A, Science and Society

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1 | INTRODUCTION

The notion of Society 5.0, first advanced by Japanese institutions, envisions a "super-smart" social order wherein digital technologies, notably artificial intelligence (AI), fuse seamlessly with broader societal needs and aspirations (Keidanren, *Society 5.0: Co-creating the future*, 2018). Such a bold vision demands a robust epistemological framework that views AI not merely as a technical artifact but as a phenomenon shaped by cultural, political, and economic contexts. It is in this sense that Edgar Morin's call for a complexity-based understanding becomes pertinent, given his argument that genuine knowledge must embrace rather than reduce the interdependencies inherent in any social or scientific phenomenon (Morin, *La Méthode*, 1977). Jacques Derrida's deconstructive lens, meanwhile, highlights the need to critically interrogate the labels and concepts we employ—"AI" among them—to unearth their hidden assumptions (Derrida, *Of Grammatology*, 1976). The saying attributed to Confucius, "when words lose their meaning, human beings lose their freedom," reminds us that conceptual clarity is no mere theoretical concern but a foundational element of informed and emancipatory discourse.

2 | HISTORICAL AND CONCEPTUAL FOUNDATIONS

In tracing the historical underpinnings of AI, one finds critical contributions from mathematics, probability theory, and algorithmic logic. Charles Hermite's exploration of polynomial equations (Hermite, "Sur la résolution de l'équation du cinquième degré," 1858) foreshadowed symbolic manipulation methods integral to computation; Louis Bachelier's *Théorie de la spéculation* (1900) provided probabilistic insights eventually influential in machine learning; Henri Poincaré's *Science and Hypothesis* (1902) furnished an epistemological perspective on uncertainty that resonates with contemporary AI challenges. Alan Turing inaugurated a new era by positing the "universal machine" and contemplating its capacity for "thinking" (Turing, "Computing Machinery and Intelligence," *Mind*, 1950). As AI matured, it incorporated frameworks from diverse fields, including neural networks, Bayesian inference, and heuristic search, transforming into a central driver of today's digital economy.

3 | AI AND SOCIETY: A MULTIDISCIPLINARY PERSPECTIVE

Since the late twentieth century, the locus of value creation in AI has shifted decisively from algorithms themselves to large-scale data, thus altering the business models at the core of this technology. Multi-sided platforms capitalize on user-provided data, aggregating it in ways that yield significant revenue streams for advertisers and other stakeholders, even as end-users access services ostensibly for "free" (Parker, Van Alstyne, & Choudary, *Platform Revolution*, 2016). This creates an environment where data is king, leading to new concerns around antitrust regulation, consumer protection, and sustainability, as the expansion of computational infrastructures brings sizable environmental costs.

Beyond market structures, AI influences social, ethical, and geopolitical domains. Sociologically, AI shapes interactions and norms by mediating communication and data flows (Habermas, *The Theory of Communicative Action*, 1984). Geopolitically, possession of substantial AI expertise and infrastructure can confer a strategic edge, intensifying competition among major economic powers and prompting debates about digital sovereignty (Acharya, *The End of American World Order*, 2014). Simultaneously, concentrated ownership of AI-related assets in a few global centers raises issues of equity, dependency, and international governance.

4 | CONCEPTUAL PITFALLS AND THE ROLE OF DATA GOVERNANCE

Against this backdrop of complexity, certain conceptual pitfalls can derail critical inquiry. A salient example is found in calls for "Responsible AI," which often assume a uniformity to AI that does not exist in practice. There is a risk of conflating everything from automated decision-making in finance to speech-generation systems into one monolithic concept of AI. In truth, AI encompasses distinct modalities of operation, each posing unique ethical and technical challenges. While the philosophical and normative impetus behind "Responsible AI" is laudable, responsibility cannot be properly allocated without analyzing the specific data, algorithms, and deployment contexts involved. By extension, one should consider the fundamental role of data governance in ensuring fairness and transparency, rather than presuming that lofty ethical declarations will suffice.

A simple Venn diagram can clarify this misconception: one circle labeled "Responsible," another labeled "AI," with only a partial overlap. The zone of genuine concern is narrower than the entire domain of AI, focusing mainly on data practices and context-specific algorithmic applications. An exclusive emphasis on "responsibility" as an abstract label can obscure the technical, legal, and social realities upon which actual accountability depends.

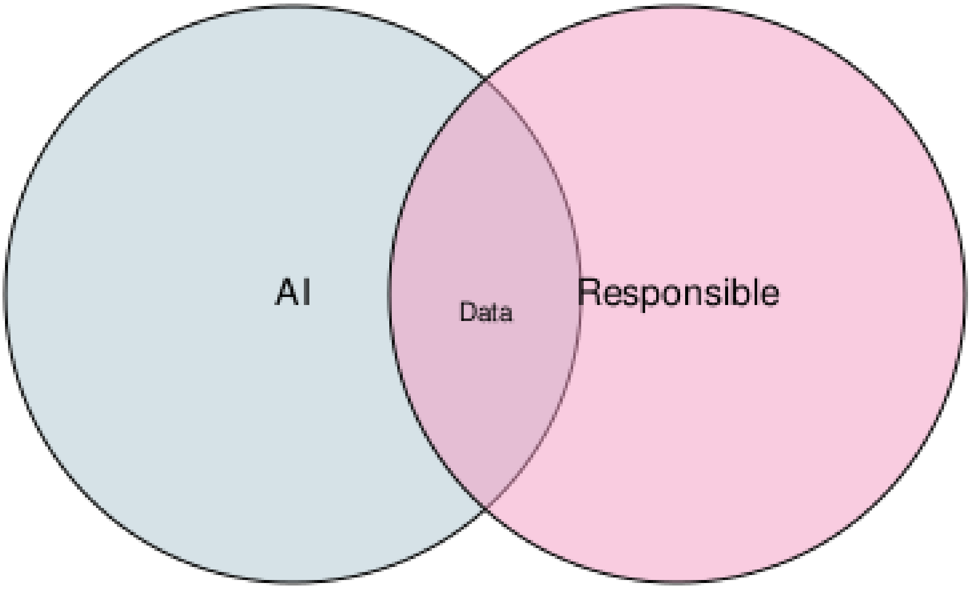

FIGURE 1 Conceptual Overlap between "Responsible" and "AI," indicating that the critical intersection pertains chiefly to data transparency, governance, and contextual regulation rather than an all-encompassing notion of responsibility.

5 | A STRUCTURED FRAMEWORK FOR AI AND SOCIETY

A parallel source of confusion often arises when we fail to distinguish the varying categories of AI usage, notably generative, explicative, and predictive systems. Although these categories overlap in certain respects, each implicates distinct objectives, technical methods, and social consequences:

Generative AI specializes in producing new content, be it text, imagery, or other media forms (Goodfellow et al., “Generative Adversarial Nets,” *Advances in Neural Information Processing Systems*, 2014). This includes deep generative models used for creative tasks, from art to language synthesis.

Explicative AI (sometimes referred to as explainable AI or XAI) focuses on elucidating how certain outputs or decisions are reached, aiming to enhance transparency and trust (Miller, “Explanation in Artificial Intelligence: Insights from the Social Sciences,” *Artificial Intelligence*, 2019). Crucial for high-stakes domains like healthcare or criminal justice, this domain seeks interpretability to allow users to understand, and potentially contest, algorithmic decisions.

Predictive AI, perhaps the most familiar form, aims at forecasting outcomes based on historical data, covering everything from credit scoring to weather forecasts (Russell & Norvig, *Artificial Intelligence: A Modern Approach*, 2020). Its primary emphasis lies in accuracy and speed, often with less direct concern for the interpretative dimension, unless regulated or demanded by the specific application context.

A helpful way to integrate these threads is to devise a structured framework that systematically maps key components. Below is a concise tabular representation designed to illustrate how an interdisciplinary lens can accommodate the multiple dimensions of AI’s societal role, from conceptual underpinnings to practical implementations and governance issues.

Table 1: High-Level Framework for AI and Society

Dimension	Primary Concern	AI Usage Examples	Key Issues & Stakeholders	Selected References
Epistemological	Conceptual clarity and deconstruction of assumptions	Generative (content creation), Explicative (explainability), Predictive (forecasting)	Philosophers, ethicists, social scientists	Derrida (1976); Morin (1977)
Technical-Scientific	Algorithmic design, data pipeline, computing infrastructure	Generative Adversarial Networks, Explainable AI interfaces, Supervised/Unsupervised Predictive models	Computer scientists, data engineers	Turing (1950); Goodfellow et al. (2014)
Economic	Business models, data as revenue source, antitrust concerns	Platform-based AI, targeted advertisement engines	Regulatory bodies, economists, platform operators	Parker et al. (2016)
Sociological	Reconfiguration of social norms, communication, identity	Social media recommender systems, digital assistants	Sociologists, policymakers, civil society	Habermas (1984)

Dimension	Primary Concern	AI Usage Examples	Key Issues & Stakeholders	Selected References
Geopolitical	Technological sovereignty, global data governance	AI in defense systems, cross-border data transfer	Governments, international organizations	Acharya (2014)
Ethical & Regulatory	Fairness, transparency, accountability	Responsible AI frameworks, data protection laws	Lawmakers, ethicists, oversight committees	Miller (2019); Russell & Norvig (2020)

Framed this way, it becomes apparent how crucial it is to match each type of AI usage—generative, explicative, or predictive—to the specific context in which it operates. For instance, a generative model deployed in creative industries poses different ethical and regulatory conundrums than a predictive system used for credit scoring. A thorough assessment of these distinctions can guard against "wrong trajectories" of debate, such as assuming that one set of ethical guidelines applies uniformly across every manifestation of AI.

6 | INTERNATIONAL COORDINATION AND THE FUTURE OF SOCIETY 5.0

Accordingly, the conversation around Society 5.0 demands that we not only integrate multi- and interdisciplinary perspectives but also remain vigilant about the conceptual boundaries we draw. While multidisciplinarity excels at enumerating pertinent questions across diverse domains—economics, sociology, computer science, and law among them—interdisciplinarity aims to converge such questions into coherent proposals. This convergence necessitates a reflexive approach that heeds Derrida's call to deconstruct our terminologies and resonates with Confucius's assertion on the power of language to shape human freedom. The aim here is not to provide conclusive answers but rather to establish a methodological and epistemological scaffold, one that steers inquiry away from simplistic or reductive paths and toward a more integrated and inclusive discourse.

7 | CONCLUSION

In so doing, the project of international coordination becomes both compelling and urgent. Technology's global impact transcends national boundaries, rendering purely local or siloed approaches insufficient. With careful attention to the diverse forms of AI—generative, explicative, and predictive—and with a structured framework that distinguishes each domain's role, stakeholders can more effectively negotiate standards, share best practices, and design equitable governance mechanisms. Society 5.0 may then serve not merely as a futuristic label but as a dynamic orientation: one that recognizes the interlocking challenges of the present and seeks collective, well-informed solutions for the future.

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