PI the Closed Loop Intelligence: From Physical Intelligence to Parallel Intelligence and Vice Versa via Organizational Intelligence

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***Brief*—Artificial intelligence (AI) is undergoing a structural transition from isolated digital assistance to organized closed-loop systems that can perceive, reason, act, and evolve. While large-scale models and AI agents have expanded the capabilities of digital intelligence, the next stage of AI will be increasingly defined by its connection to physical action, parallel simulation, organizational coordination, and continuous learning. Physical intelligence enables embodied agents to sense and act in real environments, whereas parallel intelligence provides a computational space for representing, simulating, and optimizing real systems before decisions return to physical execution. This editorial argues that the future of AI should be understood as an organized closed-loop paradigm in which physical intelligence, parallel intelligence, and organizational intelligence reinforce one another. Through intelligent organizations and AI education as representative cases, we show how external demands, agents, workflows, knowledge, resources, and feedback can be integrated into adaptive operating systems. Under this framework, intelligence is no longer merely a tool used by organizations, but becomes the mechanism through which organizations sense, coordinate, decide, act, learn, and evolve.**

***Index Terms*—Closed-loop intelligence, physical intelligence, parallel intelligence, organizational intelligence, AI agents**

I. Introduction

The rapid progress of foundation models and artificial intelligence (AI) agents has greatly expanded the ability of machines to understand instructions, synthesize information, and support human decision-making. These capabilities have already reshaped knowledge work, content creation, scientific discovery, software development, and online services.

However, intelligence that remains confined to screens and digital interfaces is still incomplete. A model may generate a technically plausible plan without executing it. It may recommend an action without observing whether the action succeeds. It may produce a decision without being responsible for the physical, organizational, or social consequences of that decision. In such systems, perception, reasoning, execution, and learning are often separated. The output of an AI model is typically treated as the end of the computational process, while the subsequent implementation and evaluation are left to humans or external systems.

This separation creates what may be called an action-feedback gap. The model can infer what should be done, but it does not necessarily participate in doing it. Even when its recommendation is executed, the resulting state of the physical or organizational environment may not be returned to the model in a structured form. Consequently, the system cannot continuously determine whether its reasoning was correct, whether its actions were effective, or how its future behavior should be improved.

The next stage of AI will therefore be defined not merely by stronger generation, larger models, or more autonomous agents, but by the ability to close this gap. Intelligence becomes operational when perception, reasoning, action, feedback, and learning are connected into a continuous loop. In such a loop, AI no longer functions only as an external assistant that provides isolated outputs. It becomes part of an adaptive system that observes the environment, evaluates alternatives, intervenes in the world, monitors the consequences, and updates its internal representations and future policies. The central issue is therefore shifting from what an individual model can generate to how intelligent systems can operate, coordinate, and evolve over time.

Physical intelligence is an essential component of this transition. Robots, autonomous vehicles, drones, smart devices, and embodied agents give AI the ability to perceive and act in real environments. They transform AI outputs into physical movement, manipulation, navigation, inspection, transportation, manufacturing, and service. Yet the physical world imposes constraints that are largely absent from purely digital environments. Actions consume energy, require time, wear down equipment, interact with uncertain surroundings, and may create irreversible safety or economic consequences. Unlike digital content generation, physical operation does not permit unlimited trial and error.

For this reason, physical intelligence cannot develop through direct interaction with the physical world alone. Intelligent systems also require an artificial environment in which physical states, alternative actions, future consequences, and operational risks can be represented and evaluated. This artificial world serves as a computational mirror of the physical world. It is constructed from real-world data, system states, operating rules, task requirements, and feedback, and may contain digital twins, simulation environments, world models, knowledge graphs, synthetic agents, and optimization systems.

The physical world and the artificial world should not be

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regarded as two isolated domains. Together, they constitute the "parallel world". The physical world provides real entities, constraints, events, actions, and feedback, while the artificial world mirrors and extends these elements through modeling, simulation, prediction, and experimentation. Parallel intelligence enables the two worlds to interact continuously: physical observations update the artificial world, artificial predictions guide physical action, and the outcomes of physical execution further revise the artificial models.

However, constructing a parallel world is not sufficient to ensure that intelligence can operate effectively at the scale of real institutions and societies. Most consequential actions are not performed by a single model, robot, or autonomous agent. They are carried out by organizations composed of people, machines, information systems, AI agents, rules, and responsibilities. A prediction must be converted into a task, a task must be assigned to an appropriate actor, resources must be allocated, risks must be reviewed, and the outcome must be evaluated and preserved as organizational knowledge.

This requirement brings organizational intelligence to the center of the discussion. Organizational intelligence coordinates physical action and artificial reasoning through roles, responsibilities, workflows, governance mechanisms, and institutional memory. It determines not only what should be done, but also who or what should do it, under what constraints, with which resources, and with what form of accountability. In this sense, organizational intelligence is the mechanism through which the interaction between the physical world and the artificial world becomes coordinated collective action.

The transition toward closed-loop intelligence can therefore be understood through three mutually dependent dimensions. Physical intelligence provides grounding and execution in the real world. The artificial world provides representation, simulation, prediction, and optimization. Organizational intelligence connects people, agents, machines, knowledge, resources, and responsibilities so that artificial decisions can be translated into governed physical actions. Together, they form a new way of parallel intelligence to organize the continuous interaction between the physical and artificial worlds, allowing them to learn from and reshape each other.

II. Physical Intelligence

Essentially, AI for science practically equals physical intelligence. Conventional artificial intelligence relies on virtual algorithms and generative frameworks confined within digital space. Physical intelligence transfers such virtual-based intelligence into real-world physical-world problems, enabling AI to deliver practical real-world value. As artificial intelligence gains widespread attention, solving classic physical problems with modern AI has become highly critical. For this reason, physical intelligence stands as the core development direction in the next-generation artificial-intelligence era.

The wide application of world-foundation models in robotics has pushed embodied intelligence into the spotlight. Actually, embodied intelligence represents a transitional stage toward full-fledged physical intelligence. Physical intelligence not only supplies practical application scenarios for embodied intelligence, but also lays the fundamental rationale for its existence and ongoing development. Putting artificial intelligence into real-world physical-related problems is exactly what embodied intelligence should achieve. Simply put, embodied intelligence is the concrete implementation of physical intelligence on practical physical-world tasks.

This whole transition creates a self-reinforcing loop: AI for science gradually evolves into science for AI. Such circular causality produces far-reaching outcomes. It has potential to reshape education, administration, and even the whole organizational structure of human society. That is why we highlight physical intelligence from the perspective of artificial intelligence nowadays. A key question therefore arises: what mechanism can sustain this circular causality and circular consequence between AI-driven scientific research and science-empowered artificial-intelligence advancement?

III. Organizational Intelligence

Currently AI, represented by large-language models and AI agents, shows a noticeable tendency toward developing super agents or artificial super intelligence. Many researchers aim to build an all-powerful single intelligent system capable of handling nearly all tasks, which is widely regarded as the mainstream route for future-generation AI. Nevertheless, this development mode brings severe hidden and huge risks.

If a super-AI-agent comes into reality, its owner will gain overwhelming power. Such concentrated power poses grave threats to human society, human civilization, and even human nature itself. Hence, pursuing a standalone supreme-intelligence system is not merely inappropriate, but fundamentally misguided and ultimately untenable. To find a better interaction pattern between humanity and artificial intelligence, we may learn from human evolution. Humans are inherently social creatures with in-born social features shaped throughout long-term environmental adaptation. Human progress originates from organizational capacity: ancient people formed families first, then communities, nations, industrial factories, and diverse social groups, which jointly drive human civilization forward. Inspired by this fact, we ought to arrange large-scale models and agents systematically to create brand-new organizational intelligence.

Structuring AI technologies in such a way allows human supervision across every link of intelligent systems. Human governance keeps AI aligned with human ethics and human nature, preventing powerful AI from being exploited by a small group for harmful purposes, and enabling all mankind to benefit from AI advances. By organizing large models and AI agents, we complete the closed-loop cycle from AI for science to science for AI, and realize the mutual iteration between physical intelligence and general artificial intelligence. Eventually, benevolent parallel intelligence emerges. For these reasons, governable, humanity-oriented organizational intelligence is more urgently required than ever before.

Fig. 1 illustrates the architecture for a special organizational intelligence [1], where both concepts of human organization operating system (H_2OS) and organization on a chip (OoC) had been purposed for its implementation.

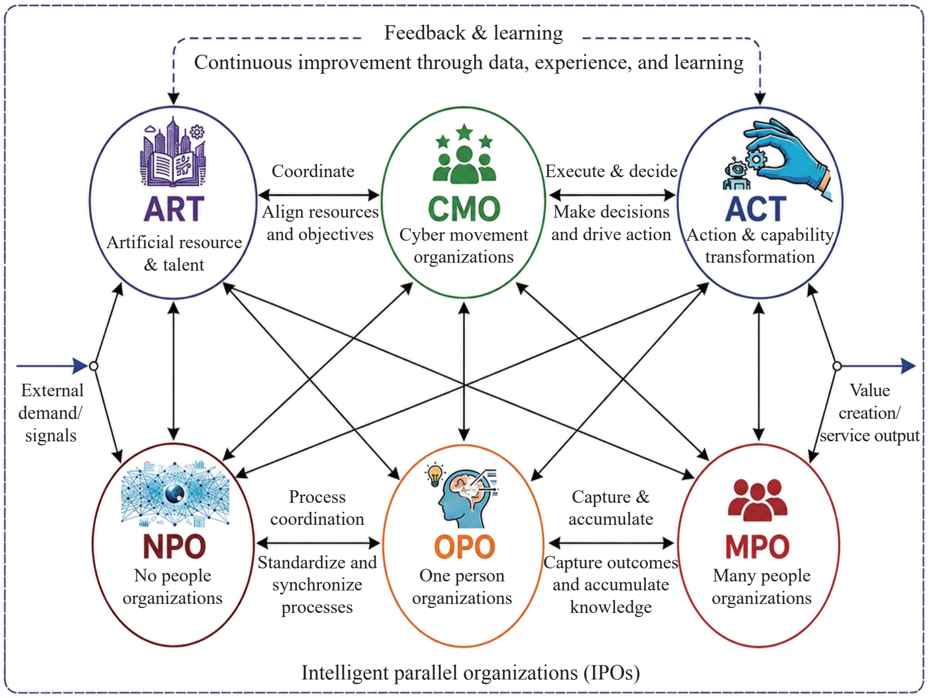

Fig. 1 H_2OS and OoC based architecture of closed-loop organizational intelligence.

IV. New Education for New Ecology

Faced with the societal transformation driven by AI breakthroughs, the entire existing education system requires comprehensive reconstruction rather than merely individual self-improvement. We put forward the PURE concept (see Eq. (1)), where PURE is parallel university of research and education (PURE I) or parallel universe for research and education (PURE II) for mandated learning from kindergarten to postgraduate studies (K21) [2, 3], or lifelong learning, for all citizens in post AI societies.

$$\text{PURE} \triangleq \text{K21} \times \text{CASE} \triangleq \text{iSTREAMS} + \text{iCDIOs} \qquad (1)$$

Within the PURE framework, two fundamental questions must be addressed: what students should learn and how knowledge is delivered. Conventional education strictly separates mathematics, physics, chemistry, and biology into isolated single-subject disciplines. Such segmented teaching mode shall be replaced by scenario-based, case-driven transdisciplinary learning.

The term CASE embodies the core idea of this new-style education. "C" stands for cognitive science, which builds fresh mindsets for understanding intelligent agents. "C" also refers to control engineering, guaranteeing effective regulation over machines and agents within cyber-space. "A" incorporates three dimensions: automatic operation, autonomous decision-making, and agential-oriented thinking for various science-and-engineering projects. This acronym highlights hands-on-while-learning practice throughout training.

With AI, especially organizational and parallel intelligence, traditional STEM evolves into iSTREAMS, while the classic CDIO develops into iCDIOs. iSTREAMS reorganizes basic disciplines around cross-field themes. iCDIOs redesign the whole cycle of conceiving, designing, implementing, and operating projects by CASE-oriented transdisciplinary thinking [4]. Together, iSTREAMS and iCDIOs reshape the whole learning process, enabling learners to master intelligence-related knowledge through cross-disciplinary physical and embodied intelligence activities.

$$\text{CiSEE} \triangleq \text{Circular } \textit{in-situ} \text{ economy and ecology} \qquad (2)$$

We hope such education system will lead to an innovative socioeconomic ecosystem jointly with AI agents, whose core principle is defined as CiSEE, see Eq. (2).

Traditional global competition relies heavily on cross-border resource and value acquisition. Competing for limited overseas resources inevitably triggers conflicts and even wars. Therefore, the *in-situ* economy becomes essential. Besides, recycling philosophy must be deeply rooted in social development, since non-renewable resources will eventually run out without repeated reuse. AI technologies greatly accelerate the construction of circular economy and ecology.

Urban waste recycling serves as a typical example. We can deploy automated robot assembly lines dedicated to garbage disposal, similar to automobile-manufacturing production lines. All citizens could assign specific recycling requirements by programming custom-built agents. These agents run on corresponding robotic systems, sorting and separating various waste materials automatically. Once a task-oriented program is generated, its corresponding agent gets deployed to robots and finishes designated sorting work efficiently. As illustrated in Fig. 2, such waste-processing systems can be readily realized with current AI and robotic techniques, no more waste sorting jobs by human.

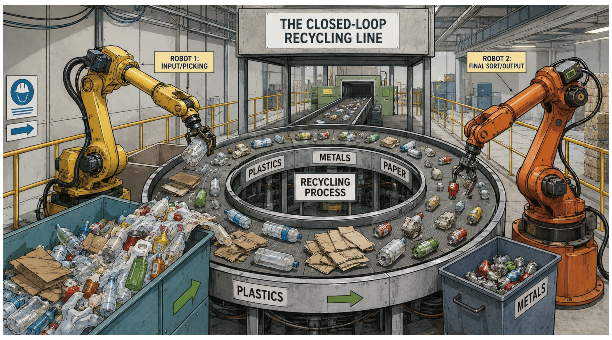

Fig. 2 Organization-on-a-chip: an illustrative architecture of closed-loop organizational intelligence. Generated by Nano Banana 2.

V. See our Hope

Some tech giants engaged in large-scale AI development stir widespread public anxiety about AI across society. Many college graduates even begin to doubt the value of studying AI. Nevertheless, we firmly believe humanity will remain in charge of AI. No matter how advanced AI becomes, it ought to stay under human supervision and governance. We need to shift away from capitalist continuous surveillance toward socialist continuous governance, and hold faith in humanity. Without hope, human existence loses its whole meaning.

Borrowing and reinterpreting Hilbert's famous motto, we replace "we must know, we will know" with "we must hope, we will hope".

$$\mathrm{SEE} \triangleq \mathrm{SCE}^{++}\mathrm{H_3O} \tag{3}$$

Actually our hope is simple, as illustrated in Eq. (3). The acronym SEE stands for sleeping well, eating well, and exercising well. We expect life to be slow, casual, enjoyable, easy, elegant, evolve, etc., instead of being trapped in fierce cutthroat competition. We want our activities for happiness, health, and helping others be organized, operated, and optimized. It will make our living and life become a new science, the science of creativity or creativity science.

This is our very basic expectation for intelligent technologies including AI, organizational intelligence, physical intelligence, and parallel intelligence. Any intelligent system should and must guarantee these basic human pursuits.

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