systems become embedded in routine practice; surveys can measure perceived fairness and digital confidence; document analysis can reconstruct procurement choices and institutional objectives; and quantitative audits can identify disparities in outcomes. Combining methods is particularly valuable because official performance metrics may omit experiences that are difficult to quantify.²¹

Participatory research is important when communities face the consequences of systems they did not design. Affected groups can help define relevant harms, identify inaccessible procedures, and interpret results. Researchers should protect participants from retaliation, avoid collecting unnecessary personal data, and report uncertainty transparently. Where possible, studies should compare AI-supported decisions with existing human procedures rather than assuming that the non-automated alternative is unbiased.

4.4 Comparative and context-sensitive research

Comparative research should avoid ranking societies along a simplistic scale from traditional to modern. Instead, it should examine how legal frameworks, administrative capacity, labour markets, language ecologies, public trust, and digital infrastructure shape AI use. The same tool may have different consequences in a university, a local municipality, and a private company. It may also work differently across regions within one country.²²

For Arabic-speaking societies, a research agenda could examine the accessibility of public digital services, Arabic and dialect performance in generative systems, the role of imported platforms in shaping local information environments, and the experiences of public employees adapting to algorithmic tools. These are proposed lines of inquiry, not claims that all Arab institutions share the same conditions. Country-level evidence and local fieldwork are required before generalisations can be made.

4.5 Ethics and limits of the proposed framework

The framework is conceptual and does not claim to measure the prevalence of AI harms or establish causal effects. Its categories are intended to guide empirical research and institutional reflection. A limitation of the current literature is that commercial systems may be opaque, rapidly changing, and difficult to reproduce. Published case studies may also overrepresent high-income settings and English-language environments. Future research should make its sampling choices explicit and document when evidence is unavailable.²³

Ethical review must address both research participation and the system under study. Researchers should consider privacy, informed consent, group harms, data security, and the possibility that publishing a vulnerability could expose participants. They should also distinguish a system's intended purpose from its actual use, since function creep can alter risk after deployment. Periodic reassessment is essential because models, data, institutional incentives, and user practices change over time.

5. GOVERNANCE AND THE CONDITIONS FOR SOCIALLY ACCOUNTABLE AI

5.1 From principles to enforceable practices

International ethics guidance emphasises human rights, dignity, fairness, transparency, accountability, and sustainability. UNESCO's Recommendation on the Ethics of Artificial Intelligence identifies policy areas that include data governance, education, communication, labour, health, gender, and environmental impacts (UNESCO, 2022). Such principles become meaningful only when translated into institutional responsibilities, review procedures, resources, and remedies.²⁴

A social-impact assessment should begin before procurement or deployment. It should identify affected groups, the decision being supported, plausible harms, alternative approaches, and the evidence needed to monitor outcomes. The assessment should be revisited after significant system changes and when complaints or incidents reveal unanticipated effects. Where a system affects fundamental rights or access to essential services, independent scrutiny and accessible appeal channels are especially important.

5.2 Transparency, explainability, and contestability

Transparency is not equivalent to publishing source code. Different audiences need different forms of explanation: technical auditors require detailed documentation; frontline workers need operational guidance; affected people need clear reasons and a route to correction; and the public needs information about purpose, oversight, and risk. Explanations should be accurate and useful rather than decorative statements that merely repeat a system's recommendation.²⁵

Contestability requires more than a theoretical right to complain. Procedures should be affordable, accessible, timely, and capable of changing an outcome. Institutions should record appeals and overrides, investigate patterns of error, and ensure that staff are not penalised for raising concerns. These measures make human oversight a substantive institutional practice rather than a symbolic safeguard.

5.3 Public participation and shared governance

AI governance is stronger when it includes the people affected by system design and deployment. Public consultations, worker representation, community panels, and partnerships with independent researchers can reveal risks that internal teams overlook. Participation must be early enough to influence choices and diverse enough to avoid giving the most digitally confident groups disproportionate voice.²⁶

Shared governance does not remove the responsibility of public authorities or developers. Instead, it makes decisions more informed and provides a basis for public accountability. Institutions should publish the questions raised during consultation, explain which changes followed, and justify why some proposals were not adopted. This creates a record against which future decisions can be assessed.

5.4 Digital literacy as a collective capacity

Digital literacy should not be framed as an individual obligation to adapt to every new system. It is a collective capacity supported by education, accessible public information, workplace training, consumer protection, and independent advice. People need to understand that AI outputs can be plausible but wrong, that data may be incomplete, and that a confident response does not establish factual reliability.²⁷

Institutions should provide training appropriate to roles and risks. A student using a writing assistant needs skills in verification and disclosure; a public employee needs to understand permitted uses, privacy duties, and escalation procedures; a manager needs to know how automated recommendations can affect staff. Such literacy should include the social and political dimensions of AI, not just operational competence.

5.5 The importance of local capacity and language inclusion

Countries and institutions need the capacity to evaluate systems developed elsewhere. This includes procurement expertise, data protection capacity, multidisciplinary research, public-interest computing, and access to

independent technical assessment. Without these capabilities, organisations may become dependent on vendors whose priorities and assumptions they cannot adequately scrutinise.²⁸

Language inclusion is part of this capacity. Public-interest datasets, locally relevant benchmarks, and community participation can improve the evaluation of Arabic and other underrepresented languages. Such work must respect privacy and intellectual property, and should not treat language communities as passive sources of data. Sustainable language infrastructure requires investment in researchers, educators, cultural institutions, and open standards.

6. DISCUSSION

The central proposition of this article is that AI should be understood as a social process organised through technical systems, institutions, and everyday practices. This perspective avoids two limitations. Technological determinism exaggerates the autonomy of systems and underestimates human and institutional choice. Purely instrumental accounts, by contrast, treat technology as a neutral tool and overlook how design and adoption can redistribute authority. A sociological approach recognises that AI both reflects social arrangements and can help reproduce or transform them.

The framework also clarifies why the social evaluation of AI cannot be reduced to model accuracy. An accurate system may still be used for an illegitimate purpose, rely on excessive data collection, or make decisions that people cannot challenge. Conversely, a system with limitations may provide value in a low-risk setting if it is used transparently, reviewed by competent people, and accompanied by remedies. Evaluation must therefore be proportionate to context and must include the distribution of benefits and burdens.²⁹

A second implication concerns the relationship between macro- and micro-level analysis. Ownership structures, data markets, and regulatory choices shape what systems are built, while local routines and user responses determine how those systems operate in practice. The interaction between these levels can produce feedback loops. A classification affects opportunities; changed opportunities influence future behaviour; and new behaviour becomes data for later classifications. Sociological research should trace these loops rather than studying a model as a static object.

A third implication is that public legitimacy depends on institutions, not simply on public attitudes. Trust cannot be manufactured by communication campaigns if errors are hidden or appeals are ineffective. It emerges when systems are understandable, institutions accept responsibility, and affected people can influence decisions. In this sense, accountability is not a constraint added after innovation; it is part of the social infrastructure required for durable and legitimate innovation.

Finally, context matters. Language resources, administrative capacity, labour relations, social inequalities, and historical experiences with institutions affect both adoption and outcomes. A global framework is useful only if it enables context-sensitive evidence rather than imposing uniform assumptions. For researchers in Arabic-speaking environments, this means documenting local practices and differences while engaging with international debates on data power, algorithmic governance, and human rights.³⁰

7. CONCLUSION

This article has argued that artificial intelligence is best understood sociologically as a socio-technical arrangement embedded in social structures, institutional goals, economic relations, and cultural practices. AI systems classify, predict, recommend, and generate, but their social significance depends on how data are produced, how categories are chosen, how outputs are used, and how people can respond. Classical sociological questions about rationalisation, authority, inequality, labour, and interaction remain essential for explaining these developments. Critical data studies further show that data extraction and algorithmic systems may concentrate power, while ethical guidance provides principles that can be translated into institutional safeguards.

The proposed framework links social inputs, mediating processes, and outcomes across distribution, agency, accountability, labour, representation, legitimacy, and sustainability. It does not presume that all AI systems create harm or that all human decisions are fair. Instead, it calls for context-sensitive empirical investigation, comparison with realistic alternatives, and attention to the capacity of affected people to contest decisions. A socially accountable approach combines technical evaluation with institutional responsibility, participatory governance, and continuing public scrutiny.

FINDINGS:

1. AI is not socially neutral: its effects are mediated by institutional priorities, data practices, and existing inequalities.
2. Algorithmic harms can arise from data representation, classification choices, organisational incentives, and unequal access to appeals.
3. Technical accuracy is necessary in many applications but is insufficient to establish fairness, legitimacy, or public value.
4. Meaningful human oversight depends on real authority, time, competence, transparency, and accessible contestation procedures.

RECOMMENDATIONS:

1. Require proportionate social-impact assessments before high-impact AI systems are procured or deployed, and repeat them when systems change.
2. Establish accessible explanation, complaint, and appeal procedures, with named institutional responsibility and independent review for high-risk uses.
3. Invest in public digital literacy, staff training, local research capacity, and evaluation resources for Arabic and other underrepresented languages.
4. Include workers, service users, and affected communities in system design and monitoring, and publish meaningful information about purpose, limitations, incidents, and outcomes.

Future research directions:

Future studies should test the proposed framework through comparative fieldwork in universities, public administrations, workplaces, and digital platforms. Mixed-method research could combine interviews, institutional document analysis, user surveys, and outcome audits to examine whether participation and appeal mechanisms reduce unequal effects. Further work is also needed on Arabic-language AI, dialect representation, the labour conditions behind digital infrastructures, and the environmental costs of large-scale systems. Longitudinal studies would be particularly valuable for identifying feedback loops and changes in professional autonomy over time.

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