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Article

Crombie, Hacking and the Emergence of Two New Styles: Data-Intensive and Network-Relational Reasoning

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Abstract

The classical taxonomy of Western scientific styles introduced by Crombie and reinterpreted by Hacking has framed how historians and philosophers understand the plurality of scientific reasoning. Yet contemporary scientific practice has expanded beyond the six established styles, revealing new ways of generating truth, constructing objects and defining evidence. We argue that two emerging modes of inquiry qualify as additional styles within the Crombie–Hacking framework. The first is the data-intensive style, whose knowledge production relies on large datasets, algorithmic extraction of patterns and high-dimensional stability rather than explicit theories or controlled experiments. It creates new scientific objects such as embeddings, latent structures and predictive signatures. Still, it introduces its own epistemic norms grounded in robustness, cross-validation and scale. The second emerging mode is the network-relational style, which treats relations rather than intrinsic properties as the basis of explanation. It creates objects such as motifs, connectomes, influence pathways and multilayer networks. Still, it establishes truth through structural coherence and relational stability across independent observations. Both modes satisfy Hacking's criteria for a scientific style: they generate new questions, create new ontological domains, authenticate themselves through internal standards and support statements that were previously impossible. By comparing these two styles with the classical six, we argue that the Crombie–Hacking taxonomy requires expansion to capture the epistemic transformations of contemporary science. The result is a more inclusive and pluralistic account of scientific rationality that reflects the current practices in biology, neuroscience, physics, epidemiology and data science.

Keywords: epistemology; scientific pluralism; methodology; ontological innovation; big data

1. INTRODUCTION

Philosophers of science have often observed that scientific inquiry relies on multiple stable reasoning practices, rather than a single, uniform method. Crombie's historical analysis of six scientific styles provided one of the earliest systematic attempts to capture this plurality through distinct modes of inquiry that generate their own standards of demonstration, types of explanation and permissible inferential moves (Crombie 1994). Hacking later adapted and extended this framework, arguing that styles do more than regulate scientific reasoning (Hacking 1985; 2002): they also create new domains of objects, determine what counts as evidence and open new conceptual possibilities. This account has shaped current discussions on pluralism, realism and the ontology of scientific practice.

Although this framework continues to be influential, contemporary sciences present forms of reasoning that place increasing pressure on the classical six-style taxonomy. Many fields now rely on large-scale computational infrastructures, high-dimensional datasets and relational analyses of complex systems. These practices appear neither as variations of existing styles nor as temporary methodological trends. Instead, they seem to meet the criteria that Crombie and Hacking used to identify a style: they generate new questions, produce new objects and establish autonomous ways

of determining when something counts as a result. Recognizing these developments is important for a contemporary account of scientific rationality.

We examine these two developments and argue that they qualify as new scientific styles. The first involves reasoning through large datasets and algorithmic pattern extraction, where knowledge is produced through stability across scales rather than through controlled experimentation or explicit theoretical models. The second involves reasoning through relational structures, where explanatory power comes from the position of elements within networks and the global patterns that emerge from local interactions. Both styles appear repeatedly across disciplines, each with its own conceptual commitments and epistemic norms.

By analyzing these developments within the Crombie–Hacking framework, we seek to clarify how scientific reasoning is evolving in the twenty-first century. The result is a revised and expanded account of scientific styles that provides new conceptual tools for the analysis of contemporary scientific practice.

2. THE CROMBIE–HACKING FRAMEWORK

Crombie proposed one of the earliest comprehensive attempts to describe scientific rationality in terms of recurring modes of inquiry rather than in terms of unified method or theory structure. His historical study identified six enduring styles of scientific reasoning that developed in different periods of Western intellectual history and that continue to shape scientific investigation (Crombie 1994). Crombie’s taxonomy does not map onto disciplinary boundaries. Instead, it captures cross-cutting patterns of thought: ways of asking questions, establishing evidence and constructing explanations that recur across domains. These styles represent stable traditions of reasoning that have guided scientific practice for centuries (Table 1).

- a) The **deductive and axiomatic style** originates in Greek mathematics and relies on explicit postulates, formal definitions and logically necessary inferences. Knowledge is established through rigorous deduction from accepted principles. This style produces ideal objects such as geometric figures, imaginary numbers or abstract algebraic structures like Riemannian metrics that gain scientific significance through deductive coherence rather than through empirical observation. The style provides certainty through formal inference and continues to play a pivotal role in theoretical physics, mathematical modeling and any domain where formal structures play a constitutive role.
- b) The **experimental and manipulative style** emerged through early modern science and centers on controlled intervention. Its epistemic authority derives from reproducible manipulation of phenomena. Investigators isolate systems, vary conditions systematically and produce stable effects that support causal claims. Instruments such as microscopes, reaction chambers and accelerators mediate between theory and the world. This style generates artificially produced phenomena like chemical reactions and diffraction paths that become part of scientific ontology once they can be repeatedly created and measured. It remains fundamental in physics, chemistry and laboratory-based biology.
- c) The **hypothetical and model-based style** develops knowledge through idealized representations that approximate complex phenomena. Investigators construct models (physical, mathematical or conceptual) and evaluate them through explanatory coherence, predictive adequacy or intelligibility. Unlike the deductive style, its emphasis is not on deriving necessary consequences from axioms but on constructing simulations and simplified systems that provide insight into mechanisms or regularities. This style is central in climate science, systems neuroscience and many areas where direct experimentation is limited or the underlying processes are not fully observable.
- d) The **classificatory style** organizes phenomena into structured hierarchies or categories. Its roots extend back to Aristotle and medieval natural history, but it persists in modern scientific taxonomy. This style identifies diagnostic features, draws boundaries and establishes ordered systems of categories that aid in explanation and prediction. The classificatory style generates

- natural kinds, species, chemical elements and standardized disease categories. It is especially prominent in systematics, mineralogy, medicine and many branches of biology.
- e) The **statistical style** matured in the twentieth century. It treats populations and distributions as fundamental units of analysis and grounds inference in probabilistic models, sampling theory and the logic of uncertainty. Evidence is established through significance tests, confidence intervals or estimates of error. This style creates new objects such as probability distributions, regression coefficients and expected values. Its reasoning supports claims about groups rather than individuals and is crucial in epidemiology, social science, genetics and any domain concerned with variation and uncertainty.
 - f) The **genetic or historical style** explains phenomena by reconstructing their temporal development. It provides accounts of how present structures arise from sequences of earlier states. This style was central in the development of geology, evolutionary biology, philology and historical linguistics. Its reasoning involves tracing lines of descent, identifying branching pathways and interpreting evidence for past transformations. The objects it creates include genealogies, geological strata, evolutionary trees and reconstructed linguistic ancestries.

Hacking reformulated Crombie’s taxonomy by emphasizing its epistemic and ontological implications. For Hacking, styles are not merely collections of methods or analytical techniques (Hacking 1985; 2002). They introduce new kinds of objects, create new conceptual possibilities and define what counts as evidence or explanation. What matters is not the truth or falsity of particular sentences, but the way each style provides its own methods for determining truth and falsehood. Styles shape not only how investigators reason but also the kinds of facts that can exist within a scientific domain. They transform the world by stabilizing new objects, practices and forms of inquiry (Ruphy 2011; Wanderer 2012; Sciortino 2017; Sciortino 2021; Martínez 2023; Sciortino 2023; Vagelli 2024).

A key element of Hacking’s interpretation is that styles are **self-authenticating**. Their standards of correctness are determined by the internal logic of the practices rather than by external philosophical justification. For instance, reproducibility authenticates experimental reasoning, deductive soundness authenticates axiomatic reasoning and statistical inference authenticates probabilistic analysis. Each style produces its own epistemic norms and validates knowledge according to criteria anchored in its internal coherence.

Two features of this framework are especially important for the present inquiry. First, styles are **historically emergent**. They arise in response to intellectual and practical challenges and evolve across centuries. Crombie’s list reflects historical developments up to the early modern period but does not delimit the set of possible styles. Second, styles are **irreducible** to one another. Each exhibits a distinct epistemic identity and introduces conceptual and ontological innovations that cannot be captured through other styles. Together, these features support a pluralistic understanding of scientific rationality and provide the conceptual basis for identifying new styles that capture the transformations occurring in contemporary scientific practice.

Table 1. The Six Classical Crombie–Hacking Styles of Scientific Reasoning. The first three were developed in the investigation of individual regularities, the last three in the investigation of the regularities of populations ordered in space and time.

Feature	Deductive– Axiomatic Style	Experimental– Manipulative Style	Hypothetical– Model-Based Style	Classificatory Style	Statistical Style	Genetic–Historical Style
Primary Aim	Derive necessary conclusions from explicit axioms	Establish causal claims through controlled intervention	Explain phenomena via idealized representations	Organize phenomena into structured categories	Analyze variation and uncertainty in populations	Explain current forms through reconstruction of temporal development
Basic Units of Analysis	Postulates, definitions, formal symbols	Experimental systems, manipulated variables, reproducible effects	Idealized models, simplified representations, analogues	Taxa, types, hierarchies, diagnostic traits	Populations, frequencies, distributions, error terms	Lineages, sequences, strata, historical transitions

Feature	Deductive– Axiomatic Style	Experimental– Manipulative Style	Hypothetical– Model-Based Style	Classificatory Style	Statistical Style	Genetic–Historical Style
Characteristic Objects	Geometric figures, formal structures, abstract entities	Experimental phenomena, instrumentally produced effects	Idealized systems, theoretical constructs	Species, minerals, diseases, chemical elements	Probability distributions, estimates, regression structures	Evolutionary trees, geological layers, linguistic ancestries
Typical Questions	What follows from given axioms? Which structures are logically possible?	What happens when conditions are varied? What causes a reproducible effect?	What simplified representation captures the core mechanism?	How should entities be grouped? What features define a kind?	What is the distribution of values? How large is the error?	How did present states arise from earlier ones? What is the lineage of a trait?
Validation Norms	Logical consistency, proof, formal soundness	Reproducibility, stability under manipulation, controlled comparison	Coherence, intelligibility, predictive adequacy	Consistency of classification, stability of diagnostic traits	Statistical significance, confidence, sampling theory	Convergence of independent lines of evidence, temporal coherence
Mode of Explanation	Deductive derivation and structural demonstration	Causal inference grounded in manipulation	Mechanistic insight through idealization	Explanation through similarity and categorical structure	Inference from probabilistic patterns	Historical or genealogical reconstruction
Sources of Evidence	Mathematical proofs, formal derivations	Controlled experiments, instrument readings	Model behavior, idealized scenarios	Morphological traits, chemical properties, diagnostic markers	Surveys, measurements, repeated samples	Fossils, stratigraphic sequences, genetic or linguistic variation
Relation to Other Styles	Distinct due to its reliance on formal necessity	Distinct due to centrality of intervention and manipulation	Distinct due to reliance on idealization rather than strict deduction	Distinct due to categorical rather than numerical or mechanistic focus	Distinct due to probabilistic rather than deterministic reasoning	Distinct due to emphasis on temporal sequences rather than static structure
Ontological Contribution	Ideal objects that exist within formal systems	Laboratory phenomena and instrumentally produced entities	Idealized constructs and simplified mechanistic surrogates	Natural kinds, taxonomic categories, classification schemes	Populations, risk parameters, distributions	Historical lineages, reconstructed ancestors, temporal structures
Epistemic Identity	Truth defined by deductive validity	Truth defined by reproducible causal effects	Truth defined by model fidelity and intelligibility	Truth defined by categorical consistency	Truth defined by probabilistic inference and error control	Truth defined by historical reconstruction and evidential convergence

3. CRITERIA FOR ADDING NEW STYLES TO THE TAXONOMY

The explanatory power of the Crombie–Hacking framework rests on the availability of principled criteria for deciding when a new pattern of reasoning should be regarded as a scientific style. Hacking’s work provides this framework, even though he never formulated an explicit checklist. His discussions across several writings reveal a recurring set of features that distinguish a style from a method, a technique or a temporary research program. These features allow the taxonomy to expand while maintaining conceptual discipline.

1. The first feature is **question-generativity**. A style must enable questions that were previously inexpressible or unintelligible. For instance, deductive reasoning introduced questions concerning necessary consequences, experimental reasoning created questions about controllability and statistical reasoning gave rise to questions about distributions and error. A candidate style must show a similar capacity to open new intellectual possibilities. The second feature is **ontological productivity**. Styles do not merely organize existing objects; they bring new kinds of objects into scientific reality. Experimental styles introduce phenomena that exist only under controlled interventions, statistical styles create populations and taxonomic styles create natural or biological kinds. A new style must display the capacity to produce objects that are not assimilable to those generated by existing styles.
2. The third feature is internal standards of validation. Hacking emphasizes that styles are self-authenticating. Each style stabilizes its own norms of evidence, such as reproducibility, deductive soundness or statistical significance. A prospective style must reveal an internal logic

of correctness that is not imported from other styles. Without such autonomy, it would represent a variant of an existing style rather than a distinct one.

3. A fourth feature is irreducibility. A style must resist assimilation to the existing six traditions. For instance, hypothetical modeling is not reducible to axiomatic deduction, even though it uses formal structures, because it relies on intelligibility and approximative fidelity rather than proof. Similarly, statistical reasoning cannot be reduced to classification, because it introduces probabilistic expectations rather than structural hierarchies. A candidate style must possess a conceptual profile that cannot be reconstructed as a combination of already recognized styles.
4. The fifth feature is historical stability. Crombie’s styles endured across centuries and remained productive in novel contexts. Hacking treated this durability as evidence that styles reflect enduring cognitive strategies rather than temporary fashions. A new style must therefore demonstrate a trajectory of consolidation across multiple scientific domains, even if its historical span is shorter due to the acceleration of contemporary science.

These criteria do not aim to restrict innovation, but rather to preserve the explanatory force of taxonomy. They ensure that the classification remains sensitive to genuine epistemic transformations rather than transient methodological trends. In the following sections, these criteria will serve as the basis for evaluating whether two emerging modes of inquiry in contemporary science qualify as new styles within the Crombie–Hacking framework.

4. THE RISE OF CONTEMPORARY SCIENTIFIC PRACTICES

During the last three decades, scientific inquiry has undergone transformations challenging the boundaries of the classical six-style taxonomy. These transformations stem from developments in computational power, digital measurement and large-scale coordination across research communities. They also stem from the increasing complexity of the systems under investigation. In many areas, investigators now tackle phenomena that cannot be fully addressed through traditional deductive, experimental or statistical approaches. New modes of reasoning have begun to appear, not as isolated tools but as stable practices with their own conceptual commitments (Table 2).

One source of change is the unprecedented production of large, heterogeneous datasets in fields as varied as genomics, climate science, neuroscience and economics. These datasets often contain dimensions that exceed the capacity of classical statistical models and they are frequently explored through methods that do not presuppose explicit hypotheses or mechanistic theories. Knowledge arises through the detection of stable patterns across massive collections of measurements and explanatory success is often defined by predictive accuracy rather than interpretability. This development suggests the emergence of a distinctive form of reasoning oriented toward high-dimensional structure.

A second source of change is the increasing attention to relational organization in complex systems. Many scientific domains have adopted frameworks based on networks, graphs and relational topologies. These frameworks treat interactions rather than intrinsic properties as the primary explanatory units. Research in ecology, epidemiology, neuroscience and systems biology now centers on questions about connectivity, modularity, influence pathways and the emergence of global patterns from local interactions. This shift reflects a relational mode of reasoning that differs from older classificatory or statistical practices.

We will show in the sequel that these developments are not mere technical innovations. They shape the logic of inquiry by defining legitimate questions, establishing new types of objects and introducing evidence standards that cannot be fully captured by existing styles. Both data-intensive and relational practices are employed across multiple domains, have begun to stabilize conceptually and participate in the production of durable scientific claims. These observations motivate the central claim of this paper: recent scientific practices display features that satisfy the criteria for new styles of reasoning.

Table 2. The seventh and eighth styles of scientific reasoning. .

Feature	Data-Intensive Style (Seventh Style)	Network-Relational Style (Eighth Style)
Primary Aim	Identify stable patterns and structures across large, heterogeneous, high-dimensional datasets	Explain system behavior through connectivity, topology and global structural organization
Basic Units of Analysis	Massive collections of measurements, high-dimensional feature spaces, algorithmic reductions	Nodes, edges, motifs, pathways, multi-layer and temporal networks
Characteristic Objects	Embeddings, latent variables, algorithmic clusters, predictive signatures, composite markers	Motifs, hubs, community structures, bridges, bottlenecks, multilayer networks, influence pathways
Typical Questions	What stable structures persist across large datasets? How do high-dimensional patterns generalize? How does predictive performance behave across contexts?	How does structure constrain behavior? How do local interactions create global patterns? What features confer robustness or vulnerability?
Validation Norms	Robustness across datasets, cross-validation, generalization, stability under analytic transformations, convergence across computational methods	Structural stability, multi-scale coherence, robustness under perturbation, consistency across analytic representations, relational explanatory adequacy
Mode of Explanation	Pattern-based inference grounded in large-scale computation rather than prior models	Relational inference grounded in connectivity patterns and topological dependencies
Sources of Evidence	Genomic, neurophysiological, environmental, astronomical and social datasets; unsupervised or supervised algorithmic analyses	Empirical or simulated networks from ecology, epidemiology, systems biology, neuroscience and social systems
Relation to Classical Styles	Distinct from statistics (no presupposed models), from experimentation (no dependence on controlled manipulation) and from hypothetical modeling (discoveries precede models)	Distinct from taxonomy (no essential traits), from statistics (topology is not correlation) and from hypothetical modeling (structural patterns emerge rather than being imposed)
Ontological Contribution	High-dimensional entities and latent structures that exist only through large-scale aggregation and algorithmic extraction	Relational entities defined by structural position and connection patterns rather than by intrinsic properties
Epistemic Identity	Truth defined by stability across diverse datasets, predictive success and algorithmic convergence	Truth defined by structural coherence, relational stability and topological robustness

4.1. Previous literature on contemporary modes of scientific reasoning

The proposal for two new scientific styles rests on a substantial body of scholarship that examines how scientific reasoning has shifted in response to large-scale computational practices and the increasing prominence of relational analyses. Although none of this literature frames these developments as extensions of the Crombie–Hacking taxonomy, it provides empirical and conceptual grounding for identifying the seventh and eighth styles.

A large body of work in philosophy of science and science studies has analyzed the rise of data-intensive research (Sætra 2018; Duke et al., 2024; Dow 2024). Leonelli’s extensive studies of data-centric biology show how the collection, curation and circulation of large datasets reorganize scientific practice and often produce results before explanatory models are available (Leonelli 2016; 2019). Humphreys has explored how computational processes create epistemic opacity and introduce autonomous forms of evidence that differ from traditional inferential structures (Humphreys 2004; 2009). Keller has discussed how computational methods reshape modeling and inference in the life sciences (Keller 2003), while Parker has examined the epistemic consequences of high-volume data use in climate science and related fields (Parker 2016; 2025). Floridi’s work on the philosophy of information provides further conceptual support by analyzing information-processing as a primary mode of scientific inquiry (Floridi 2011). Related contributions include Breiman’s influential distinction between model-based statistics and algorithmic inference (Breiman 2001) and Gray’s characterization of data-intensive research as a “fourth paradigm” of scientific discovery (Gray 2009). Collectively, this literature supports the claim that data-intensive practices constitute a distinctive mode of reasoning grounded in large-scale computational infrastructures.

Parallel research has documented the emergence of relational and network-based approaches across many scientific domains (Craver 2016; Elek and Babarczy, 2022; Herfeld and Doehne, 2025). Barabási and Albert’s work on scale-free networks (Barabási and Albert 1999), Newman’s comprehensive treatment of network structure and analysis (Newman 2010) and the foundational small-world model developed by Watts and Strogatz (Watts and Strogatz 1998) have shown that structural patterns often provide the most informative basis for explanation. In biology, Alon’s analysis of network motifs demonstrates how recurrent interaction patterns form the building blocks of cellular and regulatory systems (Alon 2006). Rosen’s relational biology provides an early philosophical articulation of systems in which relations have explanatory priority over intrinsic

components (Rosen 1991). In neuroscience, connectomics has been established as a framework that interprets brain function through patterns of connectivity rather than through isolated regions (Bassett and Sporns 2017; Barabási et al. 2023; Seguin, Sporns and Zalesky 2023). Similar developments appear in ecology (Proulx, Promislow and Phillips 2005), epidemiology (Meyers 2007) and social science (Emirbayer 1997), where networks serve as fundamental explanatory resources.

These bodies of scholarship share a common structure. They treat large-scale data patterns or relational architectures as legitimate sources of knowledge. They emphasize that significant scientific results increasingly arise through computational exploration, emergent structure or interaction patterns rather than through classical hypothesis formation or controlled experimentation. They also show that new objects—such as latent embeddings, motifs or multilayer networks—acquire scientific significance through their stability and explanatory or predictive power.

Despite these convergences, the literature has not interpreted these developments in terms of the styles' tradition. Scholars typically describe them as methodological transformations, epistemic cultures or domain-specific frameworks rather than as new reasoning structures with ontological and epistemic autonomy. Our argument goes beyond these accounts by situating data-intensive and network-relational inquiry within the Crombie–Hacking framework. Doing so provides a philosophical interpretation that integrates scattered observations across diverse fields into a unified conceptual structure. We show how these developments bring about new objects, new norms of evidence and new forms of scientific intelligibility, thereby qualifying them as distinct scientific styles.

5. DEFINING THE DATA-INTENSIVE STYLE

The data-intensive style emerges in scientific contexts where investigators deal with quantities of information that exceed the analytic capacities of classical statistical or model-based approaches. In this setting, inquiry proceeds by detecting regularities across high-volume, high-dimensional collections of measurements. The central epistemic activity is the extraction of stable patterns from data rather than the testing of hypotheses derived from prior theories. This shift does not make theories or hypotheses obsolete, but it changes the order in which reasoning proceeds. Patterns are often discovered before explanatory models are available and the significance of a structure is established through its persistence across independent datasets rather than through direct alignment with mechanistic expectations.

This style is characterized by using algorithmic procedures that identify structure within data spaces where human intuition has limited reach. Machine learning methods, clustering techniques and dimensionality-reduction algorithms serve as tools for revealing latent organization. These procedures often operate without explicit assumptions about underlying causal processes. They therefore allow investigators to work with domains that are difficult to express through traditional models, such as genome-wide associations, multichannel neural recordings or large-scale environmental measurements (Musick et al., 2015; Bycroft et al., 2018; Li et al., 2022; Sun et al., 2023;). The data-intensive style introduces new kinds of scientific objects. Examples include embeddings that capture the geometry of high-dimensional spaces, latent variables inferred from unsupervised analyses, predictive signatures that correlate with future outcomes and composite markers that do not correspond to single observable features. These objects acquire ontological stability through their reproducibility across independent datasets and their effectiveness in prediction or classification. Their status does not depend on whether they correspond to a familiar physical or biological property, rather their reality is tied to the stability of the patterns they encode.

Epistemic validation in this style relies on criteria differing from those used in model-based or statistical reasoning. Truth is associated with performance across diverse datasets, robustness under noise and stability when analytic parameters are varied. A result is accepted when it persists through extensive cross-validation and can be replicated by independent groups operating on distinct data resources. These norms authenticate the style internally, because they provide standards of correctness that do not require derivation from the epistemic norms of other styles.

The data-intensive style also generates questions that were previously inaccessible. Investigators ask how patterns behave across scales, how structure emerges in spaces with thousands or millions of variables and which regularities remain stable when data sources are heterogeneous. These questions cannot be expressed in classical styles because they presuppose an epistemic environment where the primary units of analysis are large, complex datasets rather than controlled experiments or well-defined models.

Together, these features indicate that the data-intensive mode of inquiry has become an autonomous and productive reasoning practice. It creates new objects, introduces new norms of evidence and expands the conceptual space of scientific questions. The next sections analyze these characteristics in more depth and evaluate how they align with the criteria for identifying a scientific style.

5.1. *New ontologies in data-intensive science*

A distinguishing feature of a scientific style is its capacity to generate new ontological domains. In the data-intensive style, this capacity arises from the way computational analyses reorganize scientific objects. The central entities of this style are not individual measurements, but structures that emerge only when data are aggregated and analyzed at scale. These structures acquire scientific significance through their stability, their predictive value and their persistence across independent datasets. They represent objects that did not exist as meaningful units before large-scale computational practices became common.

One group of entities involves **embeddings**, which are vector or geometric representations of complex objects such as genes, images, molecular structures or linguistic tokens. These embeddings encode relationships in high-dimensional space and serve as compact representations of similarity or functional proximity. Investigators use them to infer groupings, predict associations or identify latent features that cannot be observed directly. Embeddings are not mere summaries of data: they are new objects that play active roles in explanation and prediction.

Another category includes **latent variables** inferred through unsupervised or semi-supervised analyses. These variables do not correspond to single observable properties but to patterns of co-variation that recur across samples. For example, latent factors in neural recordings represent modes of population activity, while latent signatures in genomics represent composite markers underlying complex traits. Their ontological status arises from their stability across datasets and their utility in generating successful predictions, rather than from any direct measurable feature.

A further class of objects comprises **predictive signatures**. These are complex, often non-interpretable combinations of features that correlate reliably with future events, such as disease progression or system failure. Their significance does not depend on a mechanistic explanation but on their capacity to provide actionable knowledge. Once validated across independent datasets, these signatures become part of the operational ontology of a domain, guiding research and intervention even when their internal structure remains opaque.

The data-intensive style also produces **composite markers** that integrate data from multiple modalities. Examples include risk scores derived from genomic, behavioral and environmental inputs or multi-source indicators used in climate modeling. These markers have no single physical or biological correlates, but their identity is defined by their integrative structure and their reproducibility across large datasets.

These objects illustrate that the data-intensive style is not a methodological extension of statistical reasoning. It brings into existence entities that have no natural place within the older styles. Their emergence fulfills one of Hacking's central criteria for a scientific style: the production of new, durable objects that reshape the space of scientific possibilities.

5.2. *Epistemic norms and internal validation*

A scientific style relies on internally generated criteria that determine when a result is deemed acceptable. In the data-intensive style, validation is grounded in norms that emerge from large-scale

computational practice rather than from the epistemic structures of the classical statistical or experimental styles. These norms are shaped by the challenges of high-dimensional data, heterogeneity across sources and the limited interpretability of many algorithmic methods. As a result, the criteria for correctness develop within the practice itself and reflect the constraints and opportunities of data-centric inquiry.

A central norm is **robustness across datasets**. A result gains credibility when it appears consistently in independent collections of data differing in origin, scale or measurement technique. This expectation is stronger than the reproducibility norms found in experimental reasoning. Instead of repeating a controlled intervention, investigators seek convergence across large, diverse corpora. In this context, reproducibility is demonstrated by the survival of a pattern under substantial variation in input conditions.

A second norm is **stability under analytic transformations**. Computational procedures often involve choices of tuning parameters, model architectures and preprocessing steps. A result is considered valid when it remains stable under a broad range of these choices. This requirement is internal to the data-intensive style because it does not rely on external theory. Instead, it reflects the recognition that high-dimensional structures can be artifacts of analytic paths unless they persist under systematic perturbations.

A third norm involves **performance criteria**, typically expressed through measures of predictive accuracy or classification success. A result is accepted when it consistently outperforms baselines across multiple folds of cross-validation and across distinct partitions of data. These criteria define truth operationally within the style, because predictive stability becomes the marker of epistemic success. The associated notion of correctness differs from that of statistical inference, which relies on sampling theory, and from that of hypothesis testing, which depends on explicit model assumptions.

A fourth norm is **generalization beyond training data**. Investigators assess whether a pattern discovered in one context applies to new, previously unseen contexts. This form of validation demonstrates independence from the particularities of a dataset, becoming a measure of how well a structure captures underlying regularities rather than noise. The expectation of generalization is not a statistical holdover; it follows from the scale and complexity of the systems examined, which call for methods that can operate across heterogeneous sources.

A final norm is **algorithmic convergence**. When different computational routes produce similar structures, investigators treat the result as more credible. Convergence between unsupervised and supervised methods or between linear and non-linear procedures provides a signal that the object of interest reflects a genuine regularity in the data and not a specific feature of a particular algorithm.

These norms show that the data-intensive style is not reducible to traditional statistical reasoning. It authenticates itself through practices arising within large-scale computational environments and addressing the distinctive challenges posed by high-dimensional information. This internal epistemic structure supports the claim that the data-intensive mode qualifies as a distinct scientific style. The next section explores how these features distinguish it from the established six styles in the Crombie–Hacking taxonomy.

5.3. Distinctiveness from the classical six styles

To qualify as a distinct scientific style within the Crombie–Hacking taxonomy, the data-intensive mode must resist assimilation to the classical six traditions. Although it shares surface similarities with some of these styles, its conceptual commitments, epistemic standards and ontological outputs differ in ways that indicate genuine independence.

The data-intensive style is not a variant of **statistical reasoning**, even though both involve numerical analysis. Classical statistics focus on probabilistic models, sampling distributions and explicit assumptions about populations. Its epistemic norms depend on hypotheses, confidence intervals and the logic of inference. In turn, the data-intensive style rarely relies on model-based assumptions. It often proceeds without an explicit representation of populations or sampling frameworks and evaluates results through stability across scale rather than through calculable error.

Many of its objects, e.g., embeddings, latent spaces or algorithmic clusters, have no place within classical statistical ontology.

It is also distinct from the **experimental style**. Experimental reasoning emphasizes controllability, intervention and reproducibility under well-defined conditions. Evidence is accepted when results reappear in carefully structured environments. The data-intensive style does not depend on controlled interventions. Instead, it relies on convergence across heterogeneous datasets, many of which are observational or opportunistic. Its notion of reproducibility concerns persistence across variation in measurement sources, rather than repeated manipulation of a controlled system.

The data-intensive style cannot be reduced to the **hypothetical and model-based style**, which relies on constructing idealized representations and evaluating them through fit, intelligibility or explanatory coherence. Data-intensive inquiry often proceeds without these models. Many computational procedures identify patterns lacking a corresponding mechanistic representation and remaining significant even when no interpretive framework is available. The orientation toward discovery prior to model formation indicates a fundamental difference in the order of reasoning.

It also differs from the **taxonomic style**, which organizes phenomena into structured categories based on stable diagnostic features. Data-intensive practices do produce clusters and groupings, but these are not categories defined by essential properties. Instead, they are algorithmic objects that exist through patterns of co-variation and that may change under new sampling regimes. Their status does not resemble classical taxonomic kinds and depends on criteria of stability and predictive value.

The **axiomatic and deductive style** is clearly distinct from the data-intensive mode. Deductive reasoning builds knowledge through explicit postulates and logical inference, while data-intensive reasoning often works in environments where formal models are limited or absent. Its epistemic norms concern performance and robustness rather than logical entailment.

Finally, the data-intensive style is not an extension of the **genetic or historical style**, which explains phenomena by reconstructing temporal sequences or lines of descent. While data-intensive techniques can be used to analyze historical processes, the reasoning structure is not genealogical since it centers on high-dimensional patterns rather than temporal development.

Taken together, these comparisons demonstrate that the data-intensive mode cannot be mapped onto the existing six styles. It introduces new objects, establishes distinct epistemic norms and reorders the sequence through which questions, evidence and explanations arise. These features support its classification as a separate style of scientific reasoning. The next section introduces the second candidate style examined in this paper: the network-relational mode.

6. DEFINING THE NETWORK-RELATIONAL STYLE

The network-relational style centers on the idea that explanation and prediction are grounded in patterns of interconnection rather than in the intrinsic properties of individual elements. In this mode of inquiry, investigators treat a system as a set of nodes linked by relations that vary in strength, direction or temporal character. The scientific significance of any element depends on its position within this relational structure and on the global patterns arising from local interactions. This approach is increasingly common in fields that tackle complex or interconnected systems, such as ecology, epidemiology, neuroscience, systems biology and computer science.

The network-relational style does not represent a simple application of graph theory. Instead, it encompasses a broader pattern of reasoning in which structure becomes the primary basis of scientific knowledge. Investigators ask how influence propagates through interconnected pathways, how modular regions coordinate and how global organization emerges from distributed interactions. The focus lies on motifs, hubs, centrality measures, path lengths and multi-layer configurations. These components become the fundamental units of explanation and the system's behavior is understood through the architecture of its relational network.

This style reconfigures what counts as a scientific object. Instead of viewing units as self-contained entities with intrinsic causal powers, investigators treat them as elements embedded within wider webs of dependence. In neuroscience, for example, functional roles are attributed to

nodes based on their connectivity profiles rather than on properties of individual neurons, while species in ecology are identified as keystones through their positions within food webs (Sabir et al., 2023; Cao et al., 2023; Wu et al., 2024; Schlegel et al., 2024). In epidemiology, transmission patterns are explained by contact networks rather than by population averages (Craft 2015; Liu et al., 2019; Taube et al., 2022). These examples illustrate how the style shifts attention from isolated variables to structural organization.

The network-relational style also introduces new types of questions. Instead of asking why a particular element exhibits a certain behavior, investigators ask how its behavior contributes to or depends on broader structural patterns. This shift opens inquiries into resilience, cascading effects, structural bottlenecks and the conditions under which local disruptions propagate globally. Many of these questions have no clear formulation within the classical styles because they presuppose a system-level view grounded in relational topology.

What distinguishes this style from earlier classificatory or statistical traditions is its emphasis on interaction patterns as the central explanatory resource. Classification organizes entities into discrete groups and statistics captures relations among variables, but neither tradition treats the architecture of interactions as the foundation of explanation. The network-relational mode views the relational environment as constitutive of the system's behavior and it derives epistemic significance from structural features that extend across scales.

This style therefore represents an emerging mode of reasoning that is both conceptually and epistemically distinct. In the following sections, the paper examines the ontological and epistemic consequences of this style and evaluates its suitability for inclusion within the Crombie–Hacking taxonomy.

6.1. *Ontological productivity of the network-relational style*

A defining feature of a scientific style, according to the Crombie–Hacking framework, is its ability to generate new kinds of scientific objects. The network-relational style accomplishes this by shifting attention from isolated units to structured patterns of interaction. Its ontological contributions arise from the idea that relational architecture is not a secondary feature of a system but a primary source of scientific reality. As a result, objects that acquire significance in this style are defined through their roles within networks and through the structural properties of the network itself.

One category of such objects consists of **motifs**, or recurring subgraph patterns that appear more frequently than expected under null models. Motifs serve as basic building blocks for understanding local functional organization. For instance, feed-forward loops in gene regulatory networks, triadic closures in social networks and recurrent circuits in neural systems gain explanatory force because they embody reproducible modes of interaction. These motifs do not correspond to isolated components or classical categories, rather exist only through the relational analysis that reveals their prevalence and functional roles.

Another group of objects includes **hubs**, **bridges** and **bottlenecks**, which are defined by their positions within the larger structure. These elements acquire scientific significance by virtue of their connectivity and their roles in mediating flow, influence or stability. For example, a species may count as a keystone because its removal dramatically alters the structure of a food web, even if it is not abundant or physiologically distinctive. Similarly, a brain region may be central not because of its intrinsic properties, but because it integrates distinct functional modules. These objects illustrate how the relational style shifts explanatory focus from intrinsic attributes to structural roles.

The network-relational style also introduces **multi-layer networks** and **hypergraphs** as ontological units. These structures capture systems where interactions occur across several domains or involve more than two participants. In systems biology, multi-layer networks integrate genetic, metabolic and signaling interactions. In epidemiology, they represent the interaction between physical contacts, mobility patterns and environmental exposure. These structures do not map onto

the categories of the classical styles. Their existence depends on a relational ontology that treats connection types and cross-layer couplings as fundamental components of inquiry.

A further set of objects includes **influence pathways**, **cascade structures** and **feedback corridors**, which represent sequences of connections through which effects propagate. These objects are especially important when investigators study cascading failures in power grids, contagion in social systems or coordinated activation in neural ensembles. Their scientific significance cannot be captured by models that treat variables independently. They gain reality through analyses that reveal the system's dynamic reaction to disturbance.

Finally, the network-relational style creates **community structures**, which are groups of nodes interacting more densely with each other than with the rest of the system. Communities often correspond to functional modules, ecological guilds or social groups. Their ontological status depends on patterns of relation rather than on defining intrinsic features. The identity of a community rests on the density of its connections and changes in structure can transform or dissolve it. This form of object is distinct from classificatory kinds because it is relational, dynamic and often multi-scale.

These examples illustrate that the network-relational style is ontologically productive in the sense required for a scientific style. It generates objects that have no natural place within the classical six traditions and that become fundamental to explanation, prediction and intervention.

6.2. Evidence and truth in the network-relational style

For a mode of inquiry to qualify as a scientific style in the Crombie–Hacking sense, it must possess internal standards that determine when a result counts as established. In the network-relational style, epistemic validation arises from the structural features of networks and the reproducibility of relational patterns across contexts. They authenticate the style from within and reflect the epistemic demands of systems whose behavior depends on connectivity rather than isolated properties.

One norm involves **structural stability**. A relational claim gains credibility when the underlying pattern of connections persists across independent datasets, measurement techniques or sampling resolutions. For example, the modular organization of a connectome, the trophic structure of an ecosystem or the clustering patterns of a social network are considered reliable when they appear consistently despite changes in data collection or analytic procedures. Structural stability functions as a marker of objectivity within the style, analogous to reproducibility in experimental practice.

A second norm is **multi-scale coherence**. Many systems exhibit patterns recurring at different spatial or temporal scales. A result gains epistemic weight when it aligns with this multi-scale organization. In neuroscience, for instance, hub regions can be identified at micro, meso and macro scales and their significance is strengthened when relational features remain recognizable across levels. This form of coherence is internal to the style because it concerns the way relational architecture constrains and supports explanatory claims.

A third norm concerns **robustness under perturbation**. Investigators assess whether structural features persist when networks are altered through node removal, edge rewiring or targeted disruptions. A pattern that remains identifiable under these perturbations is treated as more meaningful than one that vanishes under minor changes. This approach is employed in ecology to identify keystone species, in epidemiology to evaluate transmission vulnerabilities and in systems biology to assess regulatory stability.

A fourth epistemic norm is **consistency across analytic representations**. Different methods can represent networks in ways that emphasize distinct features such as adjacency matrices, Laplacian embeddings or modularity partitions. When a relational structure appears across multiple analytic representations, it gains credibility as a genuine feature of the system rather than an artifact of a particular analytic choice. This expectation mirrors the convergence norms found in the data-intensive style, but its content is specifically relational.

Another norm involves **explanatory sufficiency through structural inference**. A relational claim is accepted when it accounts for system behavior through reference to connectivity patterns

alone, without requiring detailed knowledge of intrinsic unit properties. For example, the spread of a contagion can be explained through contact patterns even when individual-level susceptibilities remain unknown. In these cases, the explanatory force derives from the network structure itself. This form of inference is distinct from statistical correlation and from mechanistic description, reflecting a commitment to relational organization as an independent source of understanding.

These epistemic norms show that the network-relational style is not a methodological extension of existing traditions. Its standards of truth and evidence arise from the logic of relational organization and the constraints of interconnected systems. The next section shows how this style differs systematically from the classical six styles.

6.3. Differences from the classical six styles

To determine whether the network-relational mode qualifies as a scientific style, it is necessary to compare it with the established six traditions in the Crombie–Hacking taxonomy. Although relational reasoning intersects with several classical modes, its conceptual foundations and evidential norms differ in systematic ways that indicate genuine independence.

The network-relational mode is distinct from the **taxonomic style**, which classifies entities according to essential or diagnostic features. Taxonomic reasoning produces static hierarchies and category-based distinctions. By contrast, the relational mode does not assign entities to fixed classes. It treats communities, modules and clusters as dynamic units defined by patterns of interaction rather than by intrinsic traits. Their identity depends on structural context and they may dissolve or reorganize when connectivity changes. These features have no analogue in classical taxonomic reasoning.

It differs from **statistical reasoning** because relational explanations do not rely on probabilistic relations among variables. The structure of a network is not simply a set of correlations. It is a topological object whose significance arises from properties such as path length, degree distribution or structural motifs. These features represent organizational principles that cannot be reduced to variable-based associations. Even when statistics is used to quantify structural features, the explanatory role of the network arises from its architecture rather than from probabilistic inference.

The relational style also diverges from the **hypothetical and model-based tradition**. Model-based reasoning seeks intelligibility through idealized constructs, while relational analysis seeks intelligibility through discovered structural patterns. Many relational claims are not derived from pre-formulated models, but emerge from the analysis of connectivity data. The explanatory force lies in the pattern itself, not in its representation as an idealized model with simplified assumptions.

The **experimental style** centers on controllable interventions and the production of reproducible phenomena. Although relational analyses may use experimental data, the style itself does not depend on manipulation. Its validity arises from structural stability across networks, not from repeated interventions in controlled settings. Moreover, experimental phenomena often concern specific objects or mechanisms, while relational explanations concern global architectures that are not amenable to direct experimental control.

The **axiomatic and deductive style** remains far removed from relational reasoning. Deductive inquiry relies on explicit postulates and formal inference, whereas the relational mode identifies structures that emerge from empirical or computational analysis. Even when graph theory informs the analysis, the reasoning does not proceed by deriving theorems from axioms. The relational style depends on empirical structures and their stability, not on formal derivation.

Finally, the relational mode differs from the **genetic or historical style**, which explains phenomena through temporal sequences and lines of descent. Although networks can change over time, relational explanation does not depend on genealogical chains. It focuses on the topology of connections at particular stages and on structural dependencies, rather than on historical origins.

These systematic differences show that relational inquiry cannot be subsumed under the classical six styles. It possesses its own subject matter, its own characteristic questions and its own

epistemic norms. Its autonomy supports the claim that it qualifies as a new scientific style within the expanded Crombie–Hacking framework.

7. DO THE TWO NEW STYLES MEET HACKING’S CRITERIA?

Hacking’s reformulation of Crombie’s taxonomy identifies scientific styles by the roles they play in shaping what questions can be asked, what objects can be investigated and what forms of reasoning count as legitimate. A proposed style must therefore satisfy several conditions. This section evaluates the data-intensive and network-relational modes considering these criteria and examines whether they qualify as distinct styles within the expanded taxonomy.

Question-generativity is evident in both modes. Data-intensive inquiry introduces questions about high-dimensional structure, pattern stability across heterogeneous datasets and predictive performance that cannot be expressed within the constraints of classical models. The network-relational mode introduces questions about connectivity, structural coherence and the interplay between local interactions and global organization. These questions do not arise naturally in the classical styles because they presuppose epistemic environments shaped by large-scale computation and relational analysis.

Ontological productivity is fulfilled in both cases. The data-intensive style produces embeddings, latent factors, composite markers and algorithmic clusters as new scientific objects not corresponding to pre-existing categories or mechanistic units. Their identity depends on their stability within high-dimensional spaces. The network-relational style produces motifs, hubs, multi-layer networks, community structures and influence pathways. These objects exist only within a relational ontology and have no equivalents in the established traditions. The ontological contributions of both modes are consistent with the role Hacking assigns to styles as engines of conceptual and ontological innovation.

Internal standards of validation are also present. Data-intensive inquiry authenticates its results through robustness across datasets, stability under analytic transformations, predictive success, generalization beyond training contexts and convergence between different computational approaches. These norms differ from those of experimental reproducibility, statistical inference or model-based coherence. The network-relational style validates its claims through structural stability, multi-scale coherence, robustness under perturbation, consistency across analytic representations and explanatory sufficiency derived from connectivity patterns alone. These standards reflect the internal epistemic logic of each style rather than borrowed norms from the classical six.

Irreducibility becomes clear once one examines how both styles diverge from the classical traditions. The data-intensive mode is not an extension of statistical, experimental or hypothetical reasoning because its conceptual and epistemic commitments differ systematically from those of each classical style. The network-relational mode is not reducible to taxonomy, correlation-based statistics, model construction or genealogical reconstruction. In each case, the central explanatory and evidential principles lie outside the structures of the existing styles.

Historical stability is the most challenging criterion to evaluate, given the relatively recent emergence of these practices. However, both modes exhibit signs of consolidation across multiple disciplines. Data-intensive reasoning has become fundamental in genomics, neuroscience, climate science, observational astronomy and computational social science. Network-relational reasoning now shapes ecology, epidemiology, systems biology and cognitive neuroscience. These developments indicate that both modes have moved beyond isolated applications and have begun to stabilize as cross-disciplinary forms of inquiry. Although their histories are short compared to classical styles, the rapid pace of scientific transformation suggests that stability must be assessed relative to contemporary research timescales.

Taken together, these considerations show that the data-intensive and network-relational modes satisfy the criteria for classification as scientific styles. Their recognition within the Crombie–Hacking framework supports a more accurate and pluralistic understanding of scientific practice.

8. CONCLUSION

Crombie's taxonomy and Hacking's revision have provided a durable framework for understanding the diversity of scientific reasoning. The six classical styles capture long-standing traditions that continue to structure inquiry and shape scientific objectivity. Yet contemporary scientific practice reveals patterns of reasoning that do not fit comfortably within this established taxonomy. The growth of data-intensive and network-relational approaches indicates that new modes of inquiry have begun to crystallize, each with its own conceptual commitments, evidential norms and ontological contributions.

We argued that these developments qualify as new scientific styles within the Crombie–Hacking framework. The data-intensive style introduces questions and objects depending on large-scale computation and high-dimensional structure. Its epistemic norms differ from those of statistical or experimental reasoning, emphasizing robustness across datasets, algorithmic convergence and predictive performance. The network-relational style reorients explanation toward patterns of connectivity and global structure. It generates new objects, such as motifs and multilayer networks and validates claims through structural stability and multi-scale coherence.

Both styles satisfy the criteria that Hacking associated with scientific styles. They generate new areas of inquiry, produce novel ontological domains, authenticate themselves internally, resist reduction to the classical traditions and show signs of stabilization across disciplines. Their recognition extends the original taxonomy and illustrates how scientific rationality evolves in response to new tools, new forms of data and new theoretical challenges.

Our expanded taxonomy also refines philosophical debates on pluralism, realism and the dynamics of scientific change. It supports a pluralistic conception of science that is responsive to contemporary practice and recognizes the emergence of new epistemic structures. It suggests that scientific change often involves the development of new reasoning forms coexisting with established ones rather than the replacement of entire theoretical frameworks. These insights offer a more accurate picture of how scientific knowledge grows and how investigators navigate increasingly complex domains.

The addition of two new styles does not represent a closure of the taxonomy. Instead, it demonstrates that the Crombie–Hacking framework is flexible enough to accommodate the evolving landscape of scientific practice. As science continues to develop, new styles may emerge, shaped by future technologies, conceptual innovations and challenges in understanding complex systems. Recognizing this open-ended character is essential for maintaining a philosophical account that reflects the dynamic nature of scientific reasoning.

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References

1. Alon, Uri. *An Introduction to Systems Biology: Design Principles of Biological Circuits*. Boca Raton: CRC Press, 2006.
2. Barabási, Albert-László and Réka Albert. "Emergence of Scaling in Random Networks." *Science* 286, no. 5439 (1999): 509–512.
3. Barabási, D. L., G. Bianconi, E. Bullmore, M. Burgess, S. Chung, et al. "Neuroscience Needs Network Science." *Journal of Neuroscience* 43, no. 34 (2023): 5989–95. <https://doi.org/10.1523/JNEUROSCI.1014-23.2023>
4. Bassett, Danielle S. and Olaf Sporns. "Network Neuroscience." *Nature Neuroscience* 20, no. 3 (2017): 353–64. <https://doi.org/10.1038/nn.4502>
5. Bycroft, Clare, Colin Freeman, Desislava Petkova, Gavin Band, Lloyd T. Elliott, Kevin Sharp, Alan Motyer, et al. "The UK Biobank Resource with Deep Phenotyping and Genomic Data." *Nature* 562, no. 7726 (2018): 203–9. <https://doi.org/10.1038/s41586-018-0579-z>
6. Breiman, Leo. "Statistical Modeling: The Two Cultures." *Statistical Science* 16, no. 3 (2001): 199–231.
7. Cao, Hui, Todd Lencz, Jorge A. Gallego, Juan M. Rubio, Michael John, et al. "A Functional Connectome-Based Neural Signature for Individualized Prediction of Antipsychotic Response in First-Episode Psychosis." *American Journal of Psychiatry* 180, no. 11 (2023): 827–35. <https://doi.org/10.1176/appi.ajp.20220719>
8. Craft, Meggan E. "Infectious Disease Transmission and Contact Networks in Wildlife and Livestock." *Philosophical Transactions of the Royal Society B: Biological Sciences* 370, no. 1669 (2015): 20140107. <https://doi.org/10.1098/rstb.2014.0107>
9. Craver, Carl F. "The Explanatory Power of Network Models." *Philosophy of Science* 83, no. 5 (2016): 698–709. <https://doi.org/10.1086/687856>
10. Crombie, A. C. *Styles of Scientific Thinking in the European Tradition: The History of Argument and Explanation Especially in the Mathematical and Biomedical Sciences and Arts*. 3 vols. London: Duckworth, 1994.
11. Dow, Julian A. T. "Big Data and Experimental Biology: The Complementary Roles of Hypothesis-Led and Blue Skies Research." *Journal of Experimental Biology* 227, no. 18 (2024): jeb246692. <https://doi.org/10.1242/jeb.246692>
12. Duke, Rebecca, Ryan McCoy, Christopher Risko and Jeffrey R. S. Bursten. "Promises and Perils of Big Data: Philosophical Constraints on Chemical Ontologies." *Journal of the American Chemical Society* 146, no. 17 (2024): 11579–91. <https://doi.org/10.1021/jacs.3c11399>
13. Elek, Gábor and Eszter Babarczy. "Taming Vagueness: The Philosophy of Network Science." *Synthese* 200, no. 2 (2022): 1–31. <https://doi.org/10.1007/s11229-022-03622-0>
14. Emirbayer, Mustafa. "Manifesto for a Relational Sociology." *American Journal of Sociology* 103, no. 2 (1997): 281–317.
15. Floridi, Luciano. *The Philosophy of Information*. Oxford: Oxford University Press, 2011.
16. Gray, Jim. *The Fourth Paradigm: Data-Intensive Scientific Discovery*. Edited by Tony Hey, Stewart Tansley and Kristin Tolle. Redmond: Microsoft Research, 2009.
17. Hacking, Ian. "Styles of Scientific Reasoning." In *Post-Analytic Philosophy*, edited by John Rajchman and Cornel West, 145–164. New York: Columbia University Press, 1985.

18. Hacking, Ian. *Historical Ontology*. Cambridge, MA: Harvard University Press, 2002.
19. Herfeld, Catherine and Malte Doehne. "Empirical Network Analysis as a Method for Philosophy of Science." In *Methods in Philosophy of Science: A User's Guide*, edited by Sophie Veigl and Adrian Currie. Cambridge, MA: MIT Press, 2025.
20. Humphreys, Paul. *Extending Ourselves: Computational Science, Empiricism and Scientific Method*. Oxford: Oxford University Press, 2004.
21. Humphreys, Paul. "The Philosophical Novelty of Computer Simulation Methods." *Synthese* 169, no. 3 (2009): 615–626.
22. Keller, Evelyn Fox. *Making Sense of Life: Explaining Biological Development with Models, Metaphors and Machines*. Cambridge, MA: Harvard University Press, 2003.
23. Leonelli, Sabina. *Data-Centric Biology: A Philosophical Study*. Chicago: University of Chicago Press, 2016.
24. Leonelli, Sabina. "The Challenges of Big Data Biology." *eLife* 8 (2019): e47381.
25. Li, Min, Shanshan Cheng, Jinlong Fan, Zhenyu Shang, and Haibo Wan. "Many Heads Are Better than One: A Multiscale Neural Information Feature Fusion Framework for Spatial Route Selections Decoding from Multichannel Neural Recordings of Pigeons." *Brain Research Bulletin* 184 (2022): 1–12. <https://doi.org/10.1016/j.brainresbull.2022.03.007>
26. Liu, Ming-Xin, Si-Si He, and Yu-Zhong Sun. "The Impact of Media Converge on Complex Networks on Disease Transmission." *Mathematical Biosciences and Engineering* 16, no. 6 (2019): 6335–49. <https://doi.org/10.3934/mbe.2019316>
27. Martínez, María Laura. "Ian Hacking's Contributions to Historical Reflection on Science." In *Handbook for the Historiography of Science*, edited by María Laura Condé and Marlon Salomon. *Historiographies of Science*. Cham: Springer, 2023. https://doi.org/10.1007/978-3-030-99498-3_10-2
28. Meyers, Lauren A. "Contact Network Epidemiology: Bond Percolation Applied to Infectious Disease Prediction and Control." *Bulletin of the American Mathematical Society* 44, no. 1 (2007): 63–86.
29. Musick, Kimber M., Javier Rigosa, Sriram Narasimhan, Stephan Wurth, Marco Capogrosso, Daniel J. Chew, James W. Fawcett, Silvestro Micera, and Stéphanie P. Lacour. "Chronic Multichannel Neural Recordings from Soft Regenerative Microchannel Electrodes during Gait." *Scientific Reports* 5 (2015): 14363. <https://doi.org/10.1038/srep14363>
30. Newman, M. E. J. *Networks: An Introduction*. Oxford: Oxford University Press, 2010.
31. Parker, Wendy S. "Reanalyses and Observations: What's the Difference?" *Bulletin of the American Meteorological Society* 97, no. 9 (2016): 1565–1572 Proulx, Stephen R., Daniel E. L. Promislow and Patrick C. Phillips. "Network Thinking in Ecology and Evolution." *Trends in Ecology and Evolution* 20, no. 6 (2005): 345–353.
32. Parker, Wendy S. *Climate Science*. Cambridge: Cambridge University Press, 2025. Rosen, Robert. *Life Itself: A Comprehensive Inquiry into the Nature origin and Fabrication of Life*. New York: Columbia University Press, 1991.
33. Ruphy, Stéphanie. "From Hacking's Plurality of Styles of Scientific Reasoning to 'Foliated' Pluralism: A Philosophically Robust Form of Ontologico-Methodological Pluralism." *Philosophy of Science* 78, no. 5 (2011): 1212–22. <https://doi.org/10.1086/664571>
34. Sabir, Z., M. R. Ali, and R. Sadat. "Gudermannian Neural Networks Using the Optimization Procedures of Genetic Algorithm and Active Set Approach for the Three-Species Food Chain Nonlinear Model." *Journal of Ambient Intelligence and Humanized Computing* 14, no. 7 (2023): 8913–22. <https://doi.org/10.1007/s12652-021-03638-3>
35. Sætra, Henrik Skaug. "Science as a Vocation in the Era of Big Data: The Philosophy of Science behind Big Data and Humanity's Continued Part in Science." *Integrative Psychological and Behavioral Science* 52, no. 4 (2018): 508–22. <https://doi.org/10.1007/s12124-018-9447-5>
36. Schlegel, Philipp, Yizhen Yin, Alexander S. Bates, Stephan Dorkenwald, Karin Eichler, Peter Brooks, Daniel S. Han, et al.; FlyWire Consortium; Marta Costa; H. Sebastian Seung; Mani Murthy; Volker Hartenstein; Davi D. Bock; Gregory S. X. E. Jefferis. "Whole-Brain Annotation and Multi-Connectome Cell Typing of *Drosophila*." *Nature* 634, no. 8032 (2024): 139–52. <https://doi.org/10.1038/s41586-024-07686-5>
37. Sciortino, Luca. "On Ian Hacking's Notion of Style of Reasoning." *Erkenntnis* 82, no. 2 (2017): 243–64.

38. Sciortino, Luca. "The Emergence of Objectivity: Fleck, Foucault, Kuhn and Hacking." *Studies in History and Philosophy of Science* 88 (2021): 128–37.
39. Sciortino, Luca. Ian Hacking's Styles of Reasoning, Contingency and the Evolution of Science. In *History of Rationalities: Ways of Thinking from Vico to Hacking and Beyond*, 350–. New York: Palgrave-Macmillan, 2023.
40. Seguin, Caio, Olaf Sporns and Andrew Zalesky. "Brain Network Communication: Concepts, Models and Applications." *Nature Reviews Neuroscience* 24, no. 9 (2023): 557–74. <https://doi.org/10.1038/s41583-023-00718-5>
41. Sun, Jie, Jun Zhao, Fan Jiang, Li Wang, Qian Xiao, Fang Han, et al. "Identification of Novel Protein Biomarkers and Drug Targets for Colorectal Cancer by Integrating Human Plasma Proteome with Genome." *Genome Medicine* 15, no. 1 (2023): 75. <https://doi.org/10.1186/s13073-023-01229-9>
42. Taube, Jennifer C., Patrick B. Miller, and John M. Drake. "An Open-Access Database of Infectious Disease Transmission Trees to Explore Superspreader Epidemiology." *PLoS Biology* 20, no. 6 (2022): e3001685. <https://doi.org/10.1371/journal.pbio.3001685>
43. Watts, Duncan J. and Steven H. Strogatz. "Collective Dynamics of 'Small-World' Networks." *Nature* 393 (1998): 440–442.
44. Vagelli, Matteo. "Hacking's Styles of Scientific Reasoning." In *Reconsidering Historical Epistemology*, vol. 61. *Studies in History and Philosophy of Science*. Cham: Springer, 2024. https://doi.org/10.1007/978-3-031-61555-9_8
45. Wanderer, Jeremy. "'The Happy Thought of a Single Man': On the Legendary Beginnings of a Style of Reasoning." *Studies in History and Philosophy of Science Part A* 43, no. 4 (2012): 640–48. <https://doi.org/10.1016/j.shpsa.2012.07.006>
46. Wu, Xiong, Ting Zhang, Ting Zhang, and Sungho Park. "The Impact of Gut Microbiome Enterotypes on Ulcerative Colitis: Identifying Key Bacterial Species and Revealing Species Co-Occurrence Networks Using Machine Learning." *Gut Microbes* 16, no. 1 (2024): 2292254. <https://doi.org/10.1080/19490976.2023.2292254>

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