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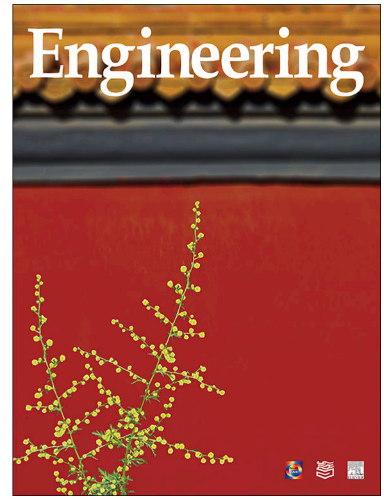

Views & Comments

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PII: S2095-8099(26)00199-2
DOI: https://doi.org/10.1016/j.eng.2026.04.008
Reference: ENG 2322

To appear in: *Engineering*

Received Date: 23 January 2026
Revised Date: 1 April 2026
Accepted Date: 7 April 2026

Please cite this article as: W. Shen, Y. He, Evolution of Agent Concept in Intelligent Manufacturing, *Engineering* (2026), doi: https://doi.org/10.1016/j.eng.2026.04.008

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Evolution of Agent Concept in Intelligent Manufacturing

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1. Introduction

Manufacturing systems are characterized by complexity, distributed decision-making, and the need for coordinated actions to achieve system-level production objectives. Agents play an important role in distributed perception, autonomous decision-making, and the real-time coordination of collaborative intelligent manufacturing systems [1]. Typical application scenarios include distributed production planning, dynamic rescheduling, the predictive maintenance of critical equipment, adaptive process control for quality improvements, autonomous intra-logistic coordination, and cross-system production orchestration.

The agent concept was initially used for software systems that can actively perceive the environment, make autonomous decisions, and take actions. It has been developed and applied in intelligent manufacturing for more than three decades [2]. Nie et al. [3] proposed a multiagent and cloud-edge orchestration framework for distributed production control in manufacturing to organize idle manufacturing resources and achieve collaborative production execution and real-time exception handling. Zhang et al. [4] presented a multiagent system approach for digital twin shop-floor resilient control, which was validated in a chemical fiber production case for its effectiveness in real-time scheduling and equipment fault handling. With the continuous development of artificial intelligence (AI), the concept, architecture, and core technical focus of agents are constantly evolving. The rise of reinforcement learning (RL) introduced a different perspective and architecture of agents for intelligent manufacturing applications. Li et al. [5] proposed a holistic system process modeling and control approach based on multiagent RL for integrated manufacturing system process control. Zhang et al. [6] proposed a collaborative agent RL framework based on an attention mechanism and disjunctive graph embedding for flexible job shop scheduling problems. Recently, large language model (LLM)-based AI agents have emerged as a promising approach that expands the scope and expectations associated with agent-based systems for intelligent manufacturing [7].

Currently, there exists some confusion regarding the concept of "agent" within related research communities. This short article discusses the evolution of the agent concept in the context of intelligent manufacturing and explores future opportunities and challenges.

2. Evolution of agent concept

The evolution of the agent concept is shown in Fig. 1, initially from distributed AI (DAI), to its use in RL, and finally based on LLMs in recent times. It presents a trend from rule-driven units to learning-driven policy entities and then to cognitive autonomous systems.

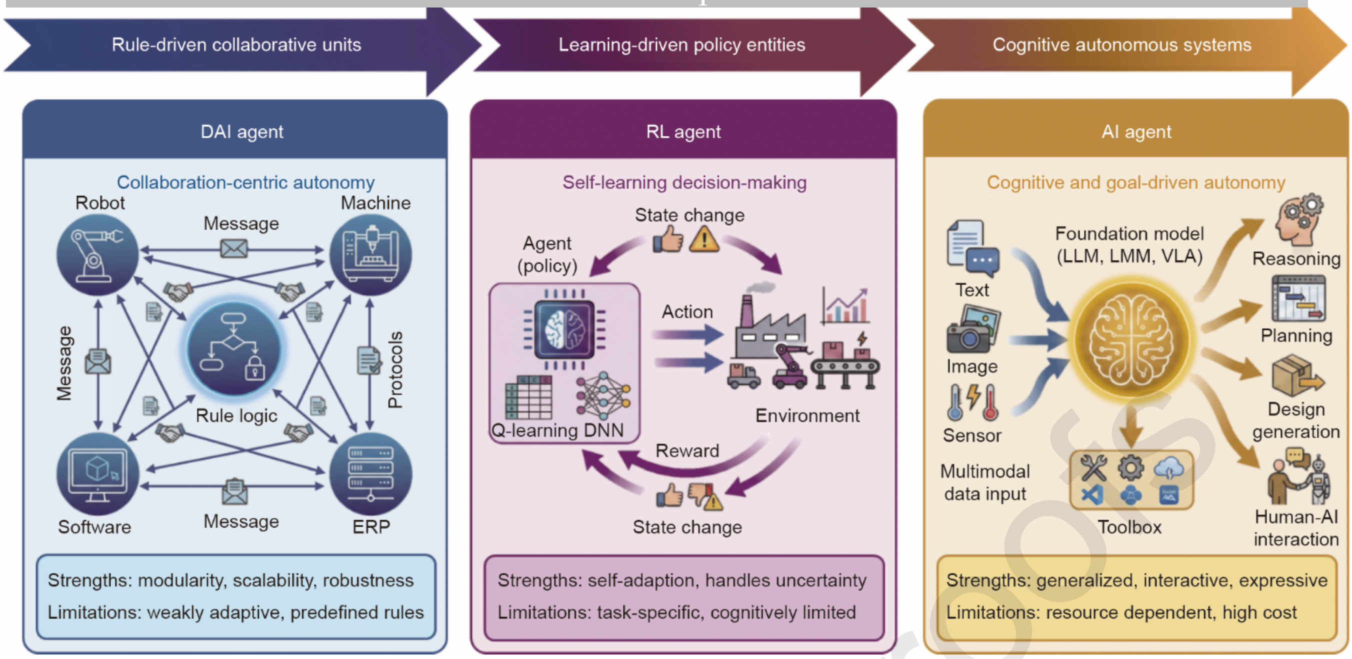


Fig. 1. Evolution of agent concept. ERP: enterprise resource planning; LMM: large multimodal model; VLA: vision-language-action model.

2.1. DAI agent

(1) Definition and orientation: collaboration-centric autonomy. The early concept of agents originated in DAI. In this article, we shall refer to it as a DAI agent. The widely accepted definition of a DAI agent by Jennings and Wooldridge [8] considers an agent as a computer system situated in an environment that is capable of autonomous action to meet its design objectives. In the context of intelligent manufacturing, we define a DAI agent as a software system that communicates and cooperates with other software systems to solve complex problems beyond the capabilities of individual systems [9]. Such a DAI agent can represent a manufacturing resource (e.g., a machine, automated guided vehicle, robot, or operator), an aggregation of manufacturing resources (e.g., shop floor), or a software tool (e.g., computer-aided design (CAD), advanced planning and scheduling (APS), enterprise resource planning (ERP), or manufacturing execution system (MES)). This representation allows physical and logical entities in manufacturing systems to be modeled uniformly, facilitating distributed scheduling, negotiation, and coordination among heterogeneous resources. Therefore, DAI agents focus primarily on structuring interactions and maintaining coherent system-level collaboration across distributed manufacturing units.

(2) Core technologies and applications: structured distributed interactions. DAI agents rely on communication protocols, message-passing mechanisms, and rule- or knowledge-driven decision logic to coordinate activities among heterogeneous resources. Graph-based interaction models and coordination mechanisms from multiagent system research further support distributed scheduling, negotiation, and workflow management across manufacturing resources and software systems, forming the backbone of flexible, reconfigurable, and holistic manufacturing system architectures [10]. Recent advancements in the Internet of things, big data, and machine learning have led to the development of multiagent systems, accelerating the development and deployment of intelligent manufacturing systems based on DAI agents [11]. DAI agents can access rich and timely data from machines, products, and processes. This enables more refined monitoring and control, and supports distributed decision-making at different enterprise levels [12]. In addition, the integration of machine-learning modules into DAI agents enables them to adapt their behaviors to constantly changing production conditions, such as demand fluctuations, machine failures, or supply-chain disruptions. Therefore, modern manufacturing systems based on DAI agents are no longer static coordination frameworks and are increasingly capable of self-organization, resilience, and continuous performance improvements.

(3) Strengths and limitations: robust but weakly adaptive. DAI agents provide modularity, scalability, and robustness through distributed decision-making and avoid a single point of failure, making them highly suitable for complex manufacturing systems. However, the reliance of early DAI agents on predefined rules, engineered knowledge, and static coordination mechanisms limits their adaptability to dynamic, data-rich environments.

2.2. RL agent

(1) Definition and orientation: self-learning decision-making. The concept of an agent in RL differs significantly from that of the DAI agent described previously, particularly in the context of single-agent RL. An RL agent interacts with an environment to learn how to achieve a specific goal. It observes the environment, acts according to its learned policies, and receives rewards or penalties. The objective is for the agent to learn a policy that maximizes its cumulative reward. When applied to intelligent manufacturing, RL agents emphasize adaptive sequential decision-making, allowing systems to autonomously improve their performance through experience. Nevertheless, when RL is implemented in a multiagent environment (i.e., multiagent RL), the meaning of an RL agent becomes similar to that of a DAI agent, particularly when these RL agents have distinct reward functions. However, DAI agents can be enhanced with RL capabilities.

(2) Core technologies and applications: policy learning under uncertainties. RL agents are supported by algorithms, such as Q-learning, policy gradient methods, actor–critic architectures, and deep RL variants [13]. These techniques enable agents to explore state–action spaces, approximate value functions, and learn policies that adapt to uncertainties in demand, resource availability, and process variability. In intelligent manufacturing, RL agents are applied to dynamic scheduling, robot path planning, energy management, and the control of autonomous transportation systems. In such scenarios, data-driven adaptation is more critical than structural coordination. In multiagent RL settings, RL agents can negotiate shared policies or independent reward structures, approaching but not fully replicating the distributed coordination in DAI systems.

(3) Strengths and limitations: adaptive but cognitively limited. The main advantage of RL agents lies in their capacity to adapt their behavior through experience, making them effective for problems with uncertain dynamics or complex optimization landscapes. However, their intelligence is typically narrow and task specific; policies are learned with respect to particular state–action representations and reward structures, with limited support for high-level reasoning, semantic understanding, or multimodal knowledge integration. Compared with DAI agents, RL agents have stronger adaptability but are less dependent on explicit coordination structures. However, their cognitive abilities are limited, and they lack broader representation and reasoning abilities. In addition, several RL approaches require substantial computational resources during the training stage, because agents must interact with the environment over a large number of episodes to explore state–action spaces and converge to effective policies. However, once trained, the inference or execution stage is typically lightweight, making RL agents suitable for real-time control or dynamic scheduling in manufacturing systems.

2.3 AI agent

(1) Definition and orientation: cognitive and goal-driven autonomy. With the rapid advancements in generative AI and LLMs, the concept of AI agents has been put forward [14]. AI agents are defined as software systems that utilize AI to pursue goals and accomplish various tasks requested by users. They are predominantly LLM-based, acting as the "brain" or core reasoning engine, but they are increasingly becoming foundation model-based to support multimodal capabilities. They are capable of learning, reasoning, planning, decision-making, and even taking actions.

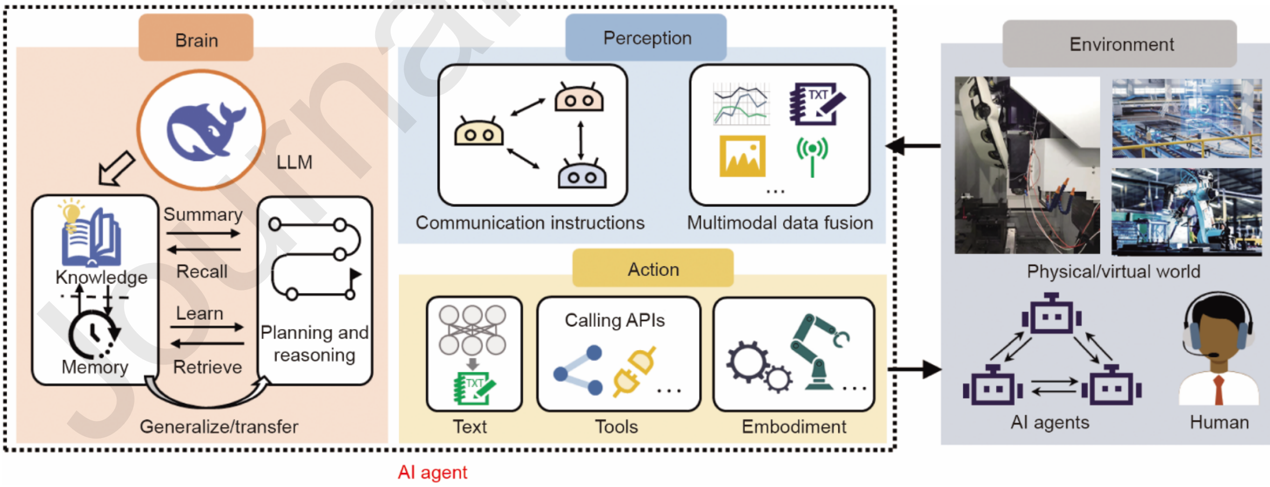


Fig. 2. Illustration of an AI Agent.

AI agents were initially proposed and developed in a single-agent mode; each AI agent operates independently to achieve a specific goal, similar to the RL agents discussed above. An AI agent utilizes external software tools and resources to accomplish the different tasks requested by users or other applications, as shown in Fig. 2. Each AI agent typically uses a single large language model (or foundation model in general). Therefore, AI agents are suitable for tasks that do not require multiple foundation models. However, complex problems or tasks are beyond the capabilities of individual AI agents with different foundation models and therefore require collaboration among multiple AI agents. When implemented in the multiagent mode, AI agents collaborate to achieve a common or individual goal, functioning in a manner similar to the DAI agents discussed above. These AI-agent-based systems capitalize on the diverse capabilities of individual AI agents to address complex problems and tasks. AI agents possess a higher level of machine intelligence, oriented toward cognition, goal-driven autonomy, and an emphasis on understanding, reasoning, and interactive problem-solving.

(2) Core technologies and applications: multimodal learning and interactions. In intelligent manufacturing environments, AI agents are predominantly functional agents, representing functions, such as design, planning, scheduling, execution and control, inspection, maintenance, and remanufacturing or disposal, as shown in Fig. 3, rather than physical agents, which represent manufacturing resources, such as machines and robots. To a large extent, their capabilities are enabled by the multimodal learning capacity of generative AI and foundation models, enabling high-level decision support and human–AI interactions across the manufacturing lifecycle. Unlike DAI agents, which emphasize collaborative problem-solving in dynamic environments, and RL agents, which specialize in learning strategies for sequential decision-making, AI agents focus on generative reasoning and interactions.

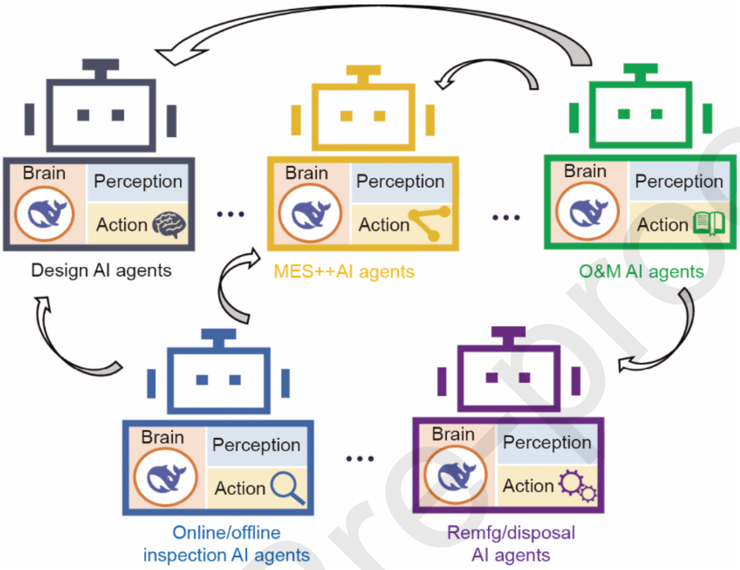


Fig. 3. AI Agents for collaborative intelligent manufacturing

(3) Strengths and limitations: expressive but resource-dependent. AI agents provide rich expressiveness, generalization, and interactive capabilities. They can interpret natural language, integrate heterogeneous information sources, coordinate tool calls, and generate multistep solutions with relatively little task-specific engineering. This makes them particularly attractive for knowledge-intensive cross-functional tasks in intelligent manufacturing. However, these advantages have notable limitations. AI agents are resource- and model-dependent and rely on large-scale models, significant computational infrastructure, and carefully managed tool integration. The training of large foundation models requires significant computational resources and large datasets, and is typically conducted by specialized organizations. During the deployment or inference stage, AI agents require nontrivial computational resources to support large model inferences, tool invocations, and multimodal processing, although the cost is generally much lower than that of model training. Their behavior can be difficult to guarantee in safety-critical or real-time scenarios, and low-level control or fine-grained optimization may still be better handled by RL agents or traditional controllers. Compared with DAI and RL agents, AI agents are highly expressive in the cognitive layer but are constrained by resource demands and controllability requirements.

3. Hybrid multiagent systems for intelligent manufacturing

Modern manufacturing systems are becoming increasingly complex, dynamic, and knowledge intensive. They involve heterogeneous resources, such as machines, robots, logistics systems, and software platforms, which are typically coordinated across multiple levels within an enterprise. Production environments are subject to uncertainties, such as demand fluctuations, machine failures, and supply-chain disruptions. These characteristics require manufacturing systems to have not only distributed coordination capabilities but also adaptive learning and advanced cognitive decision-making abilities. Future intelligent manufacturing systems are expected to integrate heterogeneous agents, including AI agents driven by large foundational models and DAI and RL agents that run using lightweight, domain-specific models or rule-based logic. Note that RL agents become DAI agents in the multiagent mode, as discussed above. On the other hand, future AI agents will also be implemented with RL agent capability, that is, adaptability. In such environments, these agents coexist and complement each other, forming hybrid multiagent systems in which cognitive, learning, and coordination capabilities are distributed across different layers of the manufacturing enterprise.

A promising development direction is for multiple AI agents to share a foundational model, thereby achieving consistent semantic understanding and interoperable reasoning across functional roles. RL agents can indirectly utilize these models, such as model-based RL or reward shaping based on underlying model insights, whereas DAI agents can interact with compressed or extracted submodels for lightweight inference. Nevertheless, while current foundation models provide powerful general reasoning and language-understanding capabilities, the knowledge embedded in such models is largely generic and not tailored to specific manufacturing contexts. Intelligent manufacturing environments involve highly specialized knowledge, including processes, equipment, production, and operational standards. Therefore, the effective deployment of foundation models in manufacturing systems often requires the integration of domain-specific knowledge sources, such as engineering databases, industrial ontologies, equipment monitoring and maintenance data, and historical production data.

The integration of AI, RL, and DAI agents in a unified framework offers considerable opportunities: AI agents enhance decision quality and human–AI interactions; RL agents enable adaptive optimization in dynamic environments; and DAI agents ensure stability, compliance, and reliable coordination. Together, these agents can support closed-loop data-driven improvements in design, planning, scheduling, execution, and maintenance, ultimately advancing manufacturing efficiency, responsiveness, and resilience. However, achieving this vision requires the addressing of several challenges:

(1) Interoperability of heterogeneous intelligence, particularly when combining foundation-model-driven cognition with learned RL policies and symbolic DAI rules;

(2) Model and data governance, ensuring consistent semantics and the safe use of shared foundation models;

(3) Scalable and reliable system integration including communication protocols, real-time constraints, and safety assurances;

(4) Human–AI collaboration, requiring workforce adaptation and new interaction paradigms.

If these challenges are adequately addressed, hybrid multiagent systems will become a core architectural paradigm for next-generation intelligent manufacturing systems, enabling factories that are not only automated but truly intelligent, adaptive, and cognitively capable.

4. Conclusion

This short article discusses the evolution of the agent concept from the DAI agent to the RL agent, and more recently, to the AI agent. This discussion highlights a clear shift from rule-driven coordination to learning-driven strategy optimization and then to strong cognitive multimodal reasoning. By comparing their directions, core technologies, and limitations, we elucidated the differences in terms of concepts and functionality.

We believe that future intelligent manufacturing systems will increasingly be based on hybrid multiagent architectures, where DAI, RL, and AI agents coexist and complement each other. In these systems, AI agents will provide advanced cognition and interaction capabilities, RL agents will provide adaptive optimization under uncertainties, and DAI agents will ensure structural robustness and distributed coordination. However, achieving this vision requires progress in interoperability, model and data governance, security and real-time assurance, and human–AI collaboration, which provide a reference for future studies on agent-enabled intelligent manufacturing.

References

[1] He Y, Shen W. Agent-based digital twins for collaborative machine intelligence solutions. IET Collab Intell Manuf 2025;7(1):e70018.

[2] Shen W, Norrie DH. Agent-based systems for intelligent manufacturing: a state-of-the-art survey. Knowl Inf Syst 1999;1:129–56.

[3] Nie Q, Tang D, Liu C, Wang L, Song J. A multi-agent and cloud-edge orchestration framework of digital twin for distributed production control. Robot Comput-Integr Manuf 2023;82:102543.

[4] Zhang C, Tao F, Ma X, Cheng Y. Multi-agent systems for digital twin shop-floor resilient control. Chin J Mech Eng 2025;In Press.

[5] Li C, Chang Q, Fan HT. Multi-agent reinforcement learning for integrated manufacturing system-process control. J Manuf Syst 2024;76:585–98.

[6] Zhang W, Zhao F, Li Y, Du C, Feng X, Mei X. A novel collaborative agent reinforcement learning framework based on an attention mechanism and disjunctive graph embedding for flexible job shop scheduling problem. J Manuf Syst 2024;74:329–45.

[7] Ren Y, Liu Y, Ji T, Xu X. AI agents and agentic AI–navigating a plethora of concepts for future manufacturing. J Manuf Syst 2025;83:126–33.

[8] Jennings NR, Wooldridge MJ. Agent technology: foundations, applications, and markets. Berlin: Springer; 1998.

[9] Shen W, Hao Q, Yoon HJ, Norrie DH. Applications of agent-based systems in intelligent manufacturing: an updated review. Adv Eng Inform 2006;20(4):415–31.

[10] Amirkhani A, Barshooi AH. Consensus in multi-agent systems: a review. Artif Intell Rev 2022;55(5):3897–35.

[11] Pulikottil T, Estrada-Jimenez LA, Ur Rehman H, Mo F, Nikghadam-Hojjati S, Barata J. Agent-based manufacturing—review and expert evaluation. Int J Adv Manuf Technol 2023;127:2151–80.

[12] Duan S., Wang D., Ren J., Lyu F., Zhang Y., Wu H., Shen, X. Distributed artificial intelligence empowered by end-edge-cloud computing: a survey. IEEE Commun Surv Tutorials 2023;25(1):591–624.

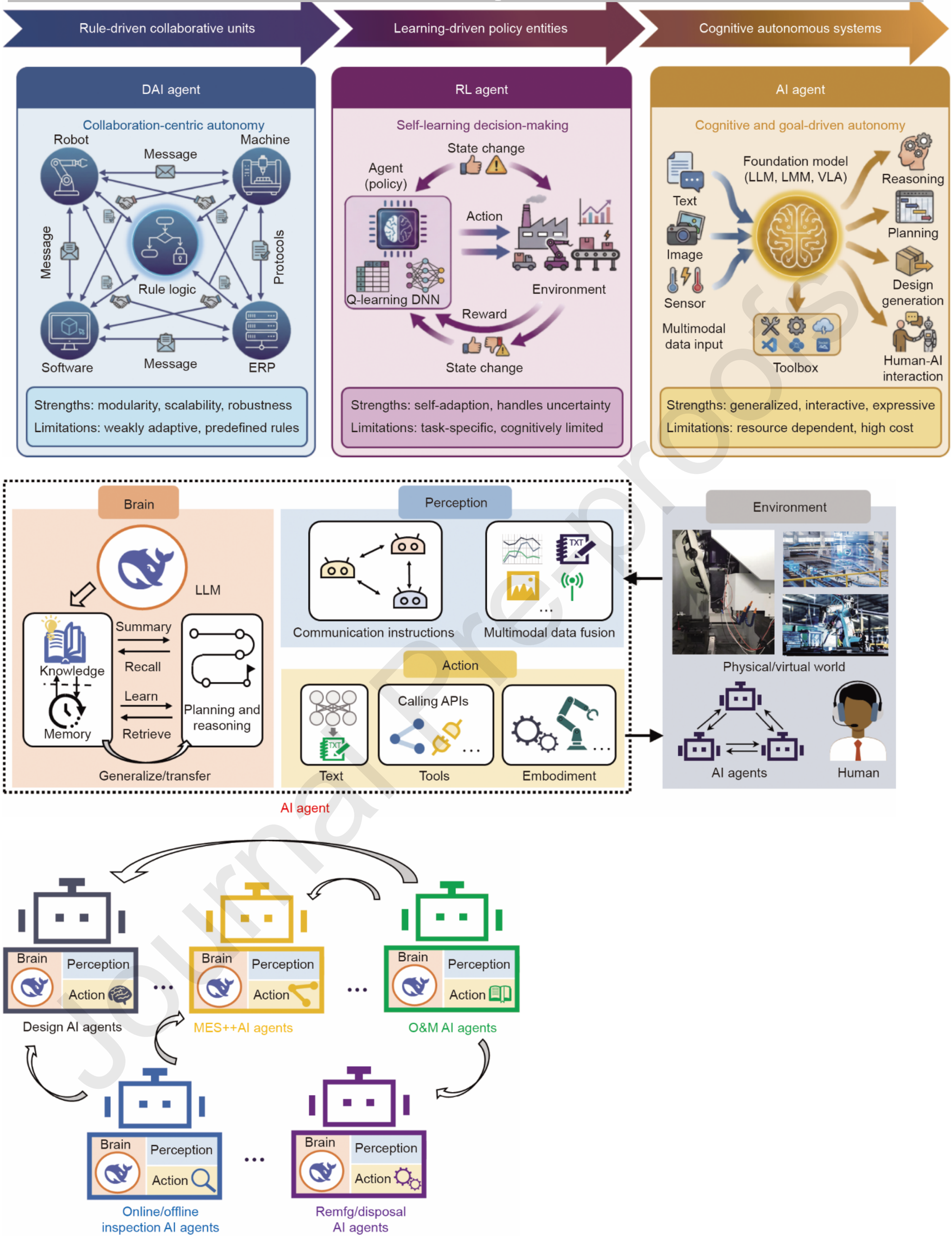
[13] Zhang K, Yang Z, Başar T. Multi-agent reinforcement learning: a selective overview of theories and algorithms. In: Vamvoudakis KG, Wan Y, Lewis FL, Cansever D, (editors). Handbook of reinforcement learning and control. Cham: Springer; 2021. p. 321–84.

[14] Durante Z, Huang Q, Wake N, Gong R, Park JS, Sarkar B, et al. Agent AI: surveying the horizons of multimodal interaction. arXiv:2401.03568.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:


Rule-driven collaborative units
Learning-driven policy entities
Cognitive autonomous systems
DAI agent
Collaboration-centric autonomy
Robot
Machine
Message
Message
Protocols
Rule logic
Software
Message
ERP
Strengths: modularity, scalability, robustness
Limitations: weakly adaptive, predefined rules
RL agent
Self-learning decision-making
State change
Agent (policy)
Action
Q-learning DNN
Environment
Reward
State change
Strengths: self-adaption, handles uncertainty
Limitations: task-specific, cognitively limited
AI agent
Cognitive and goal-driven autonomy
Foundation model (LLM, LMM, VLA)
Text
Image
Sensor
Multimodal data input
Toolbox
Reasoning
Planning
Design generation
Human-AI interaction
Strengths: generalized, interactive, expressive
Limitations: resource dependent, high cost
Brain
LLM
Summary
Recall
Learn
Retrieve
Knowledge
Memory
Planning and reasoning
Generalize/transfer
Perception
Communication instructions
Multimodal data fusion
Action
Text
Calling APIs
Tools
Embodiment
AI agent
Environment
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Human
Brain
Perception
Action
Design AI agents
MES++AI agents
O&M AI agents
Online/offline inspection AI agents
Remfg/disposal AI agents