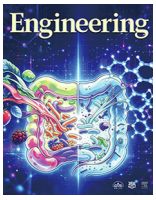
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New-Generation Intelligent Manufacturing Leading and Driving the Fourth Industrial Revolution

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ABSTRACT

This paper explains the implications of new-generation intelligent manufacturing (NGIM), identifying NGIM as an advanced paradigm and the principal form of intelligent manufacturing, arising from the deep integration of new-generation artificial intelligence (NGAI) technologies with advanced manufacturing technologies. The core characteristics of NGIM are autonomous perception, autonomous decision-making, autonomous execution, and autonomous learning, while its fundamental features include intelligentization, systematicity, and openness. Based on the fundamental theory of human–cyber–physical systems (HCPS), this paper proposes a system architecture for NGIM, in which NGIM is a large-scale system formed through the organic integration of various HCPS intelligent systems that serve different purposes and operate at different levels; an HCPS system is an augmented intelligent system comprising humans and cyber–physical system (CPS) agents; and the heart of a CPS agent is an intelligent central system consisting of a central core, data threads, and intelligent functional subsystems. This paper also explores the enabling and integrative innovation of NGIM, achieved by deeply integrating key NGAI enabling technologies with advanced manufacturing technologies. NGIM will comprehensively optimize and redefine the manufacturing industry, driving innovation and transformation in manufacturing products, production, services, and industrial models, and serving as the principal technical pathway for innovation-driven development in manufacturing. Looking ahead, manufacturing should adhere to the general principle of intelligence-led development, parallel advancement, and integrated development, while advancing digital-intelligent transformation and intelligent upgrading in stages.

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1. New-generation intelligent manufacturing is the core technology of the Fourth Industrial Revolution

1.1. The historic convergence of innovation-driven manufacturing development with the new round of scientific and technological revolution and industrial transformation

Since the mid-20th century, the Third Industrial Revolution has driven major technological advances in production efficiency, manufacturing precision, and global collaboration across the world's manufacturing sector, generating substantial economic achievements. The manufacturing sector is facing increasingly limited opportunities for efficiency gains, bottlenecks in performance optimization, and growing difficulties sustaining its factor-driven growth model. A profound technological transformation and an industrial revolution are urgently needed to overcome these constraints, cultivate new quality productive forces, and embark on an entirely new stage of development [1,2].

The accelerated evolution of a new round of scientific and technological revolution (NRSTR), together with the deepening development of the Fourth Industrial Revolution (FIR), has brought historic opportunities for innovation-driven development in manufacturing. Over the past decade, strategic breakthroughs have been made in artificial intelligence (AI) technology, and new-generation AI (NGAI) has developed rapidly to become the core technology of the NRSTR. As a general-purpose enabling technology, NGAI is being deeply integrated with advanced manufacturing technologies to create new-generation intelligent manufacturing (NGIM) technologies that are leading and driving the FIR.

The urgent demands for innovation-driven development in global manufacturing have historically converged with the NRSTR and industrial transformation. NGIM technologies emerging from the NRSTR are providing an innovative driving force that is accelerating the transformation of economic development models. By enabling a vast diversity of models and applications, these technologies are helping to bring about the FIR and have become the principal intersection between innovation-driven manufacturing and the NRSTR and industrial transformation.

1.2. NGIM is the core technology of the FIR

Throughout history, innovation-driven manufacturing has proceeded via two main pathways. The first is incremental development, which relies primarily on continuous iterative innovation in manufacturing technologies. The second is development through enablement, which relies primarily on the deep integration of general-purpose enabling technologies with advanced manufacturing technologies. This integration produces revolutionary technological innovations that drive systemic change in manufacturing. Every industrial revolution has been driven by major breakthroughs in general-purpose enabling technologies and their innovative integration with manufacturing technology.

The enabling and integrative innovations that drive an industrial revolution are general-purpose and broadly applicable; they can be used to upgrade various manufacturing systems of every kind across all industries, thereby driving comprehensive and holistic transformation throughout the manufacturing sector. The respective general-purpose enabling technologies of the first three industrial revolutions were steam engine technology, electric power technology, and digital technology. The integration of these technologies with manufacturing technologies drove the manufacturing industry to achieve the revolutionary transformation and upgrading of mechanization, electrification, and digitalization. The general-purpose enabling technology of the FIR is NGAI. NGIM technologies, formed by the deep integration of NGAI with advanced manufacturing technology, will lead and drive the revolutionary transformation and upgraded intelligentization of manufacturing, becoming the core driving force of the FIR (Fig. 1) [3].

1.3. Seizing opportunities for innovation-driven development

As the FIR unfolds, NGIM has become the central focus of industrial competition among the world's major industrial countries. These countries should firmly seize the historical opportunities presented by the FIR, make full use of the distinctive characteristics of their own manufacturing systems, and make NGIM a primary strategic priority. This will enable decisive strategic breakthroughs and drive innovation-based development in manufacturing.

2. The implications, core characteristics, and fundamental features of NGIM

2.1. The core essence of intelligent manufacturing

(1) Intelligent technologies and manufacturing technologies are being deeply integrated to form intelligent manufacturing technologies [4,5]. Here, intelligent technologies are enabling technologies that play the dominant role, while manufacturing technologies are the substantive technologies that constitute the principal part. The fundamental objective of intelligent manufacturing is to achieve the digital transformation and intelligent upgrading of the manufacturing sector (Fig. 2).

(2) Intelligent manufacturing is a broad concept encompassing the continuous evolution and iterative upgrading of technological systems, as well as complex systems engineering. It comprises three basic paradigms: digital manufacturing, "Internet+" manufacturing, and NGIM (Fig. 3) [6]. Of these, NGIM is the advanced paradigm and the principal form of intelligent manufacturing.

(3) Intelligent manufacturing is a large-scale system encompassing every aspect of innovative development in manufacturing. It has three main areas: intelligent products (i.e., intelligence in products and their design); intelligent production (i.e., intelligence in the production and manufacturing of products); and intelligent services (i.e., intelligence in manufacturing services). Supported by the industrial Internet and manufacturing cloud platforms and governed and coordinated by an intelligent central system, these parts are integrated into an integrated intelligent manufacturing system (Fig. 4) [7].

2.2. The revolutionary leap from digital manufacturing to NGIM

2.2.1. Traditional manufacturing and HPS

Humans have made and used tools to assist with diverse tasks for tens of thousands of years. During the First and Second Industrial Revolutions, revolutionary breakthroughs in power technologies, represented by the steam engine, the electric motor, and the internal combustion engine, brought manufacturing successively into the eras of mechanization and electrification. In traditional manufacturing, tools or machines are physical systems composed of mechanical, electrical, hydraulic, and other physical components. The capabilities for perception, decision-making, execution, and learning required to complete tasks are provided primarily by humans. Therefore, the essential characteristic of traditional manufacturing is the human–physical system (HPS) (Fig. 5).

2.2.2. Digital manufacturing and HCPS1.0

After the mid-20th century, the information technology revolution, primarily characterized by digitalization, ushered manufacturing into the digital manufacturing era. Digital manufacturing is the first basic

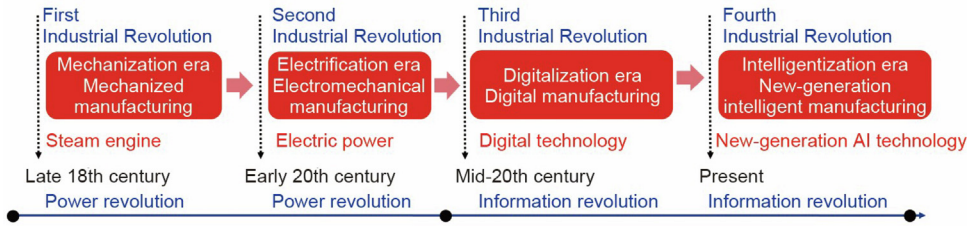


Fig. 1. The enabling and integrative innovations of the Four Industrial Revolutions. Reproduced from Ref. [3] with permission.

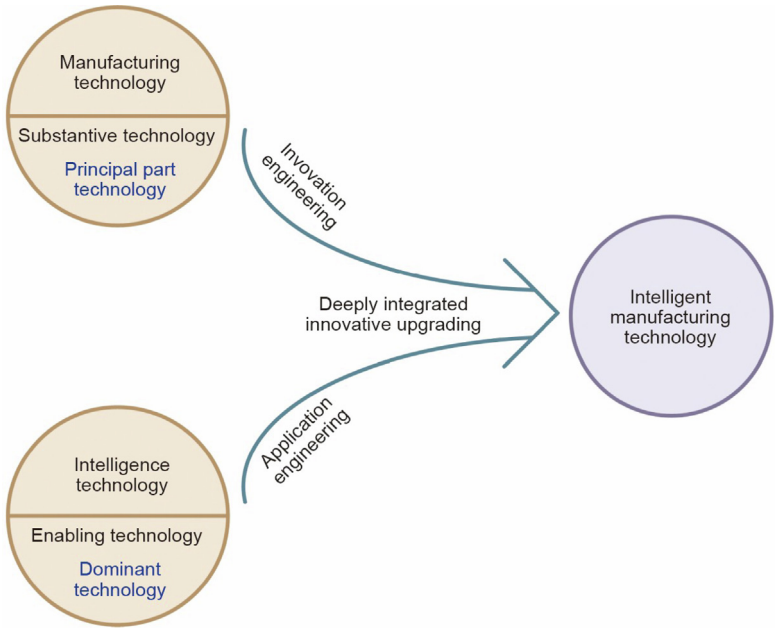


Fig. 2. Intelligent manufacturing as the innovative integration of intelligent technologies and manufacturing technologies. Reproduced from Ref. [3] with permission.

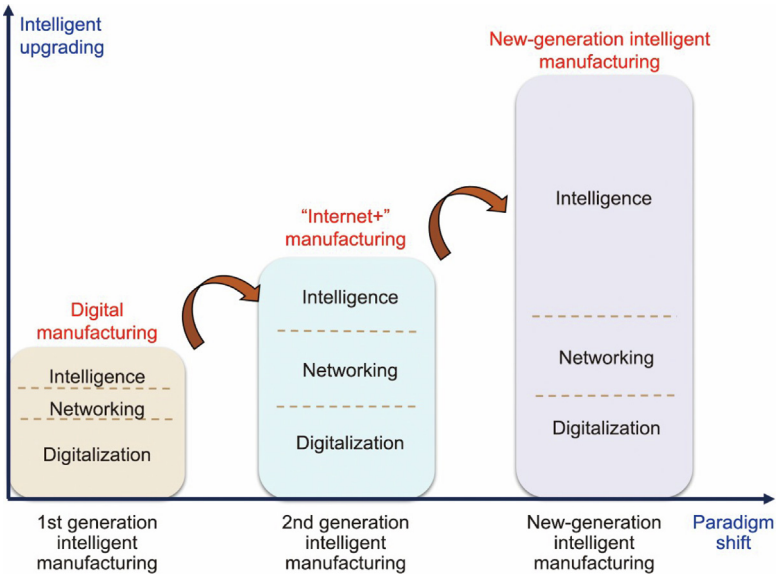


Fig. 3. The three basic paradigms of intelligent manufacturing.

paradigm of intelligent manufacturing. Its essential characteristic is the addition, between humans and physical systems, of a cyber system centered on digital computers. This cyber system assists or replaces humans in perception and decision-making and controls physical systems in executing tasks (Fig. 6). This brought about revolutionary changes relative to traditional manufacturing. Digital manufacturing evolved from traditional HPS into human–cyber–physical system (HCPS) [7–9]. Machines were transformed from physical systems into

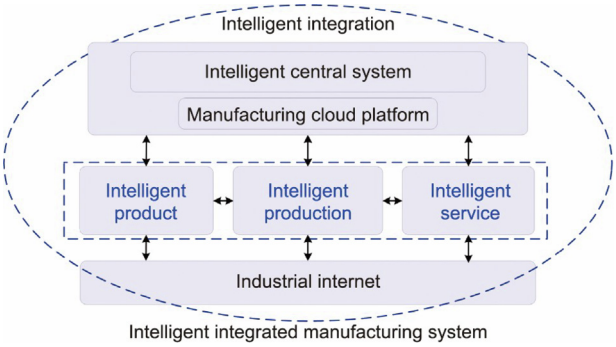


Fig. 4. The intelligent integrated manufacturing system. Reproduced from Ref. [3] with permission.

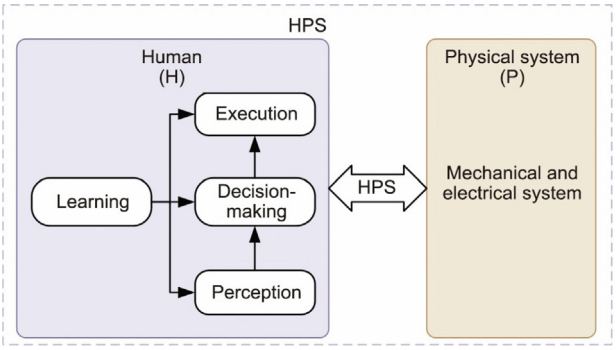


Fig. 5. The essential characteristic of traditional manufacturing: the human–physical system (HPS).

cyber–physical systems (CPS) [10], acquiring capabilities such as perception, decision-making, and execution and becoming intelligent machines to some extent. System efficiency and quality improved significantly, as did systems' capability to perform complex tasks. Human knowledge and wisdom could be transferred to cyber systems, greatly improving the efficiency of system innovation and of the dissemination, utilization, and inheritance of knowledge [11–13].

Digital manufacturing is known as first-generation intelligent manufacturing or Intelligent Manufacturing 1.0. The HCPS associated with digital manufacturing can thus be defined as HCPS1.0.

2.2.3. "Internet+" manufacturing and HCPS1.5

At the end of the 20th century, the rapid development of Internet technologies drove a transition of the manufacturing sector toward "Internet+" manufacturing. "Internet+" manufacturing remains an HCPS, but its cyber system uses network communications to effectively solve the critical problem of connectivity. Internet and cloud platforms are important components of this cyber system, significantly enhancing system functionality, performance, and value creation [14,15]. "Internet+" manufacturing is also known as second-generation intelligent manufacturing or Intelligent Manufacturing 1.5; the corresponding HCPS can thus be defined as HCPS1.5.

2.2.4. NGIM and HCPS2.0

(1) NGIM

NGIM is the deep integration of NGAI with advanced manufacturing technologies. It is the third basic paradigm of intelligent manufacturing, as well as its advanced paradigm and principal form. In 2016, AlphaGo defeated the world Go champion in a historic event marking the arrival of the NGAI era [16]. During the 60 years from 1956 to 2016, a period that can broadly be described as the AI 1.0 era, AI technologies experienced several cycles of progress and setbacks. In recent years, innovations in algorithms, the accumulation of data, and leaps in computing power have enabled strategic breakthroughs in AI, ushering in the era of NGAI, or AI 2.0. In particular, with the emergence of ChatGPT in late 2022, the large generative AI models began to exhibit capabilities for understanding and learning, together with a powerful ability to solve practical problems. This was a major leap forward in the history of AI, with milestone significance. Since then, NGAI has developed rapidly through the integration of large AI models, big data, and large-scale computing power. Its applicability has undergone a qualitative change, and it will enable hundreds of models and thousands of forms, empower thousands of industries, and bring about intelligent upgrades in every sector. NGAI has thus become the core technology of the NRSTR and a powerful engine of economic and social development.

The deep integration of NGAI technologies with advanced manufacturing technologies has given rise to NGIM [17–21]. NGIM remains an HCPS, but it has undergone revolutionary changes relative to HCPS1.0 and HCPS1.5 and can therefore be defined as HCPS2.0 (Fig. 7).

Enabled by NGAI technologies, the CPS in HCPS2.0 acquires the capabilities of autonomous perception, autonomous decision-making, autonomous execution, and autonomous learning. It can autonomously optimize the performance of tasks that were previously difficult to complete, acquire knowledge through autonomous learning, and achieve autonomous cognition and evolution. It thus becomes a CPS agent with autonomous capabilities. HCPS2.0, in turn, becomes a hybrid human–machine augmented intelligence system comprising humans and CPS agents, referred to here as an HCPS intelligent system.

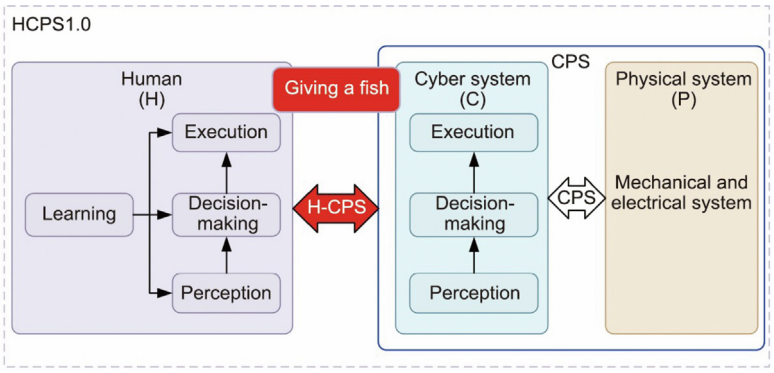


Fig. 6. The essential characteristic of digital manufacturing: HCPS1.0.

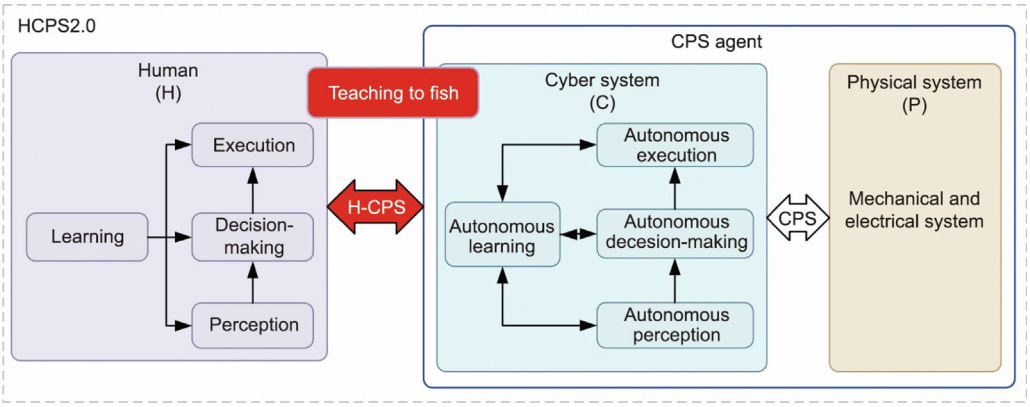


Fig. 7. The essential characteristics of NGIM: HCPS2.0.

(2) Major technological advances in NGIM

- **Substantial improvements in engineering problem-solving capabilities.** CPS agents in HCPS2.0 can complete complex tasks autonomously. The CPS in HCPS1.0 and HCPS1.5 can perceive, make decisions, and execute actions only according to preset programs, making it difficult for them to handle complex tasks involving uncertainty. In contrast, NGAI technologies give the CPS agents in HCPS2.0 the capabilities of autonomous perception, decision-making, and execution, which, when applied to changing tasks and operating conditions, greatly improve the agents' ability to complete complex tasks. Moreover, the CPS agents in HCPS2.0 can solve highly complex engineering problems. Engineering practice has long relied on three problem-solving paradigms: experimental induction, theoretical analysis, and digital simulation. Manufacturing systems, however, are generally highly nonlinear and extremely complex, presenting formidable challenges and bottlenecks that are difficult to overcome using these traditional paradigms. NGAI technologies open an entirely new path for overcoming these constraints. Enabled by big data, large-scale computing power, and NGAI algorithms, the deep integration of physics-based modeling with AI-driven data-based modeling can effectively address the modeling and solution of highly nonlinear and extremely complex manufacturing systems. This greatly enhances the ability of CPS agents to solve highly complex engineering problems.
- **Capabilities for autonomous learning and cognition.** The most fundamental change in HCPS2.0 is that its CPS agents possess the capabilities of autonomous learning and cognition. The CPS in HCPS1.0 and HCPS1.5 can perform perception–decision–execution tasks only according to preset programs and lack the capabilities for autonomous learning and cognition. Enabled by NGAI technologies, the CPS agents in HCPS2.0 have the intrinsic capabilities of autonomous learning, autonomous cognition, and autonomous evolution. This brings revolutionary changes to both the methods and the efficiency of acquiring, utilizing, transmitting, and accumulating manufacturing knowledge, significantly increasing the marginal productivity of knowledge as a core factor of production.
- **Fundamental transformation of human–machine relationships** [22–24]**.** First, the relationship between humans and CPS agents changes fundamentally, shifting from giving a fish (i.e. instructing to perform tasks) to teaching to fish (i.e. training to solve problems autonomously). This allows the respective strengths of human wisdom and machine intelligence to be fully realized and to grow through mutual inspiration, greatly unleashing the innovative potential of human wisdom and enhancing the capacity for innovation in manufacturing. Second, human–machine interactions shift from machine-centered to human-centered. One-way communication, in which humans enter commands into machines, evolves into two-way perception, real-time dialogue, and collaborative interaction between humans and machines, creating natural and efficient modes of human–machine interaction. Third, the relationship between humans and machines evolves from humans operating machines to intelligent collaboration between humans and machines. Machines evolve into autonomous agents, or digital employees, with autonomous capabilities. This liberates humans from large amounts of repetitive mental work and strenuous physical labor, allowing them to focus on more valuable creative and dominant work.

2.3. The implication of NGIM

NGIM is the advanced paradigm and principal form of intelligent manufacturing. It deeply integrates NGAI technologies with advanced manufacturing technologies, endowing intelligent manufacturing with the capabilities of autonomous perception, autonomous decision-making, autonomous execution, and autonomous learning. These capabilities give NGIM the fundamental features of intelligentization, systematicity, and openness. NGIM drives comprehensive innovation and optimization in manufacturing products, production, services, and industrial models, substantially improving manufacturing quality, efficiency, and reliability. It makes intelligent manufacturing more precise, faster, and more reliable, as well as increasingly intelligent through use.

2.4. Core characteristics of NGIM

The core characteristic of NGIM is autonomy (Fig. 7) [25].

(1) Autonomous perception

Autonomous perception involves two interlinked processes. The first is autonomous sensing. When tasks and operating conditions are complex and changeable, a CPS agent autonomously plans its sensing activities and actively selects visual, force, tactile, auditory, and other data from multiple sources and modalities for acquisition, effectively solving the data-supply problem for intelligent systems. The second is autonomous cognition. The CPS agent autonomously fuses and semantically parses the multimodal data acquired through sensing, transforming raw physical signals into structured perceptual information to achieve an accurate under-

standing of its tasks, its own state, and the external environment. Autonomous sensing solves the problem of seeing and acquiring data accurately, while autonomous cognition solves the problem of understanding what is seen. Together, they accomplish autonomous perception, providing a foundation of high-value data, information, and knowledge for autonomous decision-making, execution, and learning.

(2) Autonomous decision-making

Autonomous decision-making means that a CPS agent autonomously decomposes tasks, plans paths, evaluates trade-offs between plans, and selects actions under complex and changeable task requirements and operating conditions, using information obtained through autonomous perception and knowledge models within the system. It can also predict consequences and dynamically adjust its strategies to complete complex tasks with high quality and efficiency. Autonomous decision-making is a core capability objective of NGIM and a fundamental distinction between NGIM and the first and second generations of intelligent manufacturing. The first and second generations essentially depend on predefined rules and human intervention for decision-making. They perform well in deterministic task scenarios but often fail when tasks are complex and changeable. In contrast, autonomous decision-making in NGIM enables optimization based on knowledge and reasoning in complex environments. Rather than executing a fixed program, a CPS agent acts like an experienced expert, autonomously weighing alternatives, making judgments, and choosing actions when information is incomplete and objectives conflict. This represents a paradigmatic leap from programmed to autonomous decision-making.

(3) Autonomous execution

Autonomous execution means that a CPS agent autonomously converts abstract instructions produced by decision-making into concrete actions in the physical or digital world, under complex and changeable operating conditions. Through intelligent feedforward and real-time feedback, it precisely controls execution to ensure the stability, accuracy, and safety of its actions, translating decisions into accurate implementation. Autonomous execution is another fundamental objective of NGIM and another fundamental distinction from the first and second generations of intelligent manufacturing. With autonomous execution, NGIM no longer relies on fixed programs and parameters but autonomously adapts to changing operating conditions. The core of NGIM autonomous execution comprises two dimensions of autonomy. The first is adaptive feedforward compensation: autonomously adjusting predictive models to changing operating conditions, predicting changes in state, and applying feedforward compensation in advance to suppress deviations at their source. The second is adaptive feedback control: autonomously adjusting feedback control strategies based on changing operating conditions to correct deviations, and achieving dynamic adaptation. Together, these dimensions bring about a paradigmatic leap from programmed to autonomous execution.

(4) Autonomous learning

Knowledge is the foundation of intelligence. To possess autonomous perception, decision-making, and execution capabilities, NGIM must have matching and continuously growing knowledge. Autonomous learning means that a CPS agent autonomously acquires, generates, validates, and accumulates knowledge from multisource data, execution feedback, and operational experience, through continuous interaction with its environment. Learning occurs over the CPS agent's entire life cycle. During research and development, the agent can mine implicit knowledge and engineering mechanisms from massive previously accumulated data. During use, it can learn online from data continuously acquired by its sensing system, enabling iterative refinement of its knowledge. NGIM is fundamentally distinguished from the first and second generations of intelligent manufacturing by autonomous learning: Traditional intelligent manufacturing lacks the ability to autonomously generate and update knowledge, whereas autonomous learning allows NGIM to become smarter through use. The autonomous acquisition, generation, and refinement of knowledge are at the core of NGIM, enabling autonomous learning, autonomous cognition, and autonomous evolution.

These four links form a closed loop of perception, decision-making, execution, and learning. Learning runs through the other three links, enabling CPS agents to progress from being able to work to becoming more intelligent through work.

2.5. Fundamental features of NGIM

(1) Intelligentization—from program executors to autonomous agents

The most distinctive feature of NGIM is that it enables machines (i.e., CPSs) to evolve from passive program executors into proactive autonomous agents. The CPS agents in NGIM can interact with people in anthropomorphic ways, such as through natural language; autonomously perceive environmental conditions; autonomously optimize action plans; and autonomously predict and ensure machine health. These capabilities greatly enhance system functionality, performance, reliability, and the convenience of use and maintenance. More importantly, they can continually evolve through autonomous learning, driving the continuous development of NGIM toward ever greater intelligence.

(2) Systematicity—from information silos to an integrated system

An important feature of NGIM is its evolution from scattered information silos into an integrated system that can be dynamically optimized as a whole. NGIM strengthens system integration in two areas: integration of the functions of manufacturing principal parts; and the integration of information flows enabled by cloud platforms and network communication systems of the manufacturing system. Industrial Internet technologies provide foundational networks and data pathways for comprehensive interconnection across all elements of manufacturing systems. NGAI technologies, such as large embodied AI models and agents, offer an entirely new path toward large-scale, holistic system optimization. Instead of relying on predefined centralized decision-making and scheduling, distributed autonomous decision-making and coordination among multiple agents enable complex large-scale systems to move from rigid presets toward dynamic evolution [26]. This effectively improves the overall effectiveness of NGIM and greatly advances the holistic optimization of the manufacturing sector.

(3) Openness—from a closed system to an open ecosystem

Another important feature of NGIM is its evolution from a closed system into an open ecosystem. Openness is a prerequisite for the continuous optimization and development of complex large-scale systems, and NGAI technologies, such as agents, are key enabling technologies for achieving it. With AI agent technologies, systems can break through their previously closed boundaries to establish open ecosystems that can evolve dynamically. First, access is open: Devices, services, and participants can connect

dynamically on a plug-and-play basis. Second, collaboration is open, supporting collaboration across domains and the extension of functionality. Third, evolution is open: Systems can adapt to unknown tasks and environments through continuous learning. On this basis, various stakeholders in the manufacturing industry chain, including developers, service providers, and users, can use agent engineering to incorporate their specialized knowledge and technical capabilities into the large-scale intelligent manufacturing system, jointly building an open and collaborative innovation ecosystem.

This openness fully unleashes society's innovative potential. The manufacturing system evolves from a closed system within a single enterprise into an innovation network and a large-scale open platform, with active participation from diverse stakeholders and abundant innovative energy and vitality.

3. The NGIM architecture and its enabling and integrative innovations

3.1. The NGIM architecture

3.1.1. The large-scale system structure of NGIM

NGIM is an integrated intelligent manufacturing system covering all aspects of manufacturing, including intelligent products, intelligent production, and intelligent services (Fig. 4). It is a large-scale system formed by the organic integration of HCPS intelligent systems serving different purposes and operating at different levels. HCPS intelligent systems are the basic building blocks of NGIM (Figs. 8 and 9).

3.1.2. Architecture of an HCPS intelligent system

An HCPS intelligent system comprises humans, a cyber system, and a physical system. The cyber system and physical system together constitute a CPS agent. Accordingly, an HCPS intelligent system consists of humans and a CPS agent (Fig. 10). The physical system comprises the principal part of the system, and its composition may vary considerably depending on the purpose of the HCPS. For equipment-class HCPSs, the physical system mainly comprises a working system, a power system, and a transmission system. Its core is the working system, which determines the operating principle by which tasks are accomplished.

The cyber system plays a dominant role. It mainly comprises an intelligent central system, a sensing system, and a communication network system. Its core is the intelligent central system, which determines the level of machine intelligence.

Humans retain ultimate control over the system, and human wisdom and machine intelligence together constitute hybrid human–machine augmented intelligence.

3.1.3. Architecture of the intelligent central system

The intelligent central system is the core of a CPS agent. In essence, it combines NGAI with an advanced digital control system. It primarily performs information processing and control functions, supporting the CPS agent's autonomous capabilities. The intelligent central system comprises a central core, data threads, and intelligent functional subsystems (Fig. 11).

(1) Central core

The central core acts as the CPS agent's brain, encompassing its cerebrum, cerebellum, and brainstem. It typically adopts a cloud–edge–end architecture, providing the intelligent central system with foundational computing resources, hardware, algorithmic models, and software runtime platforms. It performs information processing, numerical computation and intelligent operation, data and knowledge storage and management, and the integration of advanced digital control systems. These functions provide the foundation for autonomous perception, decision-making, execution, and learning. The central core consists of three components: the control system, the servo system, and the coordination system.

- The control system is analogous to the CPS agent's cerebrum. It is responsible for overall command and coordination and is the primary component performing the CPS agent's autonomous perception, decision-making, and learning.
- The servo system is analogous to the CPS agent's cerebellum. It is responsible for carrying out the CPS agent's autonomous execution tasks.
- The coordination system is analogous to the CPS agent's brainstem. It connects, organizes, and coordinates the subsystems other than the control and servo systems, providing the underlying framework for the CPS agent's internal and external information connections and operational coordination. Specifically, it performs the following coordination tasks: ① connection and coordination with the sensing system; ② connection and coordination with network communications and cloud platforms; and ③ connection and coordination with the human–machine interaction system.

(2) Data threads

The data threads carry big data generated by intelligent manufacturing processes and form the data framework

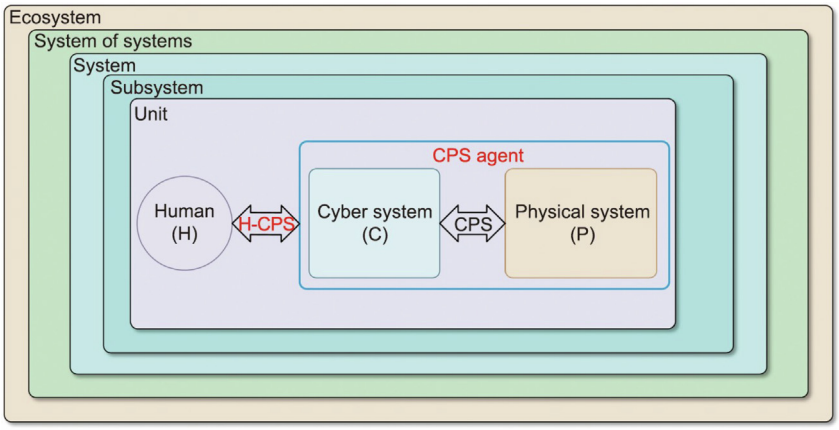


Fig. 8. The hierarchical structure and basic building blocks of NGIM.

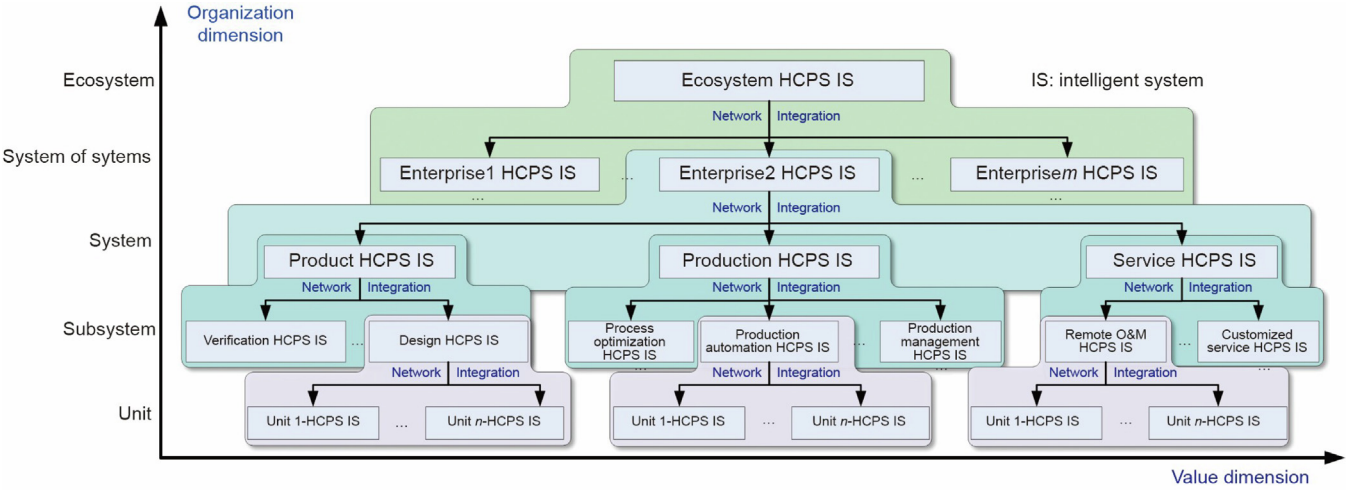


Fig. 9. A large-scale intelligent manufacturing system formed by the organic integration of various HCPS intelligent systems (ISs). $m, n \in \mathbf{N}^{+}$.

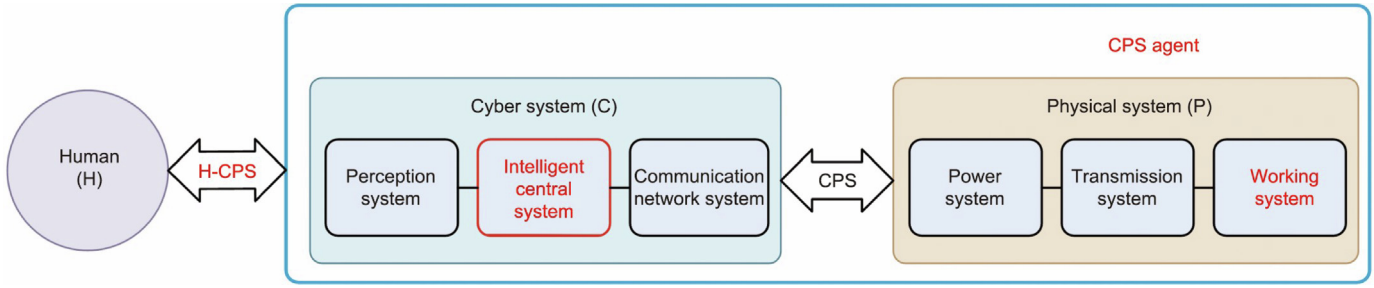


Fig. 10. Architecture of an HCPS intelligent system in NGIM.

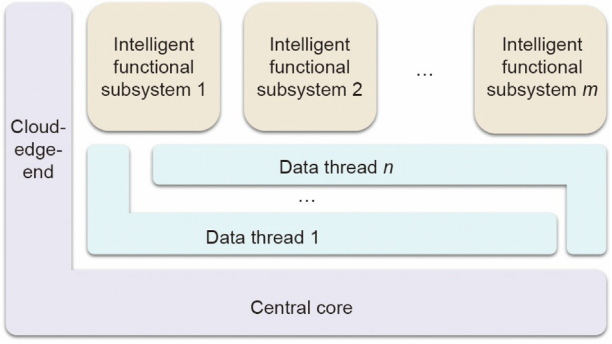


Fig. 11. Architecture of an intelligent central system.

driving the intelligent evolution of the manufacturing system. Big data from intelligent manufacturing, particularly data spanning the entire product life cycle, the entire production process, and all domains and stages of manufacturing management, are the foundation of large embodied AI models and the underlying driving force of NGIM. The central task of the data threads is to link data into an integrated whole, enabling their connection, transmission, and aggregation. On this basis, the data is progressively transformed into samples and samples are transformed into models, raising the level of abstraction at each step. This involves four specific processes:

- Data are linked across all stages to establish a data thread. End-to-end data links are built spanning the entire product life cycle, the entire production process, and all domains and stages of manufacturing management, opening up data channels among manufacturing principal parts, end devices, and systems.
- Data are acquired and aggregated across all domains and stages. Diverse, heterogeneous data scattered across design, production, management, and services are brought together to form complete data threads and to act as a foundation for the entire process.
- Moving from data to samples, data are labeled, compared, and otherwise processed to obtain higher-level data represented as samples—that is, labeled data.
- Moving from samples to models, sample data are processed and learned from to obtain an embodied-intelligence big data model.

(3) Intelligent functional subsystems

Intelligent functional subsystems are primarily responsible for functions such as product design, process optimization, precision improvement, equipment health management and maintenance, quality assurance, resource planning, production management, marketing and sales, and after-sales service, and so on. Each intelligent functional subsystem uses the data and knowledge acquired through the data threads to perform its respective intelligent functions through the four autonomous functions of perception, decision-making, execution, and learning.

For example, the remote maintenance subsystem of a particular intelligent equipment system is supported by a data thread spanning design, production, assembly, operation, and maintenance. By drawing on practical maintenance engineering experience and the knowledge of maintenance engineers, as well as integrating large embodied AI model technology and industrial agent

technology with advanced equipment-maintenance technologies, the subsystem can perform important engineering tasks to a high standard. These tasks include equipment fault diagnosis and remediation, scheduled servicing and maintenance, periodic equipment health checks, and predictive maintenance.

3.2. Enabling and integrative innovation in NGIM

NGIM is an innovation arising from the integration of NGAI technologies with advanced manufacturing technologies. In terms of AI, it is an undertaking in technology application; in terms of manufacturing, it is an undertaking in technological innovation. To advance NGIM, enabling and integrative innovation must be taken as the primary focus and the main pathway for technological innovation.

Developing NGIM is a complex undertaking involving systems engineering and enabling and integrative innovation. It depends on the coordinated evolution and integration of NGAI technologies and advanced manufacturing technologies. Within this undertaking, hybrid modeling that combines physics-based models and AI-driven data-based models lays the foundation for integrative innovation; large embodied AI model technology and industrial agent technology form the core of integrative innovation; industrial big data engineering technology provides data support for integrative innovation; and model-based systems engineering (MBSE) technology establishes the system architecture and optimization paradigm.

(1) Hybrid modeling combining physics-based models and AI-driven data-based models

The fundamental objective of NGIM is to advance the global optimization of manufacturing systems. Developing large embodied AI models for manufacturing systems is a key pathway to this optimization and a central challenge in developing NGIM [27]. Addressing this challenge first requires moving beyond traditional modeling based on a single paradigm. Hybrid modeling combines physics-based models from manufacturing engineering with AI-driven data-based models from NGAI.

Physics-based models from manufacturing engineering are grounded in physical laws and engineering knowledge and follow a deductive paradigm: Starting from first principles, a mathematical description of a system is established through logical derivation. With clear causal relationships, strong interpretability, and general applicability and reliability within the model's theoretical framework, this approach has long been a cornerstone of engineering modeling. However, when dealing with complex nonlinear systems with strongly coupled variables, analytical derivation often becomes intractable, and deductive methods alone are unable to resolve unmodeled dynamics and model mismatch.

In contrast, AI-driven data-based modeling in NGAI follows an inductive paradigm: It extracts complex relationships among variables from vast amounts of data through statistical learning. This approach can achieve highly accurate modeling within the coverage of the available big data, effectively compensating for the limitations of deductive methods in handling strong nonlinearities. However, induction does not rely on prior physical knowledge, and such a model's conclusions are probabilistic. The model's generalization capability is limited, carrying risks of hallucination and overfitting; when extrapolated, it can readily violate physical constraints and offers no guarantee of causal validity.

Hybrid modeling organically combines the causal constraints and general applicability of deduction with the high accuracy and nonlinear fitting capabilities of induction. By drawing on the respective strengths of these two approaches while overcoming their respective limitations, hybrid modeling creates a new modeling paradigm for engineering. This is a core technology for integrative innovation that enables the effective construction of large embodied AI models and, in turn, addresses the modeling challenges of NGIM systems [28–32], substantially improving their ability to solve complex engineering problems.

(2) Large embodied AI model technology

Large AI models are the most important and defining breakthrough of NGAI, providing the intelligent foundation for its entire technological system. These models fundamentally endow AI with the ability to understand and learn: to comprehend the meaning of new tasks and to infer response strategies from existing knowledge. Their fundamental significance lies in a shift in the approach to developing intelligence, from manually designing features and rules to enabling models to acquire knowledge and capabilities on their own. AI has begun to acquire a core capability of general cognition.

Large embodied AI models, or large physical AI models, represent a new stage of development in which large disembodied AI models extend into the physical world [33–37]. This approach brings large AI models out of digital space and into physical entities, allowing intelligence to act directly on the physical world. Within the NGAI technological system, large embodied AI models connect the layers above and below: They inherit the general cognitive and reasoning capabilities of large AI models while providing a unified cognitive center and an action semantics layer for physical intelligence. These models bridge the key enabling technologies of NGAI and advanced manufacturing technologies. When integrated into NGIM, large embodied AI models are embodied throughout the manufacturing life cycle, covering multiple domains, including products, production, services, and management. Large domain-specific AI models are established for these areas and extended downward to large vertical AI models, forming a hierarchical architecture at the system, domain, and vertical levels. Each large domain-specific AI model is anchored in the physical and causal constraints of its subsystem, while automated feedback from execution data drives its continuous evolution.

For NGAI, large embodied AI models represent a decisive leap from intelligence in the information domain to intelligence in the physical domain. For NGIM, they are the core engine for the intelligent upgrading of manufacturing systems.

(3) Industrial agent technology

AI agents are one of the defining breakthroughs of NGAI, marking the leap from large AI model technology as a passive tool for generating content to large AI model technology as a key vehicle for actively organizing and executing complex tasks. Industrial agent technology results from the deep integration of AI agent technology with advanced manufacturing technologies [38–41]. Its central breakthrough is a transformation in organization: It introduces agents' capacity for autonomous organization into manufacturing systems. Manufacturing processes that previously depended on human scheduling, dispatching, and coordination become closed-loop systems in which agents autonomously understand tasks, decompose objectives, plan actions, and organize task execution within physical manufacturing environments. Within the HCPS architecture of NGIM, the CPS itself is an agent that unifies the cyber and physical components. Each level, from the system and domain levels to the unit and even microtask levels, can be assembled into independent industrial agents, collectively forming a multilayered, nested ecosystem of industrial agents.

The revolutionary significance of industrial agent technology is that it endows every level of a manufacturing system with autonomous organizational capabilities, enabling a shift from a passive execution mode dependent on human organization to an active execution mode driven by agents. This provides decisive support allowing NGIM to achieve system-wide autonomy.

(4) Industrial big data engineering technology

Big data is a prerequisite and cornerstone of NGAI. Without vast amounts of big data from multiple sources, large AI models and NGAI could not exist. Industrial big data engineering technology is a system of data technologies covering the entire manufacturing chain. Its central objective is to transform scattered, heterogeneous, low-quality, and dormant raw data from manufacturing systems into structured cognitive resources that can be efficiently used by AI models. This technology covers the collection and aggregation of multisource, heterogeneous data across products, production, services, management, and other domains, as well as data cleaning, alignment, labling, transmission, use, and storage tailored to industrial requirements. The key challenge of industrial big data engineering is to organize data systematically across domains and stages, creating data threads that span the entire product life cycle, the full production process, and all areas and stages of management. This transforms data from isolated points into continuous lines and interconnected networks. Industrial big data engineering establishes a data pathway from physical manufacturing sites to intelligent models and provides high-quality datasets for NGIM [42–44]. It is thus the crucial first step in the manufacturing sector's transformation from data to knowledge to intelligence.

At present, the greatest bottleneck in advancing large embodied AI models and industrial agents is the scarcity and fragmentation of industrial data. Industrial big data engineering provides the foundational work needed to overcome this bottleneck, so its vigorous advancement is a decisive condition for the successful engineering implementation of NGIM.

(5) MBSE technology

NGIM is an exceptionally complex large-scale system. Systems engineering pursues an optimum for the system as a whole through the hierarchical decomposition and comprehensive integration of complex systems. It is the fundamental means of organizing and managing exceptionally complex manufacturing systems.

For NGIM, MBSE is the methodological foundation that enables intelligent systems to move from an accumulation of functions to integrated optimization [45,46]. MBSE represents the physical entities, information logic, and intelligent behaviors of a manufacturing system as a unified set of formal models that support computation, simulation, and verification. This shifts system design from a reliance on experience and trial and error to model-based prediction, optimization, execution, and integration.

The most important contributions of MBSE are digital threads and digital twins [47]. Digital threads connect data and models across the entire product life cycle, the full production process, and all areas and stages of management, keeping information flows and physical flows consistent and synchronized at the model level. Digital twins construct dynamic representations of physical entities—including products, equipment, production lines, and systems—in virtual space, supporting real-time state perception, behavioral simulation, performance prediction, and strategy rehearsal.

The core value of MBSE for NGIM lies in the former's provision of system-level modeling support and an environment for verifying the four autonomous capabilities of perception, decision-making, execution, and learning. MBSE brings the various technologies for integrative innovation—including hybrid modeling, large embodied AI models, industrial agents, and industrial big data—together into a technological system that can be modeled, computed, traced, and evolved. It thus plays a foundational role and provides the structural framework for the integration and optimization of manufacturing systems.

4. The comprehensive optimization and redefining of the manufacturing industry through NGIM

NGIM is the main technical pathway for achieving innovation-driven development in the manufacturing industry and will comprehensively optimize and redefine this sector. Manufacturing innovation primarily encompasses four areas: innovation in product technologies, innovation in production technologies, innovation in industrial models, and innovation in manufacturing system integration. In all these areas, NGIM is the principal pathway for achieving innovation and optimization.

(1) Innovation in product technologies

Products, particularly equipment, are the primary carriers for applying manufacturing innovations and the core of value creation. NGIM will comprehensively advance the intelligent upgrading and innovative optimization of products and their design technologies [48–50]. Intelligent vehicles, humanoid robots, and unmanned aerial vehicles are all typical examples of the intelligent upgrading and innovative optimization of equipment.

NGIM redefines the outputs and carriers of manufacturing. Looking ahead, NGIM will expand into product innovation and open up substantial opportunities for development. Products of every kind across all sectors will be comprehensively upgraded to intelligent high-end products, bringing about a fundamental transformation in manufacturing outputs and carriers.

(2) Innovation in production technologies

NGIM will drive widespread innovation and optimization in production technologies. Manufacturing equipment and systems will be comprehensively upgraded to function as autonomous agents; data and knowledge will become core factors of production, enabling a substantial increase in productivity; and production decisions will shift from a reliance on human experience to optimized decisions based on data and AI algorithms. This will bring intelligence to production process optimization, production process automation, and production management information systems, creating truly intelligent factories and enterprises and comprehensively improving the efficiency, quality, flexibility, safety, and reliability of the manufacturing sector [51].

NGIM is redefining the production model of the manufacturing industry; going forward, the industry's production mode will evolve from large-scale mass production to small-scale customized production.

(3) Innovation in industrial models

NGIM will advance the intelligent upgrading of manufacturing services, giving rise to new models and new business formats in the manufacturing sector [52–54] and redefining the industrial model. In future, NGIM will drive the manufacturing sector's transition from a product-centered to user-centered approach, fundamentally transforming its industrial model from production-oriented to service-oriented manufacturing and bringing about profound supply-side structural reform.

(4) Innovation in manufacturing system integration

Innovation in manufacturing system integration is the core of NGIM and will give rise to a new generation of intelligent integrated manufacturing systems, deepening the integration of human–cyber–physical systems at the large-system level. NGIM will achieve integration along three dimensions of manufacturing systems: vertical integration of the manufacturing organizational system, involving integration across all organizational levels, from equipment at the lowest level to decision-making at the highest level; horizontal integration of manufacturing processes, involving the integration of various subsystems across the entire manufacturing life cycle, including design, production, and service; and end-to-end integration of all entities involved in a specific task, involving system-wide integration, from requirements and task definition to service delivery. Together, these forms of integration will drive the evolution of manufacturing systems from local optimization to system-wide optimization.

NGIM is redefining the new business formats associated with large-system optimization in manufacturing. Looking ahead, these new formats will be characterized by a focus on system-wide integration, globalization, intelligentization, and sustainability, driving the manufacturing industry to fully enter a new development paradigm of large-scale system optimization ranging from the enterprise level to the industrial chain level.

In summary, NGIM will have a comprehensive and revolutionary impact on the manufacturing industry. It will redefine every aspect of this sector, achieve the overall intelligent upgrading of the industry, and lead and drive the FIR.

5. Strategic deployment for advancing NGIM

5.1. Relationships and evolution among the three basic paradigms of intelligent manufacturing

(1) Sequential development

The three basic paradigms of digital manufacturing, "Internet+" manufacturing, and NGIM emerge in successive stages. Each has its own stage-specific characteristics and key challenges to address, reflecting the phased development of intelligent manufacturing. Digital manufacturing is the foundational paradigm, "Internet+" manufacturing is the intermediate paradigm, and NGIM is the principal paradigm. These three paradigms build progressively upon each other throughout the process of manufacturing transformation and upgrading. Digital manufacturing and "Internet+" manufacturing are indispensable steps toward NGIM; without digitalization and networking, there would be no big data, no large embodied AI models, and no NGIM. Manufacturing cannot bypass the stages of digitalization and networking and proceed directly to the stage of intelligence. The foundation must be consolidated, and sustained efforts must promote the manufacturing sector from widespread digitalization and networked collaboration toward a progressive leap in intelligence.

(2) Integration

The three basic paradigms require sustained efforts toward technological integration and iterative upgrading, reflecting the integrative nature of intelligent manufacturing development. Their evolution is not a simple successive upgrade; it requires a technological pathway of parallel advancement and integrated development. At present, NGIM technologies are developing rapidly and are being extensively applied in manufacturing scenarios. While consolidating the underlying capabilities for digitalization and networking, it is necessary to promote deep integration among technologies across the different paradigms and advance multiple paradigms in parallel, accelerating the overall transformation and upgrading of the manufacturing sector.

(3) Intelligence-led development

Among the three basic paradigms, NGIM is the advanced paradigm and the principal form of intelligent manufacturing. As the core technology of the FIR, NGIM will surely lead and drive its development; moreover, NGIM's technologies can be used to leverage higher-level capabilities to improve lower-level capabilities, thereby advancing digital manufacturing and "Internet+" manufacturing toward higher levels of development. This promotes the parallel advancement and collaborative iteration of all three paradigms and comprehensively accelerates the transformation of the manufacturing industry toward intelligent manufacturing.

Looking ahead, as global industry undergoes transformation and upgrading over the coming decades, countries should advance the transformation and upgrading of their manufacturing sectors in two stages: first, the digital and intelligent transformation of manufacturing; and second, the intelligent upgrading of manufacturing.

5.2. Digital-intelligent transformation and intelligent upgrading

5.2.1. Stage one: The digital-intelligent transformation of manufacturing

In the first stage, the historical task that every industrialized country must accomplish is to achieve widespread digital and intelligent transformation of its manufacturing sector. The primary objective is to make digital transformation broadly prevalent in the sector, as indicated by 80% of manufacturing enterprises above the designated size achieving digital transformation, thereby laying a foundation for the development of NGIM. Over the past decade, substantial progress has been made in the digital transformation of the world's industrialized countries; however, overall, widespread digital transformation in manufacturing has not yet been achieved. There are still obvious shortcomings in sectoral digital development, and many small and medium-sized manufacturing enterprises are still working to overcome the major challenges of digital transformation and remain far from achieving the strategic objective. Digital transformation, therefore, is still the main objective at this stage. As the same time, NGAI technologies are maturing at an accelerated pace and are being deeply integrated into the manufacturing industry. NGIM must lead and accelerate the widespread adoption of high-quality digital transformation. Meanwhile, breakthroughs must be achieved in the research and development of NGIM technology, with pilot studies and demonstrations yielding significant results. NGIM technologies must be widely promoted and applied in enterprises, enabling manufacturing to develop new quality productive forces and achieve high-quality development.

5.2.2. Stage two: The intelligent upgrading of the manufacturing sector

Once manufacturing digitalization has been widely adopted, the world's major industrial countries will progressively enter the stage of intelligent manufacturing transformation. Countries entering this second stage will take NGIM as their primary focus, reshaping manufacturing's production methods, organizational approaches, and industrial models to achieve innovation-driven development across the global manufacturing sector.

CRediT authorship contribution statement

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Declaration of competing interest

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.

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