10.051103/ESMB.260623106
Vol.23 Iss.1 pp.54-63 International Journal of Economics & Strategic Management of Business Process (ESMB)

Thinking Artificial Intelligence Through Philosophical Traditions: Toward an Integrative Framework for Epistemic, Ethical, and Political Challenges

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Abstract— This article proposes an integrative conceptual framework for analyzing artificial intelligence (AI) through philosophical traditions. While contemporary AI debates are often fragmented across technical (model performance, interpretability), legal (liability, rights), and normative (ethics, justice) approaches, we argue that a systematic philosophical reading can organize controversies around structuring tensions and derive actionable governance implications. Building on an integrative conceptual synthesis, we apply a common analytical grid to five families of issues: (i) epistemic questions (paradigms, evidence, explainability), (ii) agency and responsibility (causality, autonomy, accountability), (iii) ethics and justice (dignity, utility, fairness, precaution), (iv) power and governance (surveillance, public sphere, institutional dispositifs), and (v) sociotechnical mediation (AI as a technical system). Our main outcome is a four-requirement model—epistemic legitimacy, distributed responsibility, justice and non-discrimination, and democratic governance—linked to operational levers (traceability, auditing, use-oriented explainability, deliberation, and oversight). The paper connects philosophical traditions to contemporary issues (bias, opacity, decision automation, algorithmic power) and offers a research and governance agenda for organizations and regulators.
Keywords— artificial intelligence; philosophy; explainability; algorithmic justice; governance; sociotechnical systems.

I. Introduction

Over the last decade, AI systems have become pervasive mediators of organizational and social life: they recommend, rank, predict, and—within specific workflows—trigger semi-automated decisions. As model capabilities have advanced, governance questions have become more salient: opacity, discriminatory outcomes, contestability, organizational dependence on non-auditable systems, and risks of manipulation and surveillance.

Contemporary scholarship offers rich but often compartmentalized responses: interpretability and explainability research (Doshi-Velez & Kim, 2017; Rudin, 2019), algorithmic fairness and discrimination (Barocas & Selbst, 2016; Selbst et al., 2019), political economy and digital power (Pasquale, 2015; Zuboff, 2019), and sociological accounts of algorithms (Gillespie, 2014; Beer, 2017). In parallel, policy-oriented frameworks propose principle sets and risk-based governance approaches (Floridi & Cowls, 2019; OECD, 2019; UNESCO, 2021) and recent regulation operationalizes compliance obligations (e.g., the EU AI Act's risk-based logic). Yet organizations still face a practical difficulty: the same phenomena (opacity, bias, automation) are discussed through different ontologies, normative assumptions, and units of analysis, which can fragment governance and obscure trade-offs.

Rather than adding another catalogue of principles, we argue that a systematic philosophical reading can organize AI controversies around a small set of structuring tensions—about knowledge, agency, justice, and power—and translate them into implementable governance requirements. The guiding research question is: how can philosophical traditions, treated as analytical lenses rather than historical surveys, help stabilize an integrative framework for AI governance that is usable by researchers, organizations, and regulators?

Our contribution is threefold. First, we provide a unified analytical grid that links philosophical traditions to concrete AI governance problems, reducing the "framework inflation" that characterizes current debates.

ISSN: 1737-9296

10.051103/ESMB.260623106

Second, we formalize a four-requirement model—epistemic legitimacy, distributed responsibility, justice and non-discrimination, and democratic governance—each connected to specific operational levers (traceability, auditability, use-oriented explainability, deliberation, and oversight). Third, we articulate a proportionality logic that helps calibrate governance intensity to contextual risk, thereby complementing compliance-oriented approaches with a diagnostic and design-oriented perspective.

To address reviewers' concerns on positioning, we explicitly differentiate our framework from existing AI ethics/governance proposals: our novelty is not the statement of general principles per se, but the systematic philosophical grounding that explains why tensions recur, how they relate to one another, and how they can be operationalized through a coherent set of governance requirements and levers.

II. Positioning AI as a philosophical and sociotechnical object

Treating AI as a philosophical object requires avoiding two symmetric reductions. The first reduces AI to technical optimization (accuracy, latency, cost), as if governance were a post-hoc constraint. The second anthropomorphizes AI by attributing agency to the model itself, obscuring the distributed character of design, training, deployment, and use. In practice, AI is an assemblage of models, data pipelines, objectives, infrastructures, interfaces, and institutional rules (Winner, 1980; Latour, 2005; Suchman, 2007).

A. Defining "intelligence": avoiding anthropomorphism

From a conceptual standpoint, high performance in pattern recognition or language generation does not imply understanding in a strong sense. Classical debates in philosophy of mind and language (e.g., Searle's critique of "strong AI" and Wittgenstein's emphasis on meaning-as-use) help disentangle computational competence from normative expectations about explanation, justification, and responsibility. For AI governance, the key implication is that governance should focus on warranted use—what the system is relied upon to do, under what conditions—rather than on metaphors of autonomous intelligence.

B. Meaning, use, and context: lessons from philosophy of language

Interpretations of AI outputs are situated: they depend on users' purposes, domain knowledge, and the institutional environment in which decisions are made. Viewing meaning as use supports a governance stance where explainability is assessed relative to stakeholders' needs (operators, auditors, affected individuals), and where the adequacy of explanations is tied to decision contexts and contestability requirements.

III. Method: an integrative conceptual synthesis

We use an integrative conceptual review and synthesis approach. The goal is not to exhaustively review all philosophical writings on technology or all AI governance documents, but to select a coherent set of philosophical lenses that jointly cover the core governance questions raised by contemporary AI: epistemic warrant, agency and accountability, justice and rights, power and institutional control, and sociotechnical mediation.

Selection protocol. We proceeded in three steps. (1) We identified the main families of governance issues in the AI literature (explainability, fairness, accountability, surveillance/power, sociotechnical design) and used them as anchor themes (Doshi-Velez & Kim, 2017; Barocas & Selbst, 2016; Pasquale, 2015; Gillespie, 2014; Zuboff, 2019). (2) For each theme, we selected philosophical traditions and representative authors based on (a) canonical influence in their subfields, (b) conceptual relevance to the theme, and (c) complementarity across traditions, so that the set collectively spans epistemology, moral and political philosophy, and philosophy of technology. (3) We applied an inclusion rule: each selected author must enable a governance-relevant inference (i.e., a clearly articulated "so what for AI governance?" claim) and must connect to at least one operational lever (auditability, traceability, explainability, oversight, deliberation, or proportionality).

Analytical grid. We coded each tradition along four common elements: (i) the concept mobilized, (ii) the AI governance issue illuminated, (iii) the tension or risk revealed, and (iv) the governance implication or research hypothesis. Table I summarizes this mapping and serves as the backbone for the subsequent discussion.

Limitations. This approach is qualitative and interpretive; it privileges conceptual coverage and governance usefulness over exhaustive representation. The selection of authors is therefore purposeful rather than comprehensive. We explicitly acknowledge that other traditions (e.g., feminist epistemology, postcolonial critique) could enrich the framework; we discuss this as a research extension in the implications section.

ISSN: 1737-9296

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IV. Analytical grid and mapping of philosophical tensions

Across traditions, AI controversies can be organized into five recurring axes: (1) epistemic questions (what counts as evidence, explanation, and warranted reliance), (2) agency and responsibility (who is causally and normatively accountable for outcomes), (3) ethics and justice (how to evaluate harms, rights, and fairness), (4) power and governance (how AI reconfigures control, surveillance, and public reason), and (5) sociotechnical mediation (how technical systems shape categories, practices, and organizational learning). This mapping structures the remainder of the paper and prepares the integrative framework introduced in Section X.

TABLE I
CONCEPTUAL MAPPING OF PHILOSOPHICAL TENSIONS APPLIED TO AI

Anchor tradition / authors	Core concept(s)	AI issue illuminated	Tension / risk	Governance implication
Kuhn (science)	Paradigm; proof regimes	Evidential standards	Over-claim; blind trust	Validation and monitoring
Wittgenstein (language)	Meaning-as-use	Stakeholder-relative explainability	One-size-fits-all XAI	Use-oriented XAI and contestation
Searle (mind)	Syntax/semantics gap	Competence vs understanding	Anthropomorphism	Humans retain normative judgment
Kant/Mill/Rawls	Dignity; utility; fairness	Fairness trade-offs	Metric myopia	Impact assessment and redress
Jonas (precaution)	Irreversibility	High-stakes harms	Underestimating long-term effects	Stronger safeguards in high-risk
Foucault/Pasquale/Zuboff	Dispositifs; surveillance	Scoring; opacity	Opacity as power	Institutional transparency and audits
Habermas/Arendt	Public reason	Automation in public services	Erosion of justification	Deliberation and independent oversight
Latour/Winner/Suchman	Sociotechnical assemblage	Data categories; objectives	Reification; dependency	Traceability and data governance

V. Epistemic axis: paradigms, evidence, and explainability

C. *A shift in regimes of proof and epistemic authority*

Machine learning often produces valid predictions without offering causal explanations. This can displace traditional regimes of proof in which justification is tied to explicit models, mechanisms, or human-understandable reasons. From a philosophy-of-science standpoint, the governance problem is not whether AI "understands", but whether reliance is warranted under uncertainty and distribution shift. Practical implications include stronger requirements for validation, monitoring, and documented assumptions—especially where decisions affect rights or access to essential services.

D. *Explainability: from cognitive ideal to use-oriented justification*

Explainability is frequently framed as an intrinsic property of models. A philosophical reading suggests a different framing: explainability is a relational requirement tied to the purposes of explanation (trust calibration, error diagnosis, contestability, learning). This supports "use-oriented explainability": explanations should be adapted to stakeholder roles and risk levels (e.g., operators vs. auditors vs. affected individuals), rather than standardized as a single technical artifact (Doshi-Velez & Kim, 2017; Rudin, 2019).

E. *From explanation to verification: robustness, drift, and epistemic responsibility*

Because models are embedded in dynamic environments, epistemic legitimacy also depends on robustness, ongoing verification, and governance of updates. Epistemic responsibility therefore includes: documenting data provenance, monitoring performance drift, managing concept drift, and ensuring that system changes remain

ISSN: 1737-9296

10.051103/ESMB.260623106

reviewable and auditable. These requirements connect directly to traceability and auditability levers, and justify proportional escalation of governance for high-impact systems.

VI. Agency and Responsibility Axis: Causality, Autonomy, Accountability

F. Responsibility as reconstruction of causal chains

AI-induced harms rarely result from a single "agent"; they emerge from pipelines of data collection, modeling choices, interface design, and organizational decision rules. Philosophical accounts of causality and responsibility motivate a governance stance where accountability requires reconstructing the causal chain: which design choices, data proxies, thresholds, and human actions contributed to an outcome? This motivates governance instruments such as traceability logs, model cards, decision logs, and structured post-incident reviews.

G. From the "responsibility gap" to distributed responsibility

The so-called responsibility gap can be reframed as a coordination failure: governance is weak when responsibilities are not allocated across roles (developers, vendors, deployers, domain owners, auditors). A distributed responsibility model specifies clear duties (risk assessment, monitoring, redress, documentation) and assigns ownership at each stage. This aligns with accountability expectations in emerging regulation and with auditing practices in risk management.

H. Human–AI cooperation: judgment, deskilling, and decision quality

AI often reshapes human judgment through automation bias, deference to scores, and deskilling. Governance should therefore address the quality of human–AI interaction: training, interface design that supports critical review, escalation protocols, and bounded delegation. These measures link responsibility to organizational learning, not only to blame allocation.

VII. Ethics and Justice Axis: Dignity, Utility, Fairness, Precaution

I. Consequences, rights, and fairness: complementary normative frames

Algorithmic governance raises simultaneously consequentialist questions (aggregate harms and benefits), deontological constraints (rights and dignity), and distributive justice concerns (fair allocation of opportunities and burdens). Rather than selecting a single doctrine, the framework treats these as complementary lenses that highlight different failure modes: harm minimization can conflict with equal treatment; efficiency can conflict with due process; group fairness constraints can conflict with individual rights.

J. Pitfalls of formalization: lessons for algorithmic fairness

Fairness metrics operationalize normative commitments, but they can also narrow the moral problem to what is measurable. Political philosophy and critical scholarship warn against "solutionism": measuring fairness without confronting structural inequality, proxy variables, and institutional contexts (Barocas & Selbst, 2016; Binns, 2018; Selbst et al., 2019). Governance implications include impact assessments, stakeholder consultation, and procedural fairness mechanisms such as explanation, contestation, and redress.

K. Precaution and irreversibility

In high-stakes or irreversible contexts—public safety, essential services, large-scale surveillance—precautionary reasoning supports stronger constraints, independent oversight, and a higher burden of justification (Jonas, 1984). This underpins the proportionality logic developed later: governance requirements intensify with risk, scale, and reversibility.

VIII. Power and Governance Axis: Dispositifs, Public Sphere, Domination

L. Dispositifs and normalization

AI systems can function as dispositifs that normalize behavior through classification, scoring, and prediction. This is not merely a technical effect: opacity and asymmetry can become sources of power. Critical accounts of algorithmic governance emphasize how black-box infrastructures can reorganize control and accountability

ISSN: 1737-9296

10.051103/ESMB.260623106

(Pasquale, 2015; Beer, 2017; Zuboff, 2019). The governance implication is to regulate not only outputs but also institutional arrangements: who controls data, objectives, and evaluation criteria.

M. Public sphere, attention, and algorithmic influence

Recommendation and ranking systems shape visibility and attention, affecting the conditions of public deliberation. When optimization targets engagement, systems can amplify sensationalism or polarization. A governance response includes transparency of objectives, independent auditing of systemic effects, and safeguards for informational integrity and pluralism.

N. Organizations: control by scores and justification duties

Within organizations, algorithmic scoring can shift management toward quantified control, potentially eroding professional discretion and fostering strategic gaming. A philosophical lens motivates "governance by reasons": decision automation should remain justifiable to affected parties through documented rationales, contestability pathways, and oversight arrangements that preserve accountability.

IX. Sociotechnical mediation: AI as a technical system

O. AI as a framing of reality: data, categories, objectives

AI systems operationalize reality by selecting data sources, defining labels, and encoding objectives. These choices embed social assumptions into technical artifacts. As a result, governance must extend upstream to data governance (provenance, representativeness, labeling practices) and downstream to how outputs are integrated into decisions (interfaces, thresholds, escalation).

P. The instrumental essence of technique and its risks

Philosophies of technology highlight that technical systems can be instrumentally rational while narrowing the space of values. When AI becomes the default mediator of decisions, organizations may overfit to what is measurable, neglecting qualitative judgment and ethical reflection. Governance levers therefore include institutional checks: periodic reviews of objectives, audits of proxies, and explicit deliberation on value trade-offs.

Q. Situated interaction and organizational learning

AI governance is not a one-off design task; it is an organizational capability. Systems evolve through updates, feedback loops, and changing contexts. This motivates continuous governance: incident reporting, post-deployment evaluation, user training, and mechanisms to incorporate stakeholder feedback into model and policy changes (Suchman, 2007).

X. An integrative framework: four requirements and operational levers

Building on the preceding axes, we propose an integrative framework that translates philosophical tensions into governance requirements and operational levers. The framework is designed to be (i) diagnostic—identifying which tensions are salient in a given AI use case—and (ii) prescriptive—specifying governance levers that can be implemented proportionally to risk and impact.

ISSN: 1737-9296

10.051103/ESMB.260623106
Vol.23 Iss.1 pp.54-63 International Journal of Economics & Strategic Management of Business Process (ESMB)

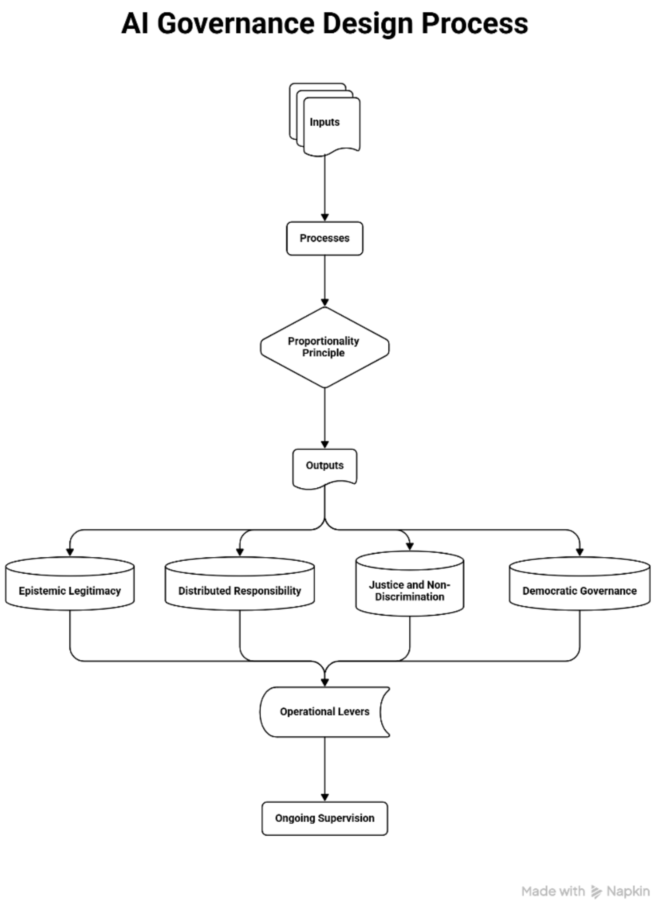

Fig. 1. From philosophical tensions to governance requirements (inputs–processes–outputs).

This figure presents our AI governance design process as a structured pipeline. It starts from inputs (philosophical tensions and AI contexts of use), which are translated into governance design processes. A central step is the proportionality principle, which functions as a calibration mechanism: governance requirements and controls are adjusted to the level of risk, the stakes involved, and the intended use. The process then yields outputs in the form of four governance requirements - epistemic legitimacy, distributed responsibility, justice and non-discrimination, and democratic governance- which jointly inform a set of operational levers (e.g., traceability, auditing, use-oriented explainability, deliberation and oversight mechanisms). Finally, these levers are embedded in ongoing supervision, ensuring continuous monitoring, accountability, and iterative adjustment throughout the AI system lifecycle.

TABLE II
FOUR GOVERNANCE REQUIREMENTS: DEFINITION, RISKS, LEVERS, OUTCOMES

Requirement	Definition / risk addressed	Operational levers (examples)	Expected outcome
1) Epistemic legitimacy	Warranted reliance: claims about model capability match evidence; risks of over-claim, drift, and opaque error modes.	Validation protocols; monitoring; documentation (data/model cards); use-oriented explainability; change control.	Reliable decisions; calibrated trust; detectability of failures.

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2) Distributed responsibility	Clear allocation of accountability across lifecycle roles; risks of responsibility gaps and diffusion of duties.	RACI-style responsibility maps; decision logs; incident management; audit trails; vendor/deployer obligations.	Imputability; traceable decisions; effective remediation and learning.
3) Justice & non-discrimination	Fair impact and protection of rights; risks of disparate impact, proxy discrimination, and procedural unfairness.	Impact assessment; fairness testing; representative data governance; contestation/redress mechanisms; human review in sensitive cases.	Reduced discriminatory harm; legitimate access decisions; procedural justice.
4) Democratic governance	Legitimacy of AI-enabled control in organizations and society; risks of surveillance, manipulation, and unaccountable power.	Independent oversight; transparency of objectives; stakeholder deliberation; limits on use; periodic external audits.	Accountable power; justified use; alignment with public values and institutional legitimacy.

R. A proportionality logic: calibrating requirements to risk and impact

The four requirements are invariant, but their intensity must be proportional to risk, scale, reversibility, and the degree to which AI outputs constrain individual options. This proportionality logic complements risk-based governance approaches (Floridi & Cowls, 2019; OECD, 2019; UNESCO, 2021) and connects directly to compliance expectations in recent regulation (e.g., the EU AI Act's high-risk obligations).

TABLE III
PROPORTIONALITY OF GOVERNANCE REQUIREMENTS BY IMPACT LEVEL

Use level	Epistemic requirement	Justice / responsibility requirement	Recommended dispositifs
Low impact (internal support)	Functional validation and basic monitoring	Business owner accountability	Logging; basic documentation; periodic review
Moderate impact (operational decisions)	Validation and drift monitoring and explainability for operators	Assigned responsibilities and basic fairness checks	Model/data cards; audits by internal control; user training
High impact (rights/essential services)	Stronger evidence; use-oriented explainability for affected parties	Impact assessment; redress; human review for edge cases	Independent audit; contestability channel; stricter change control
Critical / systemic impact	Highest burden of justification; continuous assurance	Strong safeguards; oversight and limits on use	External oversight; robust auditing; restrictions or prohibitions where necessary

XI. IMPLICATIONS: RESEARCH AGENDA AND ORGANIZATIONAL GOVERNANCE

The framework supports two complementary uses. As a diagnostic tool, it helps identify which tensions dominate a given AI use case (e.g., epistemic uncertainty vs. justice concerns vs. power asymmetries). As a design tool, it links each tension to governance levers that can be implemented in organizations (risk management, internal control, compliance, ethics boards) and assessed empirically by researchers.

S. Illustrative vignettes

Hiring algorithms. When automated scoring is used to shortlist candidates, epistemic legitimacy requires evidence that performance generalizes across applicant pools and over time; justice requires detecting proxy discrimination and ensuring contestability; distributed responsibility clarifies obligations between vendor, HR, and management; democratic governance demands transparency of criteria and limits on automated exclusion.

Credit scoring. In lending, the framework highlights the interplay between explainability (for customers and regulators), accountability (who approves and can override decisions), fairness (disparate impact and inclusion),

ISSN: 1737-9296

and governance (auditability and oversight). Proportional safeguards increase with the consequences of denial and with the risk of reinforcing financial exclusion.

Content recommendation. Recommendation systems influence attention and public discourse. The core tension shifts toward power and governance: optimization objectives can amplify manipulation or polarization. Governance responses include transparency of objectives, auditing of systemic effects, and oversight arrangements that preserve informational integrity and pluralism, while maintaining traceability and accountability for design choices.

T. Alignment with regulation and compliance

Regulatory instruments increasingly operationalize risk-based expectations for AI governance. The EU AI Act's high-risk logic, the OECD AI Principles (OECD, 2019), and UNESCO's Recommendation on the Ethics of AI (UNESCO, 2021) converge on documentation, transparency, human oversight, and accountability. Our framework complements these instruments by (i) making explicit the underlying tensions that justify obligations, (ii) proposing a proportionality logic that connects risk to governance intensity, and (iii) offering operational levers that organizations can integrate into existing internal control and risk management systems.

U. Research directions

Future empirical work can test how the four requirements interact in practice (e.g., whether stronger explainability increases perceived justice, or whether auditing mitigates responsibility diffusion), how proportionality is implemented across sectors, and how sociotechnical design choices shape downstream governance outcomes. Extensions can also incorporate additional philosophical traditions (feminist epistemology, postcolonial critique) to examine power asymmetries and context-specific fairness concerns.

XII. Conclusion

AI governance debates are often fragmented across technical, legal, and ethical languages. By mobilizing philosophical traditions as analytical lenses, this paper organizes controversies around recurring tensions and translates them into an integrative governance framework. The proposed model specifies four requirements—epistemic legitimacy, distributed responsibility, justice and non-discrimination, and democratic governance—tied to implementable levers such as traceability, auditability, use-oriented explainability, deliberation, and oversight.

Beyond principle catalogues, the contribution of the framework lies in its explanatory grounding (why tensions recur), its integrative architecture (how tensions relate), and its proportional operationalization (how governance intensity should scale with risk). We hope this approach supports both rigorous research and actionable governance for organizations and regulators navigating AI-enabled decision-making.

XIII. References

[1] Arendt, H. (1958/1998). The human condition. University of Chicago Press.
[2] Barocas, S., & Selbst, A. D. (2016). Big Data's disparate impact. California Law Review, 104(3), 671–732.
[3] Beer, D. (2017). The social power of algorithms. Information, Communication & Society, 20(1), 1–13. https://doi.org/10.1080/1369118X.2016.1216147
[4] Binns, R. (2018). Fairness in machine learning: Lessons from political philosophy. In Proceedings of the 1st Conference on Fairness, Accountability and Transparency (pp. 149–159). PMLR.
[5] Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning. arXiv:1702.08608.
[6] European Union. (2024). Regulation (EU) 2024/1689 of the European Parliament and of the Council laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). Official Journal of the European Union.
[7] Floridi, L., & Cowls, J. (2019). A unified framework of five principles for AI in society. Harvard Data Science Review, 1(1).
[8] Foucault, M. (1975/1995). Discipline and punish: The birth of the prison. Vintage.
[9] Gillespie, T. (2014). The relevance of algorithms. In T. Gillespie, P. J. Boczkowski, & K. A. Foot (Eds.), Media technologies: Essays on communication, materiality, and society (pp. 167–194). MIT Press.
[10] Habermas, J. (1984). The theory of communicative action (Vol. 1). Beacon Press.
[11] Jonas, H. (1984). The imperative of responsibility: In search of an ethics for the technological age. University of Chicago Press.
[12] Kuhn, T. S. (1962/2012). The structure of scientific revolutions (4th ed.). University of Chicago Press.
[13] Latour, B. (2005). Reassembling the social: An introduction to actor-network-theory. Oxford University Press.

ISSN: 1737-9296

10.051103/ESMB.260623106

[14] Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. Big Data & Society, 3(2). https://doi.org/10.1177/2053951716679679
[15] OECD. (2019). OECD principles on artificial intelligence. Organisation for Economic Co-operation and Development.
[16] Pasquale, F. (2015). The black box society: The secret algorithms that control money and information. Harvard University Press.
[17] Rawls, J. (1971/1999). A theory of justice (rev. ed.). Harvard University Press.
[18] Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. Nature Machine Intelligence, 1, 206–215. https://doi.org/10.1038/s42256-019-0048-x
[19] Searle, J. R. (1980). Minds, brains, and programs. Behavioral and Brain Sciences, 3(3), 417–457.
[20] Selbst, A. D., Boyd, D., Friedler, S. A., Venkatasubramanian, S., & Vertesi, J. (2019). Fairness and abstraction in sociotechnical systems. In Proceedings of the Conference on Fairness, Accountability, and Transparency (FAT* ’19) (pp. 59–68). ACM. https://doi.org/10.1145/3287560.3287598
[21] Suchman, L. (2007). Human–machine reconfigurations: Plans and situated actions (2nd ed.). Cambridge University Press.
[22] UNESCO. (2021). Recommendation on the ethics of artificial intelligence. United Nations Educational, Scientific and Cultural Organization.
[23] Winner, L. (1980). Do artifacts have politics? Daedalus, 109(1), 121–136.
[24] Wittgenstein, L. (1953/2009). Philosophical investigations. Wiley-Blackwell.
[25] Zuboff, S. (2019). The age of surveillance capitalism. PublicAffairs.

ISSN: 1737-9296