



Citation: Frontoni, E., & Epasto, S. (2025) AI as the “final frontier”? Narratives, geographies, and relationships in the human–algorithm coproduction. *Journal of Emerging Perspectives* 2: 9-16. doi: 10.36253/jep-20877

Received: April 30, 2025

Revised: September 30, 2025

Published: December 20, 2025

© 2025 Author(s). This is an open access, peer-reviewed article published by Firenze University Press (<https://www.fupress.com>) and distributed, except where otherwise noted, under the terms of the CC BY 4.0 License for content and CC0 1.0 Universal for metadata.

Data Availability Statement: All relevant data are within the paper and its Supporting Information files.

Competing Interests: The Author(s) declare(s) no conflict of interest.

ORCID

EF: 0000-0002-8893-9244

SE: 0000-0002-6420-0867

AI as the “final frontier”? Narratives, geographies, and relationships in the human–algorithm coproduction

EMANUELE FRONTONI, SIMONA EPASTO*

Department of Political Science, Communication and International Relations, University of Macerata, Italy

Email: emanuele.frontoni@unimc.it; simona.epasto@unimc.it

*Corresponding author

Abstract. This article critically interrogates the metaphor of artificial intelligence (AI) as a “final frontier,” revealing its colonial and expansionist roots and its inadequacy in capturing the embeddedness of AI systems within complex sociotechnical landscapes. Combining a geographical perspective with insights from computer engineering, we argue that the European Union’s Artificial Intelligence Act marks a paradigmatic shift from narratives of conquest to frameworks grounded in regulation, accountability, and coproduction. Through empirical vignettes in healthcare, recruitment, and criminal justice, we show how AI operates not in neutral or uncharted spaces, but within spatially and institutionally situated environments. Algorithmic systems both shape and are shaped by territorial infrastructures, legal frameworks, and social relations. By bridging disciplinary approaches, the paper advances a nuanced, interdisciplinary understanding of human–algorithm interaction – one that moves beyond deterministic imaginaries to address the spatial, political, and ethical dimensions of AI governance.

Keywords: artificial intelligence, human-algorithm coproduction, geographical embeddedness, AI regulation, interdisciplinary approach, EU AI Act, digital sovereignty.

1. CONCEPTUAL PRELUDE: BEYOND THE “FINAL FRONTIER”

The metaphorical invocation of artificial intelligence as humanity’s “final frontier” has permeated contemporary discourse with remarkable persistence, echoing the colonial and expansionist rhetoric historically associated with geographical exploration and territorial conquest (Frontoni, 2024). This linguistic framing reveals profound assumptions about the nature of technological progress, human agency, and the epistemic boundaries that define our relationship with algorithmic systems. Yet beneath this frontier metaphor lies a more complex reality of coproduction, interdependence, and mutual constitution between human and artificial intelligence that challenges simplistic narratives of technological determinism or human mastery.

The European Union's Artificial Intelligence Act, which entered into force in August 2024 and represents the world's first comprehensive regulatory framework for AI systems, provides a critical lens through which to examine these evolving human-algorithm relationships. The Act's risk-based approach, which categorizes AI applications according to their potential impact on fundamental rights and societal values, fundamentally reconceptualizes the terrain of human-machine interaction from one of unbounded technological possibility to one of carefully calibrated co-existence. This regulatory intervention signals a departure from the frontier mythology that has long characterized AI development, instead positioning artificial intelligence within a framework of accountability, transparency, and human oversight that acknowledges the profound interdependencies between algorithmic processes and human social structures.

The geographical metaphor of the frontier, with its implications of empty spaces awaiting discovery and colonization, becomes particularly problematic when applied to AI development within the European context. Unlike the historical frontiers that suggested unlimited expansion into supposedly uninhabited territories, the landscape of artificial intelligence is already densely populated with existing social relationships, institutional frameworks, and cultural practices that shape both the development and deployment of algorithmic systems. The AI Act's emphasis on conformity assessments, risk management systems, and human oversight requirements reflects an understanding that AI systems do not operate in isolation but are embedded within complex socio-technical assemblages that require careful navigation rather than wholesale conquest.

Consider the implementation of AI systems in healthcare diagnostics, where the coproduction between human expertise and algorithmic analysis becomes particularly evident. Under the AI Act's classification system, many medical AI applications fall into the high-risk category, requiring extensive documentation, testing, and human oversight mechanisms. The development of AI-powered diagnostic tools for radiology, such as those used for detecting diabetic retinopathy or analysing mammographic images, illustrates how the frontier metaphor breaks down when confronted with the reality of medical practice. These systems do not replace human radiologists but rather extend and augment their diagnostic capabilities through a process of continuous interaction and mutual calibration. The radiologist's expertise shapes the training data, validates the algorithmic outputs, and contextualizes the results within broader clinical narratives, while the AI system processes vast quantities of imaging data and identifies patterns

that might escape human attention. This relationship of coproduction challenges the frontier narrative by revealing how AI systems are not autonomous agents conquering new territories but rather collaborative tools that require ongoing human engagement and interpretation.

Similarly, the deployment of AI systems in recruitment and employment contexts, which the AI Act specifically addresses due to their potential for discrimination and bias, demonstrates the complex geographical and social dimensions of human-algorithm interaction. AI-powered recruitment tools that analyse resumes, conduct preliminary screenings, or assess candidate suitability operate within existing structures of labour markets, educational systems, and social hierarchies that profoundly shape their functioning. The Act's requirements for transparency, explainability, and bias testing acknowledge that these systems do not operate in a neutral technological space but are embedded within particular geographical and cultural contexts that influence their development, training, and application. A recruitment AI system trained on data from one European labour market may perform differently when deployed in another region with distinct educational systems, cultural norms, and employment patterns, highlighting how the supposed universality of algorithmic logic must always contend with the particularities of local social geographies.

The narrative of AI as a final frontier also obscures the ways in which algorithmic systems are deeply entangled with existing power structures and knowledge production processes. The AI Act's governance framework, with its emphasis on CE marking, conformity assessments, and notified body involvement, reflects a recognition that AI development is not a neutral technical enterprise but a fundamentally political process that shapes and is shaped by broader social relationships. The Act's requirement for fundamental rights impact assessments for high-risk AI systems acknowledges that these technologies do not simply extend human capabilities into new domains but actively reconfigure existing social relationships and institutional arrangements.

The case of AI systems in criminal justice, which the AI Act treats with particular caution through its prohibitions on certain uses and strict requirements for others, further illustrates the limitations of the frontier metaphor. Predictive policing algorithms, risk assessment tools for judicial decision-making, and automated analysis of evidence do not operate in an empty technological space but are deeply embedded within existing criminal justice institutions, legal frameworks, and social hierarchies. These systems co-produce outcomes through complex interactions between algorithmic processing, human interpretation, institutional protocols, and broader social

contexts that cannot be understood through the lens of technological expansion into uncharted territories.

The geographical dimensions of AI development within Europe also challenge the frontier narrative through their emphasis on digital sovereignty, data localization, and the protection of European values and legal traditions. The AI Act’s extraterritorial reach, which applies to AI systems used within the EU regardless of where they are developed, reflects an understanding that the governance of artificial intelligence is not simply a matter of technological innovation but of maintaining particular forms of social organization and value systems within specific geographical boundaries. This regulatory geography suggests that rather than representing a boundless frontier, AI development is increasingly subject to territorial constraints and jurisdictional negotiations that reflect broader geopolitical relationships and cultural differences.

The concept of human–algorithm coproduction that emerges from this analysis suggests a need to move beyond simplistic narratives of technological progress toward more nuanced understandings of the ways in which human and artificial intelligence systems mutually constitute each other through ongoing processes of interaction, adaptation, and learning. This coproduction is not merely a technical process but a fundamentally social and political one that involves negotiations over agency, authority, and accountability within specific institutional and cultural contexts. The AI Act’s framework for governing these relationships through risk assessment, human oversight, and transparency requirements provides one model for managing this coproduction, but it also raises broader questions about the forms of human–machine collaboration that are desirable and sustainable within democratic societies.

As we move forward in examining these questions, it becomes clear that the metaphor of AI as a final frontier may need to be replaced with more sophisticated conceptual frameworks that can account for the complex, multi-directional relationships between human and artificial intelligence systems. The European approach, as embodied in the AI Act, suggests one possible direction for this reconceptualization, emphasizing governance, accountability, and the protection of fundamental rights rather than unbounded technological expansion. However, the full implications of this shift from frontier mythology to regulatory governance remain to be explored through careful analysis of how these new frameworks shape the ongoing coproduction of human and algorithmic agency in practice (Frontoni, 2024).

On this basis, our interdisciplinary proposal unfolds: the following sections translate this frame

into a geography-of-coproduction lens, three empirical vignettes, the S.P.A.C.E. framework, and policy recommendations.

2. WHY METAPHORS MATTER IN AI

Opening with a conceptual prelude that challenges the “final frontier” metaphor and points to Europe’s risk-based turn, we then advance a geography-of-governance perspective and our joint contribution: an interdisciplinary account of human–algorithm coproduction that is spatially aware and policy-oriented. We subsequently develop a coproduction lens, three empirical vignettes (healthcare, recruitment, criminal justice), and the S.P.A.C.E. framework with policy recommendations. In practice, we combine narratives and real-world human–algorithm collaboration patterns (Frontoni, 2024) with a territorial reading of AI infrastructures, regulatory landscapes and public-value aims (Epasto, 2024a), showing how responsible adoption depends on contextual validation, accountability architectures and stakeholder engagement (Frontoni, 2024; Epasto, 2024a).

Public discourse frequently casts AI as humanity’s “next” or “final” frontier – a boundless, ungoverned domain awaiting exploration. Metaphors matter: their prime expectations, organise policy priorities, and legitimise particular forms of action. The frontier trope, forged historically in colonial expansion and the extractive logics of resource appropriation, obscures how AI is already deeply embedded in dense ecologies of institutions, infrastructures, and everyday practices. Rather than empty spaces, we encounter layered territories: standards, data centres, fibre backbones, public services, workplaces, courts, and clinics – all patterned by power relations and subject to contested governance.

We propose a shift from frontier imaginaries to a framework of coproduction: the ongoing, reciprocal shaping of algorithmic systems and human worlds across multiple scales (from code and datasets to organisations and territories). This shift clarifies the stakes of responsible AI adoption and aligns with a wider move in Europe from techno-solutionist narratives to governed innovation. (Frontoni, 2024; Jasanoff, 2004; Bowker & Star, 1999; Slotkin, 1992; Haraway, 1988; Kitchin, 2014).

3. FROM “FINAL FRONTIER” TO HUMAN–ALGORITHM COPRODUCTION

The frontier imaginary presumes linear progress and portable solutions, yet AI systems are irreducibly

Table 1. Four planes of human-algorithm coproduction (summary)

Plane	Scope	Typical elements / examples	Possible indicators / checks
Material–infrastructural	Physical + digital substrate enabling AI	Compute capacity (GPU/TPU), energy & cooling, networks, sensors/IoT, edge devices, data centres, supply chains	Energy/water use; latency; data locality; resilience; lifecycle/Scope 3 reporting
Institutional–organisational	Rules, roles, and processes around AI	Procurement specs, oversight bodies, liability allocation, labour regimes, professional protocols, QMS	Risk mgmt docs; human-oversight design; audit trails; incident reporting; vendor lock-in risk
Socio-cultural	Values, practices, and expectations	Tacit expertise, local practices, fairness expectations, trust & care norms, user training	Stakeholder mapping; participatory design records; user-facing explanations; satisfaction/trust surveys
Spatial–geopolitical	Territorial and cross-border dimensions	Territorial inequalities, cross-border data flows, standards, digital sovereignty, compliance geographies	Data-flow maps; localisation tests; standard conformance; equity across regions/populations

Notes: Examples are illustrative; indicators are suggestive and non-exhaustive.

Source: Authors' elaboration.

situated: their performance, risks and social meanings depend on how they are designed, trained and embedded within concrete institutions, infrastructures and practices (Haraway, 1988; Bowker & Star, 1999; Jasanoff, 2004). Rather than a neutral, unbounded space, AI inhabits layered territories shaped by norms, labour, infrastructures and geopolitical standards (Kitchin, 2014; Pohle & Thiel, 2020; Epasto, 2024b). This calls for a shift from exploration metaphors to a lens of coproduction, where human actors and algorithmic systems continually shape one another across settings and scales (Jasanoff, 2004; Latour, 1993).

We operationalise this shift through four intertwined planes (see Table 1):

1) the *material-infrastructural* plane (compute, energy, networks, sensors, edge devices, data centres and supply chains), which conditions feasibility, latency and environmental externalities;

2) the *institutional-organisational* plane (procurement, oversight, liability, labour regimes and professional protocols), which structures responsibilities and allocates power;

3) the *socio-cultural* plane (values, tacit expertise, local practices and expectations of fairness, trust and care), which mediates acceptance, use and contestation; and

4) the *spatial-geopolitical* plane (territorial inequalities, cross-border data flows, standards and digital sovereignty), which links AI to uneven development and regulatory geographies (Kitchin, 2014; Pohle & Thiel, 2020; Epasto, 2024a).

Seen through these planes, risks such as data colonialism, bias transfer and vendor lock-in are not accidental defects but predictable consequences of deploy-

ing generic tools without local adaptation (Couldry & Mejias, 2019; Pasquale, 2015). Conversely, place-aware design – contextual validation, transparent procurement, human oversight integrated into real workflows – turns compliance into a governance asset and aligns AI with public value and territorial needs (Veale & Zuiderveen Borgesius, 2021; Epasto, 2024b). This coproduction perspective prepares the ground for Europe's regulatory turn discussed next.

4. EUROPE'S REGULATORY TURN: THE AI ACT AS A GEOGRAPHY OF GOVERNANCE

The EU Artificial Intelligence Act establishes a risk-based architecture that classifies systems as unacceptable, high-risk, or limited-risk and attaches graduated obligations across the lifecycle – risk management, quality management, technical documentation, human oversight, and post-market monitoring (European Union, 2024). Rather than a mere checklist, these obligations compose a governance infrastructure that structures how AI is built, placed on the market, monitored, and, if needed, withdrawn (European Union, 2024).

Seen in spatial terms, the Act produces a geography of regulation: CE-marked systems circulate within the internal market; notified bodies, registries, and supervisory authorities act as nodes in an oversight network; and the Act's extraterritorial reach projects European standards along global value chains (European Union, 2024; Veale & Zuiderveen Borgesius, 2021). In this sense, compliance travels with systems, shaping procurement choices, audit pathways, and accountability across borders (Veale & Zuiderveen Borgesius, 2021).

The European risk-based turn embodied in the EU AI Act is unfolding within an increasingly competitive global regulatory arena. In the AI governance landscape, the United States leans towards market-driven innovation, progressively reinforced by strategic export controls, whilst China pursues state-led AI standard-setting, tightly coupled with industrial policy and data localisation imperatives. The European Union distinctly diverges from both approaches by treating fundamental-rights protection, ex-ante conformity assessment, human oversight, and post-market monitoring not merely as compliance obligations, but as instruments of geopolitical differentiation. Through its extraterritorial scope and the circulation of CE-marked AI systems within the internal market, the EU AI Act extends European normative influence across global AI value chains, seeking to mitigate asymmetric technological dependencies – particularly for peripheral regions – and to articulate a robust model of digital sovereignty. In this sense, regulation becomes a source of regulatory power, anchoring AI innovation to European public-value commitments and positioning Europe as a principled, yet competitive, actor in the global contest over AI governance.

Conceptually, the regime shifts practice from expansion to calibration, prioritising clearly delimited purposes, contexts, and safeguards; from universalism to localisation, by demanding context-sensitive performance metrics, domain-appropriate datasets, and stress-testing in real institutional environments; and from opacity to explicability, through documentation, traceability, and stakeholder-facing transparency duties that render reasoning and limits legible (Veale & Zuiderveen Borgesius, 2021; Floridi et al., 2018).

Read through a territorial lens, the AI Act also redistributes capabilities across places: compliance becomes a spatial practice that must align with regional policy priorities and the realities of local service delivery (Epasto, 2024). This reframes compliance from legal hurdle to governance asset, anchoring AI to public-value objectives via place-aware validation, accountable procurement, and situated human oversight (Epasto, 2024a; Veale & Zuiderveen Borgesius, 2021).

5. SPATIAL EMBEDDEDNESS: WHERE AI “LIVES” AND WHY PLACE MATTERS

AI systems are spatial technologies: they depend on energy, water, cooling and low-latency connectivity, and they benefit from proximity to data sources and users. As a result, capabilities and impacts are unevenly distributed – metropolitan cores concentrate compute, talent and

venture capital, while peripheral regions risk forms of *algorithmic dependency* when they import generic tools that are poorly adapted to local institutions (Graham & Marvin, 2001; Kitchin, 2014; Epasto, 2024a). Environmental externalities further bind AI to place: training and serving large models impose energy and water burdens that vary with local grids, climate and data-centre siting (Strubell, Ganesh & McCallum, 2019; Henderson et al., 2020).

Spatial embeddedness operates through at least three layers. Infrastructure localisation sets feasibility constraints (compute regions, edge nodes, latency budgets, data-residency rules) that influence architecture choices and service quality (Kitchin, 2014; Epasto, 2024a). Regulatory landscapes define what is permissible and how risk is governed – sectoral rules in health, employment or policing intersect with data protection and fundamental-rights safeguards (European Union, 2024; Veale & Zuiderveen Borgesius, 2021). Civic ecosystems – professional bodies, civil society, affected communities – mediate acceptance, contest harms and co-produce corrective practices; without this mediation, ostensibly “general-purpose” models can reproduce extractive data colonialism (Couldry & Mejias, 2019).

A place-aware approach consequently treats compliance as a governance asset rather than a burden: contextual validation, transparent procurement, clear human-oversight roles and continuous post-market monitoring align AI with public-value aims and territorial needs (Epasto, 2024; European Union, 2024). In short, AI does not float above space; it is built into infrastructures, rules and social contracts that are situated and therefore must be governed as such (Kitchin, 2014; Epasto, 2024).

6. EMPIRICAL VIGNETTES: COPRODUCTION IN PRACTICE

The empirical vignettes are illustrative caselets, purposely selected to exemplify how human–algorithm coproduction manifests in fundamental-rights-sensitive domains, rather than comprehensive or statistically generalisable case studies.

Each vignette has been chosen for its capacity to illuminate situated algorithmic effects across the coproduction planes introduced earlier.

6.1 Healthcare diagnostics (high-risk)

Clinical AI for imaging triage or decision support augments, rather than replaces, professional judgement; performance hinges on dataset curation, protocol

design, threshold calibration and exception handling across diverse populations and workflows (Topol, 2019; Kelly, Karthikesalingam & Suleyman, 2019; Wiens et al., 2019). Under the EU AI Act, such tools typically fall within high-risk categories, triggering obligations on risk management, human oversight, robustness and post-market monitoring (European Union, 2024). A coproduction stance translates these legal duties into operational practices: multi-site validation across hospitals, fairness analyses on clinically relevant sub-groups, drift detection linked to incident reporting, and user-facing explanations that fit real clinical routines (Wiens et al., 2019; European Union, 2024). Where implemented, human–algorithm collaboration becomes structured, not ad hoc – clarifying who verifies, who escalates and how accountability is traced (Frontoni, 2024).

Territorial takeaway. Clinical utility and equity improve when validation and oversight are embedded in local health-system workflows, with procurement requiring context-specific evidence beyond aggregate accuracy (Epasto, 2024; European Union, 2024).

6.2 Recruitment and employment (high-risk)

Automated screening and assessment interact with stratified labour markets and education systems; naively transferring models across regions can encode local hierarchies and produce disparate impacts (Raghavan et al., 2020). A coproduction approach treats HR professionals, worker representatives and candidates as stakeholders in tool selection, impact assessment and redress pathways, rather than mere end-users (Barocas, Hardt & Narayanan, 2019). Within the AI Act’s risk-based regime, organisations should implement bias impact assessments across relevant attributes and locations, provide candidate-facing notices and explanations, and schedule periodic re-validation as markets change (European Union, 2024; Veale & Zuiderveen Borgesius, 2021).

Territorial takeaway. Because labour-market structures vary geographically, audits and transparency measures must be locally informed and coupled to institutional realities (Epasto, 2024).

6.3 Criminal justice (prohibitions and high-risk zones)

Predictive policing, risk assessment and automated evidence analysis operate within historically overpoliced communities, where algorithmic feedback loops can entrench unequal surveillance and sanctioning (Ferguson, 2017; Lum & Isaac, 2016). The AI Act delineates prohibitions for certain biometric surveillance uses and

tightens controls elsewhere, emphasising traceability, documentation and meaningful human oversight (European Union, 2024). A coproduction lens centres due process: explainability to defendants, defence access to documentation, independent audits and community consultation – especially where technologies intersect with racialised or socio-economic vulnerabilities (Benjamin, 2019; European Union, 2024).

Territorial takeaway. Oversight designs should be localised – including non-AI alternatives – where harm patterns are spatially concentrated and historically rooted (Epasto, 2024).

Taken together, these vignettes show that responsible AI hinges less on abstract performance scores than on how models are situated within real infrastructures, institutions and communities – where risks, accountabilities and benefits are unevenly distributed. In practice, the AI Act’s risk-based duties only become meaningful when translated into place-aware validation, explainable workflows and sustained human oversight (European Union, 2024; Veale & Zuiderveen Borgesius, 2021). Building on this evidence – and on collaborative patterns between humans and algorithms (Frontoni, 2024) and a geography-of-governance perspective (Epasto, 2024) – the next section distils an operational framework, S.P.A.C.E., to align design and deployment with public-value objectives across contexts.

7. AN INTERDISCIPLINARY FRAMEWORK FOR RESPONSIBLE ADOPTION: S.P.A.C.E.

We translate the coproduction perspective into an operational framework – S.P.A.C.E. – that links technical choices to institutional accountability and territorial needs across the AI lifecycle (Jasanoff, 2004; Veale & Zuiderveen Borgesius, 2021; Epasto, 2024).

S.P.A.C.E. operationalises human–algorithm coproduction by translating the four coproduction planes into a pragmatic, auditable workflow across the AI lifecycle. Building on the material–infrastructural, institutional–organisational, sociocultural, and spatial–geopolitical layers outlined earlier (Table 1), the framework proceeds sequentially through: Situation mapping (S), to diagnose territorial assets and infrastructural constraints; Purpose specification (P), to set narrow, testable objectives and non-goals; Accountability architecture (A), to assign oversight roles, liabilities, and traceable audit artefacts; Contextual validation (C), to implement multi-site, multi-group robustness and fairness checks, coupled to model-drift monitoring in diverse locales and sub-populations; and Engagement & education (E), to embed stake-

holder co-design, institutional literacy, and transparent, auditable procurement. Rather than a stand-alone construct, S.P.A.C.E. acts as a spatial governance lens that calibrates AI systems to place, rights, and organisational routines, turning regulatory compliance into a co-produced public-value asset along the lifecycle. This operational proposal advances the wider coproduction scholarship on science and technology governance (Jasanoff [2004]; Haraway [1988]), as well as contemporary analyses of the EU AI Act and accountable AI adoption (Veale & Zuiderveen Borgesius [2021]; Epasto [2024]; Frontoni [2024]). Key works informing the geopolitical and situated AI governance lens include: Frontoni [2024], Jasanoff [2004], and Veale & Zuiderveen Borgesius [2021].

8. PITFALLS AND PATHWAYS

Frontier rhetoric drives *scale-at-all-costs*, obscuring local harms and institutional dependencies. Typical failure modes include: data colonialism and biased transfer when models are deployed without local adaptation (Couldry & Mejias, 2019); opacity lock-in via proprietary ecosystems that limit oversight and exit options (Pasquale, 2015); unsustainable footprints from compute-intensive pipelines (Strubell, Ganesh & McCallum, 2019; Henderson et al., 2020); and compliance theatre, i.e., paper-based conformity that ignores real workflows (Veale & Zuiderveen Borgesius, 2021).

Counter these risks through: (a) contextual validation and routine re-evaluation in live settings; (b) rights-based impact assessments with public-facing summaries; (c) procurement for auditability (documentation, interfaces for oversight, energy reporting) and interoperability to avoid lock-in; (d) federated and privacy-preserving learning where feasible; and (e) worker and community co-design to align with public value (Floridi et al., 2018; Kairouz et al., 2021; Veale & Zuiderveen Borgesius, 2021; Epasto, 2024; Frontoni, 2024).

9. POLICY RECOMMENDATIONS

1. *Regional validation hubs*. Fund cross-institutional testbeds that mirror local infrastructures and demographics; publish datasets, stress tests and post-market metrics where possible (European Union [2024]; Epasto, 2024a; Epasto, 2024b).
2. *Public-value procurement*. Require explainability artefacts, audit APIs, fairness/robustness evidence across sub-populations and locales, and *energy/water disclosures* for high-compute systems (Veale

& Zuiderveen Borgesius, 2021; Strubell, Ganesh & McCallum, 2019).

3. *Mandatory post-market monitoring (high-risk)*. Implement drift detection, incident logs, and scheduled *sunset reviews* to reassess necessity and proportionality (European Union [2024]).
4. *Rights-based impact assessments*. Standardise templates for health, employment and public administration, with public summaries and independent audit capacity (Floridi et al., 2018; Veale & Zuiderveen Borgesius, 2021).
5. *Data governance for place*. Support data trusts/commons with community oversight to ensure representativeness and legitimate reuse (Couldry & Mejias, 2019; Epasto, 2024).
6. *Skills and literacy*. Invest in interdisciplinary training for officials and professionals; recognise and formalise *human-AI collaboration patterns* in sectoral protocols (Frontoni, 2024; Epasto, 2024a).

10. CONCLUSION

Replacing the “final frontier” imaginary with situated coproduction clarifies both risks and responsibilities. Europe’s risk-based regime provides an institutional scaffold, but alignment with public value is ultimately achieved through place-aware governance: contextual validation, accountable procurement, and meaningful engagement with affected communities (European Union, 2024; Veale & Zuiderveen Borgesius, 2021; Epasto, 2024). When human–algorithm collaboration is designed and monitored within real workflows and territorial constraints, AI shifts from a project of conquest to one of care and democratic utility (Frontoni, 2024; Jasanoff, 2004; Floridi et al., 2018; Epasto, 2024a; Epasto, 2024b).

REFERENCES

- Barocas, S., Hardt, M. & Narayanan, A. (2019). *Fairness and Machine Learning*. fairmlbook.org.
- Benjamin, R. (2019). *Race After Technology: Abolitionist Tools for the New Jim Code*. Cambridge: Polity.
- Bowker, G.C. & Star, S.L. (1999) *Sorting Things Out: Classification and Its Consequences*. Cambridge, MA: MIT Press.
- Couldry, N. & Mejias, U.A. (2019). *The Costs of Connection: How Data Is Colonizing Human Life and Appropriating It for Capitalism*. Stanford, CA: Stanford University Press.

- Epasto, S. (2024a). *Geografia, sviluppo e innovazione. Scenari e traiettorie tra globalizzazione e sostenibilità*. Roma: Aracne Editrice.
- Epasto, S. (2024b). Geopolitica, geoeconomia e geofinanza: intrecci e implicazioni per una sostenibilità finanziaria inclusiva e responsabile. In Biasin, S., Giacomini, G. & Marinelli, E. (Eds) *La sostenibilità. Percorsi tra ambiente, società e governance*. Macerata: EUM.
- European Union (2024). *Artificial Intelligence Act*. Official Journal of the European Union.
- Ferguson, A.G. (2017) *The Rise of Big Data Policing: Surveillance, Race, and the Future of Law Enforcement*. New York: NYU Press.
- Floridi, L. et al. (2018). AI4People – An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds and Machines*, 28(4), 689–707.
- Frontoni, E. (2024). *AI, ultima frontiera. Capire l'intelligenza artificiale con le storie vere di collaborazione tra esseri umani e algoritmi*. Milano: ROI Edizioni.
- Graham, S. & Marvin, S. (2001). *Splintering Urbanism: Networked Infrastructures, Technological Mobilities and the Urban Condition*. London: Routledge.
- Haraway, D. (1988). Situated Knowledges: The Science Question in Feminism and the Privilege of Partial Perspective. *Feminist Studies*, 14(3), 575–599.
- Henderson, P. et al. (2020). Towards the Systematic Reporting of the Energy and Carbon Footprints of Machine Learning. *arXiv preprint arXiv:2002.05651*.
- Jasanoff, S. (2004). *States of Knowledge: The Coproduction of Science and Social Order*. London: Routledge.
- Kairouz, P. et al. (2021). Advances and Open Problems in Federated Learning. *Foundations and Trends in Machine Learning*, 14(1–2), 1–210.
- Kelly, C.J., Karthikesalingam, A. & Suleyman, M. (2019). Key challenges for delivering clinical impact with AI. *BMC Medicine*, 17, 195.
- Kitchin, R. (2014). *The Data Revolution: Big Data, Open Data, Data Infrastructures and Their Consequences*. London: SAGE.
- Latour, B. (1993). *We Have Never Been Modern*. Cambridge, MA: Harvard University Press.
- Lum, K. & Isaac, W. (2016). To Predict and Serve? *Significance*, 13(5), 14–19.
- Noble, S.U. (2018). *Algorithms of Oppression: How Search Engines Reinforce Racism*. New York: NYU Press.
- Pasquale, F. (2015). *The Black Box Society: The Secret Algorithms That Control Money and Information*. Cambridge, MA: Harvard University Press.
- Pohle, J. & Thiel, T. (2020). Digital sovereignty. *Internet Policy Review*, 9(4).
- Raghavan, M., Barocas, S., Kleinberg, J. & Levy, K. (2020). Mitigating bias in algorithmic hiring: Evaluating claims and practices. In *Proceedings of FAT '20* (pp. 469–481). New York: ACM.
- Slotkin, R. (1992). *Gunfighter Nation: The Myth of the Frontier in Twentieth-Century America*. Norman: University of Oklahoma Press.
- Strubell, E., Ganesh, A. & McCallum, A. (2019). Energy and Policy Considerations for Deep Learning in NLP. In *Proceedings of ACL 2019* (pp. 3645–3650). Florence: ACL.
- Topol, E. (2019). *Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again*. New York: Basic Books.
- Veale, M. & Zuiderveen Borgesius, F. (2021). Demystifying the Draft EU Artificial Intelligence Act. *Computer Law Review International*, 22(4), 97–112.
- Wiens, J. et al. (2019). Do no harm: a roadmap for responsible machine learning in health care. *Nature Medicine*, 25, 1337–1340.