

Article type: Editorial

# Ecosystem Intelligence: Viability, Agency, and Transformation in Complex Ecosystems

Zheng Grace Ma <sup>1,\*</sup>, Anders Drachen <sup>2</sup>, Hongbo Duan <sup>3</sup> and Bo Nørregaard Jørgensen <sup>1</sup>

<sup>1</sup> SDU Center for Energy Informatics, The Maersk Mc-Kinney Møller Institute, Faculty of Engineering, University of Southern Denmark, Odense, Denmark; [zma@mmmi.sdu.dk](mailto:zma@mmmi.sdu.dk) (Z.G.M.); <https://orcid.org/0000-0002-9134-1032> (Z.G.M.); [bnj@mmmi.sdu.dk](mailto:bnj@mmmi.sdu.dk) (B.N.J.); <https://orcid.org/0000-0001-5678-6602> (B.N.J.)

<sup>2</sup> SDU Metaverse Lab, The Maersk Mc-Kinney Møller Institute, Faculty of Engineering, University of Southern Denmark, Odense, Denmark; [adrac@mmmi.sdu.dk](mailto:adrac@mmmi.sdu.dk) (A.D.); <https://orcid.org/0000-0002-1002-0414> (A.D.)

<sup>3</sup> School of Economics and Management, University of Chinese Academy of Sciences (UCAS), Beijing, China; [hbd@ucas.ac.cn](mailto:hbd@ucas.ac.cn); <https://orcid.org/0000-0001-5143-4413> (H.D.)

\* Correspondence: [zma@mmmi.sdu.dk](mailto:zma@mmmi.sdu.dk)

**Received:** 13 September 2026 | **Accepted:** 13 September 2026 | **Published:** 14 September 2026

**Peer review:** Editorial; not externally peer reviewed. Handling editor: Signe Rude Madsen.

**Cite this article:** Ma, Z. G., Drachen, A., Duan, H., & Jørgensen, B. N. (2026). Ecosystem Intelligence: Viability, Agency, and Transformation in Complex Ecosystems. *Ecosystem Intelligence*, 1(1). Retrieved from <https://tidsskrift.dk/JournalEcosystemIntelligence/article/view/171525>

**Copyright:** © 2026 by the authors. Published by the University of Southern Denmark, hosted on tidsskrift.dk by the Royal Danish Library, under the CC BY 4.0 licence (<https://creativecommons.org/licenses/by/4.0/>).

## Abstract

This founding editorial introduces Ecosystem Intelligence as an emerging field for studying how complex ecosystems become knowable, coordinate action, remain viable, and transform under uncertainty. The proposed field is evolutionary: it integrates insights from established systems, intelligence, resilience, transition, and governance traditions around a distinct research problem: how distributed sensing, interpretation, agency, disturbance absorption, and reorganization affect ecosystem viability. The editorial also acknowledges narrower previous uses of the phrase “ecosystem intelligence” in business-ecosystem analytics and AI-based platform research and proposes a broader scientific meaning centered on distributed ecosystem-level capacity and viability. This editorial proposes the following initial definition: Ecosystem Intelligence is the distributed capacity of a complex ecosystem to sense changing conditions, interpret their significance, coordinate heterogeneous human, artificial, institutional, infrastructural, economic, and environmental components, absorb disturbance, and reorganize under uncertainty while sustaining or restoring ecosystem viability. The editorial clarifies the scientific gap, distinguishes adjacent traditions, proposes four interdependent research areas, introduces an initial Ecosystem Intelligence Diagnostic Protocol, explains how bounded empirical testbeds can be developed across diverse domains, and presents the journal Ecosystem Intelligence and the Ecosystem Intelligence Academy community as complementary forums for building this field through research, debate, and participation. The proposed definition, boundary, research areas, diagnostic protocol, and approach to empirical grounding and testbed development are offered for discussion, testing, refinement, and further development.

**Keywords:** Ecosystem Intelligence; Ecosystem Viability; Distributed Agency; Collective and Hybrid Intelligence; Ecosystem Sensemaking; Complex Ecosystems; Viability Diagnostics; Adaptive Transformation; Governability

# 1. Ecosystem Intelligence: Definition, Urgency, and Scientific Gap

Contemporary societies increasingly depend on ecosystems whose behavior cannot be explained by any single technology, organization, market, infrastructure, policy, or environmental condition alone. Energy systems, industrial value chains, urban infrastructures, digital platforms, climate-transition pathways, mobility systems, water systems, food systems, health systems, and innovation networks are no longer isolated systems with clearly bounded technical functions. They are complex ecosystems in which physical infrastructures, digital technologies, artificial agents, human behavior, economic incentives, institutional rules, environmental constraints, and political decisions interact continuously. The ecosystem idea has long been used in strategy and innovation to describe interdependence among firms, complementors, users, and activities (Adner, 2017; Iansiti & Levien, 2004; Jacobides et al., 2018; Moore, 1993). Ecosystem Intelligence extends this concern beyond organizational interdependence to the distributed intelligence and viability of complex ecosystems as a whole.

These ecosystems are becoming more intelligent in multiple senses. They sense through sensors, platforms, markets, models, user interactions, institutional reporting, and environmental monitoring. They interpret through human expertise, organizational routines, algorithms, simulations, dashboards, standards, and policy processes. They coordinate through infrastructure control, market signals, digital platforms, regulatory arrangements, artificial agents, and distributed human decisions. They adapt through learning, redesign, investment, institutional reform, behavioral change, and technological substitution. Yet growth in component-level, locally bounded, or purported intelligence does not automatically constitute Ecosystem Intelligence at ecosystem scale. More data can generate visibility without understanding. More optimization can generate local efficiency while increasing systemic fragility. More connectivity can accelerate coordination while amplifying cascading failure. Recent research on interconnected and cascading risks shows how shocks can propagate across domains and scales (Pescaroli & Alexander, 2018; Rocha et al., 2018). More automation can improve response speed while weakening human oversight, accountability, and institutional learning.

The urgency of Ecosystem Intelligence arises from this tension. Societies are attempting to decarbonize energy systems, build resilient infrastructures, govern artificial intelligence, manage climate risk, reorganize industries, and coordinate human and technological agencies across increasingly interdependent domains. These technical, organizational, economic, and environmental challenges also operate at ecosystem level because relevant knowledge, agency, control, and consequences are distributed across many interacting components. No single actor can fully observe, optimize, govern, or transform the ecosystem alone.

This editorial proposes the following initial definition: Ecosystem Intelligence is **the distributed capacity of a complex ecosystem to sense changing conditions, interpret their significance, coordinate heterogeneous human, artificial, institutional, infrastructural, economic, and environmental components, absorb disturbance, and reorganize under uncertainty while sustaining or restoring ecosystem viability**. In this framework, ecosystem viability denotes the continued or recoverable ability of an ecosystem to maintain its essential functions and contextually specified social, institutional, economic, infrastructural, and environmental conditions across relevant scales and time horizons, while retaining the capacity for adaptation and responsible transformation. The field is concerned with ecosystems in which knowledge, agency, control, and consequences are distributed across multiple interacting components, and where ecosystem outcomes cannot be explained by the behavior of any single actor, technology, organization, or infrastructure alone. The definition provides a clear starting point for inquiry and remains open to empirical testing, conceptual debate, refinement, and alternative proposals.

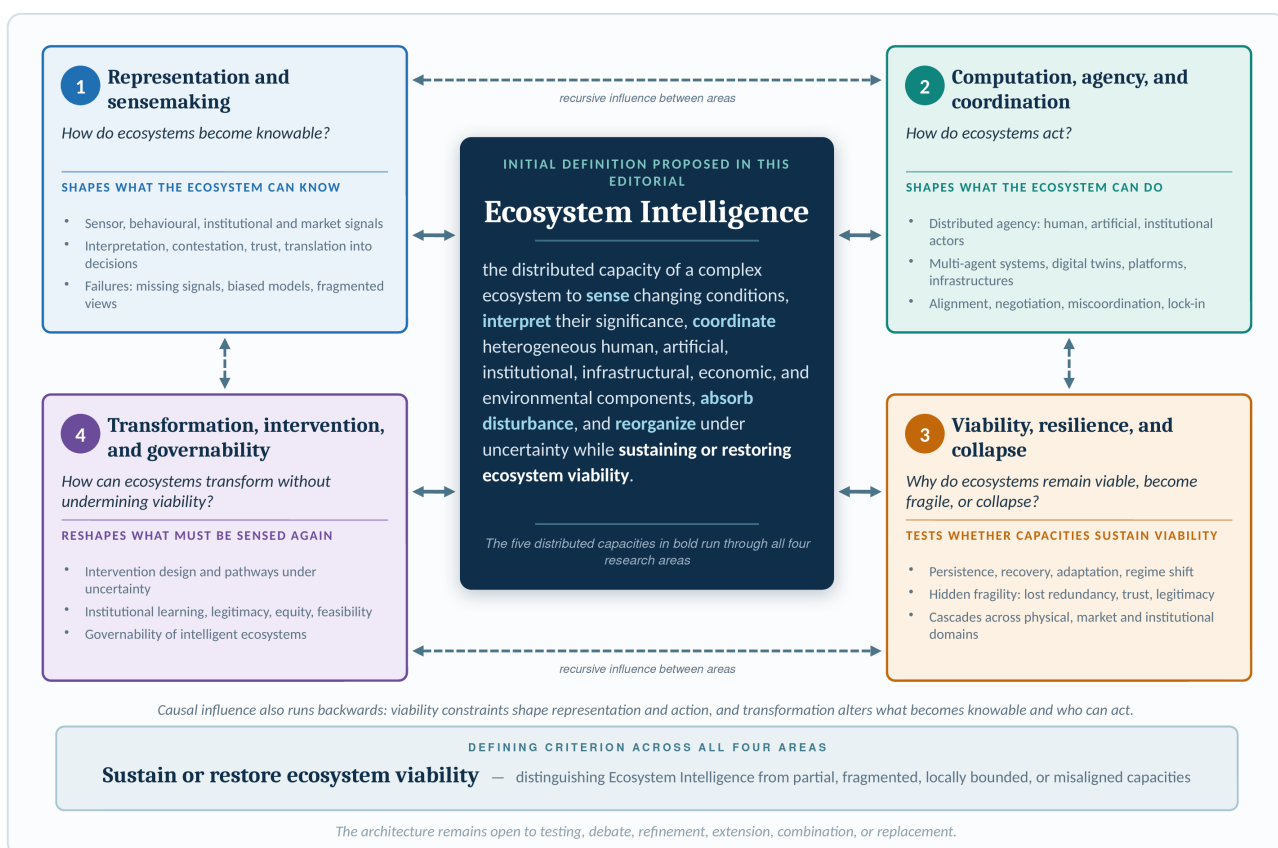
The initial framework is organized around four guiding questions:

- How do ecosystems become knowable?
- How do ecosystems act?
- Why do ecosystems remain viable, become fragile, or collapse?

- How can ecosystems transform without undermining viability?

This definition makes the scientific gap explicit. Existing research has produced powerful theories of systems, complexity, resilience, cognition, artificial intelligence, governance, and transition. An established field has yet to explain when distributed sensing, interpretation, coordination, disturbance absorption, and reorganization jointly constitute Ecosystem Intelligence by sustaining or restoring viability, or when partial, fragmented, locally bounded, or misaligned capacities contribute to fragility, lock-in, inequity, collapse, or transformation failure. Ecosystem Intelligence is proposed to address this gap. Improvements in ecosystem connectivity, automation, and optimization address only part of this problem. **Its central question is how intelligence at ecosystem scale affects the conditions under which complex ecosystems remain viable, adaptive, governable, and transformable.**

Accordingly, this founding editorial proceeds from theoretical foundations and boundary conditions to four proposed research areas, translates them into the initial Ecosystem Intelligence Diagnostic Protocol (EI-DP), and explains how the framework can guide empirical grounding and the development of bounded testbeds across diverse domains. It concludes by defining the complementary roles of the journal Ecosystem Intelligence and the Ecosystem Intelligence Academy and inviting the research community to test, debate, refine, extend, or replace the proposed framework.



**Figure 1.** Initial conceptual architecture of Ecosystem Intelligence and its four proposed research areas. The initial definition proposed in this editorial is placed at the centre of four proposed and evolving research areas: (1) representation and sensemaking; (2) computation, agency, and coordination; (3) viability, resilience, fragility, and collapse; and (4) transformation, intervention, and governability. Bidirectional links indicate interdependence and recursive influence, while the numbering serves solely to organize the exposition. The framework-wide viability criterion applies across all four areas and distinguishes Ecosystem Intelligence from partial, fragmented, locally bounded, or misaligned capacities. The architecture remains open to testing, debate, refinement, extension, combination, or replacement.

## 2. Theoretical Foundations and Evolutionary Emergence of Ecosystem Intelligence

Ecosystem Intelligence emerges as an evolutionary field that builds on existing theories while addressing a problem that exceeds the explanatory scope of each individual tradition. General systems theory established that organized wholes cannot be understood only by decomposing them into isolated parts (von Bertalanffy, 1968). The architecture of complexity showed how hierarchies, near-decomposability, and interactions among parts shape complex organized systems (Simon, 1962). Cybernetics developed foundational concepts of feedback, control, communication, and regulation in biological, mechanical, and social systems (Ashby, 1956; Wiener, 1948). The viable system model added an explicit concern with the conditions under which systems remain capable of independent existence in changing environments (Beer, 1984).

Complexity science and complex adaptive systems research advanced the study of emergence, nonlinear dynamics, self-organization, adaptation, path dependence, and co-evolution (Holland, 1995; Preiser et al., 2018). Network science has shown how topology, connectivity, centrality, modularity, and interdependence shape robustness, diffusion, cascading failure, and systemic risk (Albert & Barabási, 2002). System dynamics provided methods for understanding feedback, accumulation, delays, and long-term behavior in complex systems (Forrester, 1961; Meadows, 2008). These traditions provide essential foundations for understanding interdependence, feedback, adaptation, and emergent behavior.

Ecology and resilience research shifted attention from equilibrium and efficiency to persistence, disturbance, adaptation, and regime shifts (Folke et al., 2021; Holling, 1973; Rocha et al., 2018). Social-ecological systems research demonstrated that resources, users, governance arrangements, and ecological conditions must be analyzed as interdependent components (Berkes & Folke, 1998; Keys et al., 2019; Ostrom, 2009). Autopoiesis and cognition introduced influential ways of thinking about living systems, self-production, and the relation between organization and cognition (Maturana & Varela, 1980). Sustainability transitions research showed how technological, institutional, market, cultural, and policy processes interact across multiple levels and time horizons (Geels, 2002, 2020). These traditions help explain persistence, adaptation, resource governance, and long-term transformation.

Ecosystem Intelligence also draws on theories of cognition, sensemaking, interaction, and agency. Distributed cognition moved the unit of cognitive analysis beyond the individual mind and showed how cognition can be distributed across people, tools, representations, routines, and environments (Hutchins, 1995). Organizational sensemaking demonstrated that interpretation, ambiguity reduction, and collective meaning formation are central to action under uncertainty (Weick, 1995). Research on situated human-machine interaction showed that action emerges through the continuous interaction of plans, context, interpretation, and artifacts (Suchman, 1987). Multi-agent systems and distributed artificial intelligence provide theories and methods for understanding autonomous, interacting, cooperative, or self-interested agents (Jennings, 2000; Wooldridge, 2009). Digital twins and simulation environments provide representational and experimental capacities for studying complex systems before interventions are made in the physical world (Grieves & Vickers, 2017). Contemporary machine behaviour and human-centered AI research further demonstrates that artificial agents must be studied through interaction, context, oversight, and social consequences (Rahwan et al., 2019; Shneiderman, 2020).

Collective intelligence research examines how groups may exhibit problem solving capacities that cannot be reduced to the abilities of individual members (Woolley et al., 2010). Hybrid intelligence research studies arrangements that combine complementary human and artificial capabilities (Dellermann et al., 2019; Seeber et al., 2020), while hybrid collective intelligence extends this concern to coordinated human-AI collectives (Peeters et al., 2021). These are close foundations for Ecosystem Intelligence. Ecosystem Intelligence extends the object of inquiry beyond human groups or human-AI teams to include institutions, infrastructures, markets, and environmental feedback as constituent and constraining components, while placing ecosystem viability at the center. The relationships among these traditions remain open to comparison and debate.

The phrase ecosystem intelligence also has prior, narrower uses. It has described visual and analytical capabilities that help decision makers explore business ecosystems (Basole et al., 2018; Basole et al., 2024)

and methods for mapping the structures and dynamics of AI-based assistant platform ecosystems (Schmidt et al., 2022). Those contributions treat ecosystem intelligence primarily as analytics about an ecosystem or as a capability for understanding a particular platform ecosystem. Building on these established uses, this editorial proposes a broader scientific field in which Ecosystem Intelligence denotes the distributed capacity of a complex ecosystem specified in the definition above, with ecosystem viability as its constitutive concern. These theories and methodologies provide the foundations of Ecosystem Intelligence. The need for a new field arises because contemporary ecosystems combine their concerns in ways that exceed their separate boundaries. Complex ecosystems are simultaneously representational, computational, behavioral, infrastructural, economic, institutional, environmental, and political. Feedback and control are distributed across multiple components and lack a single controller. Cognition and interpretation are likewise distributed across heterogeneous actors. Agency is distributed across humans, artificial agents, organizations, markets, infrastructures, and institutions. Resilience and transition arise through the ways in which the ecosystem senses, interprets, coordinates, and reorganizes, thereby shaping persistence and transformation. Therefore, Ecosystem Intelligence emerges as a field that integrates these foundations around a distinct object: the intelligence and viability of complex ecosystems.

**Table 1.** Adjacent traditions and the distinctive extension proposed by Ecosystem Intelligence.

| Adjacent tradition                                              | Primary object                                            | Established contribution                                                                         | Distinctive extension proposed by Ecosystem Intelligence                                                                                |
|-----------------------------------------------------------------|-----------------------------------------------------------|--------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------|
| Systems, cybernetics, and viable systems                        | Organized systems and regulation                          | Feedback, control, communication, and conditions for viability                                   | Distributed interpretation and agency across heterogeneous components where no actor is a complete controller                           |
| Complex adaptive systems and network science                    | Emergence, interaction, and network structure             | Nonlinearity, self-organization, topology, cascades, and systemic risk                           | Connects these mechanisms to sensing, interpretation, coordination, reorganization, and ecosystem viability                             |
| Resilience and social-ecological systems                        | Persistence, adaptation, resources, users, and governance | Disturbance response, regime shifts, adaptive governance, and coupled social-ecological dynamics | Adds artificial agents, digital infrastructures, computational representation, and intelligence as an explicit ecosystem-level capacity |
| Collective and hybrid intelligence                              | Groups, teams, and human-AI collectives                   | Emergent problem solving and complementary human-artificial capabilities                         | Extends beyond teams to institutions, infrastructures, markets, and environmental feedback, with viability as the constitutive test     |
| Artificial intelligence, multi-agent systems, and digital twins | Algorithms, agents, coordination, and representation      | Prediction, optimization, autonomous action, simulation, and computational coordination          | Treats these as components and methods; their presence alone is not evidence of Ecosystem Intelligence                                  |
| Business and platform ecosystems                                | Firms, complementors, platforms, and value creation       | Roles, interdependence, governance, complementarity, and ecosystem analytics                     | Broadens the unit beyond organizational actors and asks how distributed capacities sustain or restore ecosystem viability               |
| Sustainability transitions and integrated assessment            | Long-term pathways and system transformation              | Multi-level change, scenarios, policy pathways, and climate-economy trade-offs                   | Explains how ecosystems become knowable, coordinate action, and preserve viability while transformation occurs                          |

Therefore, the scientific gap concerns the absence of a shared explanatory programme that connects three levels at once: distributed capacities, their interaction across heterogeneous ecosystem components, and their demonstrated relationship with viability under disturbance and transformation. This conjunction is the proposed field's distinctive object and the basis on which its necessity should be tested.

### 3. Boundary and Distinctive Contribution of Ecosystem Intelligence

Ecosystem Intelligence is concerned with complex ecosystems in which multiple heterogeneous components interact across boundaries, where knowledge and agency are distributed, where consequences unfold across spatial and temporal scales, and where no single actor has complete visibility, authority, or control. A research problem belongs to Ecosystem Intelligence when ecosystem outcomes cannot be explained by one technology, one organization, one infrastructure, one policy, one market mechanism, or one environmental driver alone. This boundary provides an initial basis for identifying field-relevant problems; research may test, refine, extend, or propose alternatives to it. Therefore, interdependence or multicausality supplies a necessary starting condition and requires the additional elements specified below. A contribution to Ecosystem Intelligence should make explicit: (1) the ecosystem boundary, focal level, and heterogeneous components; (2) one or more of the defined capacities - sensing, interpretation, coordination, disturbance absorption, or reorganization - and their ecosystem-level interactions; and (3) how those interactions sustain or restore specified viability conditions, or why partial, fragmented, or misaligned capacities fail to do so. A study may focus on selected capacities, provided that it locates its focal mechanism within this explanatory chain.

This boundary distinguishes Ecosystem Intelligence from several adjacent traditions. It differs from artificial intelligence by locating intelligence within wider arrangements that situate algorithms, models, and agents among human, institutional, infrastructural, economic, and environmental components (Selbst et al., 2019). Within these arrangements, ecosystem intelligence encompasses artificial agents, human judgment, institutional rules, infrastructures, markets, environmental feedback, and collective sensemaking. It differs from multi-agent systems by extending coordination analysis beyond computational agents to heterogeneous human, artificial, institutional, infrastructural, economic, and environmental components. It differs from digital twins because representation and simulation acquire ecosystem-level significance through their links to interpretation, coordination, viability, and transformation.

Ecosystem Intelligence also differs from resilience theory, social-ecological systems, and sustainability transitions, although it learns from all three. Resilience research explains persistence, adaptation, and regime shifts. Ecosystem Intelligence extends this explanation by examining how distributed sensing, interpretation, and agency create or undermine resilience. Social-ecological systems research explains interdependence among resources, users, governance, and ecological conditions. Ecosystem Intelligence expands this analytical frame to include artificial agents, digital infrastructures, data-driven representation, platform-mediated behavior, and computational coordination. Sustainability transitions research explains long-term transformation pathways. Ecosystem Intelligence complements this account by examining how ecosystems perceive, interpret, coordinate, and remain viable during transformation.

Intelligence is treated here as an analytical proposition with explicit criteria: complexity, connectivity, adaptation, digitalization, or optimization alone does not warrant the label. An Ecosystem Intelligence explanation must identify which distributed capacities in the definition are present, how they operate across heterogeneous components, and how they contribute to sustaining or restoring ecosystem viability. Sensors, algorithms, automation, or multiple actors provide only partial evidence of Ecosystem Intelligence. Arrangements that appear intelligent at the level of a component, actor, or short-term performance measure may still weaken ecosystem viability; such cases are analytically important precisely because they reveal the difference between component-level capability and ecosystem-level intelligence. Consequently, an isolated algorithm performance study, a single-asset digital twin used only for prediction, or a sectoral study that uses ecosystem only as a descriptive label may provide a useful building block. Its contribution to Ecosystem Intelligence depends on establishing the required ecosystem-level connection.

The distinctive contribution of Ecosystem Intelligence is the connection between intelligence and viability. Performance and viability are related yet distinct. A system can perform well according to a narrow metric while becoming less viable as an ecosystem. A market can minimize short-term cost while creating long-term infrastructure vulnerability. A digital platform can increase engagement while weakening trust, autonomy, or social resilience. An energy system can optimize dispatch while generating rebound peaks, congestion, or

investment misalignment. A climate pathway can appear cost-efficient in a model while facing barriers from institutions, behavior, infrastructure readiness, and political feasibility.

Ecosystem viability is thus treated as the evaluative condition against which the capacities constituting Ecosystem Intelligence are assessed. Resilience forms one dimension of this broader conception of viability. Sensing, interpretation, coordination, disturbance absorption, and reorganization are explanatory capacities and processes whose effects on viability must be demonstrated empirically.

Accordingly, Ecosystem Intelligence studies both the conditions under which distributed capacities constitute ecosystem-level intelligence and the failure modes that prevent them from doing so. It asks how sensing, interpretation, coordination, disturbance absorption, and reorganization collectively sustain or restore viability and how partial, fragmented, locally bounded, or misaligned capacities create new vulnerabilities.

To make viability empirically researchable, each study must define viability in relation to its ecosystem boundary, relevant functions, stakeholders, scales, time horizons, disturbances, and trade-offs. This contextual definition takes precedence over any universal index. Viability evidence should distinguish persistence, recovery, adaptation, and reorganization, and should reveal when benefits or resilience at one subsystem, scale, or period shift risk elsewhere or later. Research on Anthropocene risk, cascading regime shifts, and safe system boundaries offers relevant, non-exhaustive starting points (Keys et al., 2019; Rocha et al., 2018; Rockström et al., 2023). Developing and validating domain-sensitive viability diagnostics remains a central open task; Section 5.2 translates this conceptual requirement into the initial Ecosystem Intelligence Diagnostic Protocol.

## 4. Four Proposed Research Areas of Ecosystem Intelligence

This editorial organizes Ecosystem Intelligence around four guiding questions derived from the field's definition: how ecosystems become knowable; how they act; why they remain viable, become fragile, or collapse; and how they can transform without undermining viability. These questions connect the core capacities of sensing, interpretation, coordination, disturbance absorption, and reorganization with distinct but recursively related analytical concerns.

Accordingly, the four proposed research areas are representation and sensemaking; computation, agency, and coordination; viability, resilience, and collapse; and transformation, intervention, and governability. They are intended as a provisional organizing framework whose scope, boundaries, and composition may be debated, combined, extended, supplemented, or replaced as the field develops.

### 4.1 Ecosystem Representation, Behavioral Analytics, and Sensemaking

The first proposed research area concerns ecosystem representation, behavioral analytics, and sensemaking. Data become actionable in complex ecosystems through processes of selection, structuring, interpretation, contestation, trust formation, and translation into decisions. Ecosystem sensemaking concerns how relevant conditions become visible and meaningful across heterogeneous components. These conditions may be represented through sensor data, behavioral traces, digital interaction data, infrastructure states, organizational knowledge, institutional indicators, market signals, environmental measurements, and experiential knowledge.

Representation can also fail. Missing signals, misleading indicators, fragmented dashboards, biased models, incompatible metrics, and interpretations detached from lived or operational realities can produce incomplete or distorted understandings of ecosystem conditions. Therefore, behavioral analytics, user research, human-computer interaction, telemetry, and data-driven sensemaking are central because Ecosystem Intelligence depends on how human and artificial components perceive, interpret, and adapt to one another. Recent social-ecological research likewise shows why behavior must be represented as adaptive, heterogeneous, and dynamically coupled to institutional and environmental conditions (Schill et al., 2019).

Game analytics provides a concrete methodological example. Telemetry-based user research can connect interaction traces to interpretable evidence about user experience and behavior (Seif El-Nasr et al., 2013). Behavioral clustering and social-structure analysis show how individual actions can be aggregated into group-level and ecosystem-level patterns (Bauckhage et al., 2015; Schiller et al., 2019). Large-scale game telemetry has also been used to examine cross-cultural behavior and policy intervention effects, illustrating how digital ecosystems can support sensemaking at population scale (Zendle, Flick, Gordon-Petrovskaya, et al., 2023; Zendle, Flick, Halgarth, et al., 2023).

## 4.2 Ecosystem Computation, Agency, and Coordination

The second proposed research area concerns ecosystem computation, agency, and coordination. Complex ecosystems act through agency distributed across multiple decision centers. Human actors, artificial agents, organizations, markets, infrastructures, platforms, institutional rules, and environmental constraints jointly shape action. The resulting ecosystem behavior emerges through interactions among these heterogeneous forms of agency.

Multi-agent systems, distributed artificial intelligence, optimization, platform architectures, digital twins, and intelligent infrastructures provide important methods for studying such coordination. Recent research differentiates operational digital twins from static models and identifies open challenges in bidirectional data integration (Fuller et al., 2020; Wright & Davidson, 2020). Human-AI coordination research likewise emphasizes teaming, oversight, and complementary authority as safeguards against unrestricted automation (Seeber et al., 2020; Shneiderman, 2020).

The central challenge includes technical coordination as well as alignment, negotiation, conflict, adaptation, and unintended consequences across heterogeneous forms of agency. Ecosystem Intelligence asks how human and artificial agents interact with infrastructure constraints, institutional rules, economic incentives, and environmental pressures, and how these interactions generate coordination, miscoordination, lock-in, or transformation. Energy ecosystems provide one illustrative setting in which multi-agent models, digital twins, and infrastructure-aware simulations can examine distributed coordination under operational and institutional constraints (Cong et al., 2025; Ma et al., 2019; Værbak et al., 2024).

## 4.3 Ecosystem Viability, Resilience, Fragility, and Collapse

The third proposed research area concerns ecosystem viability, resilience, fragility, and collapse. It studies why some ecosystems sustain or restore essential functions under disturbance, while others become vulnerable or fail. Viability concerns continued or recoverable functioning under changing conditions. Resilience concerns persistence, recovery, and adaptation; fragility describes vulnerability that may remain hidden during normal operation; and collapse occurs when essential functions can no longer be maintained or restored. This area connects resilience theory, network robustness, cascading failure, systemic risk, behavioral feedback, and institutional misalignment (Keys et al., 2019; Pescaroli & Alexander, 2018; Rocha et al., 2018).

Ecosystem Intelligence asks how distributed sensing, interpretation, coordination, disturbance absorption, and reorganization shape these outcomes. An ecosystem may appear functional while losing redundancy, diversity, interpretability, adaptive capacity, trust, legitimacy, or coordination capacity. Local adaptation may transfer risk across actors, sectors, scales, or time horizons, while delayed or fragmented responses allow strain to accumulate. Physical disruption can propagate across interconnected infrastructures; institutional failure can intensify environmental risk; and adaptation in one part of an ecosystem can generate vulnerability elsewhere.

Research on interconnected infrastructures shows how disruption in one system can cascade through dependent services and organizational arrangements (Pescaroli & Alexander, 2018; Rinaldi et al., 2001). Social-ecological research demonstrates how interacting pressures can produce regime shifts within and across scales, while apparently stable conditions may conceal declining adaptive capacity (Adger et al., 2005; Rocha

et al., 2018). Studies of Anthropocene risk and safe and just Earth-system boundaries further show that viability must be evaluated across environmental, social, and temporal dimensions, including the distribution of risks and consequences (Keys et al., 2019; Rockström et al., 2023).

#### 4.4 Ecosystem Transformation, Intervention, and Governability

The fourth proposed research area concerns ecosystem transformation, intervention, and governability. Complex ecosystems cannot be transformed through technical redesign alone. Transformation involves infrastructure investment, behavioral change, economic incentives, institutional reform, technological substitution, political legitimacy, environmental constraints, and learning across actors. Integrated assessment, scenario analysis, transition studies, policy modelling, intervention design, and governance research are essential to this proposed research area (Hirt et al., 2020; Trutnevyte et al., 2019). Recent evidence shows that societal factors and feedbacks can materially alter modelled energy and emissions pathways and must therefore be represented explicitly (Fisch-Romito et al., 2025; Moore et al., 2022).

Within this wider transformation problem, Ecosystem Intelligence adds a specific concern: how can ecosystems be changed without undermining the conditions that make them viable? This concern encompasses the governability of intelligent ecosystems, the design of interventions under uncertainty, the economic and financial feasibility of transformation pathways, the legitimacy of decision processes, and the capacity of institutions to learn from ecosystem feedback. Integrated assessment research illustrates why robust judgments of transformation pathways must account for uncertainty and multiple plausible trajectories.

Carbon-neutrality pathway analysis shows that ambition, equity, policy robustness, and economic feasibility are systemically interdependent (Li & Duan, 2025; Yu et al., 2026). Research on deep decarbonization, 1.5 °C pathways, and critical minerals shows how global temperature goals interact with policy, resource, and trade constraints (Duan et al., 2020; Duan et al., 2021; Shi et al., 2025). General-equilibrium analysis further illustrates how energy and carbon-mitigation objectives can be assessed jointly through policy design (Yuan et al., 2020). Just-transition and model-transparency studies add two further governability requirements: attention to distributional consequences and the interpretability of the models used to guide action (Duan et al., 2026; Yang et al., 2026).

As shown in Figure 1, these proposed research areas operate as interdependent analytical perspectives within a recursive architecture. Representation and sensemaking shape what the ecosystem can know; computation, agency, and coordination shape what it can do; viability, resilience, and collapse research evaluates whether distributed capacities sustain or restore ecosystem viability, or remain partial, fragmented, locally bounded, or misaligned; and transformation, intervention, and governability reshape conditions that must again be sensed, interpreted, coordinated, and evaluated. Causal influence can also run in other directions: viability constraints shape representation and action, while transformation can alter what becomes knowable and who can act. Therefore, Ecosystem Intelligence emerges through the relations among the proposed research areas and their recursive interaction.

### 5. Methodological Foundations for Ecosystem Intelligence

Ecosystem Intelligence requires methodological pluralism combined with methodological coherence. Existing methods from systems research, complexity science, human-computer interaction, artificial intelligence, integrated assessment, futures studies, and governance research provide indispensable starting points. Applied separately as disciplinary toolkits, these methods fragment ecosystem intelligence across individual models, data streams, actor groups, and intervention settings. Therefore, the field needs to establish integrative ecosystem methodologies that can define ecosystem boundaries, represent distributed states, model cross-dimensional interaction, trace behavioral and institutional dynamics, diagnose viability, and test transformation pathways under uncertainty.

## 5.1 Methodological Building Blocks and Their Integration in Ecosystem Intelligence

Several established methodologies provide essential building blocks. Conceptual modelling is needed to define ecosystem boundaries, components, relationships, feedback loops, viability conditions, and cross-dimensional mechanisms. Network analysis is needed to study connectivity, centrality, modularity, diffusion, dependency, robustness, and cascading failure (Albert & Barabási, 2002). Agent-based modelling and multi-agent systems are needed to examine distributed agency, adaptive behavior, cooperation, competition, negotiation, and emergent coordination (Jennings, 2000; Lamperti et al., 2019; Wooldridge, 2009). System dynamics is needed to study feedback structures, accumulation, delay, nonlinear change, and long-term behavior (Forrester, 1961; Meadows, 2008). Digital-twin and virtual-lab approaches are needed to connect representation, simulation, experimentation, and decision support (Fuller et al., 2020; Grieves & Vickers, 2017; Wright & Davidson, 2020). In energy ecosystem research, business ecosystem modelling has demonstrated how stakeholder, market, and infrastructure relations can be represented in a single analytical frame (Ma, 2019). Ontology-supported multi-agent systems and digital twins provide complementary methods for formalizing agent relations and testing grid coordination in simulated settings (Ma et al., 2019; Værbak et al., 2024). Control-room infostructure and smart-grid cybersecurity research show that situation awareness and cybersecurity are integral to resilient future power systems (Jørgensen & Ma, 2026a, 2026b). Sequential-gate evaluation also illustrates how institutional admissibility and technical performance can be treated as ordered conditions when assessing intervention feasibility before deployment (Ma et al., 2026).

Other established methodologies are equally important. Integrated assessment modelling is needed to examine climate-economic pathways, policy scenarios, technology transitions, and long-term transformation constraints (Hirt et al., 2020; Rotmans & van Asselt, 2001; Trutnevyte et al., 2019; Weyant, 2017). Behavioral analytics, user research, human-computer interaction, and interaction design are needed to understand how human actors perceive, respond to, and reshape ecosystem conditions, and how representations, interfaces, and digital environments mediate ecosystem sensemaking (Dix et al., 2004; Dourish, 2001; Suchman, 1987). Scenario-based analysis and futures methods are needed to examine uncertainty, alternative pathways, and long-term robustness (Amer et al., 2013; van der Heijden, 2005; Wack, 1985). Case studies, field observations, interviews, workshops, participatory modelling, and stakeholder-engagement methods are needed because ecosystem intelligence is enacted in real institutional, organizational, and social contexts (Reed, 2008; Voinov & Bousquet, 2010; Yin, 2018). Game analytics offers one example of methodological integration: telemetry-based user research connects traces to interpretable behavior (Seif El-Nasr et al., 2013), while behavioral clustering and social-structure analysis aggregate individual actions into broader patterns of group activity (Bauckhage et al., 2015; Schiller et al., 2019). In climate-economy research, robust policy-assessment and machine-learning-supported transparency methods address model uncertainty and interpretability in transformation analysis (Duan et al., 2026; Li & Duan, 2025).

Therefore, the methodological contribution of Ecosystem Intelligence lies in establishing new ways to integrate existing methods around ecosystem-level questions. At least four methodological families are needed: ecosystem boundary-formation methods for determining what belongs to an ecosystem and why; multi-layer representation and sensemaking methods for connecting physical, digital, behavioral, institutional, economic, and environmental signals; viability diagnostics for identifying resilience, fragility, lock-in, and collapse risks; and virtual-lab and intervention methods for testing transformation pathways before acting in real ecosystems. The guiding questions are shared across methods: what does the ecosystem need to sense; who or what interprets the signal; how is interpretation converted into action; which actors, agents, infrastructures, or institutions coordinate, conflict, or adapt; what forms of fragility are created; which viability conditions are preserved or lost; and how can intervention support transformation without destabilizing the ecosystem? These questions provide the methodological bridge between modelling, analytics, experimentation, fieldwork, and governance research.

## 5.2 Initial Ecosystem Intelligence Diagnostic Protocol

To turn the definition and four proposed research areas into a reproducible starting point, this editorial proposes an initial Ecosystem Intelligence Diagnostic Protocol (EI-DP). The EI-DP specifies the minimum analytical outputs needed to compare studies across methods and testbeds while remaining adaptable to different domains and methodological traditions.

1. Bound the ecosystem. Define the problem-led boundary, focal level, relevant spatial and temporal scales, and the external conditions treated as consequential. Required output: a justified boundary statement and unit of analysis.
2. Map heterogeneous components and distributed agency. Identify human, artificial, institutional, infrastructural, economic, and environmental components; locate information, authority, resources, dependencies, and exposure to consequences. Required output: a component-agency map.
3. Trace the intelligence process. Examine how relevant changes are sensed, how their significance is interpreted, how responses are coordinated, how disturbances are absorbed, and how reorganization occurs. Identify missing, delayed, conflicting, or opaque links. Required output: an evidence-based process model.
4. Specify viability conditions. State the functions and conditions that must be maintained or restored, for whom, at which level, over what time horizon, and with which thresholds, trade-offs, and indicators. Candidate indicators may include service continuity, robustness and recovery time, redundancy and diversity, resource adequacy, adaptive capacity, interpretability of system state, coordination capacity, trust, legitimacy, and the distribution of risks and benefits; their relevance must be justified for the ecosystem under study. Required output: a domain-sensitive viability profile grounded in the specified ecosystem context.
5. Test disturbances and transformation pathways. Use empirical observation, comparison, simulation, scenarios, interventions, or mixed methods to examine shocks, adaptations, cross-scale spillovers, and alternative reorganizations. Required output: evidence about robustness, recovery, adaptation, reorganization, and failure modes under uncertainty.
6. Classify and compare the outcome. Determine whether the observed distributed capacities sustain or restore the specified viability conditions. If they do not, classify the explanation as component-level capability, fragmentation, local or temporal misalignment, coordination failure, or another empirically justified deficiency. Required output: a testable conclusion and implications for revising the boundary, model, indicators, or intervention.

The EI-DP makes the framework falsifiable in a practical sense: sensors, algorithms, multiple actors, adaptation, or good short-term performance cannot establish Ecosystem Intelligence by assertion. Evidence must connect the focal capacities to ecosystem-level viability, while counter-evidence can show that the presumed intelligence is partial, misaligned, or absent. Comparing these outputs across studies will allow the protocol itself to be criticized and improved.

## 6. Empirical Grounding and Illustrative Testbed Development

Ecosystem Intelligence must be empirically grounded in bounded settings where distributed sensing, interpretation, agency, disturbance response, viability, and transformation can be observed and tested. Broad areas such as energy, healthcare, urban mobility, industrial supply chains, digital platforms, and climate governance constitute empirical domains. A domain becomes an empirical testbed when a study specifies the ecosystem boundary and focal level; identifies the relevant heterogeneous components, relationships, data, and forms of agency; defines the disturbances, interventions, or transformation pathways to be examined; and establishes context-sensitive viability conditions. Testbeds may be observational, comparative,

experimental, simulated, or hybrid. The Ecosystem Intelligence Diagnostic Protocol provides a common structure for developing and comparing them.

A wide range of empirical domains can expose Ecosystem Intelligence problems because they combine different forms of interdependence, feedback, governance, technological mediation, behavioral response, and environmental constraint (Berkes & Folke, 1998; Geels, 2002; Ostrom, 2009). Illustrative domains include energy; healthcare; urban and mobility; industrial and supply-chain; food, water, and land-use; digital platform and media; digital creative and game; climate adaptation and environmental governance; climate-economy; and emergency, security, and infrastructure-resilience ecosystems. These examples are non-exhaustive and non-hierarchical. They do not establish a prescribed set of testbeds, and contributions may develop testbeds in any domain that satisfies the boundary and contribution criteria of Ecosystem Intelligence.

Energy ecosystems can expose real-time coordination among physical infrastructures, markets, regulators, human actors, digital systems, and artificial agents under environmental and operational constraints (Lund et al., 2017; Strbac, 2008). Healthcare ecosystems can expose distributed clinical, organizational, and experiential knowledge; professional judgment; patient and caregiver agency; digital health platforms; resource allocation; privacy; safety; equity; and ethical governability (Greenhalgh et al., 2017; Greenhalgh & Papoutsi, 2018; Plsek & Greenhalgh, 2001). Urban and mobility ecosystems can reveal interactions among infrastructure capacity, digital platforms, travel behavior, land use, emissions, governance, and social equity (Banister, 2008; Batty, 2013). City-level decarbonization research further shows that emissions efficiency, economic structures, and sectoral constraints can produce different transformation challenges across cities (Duan et al., 2025). Industrial and supply-chain ecosystems can reveal dependencies, disruptions, platformization, logistics, circularity, and resilience across organizations and infrastructures (Christopher & Peck, 2004; Ivanov et al., 2019). Industrial energy-flexibility research also shows how physical, operational, digital, market, and policy conditions jointly shape climate resilience (Ma et al., 2025).

Food, water, and land-use ecosystems can expose relationships among environmental constraints, resource governance, climate adaptation, production systems, consumption, and institutional coordination (D'Odorico et al., 2018; Pahl-Wostl, 2007; Rockström et al., 2009). Digital platform and media ecosystems can expose algorithmic agency, behavioral feedback, attention dynamics, trust, misinformation, content moderation, and emergent collective behavior (Gillespie, 2018; Hein et al., 2020; van Dijck et al., 2018). Climate adaptation, environmental governance, and climate-economy ecosystems can expose long-term uncertainty, contested values, resource constraints, distributional consequences, policy robustness, and the limits of prediction (Adger et al., 2005; Keys et al., 2019; Moser & Ekstrom, 2010; Rockström et al., 2023). Emergency, security, and infrastructure-resilience ecosystems can expose rapid sensemaking, cascading failure, multi-actor coordination, and recovery under stress (Comfort, 2007; Pescaroli & Alexander, 2018; Rinaldi et al., 2001). Further illustrations include digital creative and game ecosystems, in which artificial agents, player communities, evolving rules, and knowledge propagation shape ecosystem behavior (Costa et al., 2024; Thaicharoen et al., 2023). Climate-economy and adaptation studies also show how climate variability can produce heterogeneous economic effects and how adaptive responses such as air-conditioning adoption can reshape electricity demand (Duan et al., 2022; Duan et al., 2023).

Within these and other domains, individual studies must convert broad application areas into researchable ecosystem configurations. Illustrative testbeds might include a regional electricity-distribution ecosystem connecting system operators, aggregators, households, regulators, markets, and digital-control infrastructures; a regional healthcare ecosystem connecting hospitals, primary care, municipal services, patients, caregivers, digital health platforms, and regulatory institutions; an online platform ecosystem involving users, algorithms, moderators, complementors, advertisers, and platform-governance arrangements; a metropolitan mobility ecosystem connecting public transport, road infrastructures, digital services, travelers, operators, and public authorities; or a river-basin ecosystem connecting water infrastructures, agricultural production, communities, environmental processes, markets, and governance institutions. These examples illustrate possible

configurations only. A single empirical domain may support many differently bounded testbeds, and one testbed may span several domains.

Across any testbed, the central analytical task is to examine how distributed capacities operate across heterogeneous components and how they affect explicitly defined viability conditions. Researchers should identify how relevant changes become visible and meaningful, how interpretations are converted into action, how authority and agency are distributed, how disturbances are absorbed, how reorganization occurs, and which forms of viability, fragility, or transformation result. The relevant indicators and methods will differ across domains, stakeholders, spatial scales, and time horizons. Comparability arises through the common analytical outputs of the EI-DP, including the boundary statement, component-agency map, intelligence-process model, viability profile, disturbance or transformation analysis, and outcome classification.

Empirical testbeds therefore serve as instruments for testing the proposed framework, not as fixed application categories for the field. Studies across diverse domains may confirm relationships proposed by Ecosystem Intelligence, identify mechanisms that are absent from the initial framework, reveal conflicting definitions of viability, or demonstrate that alternative concepts and analytical structures are needed. The development, comparison, and critique of empirical testbeds should contribute to the continuing refinement of Ecosystem Intelligence as an open and evolving field.

## 7. The Journal Ecosystem Intelligence: Scope and Contributions

The journal Ecosystem Intelligence is launched to provide a dedicated scholarly venue for this emerging field. Its purpose is to support research that advances the understanding, modelling, design, critique, governance, and transformation of complex ecosystems in which intelligence, agency, and viability are distributed. The journal's scope extends across sectors, technologies, and application domains wherever distributed sensing, interpretation, coordination, viability, fragility, transformation, and governability are central research problems.

To support this purpose, the journal is hosted on Tidsskrift.dk, operated by the Royal Danish Library. This host was chosen because library stewardship and the national platform provide a credible, accessible, and durable institutional home for a new scholarly journal and community. The platform supports dissemination and scholarly continuity while leaving the journal's intellectual development open to international and interdisciplinary participation.

The journal welcomes theoretical and conceptual contributions that define, refine, compare, and critique the concepts of ecosystem intelligence, ecosystem viability, distributed agency, hybrid intelligence, ecosystem sensemaking, adaptive transformation, governability, and related constructs. Such contributions may clarify boundaries between Ecosystem Intelligence and adjacent fields, develop new conceptual models, or examine the philosophical and epistemological implications of treating intelligence as an ecosystem-level capacity.

The journal welcomes methodological and computational contributions that develop or integrate methods for ecosystem modelling, representation, simulation, analysis, experimentation, and decision support. Relevant work includes digital twins, virtual testbeds, agent-based modelling, multi-agent systems, network analysis, system dynamics, integrated assessment, behavioral analytics, human-computer interaction, explainable artificial intelligence, scenario methods, participatory modelling, and mixed-method ecosystem research. Methodological papers should demonstrate a substantive advance in understanding ecosystem intelligence alongside any technical improvement.

The journal welcomes empirical contributions across diverse complex ecosystem domains. Such contributions may develop, apply, compare, or critique bounded empirical testbeds. The central requirement is that they advance understanding of ecosystem-level sensing, interpretation, coordination, viability, fragility, transformation, or governability.

The journal welcomes design, intervention, and governance contributions that examine how ecosystems can be shaped, steered, redesigned, or transformed responsibly under uncertainty. These may include studies of policy instruments, market design, institutional arrangements, human-AI coordination, digital infrastructure, participatory governance, transition pathways, resilience interventions, and evaluation frameworks. The journal is particularly interested in work that identifies when interventions strengthen ecosystem viability and when they create unintended vulnerabilities.

The journal also welcomes critical and reflective contributions. Ecosystem Intelligence requires a critical stance toward digitalization and artificial intelligence. It must examine the conditions under which component-level, partial, or purported intelligence fails, misleads, excludes, destabilizes, creates new dependencies, or falls short of Ecosystem Intelligence. It must study the politics of representation, the ethics of data-driven ecosystem governance, the risks of automation, the limits of optimization, the consequences of unequal agency, and the difficulty of governing ecosystems that no actor fully controls. Therefore, the field must combine scientific ambition with reflexive awareness of power, uncertainty, responsibility, and unintended consequences.

In addition to original research articles, the journal may host reviews, perspectives, methodological tutorials, debate articles, special issues, data and infrastructure papers, and domain-focused collections. This breadth is important because a new field develops through definitions, disagreements, methods, empirical demonstrations, replications, critiques, and shared research infrastructure.

## 8. The Ecosystem Intelligence Academy and an Open Research Community

The journal is accompanied by the Ecosystem Intelligence Academy community ([ecosystemintelligence.academy](https://ecosystemintelligence.academy)). The journal provides a peer-reviewed venue for scholarship, while the community platform supports broader exchange among scholars and practitioners, communicates initiatives and opportunities, and creates space for proposals and debate about the field's definition, boundary, proposed research areas, methods, empirical grounding, and testbed development. Together, the journal and community provide complementary infrastructure through which the framework can evolve.

A research community grows through shared questions, useful concepts, credible methods, productive disagreement, and repeated encounters among scholars who recognize that they are addressing related problems. Therefore, the Ecosystem Intelligence Academy creates conditions for an international and interdisciplinary community to form through exchange, collaboration, and productive disagreement across different interpretations of the framework.

The field should be open to multiple entry points. Researchers in computer science, engineering, data science, behavioral science, human-computer interaction, environmental studies, economics, management, governance, geography, urban studies, transition studies, infrastructure studies, and design research may all encounter ecosystem intelligence problems from different angles. Some will begin with computation and coordination. Others will begin with behavior and sensemaking, resilience and collapse, climate-economic transformation, or governance under uncertainty. The Academy should make these perspectives mutually visible and help them develop shared language without requiring premature consensus.

An open community also requires critical debate. The meaning of ecosystem viability will differ across domains and stakeholders. What appears viable from an infrastructure perspective may not be viable from a social, ecological, economic, or institutional perspective. What appears intelligent from a computational perspective may be opaque, exclusionary, or fragile from a governance perspective. Therefore, Ecosystem Intelligence must develop as a community capable of disagreement about definitions, metrics, values, and methods, while still sharing the ambition to understand ecosystem-level intelligence and viability.

The community should also be intergenerational and international. Early-career researchers need conceptual foundations and methodological bridges that allow them to move across disciplinary boundaries. Established

scholars need a venue where their existing theories can be extended into ecosystem-level questions. Practitioners, policy actors, infrastructure operators, designers, and domain experts can contribute empirical knowledge and problem framings that keep the field grounded. The Academy can connect these participants through dialogue, events, collaborative initiatives, and accessible exchanges that complement the journal's peer-reviewed scholarship.

## 9. Invitation to Shape the Emerging Field of Ecosystem Intelligence

The launch of Ecosystem Intelligence is an invitation to shape a field at the moment of its emergence. The field will be valuable only if it helps researchers move beyond fragmented accounts of complex systems and toward deeper explanations of how ecosystems become knowable, how they act, why they remain viable or fail, and how they can be transformed responsibly under uncertainty.

Scholars and practitioners are invited to use the journal for rigorously developed scholarly contributions and the Ecosystem Intelligence Academy for broader exchange, emerging proposals, dialogue, and community-building. Participation may support the proposed framework, revise it, challenge it, or advance alternatives.

The definition, boundary, proposed research areas, diagnostic protocol, and approach to empirical grounding and testbed development introduced in this editorial provide revisable starting points for a shared research agenda. They are expected to be debated, tested, modified, extended, or replaced as evidence and theory develop. The task ahead is to determine when distributed capacities constitute Ecosystem Intelligence by sustaining or restoring viable, adaptive, and responsible ecosystems, and why partial, fragmented, or misaligned capacities fail to do so.

### Author Contributions

Conceptualization, Z.G.M., A.D., H.D. and B.N.J.; Methodology, Z.G.M., A.D., H.D. and B.N.J.; Writing – original draft, Z.G.M., A.D., H.D. and B.N.J.; Writing – review & editing, Z.G.M., A.D., H.D. and B.N.J.; Visualization, Z.G.M.; Project administration, Z.G.M. All authors have read and agreed to the published version of the manuscript.

### Funding

This research received no external funding.

### Institutional Review Board Statement

Not applicable.

### Informed Consent Statement

Not applicable.

### Data and Code Availability Statement

Not applicable. No new data were created or analysed in this editorial.

### Use of Generative AI

During the preparation of this manuscript, the authors used OpenAI ChatGPT (GPT-5.6) to support manuscript structuring, language refinement. The authors reviewed and edited the output and take full responsibility for the content of this publication.

### Acknowledgments

The authors thank the Royal Danish Library for hosting the journal Ecosystem Intelligence on Tidsskrift.dk.

### Conflicts of Interest

The authors are members of the editorial team of Ecosystem Intelligence and this editorial was not externally peer reviewed. The authors declare no other conflicts of interest.

## Abbreviations

The following abbreviations are used in this manuscript:

|              |                                            |
|--------------|--------------------------------------------|
| <b>AI</b>    | Artificial intelligence                    |
| <b>EI</b>    | Ecosystem Intelligence                     |
| <b>EI-DP</b> | Ecosystem Intelligence Diagnostic Protocol |

## References

- Adger, W. N., Hughes, T. P., Folke, C., Carpenter, S. R., & Rockström, J. (2005). Social-ecological resilience to coastal disasters. *Science*, 309(5737), 1036-1039. <https://doi.org/10.1126/science.1112122>
- Adner, R. (2017). Ecosystem as structure: An actionable construct for strategy. *Journal of Management*, 43(1), 39-58. <https://doi.org/10.1177/0149206316678451>
- Albert, R., & Barabási, A.-L. (2002). Statistical mechanics of complex networks. *Reviews of Modern Physics*, 74(1), 47-97. <https://doi.org/10.1103/RevModPhys.74.47>
- Amer, M., Daim, T. U., & Jetter, A. (2013). A review of scenario planning. *Futures*, 46, 23-40. <https://doi.org/10.1016/j.futures.2012.10.003>
- Ashby, W. R. (1956). *An introduction to cybernetics*. Chapman & Hall.
- Banister, D. (2008). The sustainable mobility paradigm. *Transport Policy*, 15(2), 73-80. <https://doi.org/10.1016/j.transpol.2007.10.005>
- Basole, R. C., Park, H., & Seuss, C. D. (2024). Complex business ecosystem intelligence using AI-powered visual analytics. *Decision Support Systems*, 178, 114133. <https://doi.org/10.1016/j.dss.2023.114133>
- Basole, R. C., Srinivasan, A., Park, H., & Patel, S. (2018). ecoxight: Discovery, exploration, and analysis of business ecosystems using interactive visualization. *ACM Transactions on Management Information Systems*, 9(2), Article 6. <https://doi.org/10.1145/3185047>
- Batty, M. (2013). *The new science of cities*. MIT Press.
- Bauckhage, C., Drachen, A., & Sifa, R. (2015). Clustering Game Behavior Data. *IEEE Transactions on Computational Intelligence and AI in Games*, 7(3), 266-278. <https://doi.org/10.1109/TCIAIG.2014.2376982>
- Beer, S. (1984). The viable system model: Its provenance, development, methodology and pathology. *Journal of the Operational Research Society*, 35(1), 7-25. <https://doi.org/10.1057/jors.1984.2>
- Berkes, F., & Folke, C. (Eds.). (1998). *Linking social and ecological systems: Management practices and social mechanisms for building resilience*. Cambridge University Press.
- Christopher, M., & Peck, H. (2004). Building the resilient supply chain. *The International Journal of Logistics Management*, 15(2), 1-14. <https://doi.org/10.1108/09574090410700275>
- Comfort, L. K. (2007). Crisis management in hindsight: Cognition, communication, coordination, and control. *Public Administration Review*, 67(s1), 189-197. <https://doi.org/10.1111/j.1540-6210.2007.00827.x>
- Cong, L., Christensen, K., Værbak, M., Jørgensen, B. N., & Ma, Z. G. (2025). Empirically Informed Multi-Agent Simulation of Distributed Energy Resource Adoption and Grid Overload Dynamics in Energy Communities. *Electronics*, 14(20), 4001. <https://doi.org/10.3390/electronics14204001>
- Costa, L. M., Drachen, A., Souza, F. C. M., & Xexéo, G. (2024). Artificial Intelligence in MOBA Games: A Multivocal Literature Mapping. *IEEE Transactions on Games*, 16(2), 250-269. <https://doi.org/10.1109/TG.2023.3282157>
- Dellermann, D., Ebel, P., Söllner, M., & Leimeister, J. M. (2019). Hybrid intelligence. *Business & Information Systems Engineering*, 61(5), 637-643. <https://doi.org/10.1007/s12599-019-00595-2>
- Dix, A., Finlay, J., Abowd, G. D., & Beale, R. (2004). *Human-computer interaction* (3rd ed.). Pearson.
- D'Odorico, P., Davis, K. F., Rosa, L., Carr, J. A., Chiarelli, D., Dell'Angelo, J., Gephart, J. A., MacDonald, G. K., Seekell, D. A., Suweis, S., & Rulli, M. C. (2018). The global food-energy-water nexus. *Reviews of Geophysics*, 56(3), 456-531. <https://doi.org/10.1029/2017RG000591>

- Dourish, P. (2001). *Where the action is: The foundations of embodied interaction*. MIT Press.
- Duan, H., Ming, X., Zhang, X.-B., Sterner, T., & Wang, S. (2023). China's adaptive response to climate change through air-conditioning. *iScience*, 26(3), 106178. <https://doi.org/10.1016/j.isci.2023.106178>
- Duan, H., Mu, T., & Yu, Q. (2025). City-level analysis of carbon reduction potential and decarbonization challenges in China. *Cities*, 158, 105636. <https://doi.org/10.1016/j.cities.2024.105636>
- Duan, H., Rogelj, J., Veysey, J., & Wang, S. (2020). Modeling deep decarbonization: Robust energy policy and climate action. *Applied Energy*, 262, 114517. <https://doi.org/10.1016/j.apenergy.2020.114517>
- Duan, H., Sun, Y., Tang, Y., Iyer, G., & Li, X. (2026). Leveraging machine learning to reveal transparency in integrated assessment model ensembles. *Climatic Change*, 179(5), 98. <https://doi.org/10.1007/s10584-026-04181-w>
- Duan, H., Yuan, D., Cai, Z., & Wang, S. (2022). Valuing the impact of climate change on China's economic growth. *Economic Analysis and Policy*, 74, 155-174. <https://doi.org/10.1016/j.eap.2022.01.019>
- Duan, H., Zhou, S., Jiang, K., Bertram, C., Harmsen, M., Kriegler, E., van Vuuren, D. P., Wang, S., Fujimori, S., Tavoni, M., Ming, X., Keramidas, K., Iyer, G., & Edmonds, J. (2021). Assessing China's efforts to pursue the 1.5°C warming limit. *Science*, 372(6540), 378-385. <https://doi.org/10.1126/science.aba8767>
- Fisch-Romito, V., Jaxa-Rozen, M., Wen, X., & Trutnevyte, E. (2025). Multi-country evidence on societal factors to include in energy transition modelling. *Nature Energy*, 10(4), 460-469. <https://doi.org/10.1038/s41560-025-01719-7>
- Folke, C., Polasky, S., Rockström, J., Galaz, V., Westley, F., Lamont, M., Scheffer, M., Österblom, H., Carpenter, S. R., Chapin, F. S., Seto, K. C., Weber, E. U., Crona, B. I., Daily, G. C., Dasgupta, P., Gaffney, O., Gordon, L. J., Hoff, H., Levin, S. A., ... Walker, B. H. (2021). Our future in the Anthropocene biosphere. *Ambio*, 50(4), 834-869. <https://doi.org/10.1007/s13280-021-01544-8>
- Forrester, J. W. (1961). *Industrial dynamics*. MIT Press.
- Fuller, A., Fan, Z., Day, C., & Barlow, C. (2020). Digital twin: Enabling technologies, challenges and open research. *IEEE Access*, 8, 108952-108971. <https://doi.org/10.1109/ACCESS.2020.2998358>
- Geels, F. W. (2002). Technological transitions as evolutionary reconfiguration processes: A multi-level perspective and a case-study. *Research Policy*, 31(8-9), 1257-1274. [https://doi.org/10.1016/S0048-7333\(02\)00062-8](https://doi.org/10.1016/S0048-7333(02)00062-8)
- Geels, F. W. (2020). Micro-foundations of the multi-level perspective on socio-technical transitions: Developing a multi-dimensional model of agency through crossovers between social constructivism, evolutionary economics and neo-institutional theory. *Technological Forecasting and Social Change*, 152, 119894. <https://doi.org/10.1016/j.techfore.2019.119894>
- Gillespie, T. (2018). *Custodians of the internet: Platforms, content moderation, and the hidden decisions that shape social media*. Yale University Press.
- Greenhalgh, T., & Papoutsis, C. (2018). Studying complexity in health services research: Desperately seeking an overdue paradigm shift. *BMC Medicine*, 16, 95. <https://doi.org/10.1186/s12916-018-1089-4>
- Greenhalgh, T., Wherton, J., Papoutsis, C., Lynch, J., Hughes, G., A'Court, C., Hinder, S., Fahy, N., Procter, R., & Shaw, S. (2017). Beyond adoption: A new framework for theorizing and evaluating nonadoption, abandonment, and challenges to the scale-up, spread, and sustainability of health and care technologies. *Journal of Medical Internet Research*, 19(11), e367. <https://doi.org/10.2196/jmir.8775>
- Grieves, M., & Vickers, J. (2017). Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In F.-J. Kahlen, S. Flumerfelt, & A. Alves (Eds.), *Transdisciplinary perspectives on complex systems* (pp. 85-113). Springer. [https://doi.org/10.1007/978-3-319-38756-7\\_4](https://doi.org/10.1007/978-3-319-38756-7_4)
- Hein, A., Schreieck, M., Riasanow, T., Setzke, D. S., Wiesche, M., Böhm, M., & Krcmar, H. (2020). Digital platform ecosystems. *Electronic Markets*, 30(1), 87-98. <https://doi.org/10.1007/s12525-019-00377-4>
- Hirt, L. F., Schell, G., Sahakian, M., & Trutnevyte, E. (2020). A review of linking models and socio-technical transitions theories for energy and climate solutions. *Environmental Innovation and Societal Transitions*, 35, 162-179. <https://doi.org/10.1016/j.eist.2020.03.002>
- Holland, J. H. (1995). *Hidden order: How adaptation builds complexity*. Addison-Wesley.
- Holling, C. S. (1973). Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics*, 4, 1-23. <https://doi.org/10.1146/annurev.es.04.110173.000245>

- Hutchins, E. (1995). *Cognition in the wild*. MIT Press.
- Iansiti, M., & Levien, R. (2004). *The keystone advantage: What the new dynamics of business ecosystems mean for strategy, innovation, and sustainability*. Harvard Business School Press.
- Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research*, 57(3), 829-846. <https://doi.org/10.1080/00207543.2018.1488086>
- Jacobides, M. G., Cennamo, C., & Gawer, A. (2018). Towards a theory of ecosystems. *Strategic Management Journal*, 39(8), 2255-2276. <https://doi.org/10.1002/smj.2904>
- Jennings, N. R. (2000). On agent-based software engineering. *Artificial Intelligence*, 117(2), 277-296. [https://doi.org/10.1016/S0004-3702\(99\)00107-1](https://doi.org/10.1016/S0004-3702(99)00107-1)
- Jørgensen, B. N., & Ma, Z. G. (2026a). Cybersecurity and Resilience of Smart Grids: A Review of Threat Landscape, Incidents, and Emerging Solutions. *Applied Sciences*, 16(2), 981. <https://doi.org/10.3390/app16020981>
- Jørgensen, B. N., & Ma, Z. G. (2026b). Infostructure: A Scoping Review and Reference Architectural Framework for Situation Awareness in Future Power System Control Rooms. *Energies*, 19(6), 1472. <https://doi.org/10.3390/en19061472>
- Keys, P. W., Galaz, V., Dyer, M., Matthews, N., Folke, C., Nyström, M., & Cornell, S. E. (2019). Anthropocene risk. *Nature Sustainability*, 2(8), 667-673. <https://doi.org/10.1038/s41893-019-0327-x>
- Lamperti, F., Mandel, A., Napoletano, M., Sapio, A., Roventini, A., Balint, T., & Khorenzhenko, I. (2019). Towards agent-based integrated assessment models: Examples, challenges, and future developments. *Regional Environmental Change*, 19(3), 747-762. <https://doi.org/10.1007/s10113-018-1287-9>
- Li, G., & Duan, H. (2025). Robustness assessment of climate policies towards carbon neutrality: A DRO-IAMs approach. *Computers & Operations Research*, 174, 106879. <https://doi.org/10.1016/j.cor.2024.106879>
- Lund, H., Østergaard, P. A., Connolly, D., & Mathiesen, B. V. (2017). Smart energy and smart energy systems. *Energy*, 137, 556-565. <https://doi.org/10.1016/j.energy.2017.05.123>
- Ma, Z. G. (2019). Business Ecosystem modeling - The Hybrid of System Modeling and Ecological Modeling: An application of the smart grid. *Energy Informatics*, 2(1), 35. <https://doi.org/10.1186/s42162-019-0100-4>
- Ma, Z. G., Billanes, J. D., & Jørgensen, B. N. (2025). Climate Resilience and Energy Flexibility in Industrial Systems: A Scoping Review of Concepts, Technologies, Applications, and Policy Links. *Energies*, 18(18), 4985. <https://doi.org/10.3390/en18184985>
- Ma, Z. G., Cong, L., & Jørgensen, B. N. (2026). Deployment Feasibility as a Layered Construct: A Sequential Gate Framework for Evaluating Battery Dispatch Strategies in Distribution Grids. *Energies*, 19(10), 2424. <https://doi.org/10.3390/en19102424>
- Ma, Z. G., Schultz, M. J., Christensen, K., Værbak, M., Demazeau, Y., & Jørgensen, B. N. (2019). The Application of Ontologies in Multi-Agent Systems in the Energy Sector: A Scoping Review. *Energies*, 12(16), 3200. <https://doi.org/10.3390/en12163200>
- Maturana, H. R., & Varela, F. J. (1980). *Autopoiesis and cognition: The realization of the living*. D. Reidel Publishing Company.
- Meadows, D. H. (2008). *Thinking in systems: A primer*. Chelsea Green Publishing.
- Moore, F. C., Lacasse, K., Mach, K. J., Shin, Y. A., Gross, L. J., & Beckage, B. (2022). Determinants of emissions pathways in the coupled climate-social system. *Nature*, 603(7899), 103-111. <https://doi.org/10.1038/s41586-022-04423-8>
- Moore, J. F. (1993). Predators and prey: A new ecology of competition. *Harvard Business Review*, 71(3), 75-86.
- Moser, S. C., & Ekstrom, J. A. (2010). A framework to diagnose barriers to climate change adaptation. *Proceedings of the National Academy of Sciences*, 107(51), 22026-22031. <https://doi.org/10.1073/pnas.1007887107>
- Ostrom, E. (2009). A general framework for analyzing sustainability of social-ecological systems. *Science*, 325(5939), 419-422. <https://doi.org/10.1126/science.1172133>
- Pahl-Wostl, C. (2007). Transitions towards adaptive management of water facing climate and global change. *Water Resources Management*, 21(1), 49-62. <https://doi.org/10.1007/s11269-006-9040-4>

- Peeters, M. M. M., van Diggelen, J., van den Bosch, K., Bronkhorst, A., Neerincx, M. A., Schraagen, J. M., & Raaijmakers, S. (2021). Hybrid collective intelligence in a human-AI society. *AI & Society*, 36(1), 217-238. <https://doi.org/10.1007/s00146-020-01005-y>
- Pescaroli, G., & Alexander, D. E. (2018). Understanding compound, interconnected, interacting, and cascading risks: A holistic framework. *Risk Analysis*, 38(11), 2245-2257. <https://doi.org/10.1111/risa.13128>
- Plsek, P. E., & Greenhalgh, T. (2001). The challenge of complexity in health care. *BMJ*, 323(7313), 625-628. <https://doi.org/10.1136/bmj.323.7313.625>
- Preiser, R., Biggs, R., De Vos, A., & Folke, C. (2018). Social-ecological systems as complex adaptive systems: Organizing principles for advancing research methods and approaches. *Ecology and Society*, 23(4), 46. <https://doi.org/10.5751/ES-10558-230446>
- Rahwan, I., Cebrian, M., Obradovich, N., Bongard, J., Bonnefon, J.-F., Breazeal, C., Crandall, J. W., Christakis, N. A., Couzin, I. D., Jackson, M. O., Jennings, N. R., Kamar, E., Kloumann, I. M., Larochelle, H., Lazer, D., McElreath, R., Mislove, A., Parkes, D. C., Pentland, A., ... Wellman, M. (2019). Machine behaviour. *Nature*, 568(7753), 477-486. <https://doi.org/10.1038/s41586-019-1138-y>
- Reed, M. S. (2008). Stakeholder participation for environmental management: A literature review. *Biological Conservation*, 141(10), 2417-2431. <https://doi.org/10.1016/j.biocon.2008.07.014>
- Rinaldi, S. M., Peerenboom, J. P., & Kelly, T. K. (2001). Identifying, understanding, and analyzing critical infrastructure interdependencies. *IEEE Control Systems Magazine*, 21(6), 11-25. <https://doi.org/10.1109/37.969131>
- Rocha, J. C., Peterson, G., Bodin, Ö., & Levin, S. (2018). Cascading regime shifts within and across scales. *Science*, 362(6421), 1379-1383. <https://doi.org/10.1126/science.aat7850>
- Rockström, J., Gupta, J., Qin, D., Lade, S. J., Abrams, J. F., Andersen, L. S., Armstrong McKay, D. I., Bai, X., Bala, G., Bunn, S. E., Ciobanu, D., DeClerck, F., Ebi, K., Gifford, L., Gordon, C., Hasan, S., Kanie, N., Lenton, T. M., Loriani, S., ... Zhang, X. (2023). Safe and just Earth system boundaries. *Nature*, 619(7968), 102-111. <https://doi.org/10.1038/s41586-023-06083-8>
- Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin, F. S., III, Lambin, E. F., Lenton, T. M., Scheffer, M., Folke, C., Schellnhuber, H. J., Nykvist, B., de Wit, C. A., Hughes, T., van der Leeuw, S., Rodhe, H., Sörlin, S., Snyder, P. K., Costanza, R., Svedin, U., ... Foley, J. A. (2009). A safe operating space for humanity. *Nature*, 461(7263), 472-475. <https://doi.org/10.1038/461472a>
- Rotmans, J., & van Asselt, M. B. A. (2001). Uncertainty management in integrated assessment modeling: Towards a pluralistic approach. *Environmental Monitoring and Assessment*, 69(2), 101-130. <https://doi.org/10.1023/A:1010722120729>
- Schill, C., Anderies, J. M., Lindahl, T., Folke, C., Polasky, S., Cárdenas, J. C., Crépin, A.-S., Janssen, M. A., Norberg, J., & Schlüter, M. (2019). A more dynamic understanding of human behaviour for the Anthropocene. *Nature Sustainability*, 2(12), 1075-1082. <https://doi.org/10.1038/s41893-019-0419-7>
- Schiller, M. H., Wallner, G., Schinnerl, C., Calvo, A. M., Pirker, J., Sifa, R., & Drachen, A. (2019). Inside the group: Investigating social structures in player groups and their influence on activity. *IEEE Transactions on Games*, 11(4), 416-425. <https://doi.org/10.1109/TG.2018.2858024>
- Schmidt, R., Alt, R., & Zimmermann, A. (2022). Ecosystem intelligence for AI-based assistant platforms. *Proceedings of the 55th Hawaii International Conference on System Sciences*, 4316-4325. <https://doi.org/10.24251/HICSS.2022.527>
- Seeber, I., Bittner, E., Briggs, R. O., de Vreede, T., de Vreede, G. J., Elkins, A., Maier, R., Merz, A. B., Oeste-Reiß, S., Randrup, N., Schwabe, G., & Söllner, M. (2020). Machines as teammates: A research agenda on AI in team collaboration. *Information & Management*, 57(2), 103174. <https://doi.org/10.1016/j.im.2019.103174>
- Seif El-Nasr, M., Desurvire, H., Aghabeigi, B., & Drachen, A. (2013). Game Analytics for Game User Research, Part 1: A Workshop Review and Case Study. *IEEE Computer Graphics and Applications*, 33(2), 6-11. <https://doi.org/10.1109/MCG.2013.26>
- Selbst, A. D., Boyd, D., Friedler, S. A., Venkatasubramanian, S., & Vertesi, J. (2019). Fairness and abstraction in sociotechnical systems. In *Proceedings of the 2019 Conference on Fairness, Accountability, and Transparency* (pp. 59-68). Association for Computing Machinery. <https://doi.org/10.1145/3287560.3287598>

- Shi, H., Heng, J., Duan, H., Li, H., Chen, W., Wang, P., Cui, L., & Wang, S. (2025). Critical mineral constraints pressure energy transition and trade toward the Paris Agreement climate goals. *Nature Communications*, 16, 4496. <https://doi.org/10.1038/s41467-025-59741-y>
- Shneiderman, B. (2020). Human-centered artificial intelligence: Reliable, safe & trustworthy. *International Journal of Human-Computer Interaction*, 36(6), 495-504. <https://doi.org/10.1080/10447318.2020.1741118>
- Simon, H. A. (1962). The architecture of complexity. *Proceedings of the American Philosophical Society*, 106(6), 467-482.
- Strbac, G. (2008). Demand side management: Benefits and challenges. *Energy Policy*, 36(12), 4419-4426. <https://doi.org/10.1016/j.enpol.2008.09.030>
- Suchman, L. A. (1987). *Plans and situated actions: The problem of human-machine communication*. Cambridge University Press.
- Thaicharoen, S., Gow, J., & Drachen, A. (2023). An Ecosystem Framework for the Meta in Esport Games. *Journal of Electronic Gaming and Esports*, 1(1). <https://doi.org/10.1123/jege.2022-0045>
- Trutnevyte, E., Hirt, L. F., Bauer, N., Cherp, A., Hawkes, A., Edelenbosch, O. Y., Pedde, S., & van Vuuren, D. P. (2019). Societal transformations in models for energy and climate policy: The ambitious next step. *One Earth*, 1(4), 423-433. <https://doi.org/10.1016/j.oneear.2019.12.002>
- Værbak, M., Billanes, J. D., Jørgensen, B. N., & Ma, Z. G. (2024). A Digital Twin Framework for Simulating Distributed Energy Resources in Distribution Grids. *Energies*, 17(11), 2503. <https://doi.org/10.3390/en17112503>
- van der Heijden, K. (2005). *Scenarios: The art of strategic conversation* (2nd ed.). Wiley.
- van Dijck, J., Poell, T., & de Waal, M. (2018). *The platform society: Public values in a connective world*. Oxford University Press.
- Voinov, A., & Bousquet, F. (2010). Modelling with stakeholders. *Environmental Modelling & Software*, 25(11), 1268-1281. <https://doi.org/10.1016/j.envsoft.2010.03.007>
- von Bertalanffy, L. (1968). *General system theory: Foundations, development, applications*. George Braziller.
- Wack, P. (1985). Scenarios: Uncharted waters ahead. *Harvard Business Review*, 63(5), 73-89.
- Weick, K. E. (1995). *Sensemaking in organizations*. SAGE Publications.
- Weyant, J. (2017). Some contributions of integrated assessment models of global climate change. *Review of Environmental Economics and Policy*, 11(1), 115-137. <https://doi.org/10.1093/reep/rew018>
- Wiener, N. (1948). *Cybernetics: Or control and communication in the animal and the machine*. MIT Press.
- Wooldridge, M. (2009). *An introduction to multiagent systems* (2nd ed.). Wiley.
- Woolley, A. W., Chabris, C. F., Pentland, A., Hashmi, N., & Malone, T. W. (2010). Evidence for a collective intelligence factor in the performance of human groups. *Science*, 330(6004), 686-688. <https://doi.org/10.1126/science.1193147>
- Wright, L., & Davidson, S. (2020). How to tell the difference between a model and a digital twin. *Advanced Modeling and Simulation in Engineering Sciences*, 7, 13. <https://doi.org/10.1186/s40323-020-00147-4>
- Yang, Z., Duan, H., Yuan, Y., & Li, A. (2026). Alleviating income and energy consumption inequality with just transition toward carbon neutrality. *Energy Economics*, 158, 109344. <https://doi.org/10.1016/j.eneco.2026.109344>
- Yin, R. K. (2018). *Case study research and applications: Design and methods* (6th ed.). SAGE Publications.
- Yu, S., Zhao, F., Yang, L., Yao, X., Li, Z., Wei, N., & Duan, H. (2026). Navigating ambition and equity: Systemic co-dependency in China's carbon neutrality pathways. *Environmental Science & Technology*, 60(21), 14934-14948. <https://doi.org/10.1021/acs.est.5c15542>
- Yuan, Y., Duan, H., & Tsvetanov, T. G. (2020). Synergizing China's energy and carbon mitigation goals: General equilibrium modeling and policy assessment. *Energy Economics*, 89, 104787. <https://doi.org/10.1016/j.eneco.2020.104787>
- Zendle, D., Flick, C., Gordon-Petrovskaya, E., Ballou, N., Xiao, L. Y., & Drachen, A. (2023). No evidence that Chinese playtime mandates reduced heavy gaming in one segment of the video games industry. *Nature Human Behaviour*, 7(10), 1753-1766. <https://doi.org/10.1038/s41562-023-01669-8>

Zendle, D., Flick, C., Halgarth, D., Ballou, N., Demediuk, S., & Drachen, A. (2023). Cross-cultural Patterns in Mobile Playtime: An analysis of 118 billion hours of human data. *Scientific Reports*, 13(1), 386. <https://doi.org/10.1038/s41598-022-26730-w>