# *Parallel Publishing: Toward a Living Knowledge Infrastructure for Intelligent Science and Technology*

Wendy Ding, Jun Huang, Fei Lin, Qinghua Ni, Siji Ma, and Thales S. W. Theseus

***Abstract*—Scientific knowledge is increasingly becoming part of the operational substrate of intelligent systems and intelligent industries, rather than serving only as a record of scholarly communication. As these systems move toward closed-loop integration of perception, decision, and control, the infrastructures that produce, validate, update, and circulate knowledge become correspondingly important. Yet contemporary scientific publishing still relies on static articles, delayed review cycles, document-centered dissemination, and weak machine readability, creating a knowledge-automation bottleneck for agent-based intelligence. Drawing on parallel intelligence and the artificial systems, computational experiments, and parallel execution (ACP) approach, this letter proposes parallel publishing: a living knowledge infrastructure that runs in parallel with physical, cyber, and social systems, continuously transforming research signals, operational feedback, and scientific claims into structured, verifiable, and machine-usable knowledge units. A three-layer architecture is presented, together with a conceptual representation of structured knowledge units and four defining design properties: continuity, structured verifiability, incentive alignment, and decentralized resilience. An autonomous-driving scenario further illustrates how operational feedback can be converted into verifiable knowledge for intelligent systems. The analysis suggests that closing the intelligence loop depends not only on advances in models, sensors, and hardware, but also on the emergence of a knowledge layer that is current, auditable, and structured for machine use across intelligent industries and societies.**

## I. Introduction

Intelligent science and technology are increasingly shaped by systems that can perceive changing environments, reason over evolving information, coordinate decisions, and act through closed-loop control. Large language models, retrieval-augmented generation, world models, reinforcement learning, multi-agent systems, and embodied intelligence are accelerating this transition [1–5]. In this setting, the core challenge is no longer only how to build more capable models, but also how to support such models with reliable, current, verifiable, and machine-usable knowledge.

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This challenge is particularly important for intelligent industries. Industrial robots, autonomous vehicles, medical systems, agricultural agents, decision theaters, and cyber-physical-social systems all depend on knowledge that changes over time [6, 7]. Yet the major source of validated scientific knowledge remains the academic publishing system, whose dominant workflow is still organized around manuscript submission, delayed review, static publication, and document-based dissemination. This produces a knowledge-automation bottleneck: the knowledge that intelligent systems require—current, structured, verifiable, and machine-callable—is not the knowledge that the publishing system is designed to deliver.

McCarthy [8] characterized artificial intelligence (AI) as the automation of intelligence. From a control and systems perspective, this formulation implies that intelligence depends not only on computation, but also on the organization, validation, and automation of knowledge. If knowledge remains delayed, fragmented, weakly structured, or difficult for machines to verify, the perception-decision-control loop remains open at its upstream boundary. The stakes are concrete: in safety-critical settings, an agent that acts on stale, unverifiable, or contaminated knowledge can propagate errors through downstream decisions and physical actions, so that the cost of an inadequate knowledge layer is not merely scholarly but operational. The development of intelligent systems therefore requires a corresponding reconfiguration of the infrastructures through which knowledge is produced, validated, and made usable.

This letter proposes parallel publishing as a response to this gap. Drawing on parallel intelligence and the artificial systems, computational experiments, and parallel execution (ACP) approach [9–12], we view knowledge production not as a terminal archival process, but as a continuously operating process that runs in parallel with physical, cyber, and social systems. The remainder of this letter identifies the bottlenecks of static publishing, introduces the architecture and design principles of parallel publishing, and discusses its implications for intelligent industries and societies.

## II. From Static Publishing to Knowledge-Automation Bottlenecks

The current academic publishing system was designed to preserve and disseminate scholarly records for human communities. It was not designed as a real-time knowledge infrastructure for intelligent agents, nor as a machine-callable layer for intelligent systems that must learn, reason, and adapt continuously. From the perspective of knowledge automation, five structural bottlenecks are particularly salient.

### *A. Static Snapshots Rather Than Real-Time Knowledge Flows*

Conventional scientific publishing turns research outputs into static records. Its basic unit is the article, its dominant format is the document, and its validation process is organized around periodic peer review. Once published, knowledge is usually stabilized as a fixed snapshot, even when new evidence later extends, revises, or challenges the original claim. In fast-moving domains such as artificial intelligence, robotics, and autonomous systems, this temporal lag is not merely an editorial delay but a knowledge-latency problem for intelligent systems [13]. Agents that rely on retrieval, model-based updating, or world-model construction are thus often operating on knowledge produced at an earlier stage of the field [2, 3].

### *B. Publishing Systems Rather Than Usage Systems*

The existing publishing system is optimized for publication, circulation, and citation, but not for direct machine use. Most published knowledge is carried by PDF documents and article-level metadata, while claims, methods, evidence, scope conditions, confidence judgments, and provenance (PROV) remain embedded in prose, figures, and tables. As a result, knowledge is readable to humans but only weakly interpretable, callable, and composable for intelligent agents. Findable, accessible, interoperable, and reusable (FAIR) data principles, semantic-web models, nanopublications, micropublications, provenance ontologies, and knowledge graphs have offered important directions for structured scientific communication, but these approaches remain only partially integrated into mainstream publishing workflows [14–19]. In this sense, contemporary publishing remains a publication system rather than a usage system: it measures visibility and citation more readily than machine-level interpretation, verification, or reuse.

### *C. Low-Quality Proliferation and Knowledge Contamination*

A further bottleneck is the proliferation of low-quality, weakly verified, or fraudulent content. Growing concerns about retractions, paper mills, citation manipulation, and reproducibility show that the reliability of the scientific knowledge base cannot be taken for granted [20–27]. For human researchers, such content may distort scholarly judgment. For AI systems, the risk is more systemic: low-quality or fraudulent knowledge can enter training corpora, retrieval pipelines, and autonomous decision-making processes. Once incorporated into model outputs or agent behavior, such contamination may propagate across downstream systems, especially in safety-critical domains such as healthcare, transportation, and engineering.

### *D. Oligopoly Economics and Missing Incentive Layers*

Scientific publishing is also shaped by a concentrated economic structure. A small number of commercial publishers occupy a dominant position in the global journal market and capture substantial value from research outputs that are largely funded, produced, reviewed, and validated by the academic community [28, 29]. This creates an incentive mismatch: authors and reviewers are rewarded mainly through journal prestige, citation counts, and career signaling, while the production of structured, verifiable, reusable, and machine-usable knowledge is rarely rewarded directly [30]. For knowledge automation, this means that the incentive layer is missing. The system lacks mechanisms for attributing value to claim-level validation, evidence curation, machine reuse, downstream impact, and continuous updating. Without such incentive alignment, high-quality knowledge production cannot be sustained as a scalable infrastructure for intelligent systems.

### *E. Centralization and Geopolitical Fragility*

Finally, scientific knowledge remains dependent on centralized platforms, institutional licenses, commercial databases, and jurisdictional arrangements. Such arrangements may be sufficient for many human research workflows, but they create fragility for globally distributed intelligent systems that require persistent, auditable, and programmable access to knowledge. Licensing disputes, platform restrictions, sanctions regimes, and database access barriers can interrupt the availability of knowledge across countries and institutions. Emerging discussions on decentralized science, cryptographic timestamping, blockchain-based attribution, and content-addressed storage suggest possible directions for more resilient knowledge infrastructures [31–35]. From this perspective, centralization is not only an access problem but also a knowledge-security problem: the openness, neutrality, and durability of scientific knowledge are vulnerable when the knowledge layer depends on a small number of gatekeepers.

Taken together, these bottlenecks reveal that static publishing has not yet become a knowledge-automation infrastructure. It provides records for human communities, but not structured, verifiable, incentive-aligned, and resilient knowledge flows for intelligent agents. Table 1 maps each static publishing feature to its knowledge-automation bottleneck and the corresponding parallel publishing response.

## III. PARALLEL PUBLISHING: ARCHITECTURE AND DESIGN PRINCIPLES

### *A. Definition and System Architecture*

Parallel publishing refers to a continuously operating knowledge infrastructure that transforms research signals into structured, verifiable, and machine-usable knowledge units [36]. It does not treat publishing as the final archival stage of research, but as an ongoing process of knowledge structuring, validation, updating, and circulation. In this sense, parallel publishing is not merely digital publishing, open access, or

**Table 1** Knowledge-automation bottlenecks and parallel publishing responses.

| Static publishing | Bottleneck | Parallel publishing |
|---|---|---|
| Static articles | Delayed updating | Continuous knowledge flows |
| PDF documents | Weak machine usability | Structured knowledge units |
| Limited provenance | Weak auditability | Verifiable evidence chains |
| Metric-driven incentives | Weak attribution | Usage-based contribution tracking |
| Platform dependence | Access fragility | Decentralized resilience |

automated manuscript processing. It is a knowledge-layer architecture for intelligent science and technology.

At the system level, parallel publishing connects three layers. The first is the signal layer, where observations, experiments, simulations, field data, industrial feedback, and social interactions are generated. The second is the knowledge layer, where such signals are structured, linked to evidence, assigned provenance, reviewed or validated, and versioned over time. The third is the intelligence layer, where knowledge units are used by agents, world models, planning systems, and decision-control processes. This three-layer structure extends the logic of parallel intelligence from physical and cyber systems to the knowledge layer [9, 10]. It provides the knowledge counterpart through which physical, cyber, and social signals can be transformed into operational knowledge for parallel execution.

Fig. 1 illustrates this architecture. The role of parallel publishing is to mediate between raw research or operational signals and the intelligent agents that require reliable knowledge. In doing so, it shifts publishing from an archival function to an active infrastructure for knowledge automation, where knowledge is continuously produced, verified, updated, and reused within intelligent systems.

### B. Structured Knowledge Units

The basic operational unit of parallel publishing is the structured knowledge unit rather than the static article alone. Such a unit captures the claim being made, the evidence supporting it, the method or reasoning path through which it is derived, its provenance, its scope of validity, its quality or confidence assessment, its validation status, and its temporal version. A conceptual representation is given by

$$K = \langle c, e, m, p, s, q, v, t \rangle \tag{1}$$

where $c$ denotes the claim, $e$ is the supporting evidence, $m$ is the method or reasoning path, $p$ is the provenance record, $s$ is the scope conditions, $q$ is the confidence or quality assessment, $v$ is the validation status, and $t$ is the temporal version, respectively.

This representation is not intended as a fixed data standard, but as a conceptual schema for understanding how scientific knowledge may become callable, auditable, and updateable. Compared with static articles, structured knowledge units are more suitable for retrieval-augmented generation, reasoning-action agents, knowledge graphs, and multi-agent coordination [2, 19, 37, 38]. They allow agents to query not only a conclusion, but also the evidence, provenance, scope conditions, confidence assessment, and validation history attached to that conclusion.

This schema deliberately reuses, rather than replaces, existing standards for structured scientific communication. The provenance field $p$ can be expressed using the PROV ontology [18]; the claim-evidence granularity of $c$ and $e$ follows the logic of nanopublications and micropublications [16, 17]; and identifiers, addressing, and metadata follow FAIR principles [14]. These approaches provide the representational substrate. Parallel publishing extends them in four respects. First, the validation status $v$ and temporal version $t$ are treated as first-class, continuously updated state coupled to live signals, rather than as fixed annotations on a deposited record. Second, knowledge units are designed to be directly callable by agents and world models within a closed perception-decision-control loop. Third, an incentive layer attributes value to contribution and reuse. Fourth, a decentralized layer provides resilience. In short, existing standards specify how knowledge can be represented; parallel publishing specifies the operating infrastructure that keeps the knowledge current, verifiable, rewarded, and resilient.

### C. Design Principles

Parallel publishing is characterized by four design principles. Continuity means that research signals are processed as

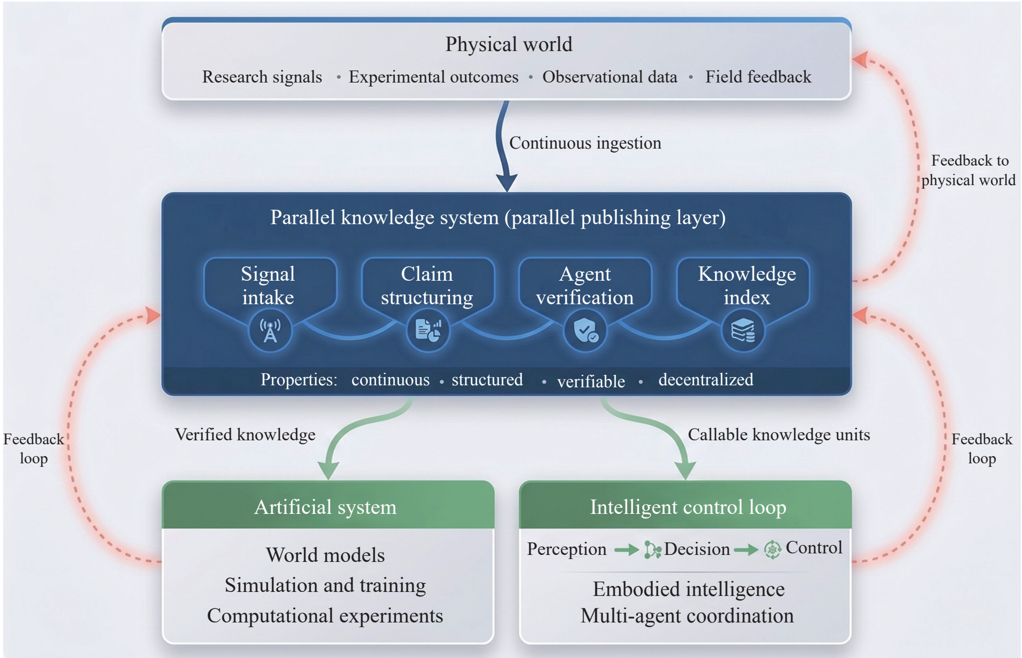


**Fig. 1** Three-layer architecture of parallel publishing, linking the signal, knowledge, and intelligence layers.

ongoing knowledge flows rather than as isolated publication events. This keeps the state of knowledge in a domain closer to the current evidentiary frontier and improves the temporal fidelity of knowledge available to intelligent systems.

Structured verifiability requires each knowledge unit to carry evidence, provenance, validation status, and scope conditions. This makes knowledge auditable and callable by intelligent agents, while also enabling human researchers and downstream systems to trace how a claim is produced, supported, revised, or rejected.

Incentive alignment links recognition and value distribution to contribution, validation, reuse, and downstream impact, rather than only to journal prestige or citation counts. Concretely, each contribution—authoring a claim, curating evidence, performing a validation, or supplying a unit that is later reused—can be recorded as a verifiable attribution record bound to a decentralized identifier [39] and time-stamped on an append-only ledger [33]. Downstream impact is then measured not only by human citation but also by machine-usage telemetry, such as how frequently a unit is retrieved or invoked by agents, and programmable rules distribute recognition accordingly. This connects parallel publishing to broader discussions on open science, decentralized science, and programmable attribution mechanisms [30, 35, 40]. The purpose is not merely to reward publication, but to sustain the production of high-quality, reusable, and machine-usable knowledge.

Decentralized resilience reduces dependence on single platforms or gatekeepers and supports open, durable, and globally accessible knowledge infrastructures through cryptographic provenance, decentralized storage, and timestamping [33, 41]. Together, these four principles shift publishing from a static archival function to a dynamic process of knowledge automation.

## IV. Parallel Publishing as a Knowledge Infrastructure for Intelligent Industries and Societies

### A. Closing the Intelligence Loop: World Models, Embodied Agents, and Multi-Agent Coordination

For intelligent systems, the most immediate role of parallel publishing is to provide dynamic knowledge for world models and agents. World models depend not only on training data and parameters, but also on continuously refreshed domain knowledge [3, 42]. If the knowledge layer is static, outdated, or unreliable, even sophisticated modeling architectures may produce inaccurate predictions or degraded decisions. Structured knowledge units provide a mechanism through which agents can retrieve current claims, inspect evidence, and update local models during reasoning and action.

This role is especially important for multi-agent and embodied systems operating in open environments. Distributed agents require shared and reasonably consistent knowledge about the domains in which they operate. Embodied agents encounter situations that lie outside their training distributions and must often rely on external knowledge during inference [4, 43]. Parallel publishing can serve as a common epistemic substrate for such systems by making knowledge not only re-trievable, but also verifiable, versioned, and reusable [37, 38].

As a concrete illustration, consider a fleet of autonomous vehicles that encounters an out-of-distribution situation, such as an unfamiliar roadwork layout combined with sensor degradation under heavy rain. Today, such an incident is typically logged locally, and any resulting insight may reach other vehicles only after a slow, document-centered research and update cycle, if at all. Under parallel publishing, the incident instead becomes a research signal that is structured into a knowledge unit: the claim $c$ might state that a given perception module underperforms under a specified condition, the evidence $e$ is drawn from on-board logs and subsequent tests, the scope $s$ restricts the claim to that condition, and $q$ records a confidence assessment. After verification, the versioned unit becomes retrievable by the rest of the fleet and by the world models that plan around it. If a later report contradicts the original finding, it is linked to the earlier unit rather than overwriting it, and the discrepancy is adjudicated through on-road and simulated computational experiments. In this way, the perception-decision-control loop is closed at the knowledge boundary: operational experience in the field is converted, in near real time, into verifiable knowledge that improves the behavior of the whole fleet.

### B. Physical Intelligence and the Knowledge-Automation Loop in Intelligent Industries

In intelligent industries, production systems, robots, sensors, industrial agents, and human experts continuously generate operational data, anomalies, failures, and performance feedback. These signals are often valuable, but they are not automatically transformed into reusable knowledge. Parallel publishing provides a mechanism through which industrial signals can be structured, validated, and returned to agents, models, and decision systems as updated knowledge.

In this way, knowledge generation and knowledge deployment form a closed automation loop: scientific research informs industrial systems; industrial systems generate new evidence; that evidence is structured into knowledge units; and the resulting knowledge flows back into intelligent systems. This creates a self-reinforcing dynamic between knowledge production and intelligent industrial operation, one whose sustaining infrastructure is precisely the kind of continuously operating, machine-readable knowledge layer that parallel publishing is intended to provide. Fig. 2 illustrates this feedback architecture and its relation to representative industrial domains.

### C. Toward Intelligent Societies: Open Knowledge, Education, and Knowledge Security

Parallel publishing may also reshape education, scientific collaboration, and societal knowledge security. Historically, major societal formations have been accompanied by corresponding knowledge infrastructures: agricultural societies organized knowledge around canonical texts and examination systems; industrial societies organized knowledge as standardized curricula transmitted through mass schooling; and the emerging intelligent society requires knowledge that is real-time, verifiable, and AI-callable, transmitted through knowledge automation rather than document-centric archiving. In this context, AI for education is not simply an application layer but also a knowledge infrastructure requirement: the

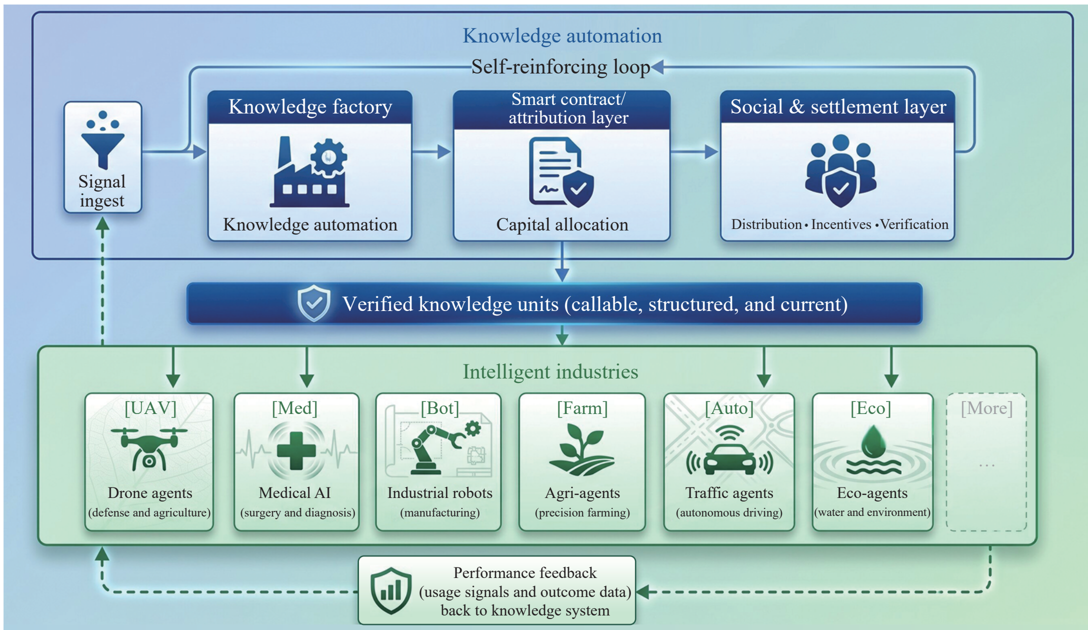


**Fig. 2** Knowledge-automation loop coupling research signals, structured knowledge units, and the industrial intelligence flywheel.

quality of knowledge available to learners and agents depends on the quality of the underlying knowledge production system.

At the societal level, the same infrastructure supports knowledge security. As intelligent systems become more deeply embedded in healthcare, transportation, manufacturing, and public infrastructure, the quality of the knowledge layer increasingly becomes a safety and governance variable [25]. Auditable provenance, transparent validation, and decentralized access can reduce dependence on opaque platforms and lower the risk of knowledge manipulation, fragmentation, and access fragility. Parallel publishing therefore points toward a broader transformation: from publishing as scholarly communication to publishing as a foundational infrastructure for intelligent science and technology—the knowledge flywheel through which intelligent systems, intelligent industries, and intelligent education draw on a common, continuously updated, and verifiable knowledge substrate.

## V. Conclusion

This letter argues that the development of intelligent systems and intelligent industries requires not only advances in models, sensors, and hardware, but also a reconfiguration of the knowledge infrastructure on which such systems depend. Static publishing creates knowledge-automation bottlenecks that limit continuous updating, structured verification, and machine use. Parallel publishing is proposed as an architecture for transforming research signals into structured, verifiable, and continuously updated knowledge units. Grounded in parallel intelligence and the ACP approach, it extends the logic of parallel systems from physical and cyber domains to the knowledge layer. By connecting knowledge production with world models, industrial agents, education, and knowledge security, parallel publishing offers a possible foundation for closing the intelligence loop in intelligent science and technology.

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