AI Autonomous Governance Factory: Concept, Architecture, and Launch Pathway

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Abstract

Manufacturing is undergoing a paradigm shift from automation to autonomization. Existing concepts such as “lights-out factories” and “unmanned factories” have yet to systematically address the fundamental question: where does a factory’s autonomous capability originate, and who governs it? This paper proposes the concept of the AI Autonomous Governance Factory (AI-AGF), defining its core as an AI system that autonomously completes the full cycle of perception, decision-making, and execution without human intervention, while systematically governing its own objectives, rules, boundaries, and risks. The paper addresses three core propositions: the inevitability argument, the dual-track architecture design, and the four-stage launch pathway. The dual-track architecture consists of the Universal Production Line (UPL) and the Standard Production Line (SPL): the UPL undertakes equipment self-supply and product prototyping, while the SPL handles high-volume production. Both tracks are coordinated by an AI governance layer, forming a physical closed loop of “equipment producing equipment.” The four-dimensional governance framework imposes systematic constraints on AI decision-making across four dimensions—objectives, rules, boundaries, and risks—advancing manufacturing governance from asset-centric to governance-centric, and engaging in structural dialogue with three industrial standards: IEC 62264, RAMI 4.0, and ISO 55000. Unlike existing research that prioritizes the technical dimension, this paper’s distinctive contribution lies in elevating “governance” to an analytical dimension of equal

importance to “autonomy”: an AI system must not only make autonomous decisions but also exercise systematic self-constraint and risk control over its own decision logic. Based on the above analysis, this paper presents four operational criteria for AI-AGF (C1–C4), a dual-track architecture blueprint, a four-dimensional governance framework, and a four-stage quantified progressive roadmap. This paper is a prospective review, with its argumentative force deriving from logical coherence, literature support, and systematic engagement with competing hypotheses.

Keywords: AI Autonomous Governance Factory; intelligent manufacturing; reconfigurable manufacturing systems; natural language script-based motion control; autonomous decision-making

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0 Introduction

0.1 Research Background and Problem Statement

Manufacturing is undergoing a paradigm shift from automation to autonomization. Zhou et al. [1] categorized intelligent manufacturing into three stages—digital manufacturing, digital-networked manufacturing, and digital-networked-intelligent manufacturing—and identified the deep integration of AI and manufacturing technology as the core of next-generation intelligent manufacturing. Yet manufacturing systems remain significantly distant from true autonomous operation. Current terms such as “lights-out factories” and “unmanned factories” describe only the external characteristics of factories (no lighting required, no personnel present), without revealing their internal operating mechanisms—what drives factory operations? Where do decisions originate? How does the system respond to uncertainty? Against this backdrop, this paper proposes the concept of the **AI Autonomous Governance Factory (AI-AGF)**, which encompasses two mutually constitutive dimensions—“autonomy” and “governance” (for detailed definition, see §1.1)—and addresses three core propositions: (1) demonstrating the inevitability of AI-governed factories; (2) designing a dual-track architecture of “Universal Production Line + Standard Production Line”; and (3) proposing a four-stage launch pathway mediated by the Natural Language Script-based Motion Control Platform (currently implemented in Chinese: Chinese-Language Scripting Motion Control Platform).

0.2 Concept Proposal and Definition

AI-AGF unifies “autonomy” and “governance” as two inseparable dimensions in manufacturing systems research: an AI system must not only make autonomous decisions but also systematically govern its own objectives, rules, boundaries, and risks. The four-dimensional governance framework can be viewed as an engineering response to the AI alignment problem in the manufacturing context (for detailed definition and comparative analysis, see §1.1). The manufacturing domain thus constitutes not merely an application scenario for AI governance technology but potentially a natural “sandbox” for validating and iterating AI governance theory.

This paper focuses its discussion of AI-AGF on the core production system (including production line architecture, process workflows, and equipment self-supply capability), without, for the moment, addressing supporting subsystems such as factory management systems, warehousing and logistics systems, and power and energy systems. Extending AI autonomous governance to the integrated operation of the full factory system represents an important direction for future research. The rationale for this paper’s focus on the core production system is as follows: the production system constitutes the “minimum viable kernel” of factory autonomization. Once AI can autonomously govern the production system, the extension to management systems, logistics systems, and energy systems follows the same governance logic (objective → rule → boundary → risk), making this an engineering extrapolation rather than a conceptual leap.

Based on the above definition, the operational definition of AI-AGF is as follows.

C1 (Autonomous Decision-Making) : The AI system autonomously completes the full closed loop from perception, to decision-making, to execution without human intervention, covering production line scheduling, process optimization, and anomaly handling.

C2 (Autonomous Governance) : The AI system exercises systematic governance over the objectives, rules, boundaries, and risks of its own decisions, possessing self-constraint and self-correction capabilities.

C3 (Dual-Track Architecture) : The factory adopts a dual-track architecture consisting of the Universal Production Line (UPL) and the Standard Production Line (SPL), with UPL possessing the capability to manufacture non-standard equipment.

C4 (Progressive Pathway) : AI autonomous governance capability is progressively established through a four-stage pathway, with verifiable quantitative milestones at each stage.

The absence of C1 or C2 means the system does not meet the essential characteristics of an AI autonomous factory and degrades to an existing manufacturing paradigm (e.g., the absence of C2 degrades it to an autonomous manufacturing system). C3 and C4 represent this paper's specific choice of engineering implementation pathway for AI autonomous factories, rather than necessary conditions of the conceptual definition [2]—there may exist alternative architectural approaches (e.g., non-dual-track equipment self-supply) or launch pathways (e.g., non-four-stage progression) that equally satisfy the core connotation of "AI autonomous governance" as defined by C1–C2.

0.3 Research Significance and Methodology

This paper adopts conceptual analysis and system synthesis as its methodology: conceptual analysis is used to extract core differentiating dimensions from existing manufacturing paradigms, while system synthesis is used to construct a tripartite argumentation system of "inevitability → architecture → pathway." This paper is a prospective review and does not involve experimental validation—its argumentative force derives from logical coherence, literature support, and systematic engagement with competing hypotheses.

The main contributions of this paper include: (1) Conceptual layer: proposing the AI-AGF concept, unifying autonomy and governance as inseparable dimensions in manufacturing systems research, filling the governance gap in existing paradigms; (2) Architectural layer: designing the UPL/SPL dual-track architecture and the four-dimensional governance framework, advancing manufacturing governance from asset-centric to governance-centric, and establishing structural dialogue with IEC 62264, RAMI 4.0, and ISO 55000; (3) Pathway layer: designing a four-stage progressive roadmap mediated by the Natural Language Script-based Motion Control Platform, with verifiable quantitative milestones at each stage, situating AI-AGF within the real-world industrial context through the five-dilemma framework.

The three technological sources underpinning this research constitute the practical foundation of the above contributions. First, the Natural Language Script-based Motion Control Platform (currently implemented in Chinese; Chinese-Language Scripting Motion Control Platform

(中文脚本运动控制平台)) upon which this study relies received national computer software copyright registration in 2022. Its original development goal was to reduce the complexity of host-computer control software development, providing non-specialist programmers with an accessible script-based control solution, thereby improving the deployment efficiency and maintainability of automation systems. As a tool that makes explicit the logic of human-machine operations, this platform serves, within this study's four-stage launch pathway, as the initial interface and transitional vehicle for the gradual migration from human-led operation to AI autonomous governance. Second, the first author has long been engaged in host-computer software development, with primary responsibilities encompassing motion-sequence design for non-standard automation equipment, integration of visual alignment algorithms, and on-site initial commissioning, debugging, and delivery acceptance of equipment at client facilities. Years of hands-on field experience have provided a solid engineering-verification foundation for the theoretical construction presented in this paper. Third, drawing on a systematic understanding of current trends in artificial intelligence and sustained accumulation in automation engineering, the first author progressively crystallized the forward-looking proposition of the "AI Autonomous Governance Factory" and further derived the "dual-track design of Universal Production Line and Standard Production Line" model. The core judgment formed in this process is that the transition from human-led operation to AI autonomous governance cannot be a discontinuous leap but requires existing engineering experience and operational rules to serve as mediating instruments for gradual migration.

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1 Literature Review and Theoretical Gap

The conceptual framework of this paper rests at the intersection of three independently evolving trajectories. The following sections examine these trajectories—the evolution of intelligent manufacturing paradigms, AI governance and safety theory, and reconfigurable manufacturing systems—identifying the governance gap in each at the current stage, and providing the literature foundation for the conceptual construction of AI-AGF.

1.1 Evolution of Intelligent Manufacturing Paradigms: From Cloud Manufacturing to AI-AGF

The conceptual evolution of intelligent manufacturing can be traced back to the 1980s [3]. On this foundation, Li et al. [4] proposed the cloud manufacturing paradigm, which virtualizes manufacturing resources into on-demand, networked services, establishing the conceptual foundation of "manufacturing as a service." This concept has a direct influence on the "dual-track synergy" vision of AI-AGF in this paper: when manufacturing capabilities can be virtualized and invoked on demand, the equipment manufacturing capacity of UPL can be dynamically allocated according to the real-time needs of SPL. Zhou et al. [1] categorized intelligent manufacturing into three evolutionary stages—digital manufacturing, digital-networked manufacturing, and digital-networked-intelligent manufacturing—identifying the deep integration of AI and manufacturing technology as the core of next-generation intelligent manufacturing, though this framework has not yet addressed the autonomous governance dimension.

Industry 5.0 shifts the paradigm's attention toward human values, sustainability, and resilience [5]. Yao Xifan et al. [5] have provided the most systematic review to date of the evolution of human-centric intelligent manufacturing, with a framework centered on the "human" as the locus of governance. Jiang Zhoumingju et al. [6] proposed a human-robot collaborative additive manufacturing framework that embodies the Industry 5.0 design principle of "human-in-the-loop." However, all such human-centric paradigms must confront a structural ceiling: when the complexity of the manufacturing system exceeds human cognitive load, human participation in the decision-making loop itself becomes a bottleneck. It is precisely in this sense that AI-AGF proposes the possibility of a paradigm shift. Specifically, the human role is elevated from an "on-the-loop operator" to an "above-the-loop strategic anchor"—that is, while retaining ultimate human control over the system, the micro-level decision loop is delegated to AI, with humans stepping back above the loop to assume strategic oversight, allowing AI to autonomously complete micro-level decision-making and governance within human-defined value boundaries.

Table 1 compares AI-AGF with five existing manufacturing paradigms along four dimensions: decision-making agent, governance mechanism, equipment self-supply, and human-machine relationship. Existing comparative research frameworks [9-10] cover the full spectrum from automated execution to data-driven optimization. The above concepts each

touch upon a particular facet of "autonomy"—automation substitution, virtual-physical mapping, cognitive reasoning, or distributed negotiation—yet none has treated "governance" as a design dimension of equal importance to "autonomy."

Concept	Decision-Making Agent	Governance Mechanism	Equipment Self-Supply	Human-Machine Relationship
AI-AGF	AI system makes autonomous decisions and exercises autonomous governance	AI exercises systematic governance over its own objectives, rules, boundaries, and risks	UPL can manufacture non-standard equipment required by the factory, achieving equipment self-supply	Progressive from human-robot collaboration to fully autonomous AI governance
Lights-Out Factory	Humans preset rules; system executes automatically	No autonomous governance; relies on external human intervention	Equipment externally procured and integrated	Machines replace physical labor; humans handle exceptions
Unmanned Factory	Humans monitor remotely; system executes automatically	No autonomous governance; human intervention required for anomalies	Equipment externally procured and integrated	Humans completely withdrawn from production site; remote management
Digital Twin Factory	Human decision-making dominates; twin models assist simulation and verification	No autonomous governance; digital twin provides informational support only	Equipment externally procured and integrated	Humans monitor and decide via digital twin interface
Cognitive	Knowledge graph-driven	Knowledge rules constrain	Equipment externally	Humans engage in collaborative

Concept	Decision-Making Agent	Governance Mechanism	Equipment Self-Supply	Human-Machine Relationship
Factory	reasoning; human-machine collaborative decision-making	reasoning boundaries; no self-correction mechanism	procured and integrated	reasoning with system via knowledge interface
Autonomous Manufacturing System	Multi-Agent autonomous negotiation; distributed decision-making	Agent-level distributed negotiation achieves local governance; no unified global governance framework	Partial research involves modular self-reconfiguration	Humans set objectives; multi-agent autonomous negotiation for execution

In summary, the qualitative transformation of AI-AGF lies not in the improvement of technical parameters but in the fundamental transfer of decision-making authority and governance architecture—transferring decision-making power from humans to the AI system and endowing it with autonomous governance capability. El Kalach [7] explicitly defines this evolution as "cognitive manufacturing," and Leng et al. [8] systematically reviewed the pathways and challenges of industrial AI's evolution toward autonomization. The above large-model-related validations were all conducted in laboratory environments, excluding common production disturbances such as abrupt lighting changes and incoming material anomalies—inference reliability in real factory settings remains to be verified, thus necessitating the "human-AI co-governance" stage in §4.2 as a reliability transition period.

1.2 AI Governance and Safety Theory: The Specificity of the Manufacturing Context

AI-AGF treats "governance" as an analytical dimension of equal importance to "autonomy," a stance that engages in a deep dialogue with AI safety research.

Russell [9] systematically demonstrated the fundamental nature of the AI control problem—ensuring that AI behavior remains aligned with human intentions. Amodei et al. [10] concretized this problem into five specific categories: avoiding negative side effects, reward hacking, scalable oversight, safe exploration, and robustness to distributional shift. Leike et

al. [11] and Hendrycks et al. [12] advanced research on scalable alignment and robustness from the perspectives of reward modeling and machine learning safety, respectively.

The above studies analyze general-purpose AI and discuss behavioral constraints in open environments. The manufacturing context provides a uniquely tractable engineering entry point for AI governance: objective functions are quantifiable (KPIs such as yield, OEE, and energy consumption), environmental constraints are physically enforceable (safety fences, emergency stop buttons, process parameter boundaries), and decision consequences are rapidly verifiable (the physical product serves as the ultimate arbiter). The four-dimensional governance framework of AI-AGF can thus be viewed as an engineering response to the AI alignment problem in the manufacturing context: objective governance defines "align with what," rule governance defines "the boundaries of misalignment," boundary governance defines "who has the authority to correct and when," and risk governance defines "how to degrade when alignment fails."

Furthermore, the manufacturing context introduces a type of risk that is insufficiently discussed in the AI safety literature—physical consequence risk. In purely informational domains (e.g., recommendation systems), the consequences of AI decision errors are limited to economic loss, whereas in the manufacturing context they may lead to equipment damage, personal injury, or production downtime. The severity of these physical consequences means that AI governance in manufacturing cannot rely solely on software-level safety mechanisms; it must construct a multi-layered defense system that includes a physical safety layer [13][14]. This is the fundamental reason why this paper's four-dimensional governance framework designs rule governance as a "hard constraint layer" independent of the reasoning engine and establishes a three-tier risk governance response mechanism (yellow/orange/red): rule governance, as the digital expression of the physical safety layer, ensures that the underlying safety logic of AI governance is not invalidated by iterative improvements in upper-level reasoning capabilities.

1.3 Reconfigurable Manufacturing Systems: From Modularity to AI-Driven Self-Reconfiguration

Reconfigurable manufacturing systems (RMS) provide the theoretical foundation for the AI-AGF dual-track architecture. Koren et al. proposed the core principles of RMS—modularity, integrability, convertibility, diagnosability, and customization—laying the groundwork for the transition from "dedicated rigidity" to "adjustable flexibility." ElMaraghy et

al. summarized the evolution of manufacturing systems as a three-stage progression: Dedicated Manufacturing Systems (DMS) → Flexible Manufacturing Systems (FMS) → Reconfigurable Manufacturing Systems (RMS). Todescato et al. [15] proposed a multi-agent-based reconfigurable framework, and the review by Mayer et al. [16] demonstrated that the synergy of digital twins and AI could compress the production line reconfiguration cycle from several weeks to several days. The shared data model of digital twins enables rapid adaptive reconfiguration when manufacturing resources and process workflows change, providing a digital-twin-level methodological foundation for the AI-AGF closed loop of "equipment self-supply + production line self-reconfiguration."

However, interface standards such as OPC UA over TSN have yet to be unified, and large-scale deployment has progressed far more slowly than technological expectations—hence the need for the equipment self-supply closed loop described in §3.1 to reduce dependency on the pace of external standardization. Meanwhile, real-time fidelity synchronization between digital twin models and physical entities remains a bottleneck: human engineers can rely on experience to identify model drift and pause execution, whereas in AI autonomous decision-making scenarios, model drift may directly lead to cascading propagation of erroneous decisions—hence the need for the risk governance layer within the four-dimensional governance framework described in §3.2 to serve as a safety net for drift detection and degraded operation.

AI-AGF transfers the decision-making authority for reconfiguration from human engineers to the AI governance layer. When AI perceives equipment performance degradation trends from SPL data, it can proactively trigger UPL to pre-produce replacement parts and plan SPL's modular stepwise reconfiguration before degradation progresses to failure, achieving a leap from "reactive maintenance" to "predictive autonomous reconfiguration." This is precisely the theoretical foundation for "cross-production-line globally optimal scheduling" and "design feedback closed loop" among the four system-level synergies described in §3.5 below.

The three trajectories above jointly point toward a single conclusion: AI-AGF is not an arbitrary construct but the natural convergence point of three independently evolving trajectories—the evolution of intelligent manufacturing, AI governance theory, and reconfigurable manufacturing systems.

2 The Industrial Inevitability of AI-AGF

2.1 Industrial Drivers: Cost, Flexibility, and Resilience

Beyond the technological evolution trends discussed in §1, deep-seated forces at the industrial level are equally important. AI-AGF enables production line reconfiguration within hours and rescheduling within seconds, allowing the production line to autonomously find alternative solutions under abnormal conditions and minimize production interruptions.

The following addresses three competing hypotheses in turn.

First: Overlaying AI modules on existing MES/ERP architectures can achieve autonomization. This hypothesis holds that adding AI modules atop existing MES/ERP can achieve autonomization. This paper's response: This approach overlooks the defining characteristic of AI-AGF—"equipment producing equipment." AI-augmented MES/ERP still operates within an equipment environment built by external suppliers and cannot realize the physical closed loop in which UPL autonomously manufactures non-standard equipment and delivers it to SPL. When equipment itself becomes an object of production, the boundary of the production system expands from "optimizing scheduling given equipment" to "autonomously constructing manufacturing resources"—this is a decision paradigm that hierarchical, pre-configured MES/ERP was never designed for.

Second: The reliability of AI autonomous systems is insufficient to support fully autonomous factory operation. This hypothesis holds that the reliability of current AI systems has not yet reached industrial-grade safety requirements and that AI-AGF cannot be realized in the foreseeable future. This paper's response: The four-stage progressive roadmap has built-in safety valves—the "human-AI co-governance" mechanism in Stage 2, where engineers review AI production line proposals item by item; the verification threshold of six consecutive months of zero intervention in Stage 3; and the physical safety layer of the factory's controlled environment—these three layers collectively hedge against this risk. Unlike autonomous driving, which faces an open-road long-tail scenario, the factory is highly controlled across three dimensions—physical space, process boundaries, and anomaly types—and its "long tail" is far shorter than that of open roads. Therefore, AI-AGF may well achieve reliable autonomous operation within a closed factory environment before autonomous driving does.

Third: Human-robot collaborative factories already meet requirements, obviating the need for a complete transfer of decision-making authority. This hypothesis holds that adopting "human-in-the-loop" as a design principle for manufacturing systems, using AI to augment rather than replace human decision-making, can already achieve sufficient improvements in flexibility and efficiency—Industry 5.0 [8] is a representative expression of this philosophy. This paper's response: The objective of AI-AGF is not to negate "human-in-the-loop" but to progressively transfer micro-level decision-making authority to AI within a human-defined objective framework, elevating humans from "on-the-loop operators" to "above-the-loop strategic anchors," and redirecting human attention toward value judgments and ethical oversight that only humans are capable of making.

An axiological response to the Industry 5.0 human-centric critique. The "withdrawal of humans" envisioned by the AI autonomous factory applies only to the micro-level operational decision loop—tasks that depend on repetitive judgment and instantaneous response are precisely the weak points of human cognition. At the macro level—strategic objective setting, ethical boundary safeguarding, and creative product definition—the human role gains fuller scope for value enactment precisely because it is liberated from operational minutiae. The AI autonomous factory is not a negation of Industry 5.0 but its engineering continuation: when the complexity of manufacturing systems turns "human-in-the-loop" from a safeguard into a bottleneck, elevating humans to a strategic position above the loop is precisely the most thorough implementation of "human centricity."

The above discussion has demonstrated the industrial drivers of AI-AGF across three dimensions—cost, flexibility, and resilience—and reinforced the completeness of the argumentative structure through systematic engagement with three competing hypotheses (including a dedicated axiological rebuttal of the Industry 5.0 critique). However, demonstrating inevitability solely from the perspective of "drivers" is insufficient—it is also necessary to examine, in reverse, the costs of maintaining the status quo.

While assessing the necessity of AI-AGF, one must simultaneously examine in reverse the deep-seated risks of maintaining the status quo. Currently, Chinese factories face a fivefold superimposed predicament: precipitous declines in manufacturing orders, cost-profit compression, supply chain fragility, a sharp reduction in the labor force, and a K-shaped divergence between old and new market domains (i.e., different tracks/enterprises exhibiting

diametrically opposite trajectory bifurcations) (for detailed analysis and dimension-by-dimension responses, see §5.3).

Integrating the above bidirectional argumentation—industrial drivers and structural predicaments—this paper's core judgment is: **The AI Autonomous Governance Factory possesses a high degree of realistic possibility under the dual impetus of technological evolution and industrial pressure**—the key question is not "whether" but "when, and by what pathway."

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3 AI-AGF Production Line Architecture: The Dual-Track Design of UPL and SPL

3.1 Architecture Overview and Design Philosophy

AI-AGF integrates UPL's equipment self-supply capability and SPL's high-volume production capacity within a single factory system, with AI performing unified planning and scheduling, thereby achieving a closed loop of "equipment self-supply" and "product manufacturing."

Integrating both tracks within a single AI governance framework generates four system-level synergies. **Equipment design–production feedback closed loop**: SPL performance data flows back to optimize next-generation non-standard equipment design. **Cross-production-line globally optimal scheduling**: AI dynamically allocates UPL resources based on SPL order pressure. **Cross-product knowledge transfer**: UPL's multi-product prototyping knowledge is abstracted by AI into a transferable knowledge base, with production line setup cycles decreasing as knowledge accumulates. **Immunity to equipment supply chain disruptions**: The equipment self-supply closed loop eliminates single-supplier dependency on external vendors. The synergistic effects of these four capabilities constitute the fundamental difference between AI-AGF and the traditional layout of "general-purpose workshop + dedicated production line"—the latter is coordinated by human managers and lacks autonomous cross-production-line optimization closed loops.

3.2 AI Governance Mechanism: The Four-Dimensional Closed-Loop Framework

The defining characteristic of AI-AGF lies not only in autonomous decision-making but also in the systematic governance exercised over its own decisions. The term "governance" in this paper carries three progressive layers of meaning: (i) **operational governance**—AI's real-

time constraint and correction of its own decision loop, i.e., the core connotation of "autonomous governance"; (ii) **architectural governance**—AI's global scheduling and resource optimization across the dual-track production lines; (iii) **institutional governance**—the structural alignment of the AI-AGF framework with existing industrial governance standards (IEC 62264, RAMI 4.0, ISO 55000). These three layers share a common framework but operate at different levels of abstraction. The four-dimensional closed-loop framework is detailed below.

Objective governance: AI continuously monitors a KPI set (yield, takt time, energy consumption, OEE, etc.). When indicators deviate from target thresholds, it autonomously triggers root cause analysis and generates corrective strategies, with digital twins providing a verification environment for corrective strategies.

Rule governance: The factory's safety standards, process specifications, and compliance requirements are encoded as a machine-readable rule base. Whenever AI generates any decision proposal, the rule engine automatically performs compliance checking, intercepting proposals that violate safety boundaries or process constraints. Rules are defined as (trigger condition, constraint type, constraint object, priority) quadruples, with priority ordering: safety > quality > efficiency > cost. The rule base serves as a "hard constraint layer" independent of the reasoning engine, ensuring that the governance kernel remains stable as AI reasoning capabilities evolve.

For example, a rule instance for a reflow soldering temperature zone is (heating zone measured temperature > safety upper threshold, prohibit further heating, temperature control module, safety-level). This rule takes precedence over any optimization directive targeting takt time or energy consumption, and its priority cannot be overridden by the AI reasoning engine.

Boundary governance: AI decision-making authority is hierarchically delegated—daily operational scheduling is executed autonomously, equipment design changes pass through after digital twin verification, and major decisions such as safety shutdowns must trigger a human review node. The operational audit log fully records every decision and its rationale.

Risk governance: AI continuously assesses the production system's risk state (equipment health, material supply stability, quality fluctuation trends). When the risk index exceeds thresholds, it autonomously formulates degraded operation plans.

Risk index quantification can employ a **multi-dimensional weighted comprehensive assessment method**, integrating three-dimensional weighted calculation of equipment health score, material inventory coverage rate, and quality fluctuation rate. When the factory-wide risk index exceeds preset thresholds, the AI governance layer triggers a three-tier response: (i) yellow alert—increase sampling frequency and simulation frequency; (ii) orange slowdown—reduce to 70% takt time + UPL pre-produces replacement parts; (iii) red shutdown—partial station shutdown, robots transfer already-loaded workpieces to buffer zones. Threshold calibration can reference ISO 13374 (Condition monitoring and diagnostics of machines) and ISO 55000 (Asset management) series standards, combined with factory historical operational data for Bayesian online calibration.

The severity of physical consequences in the manufacturing context requires the governance framework to include a hard-constraint expression of the physical safety layer. The fundamental reason for designing rule governance as a hard constraint layer independent of the reasoning engine lies precisely here—the hard constraints of the physical safety layer ensure that the underlying safety logic of AI governance is not invalidated by iterative improvements in upper-level reasoning capabilities.

Selecting IEC 62264 as the representative of hierarchical control, RAMI 4.0 as the representative of information models, and ISO 55000 as the representative of risk management, the engineering positioning of the four-dimensional governance framework can be illuminated through structural dialogue with these three industrial standards (Table 2).

Table 2 Governance Comparison Between the AI-AGF Four-Dimensional Framework and Three Industrial Standards

Standard	Core Contribution	Governance Gap	AI-AGF Four-Dimensional Framework Response
IEC 62264	Hierarchical control model (ERP → MES → SCADA → PLC)	Does not permit data flows to cross hierarchical levels laterally; cannot support AI cross-layer scheduling of UPL/SPL	Flattens three functional layers within the AI governance layer; maintains security isolation through rule governance hard constraints and boundary governance hierarchical authority
RAMI	Asset	Asset-centric	Advances from asset-centric to

Standard	Core Contribution	Governance Gap	AI-AGF Four-Dimensional Framework Response
4.0	Administration Shell (AAS) unified information model	architecture: describes "what assets can do," does not define "who decides when assets do what"	governance-centric: the four dimensions of objective/rule/boundary/risk respectively define what to do / what not to do / who has authority to decide / what to do when things go wrong
ISO 55000	Asset life-cycle risk management	Risk logic centered on "maximizing asset value," does not address the reliability of the decision-maker itself	Establishes risk governance as an independent dimension and sets up a three-tier response mechanism (yellow/orange/red), addressing the decision-maker reliability problem absent from the ISO 55000 framework

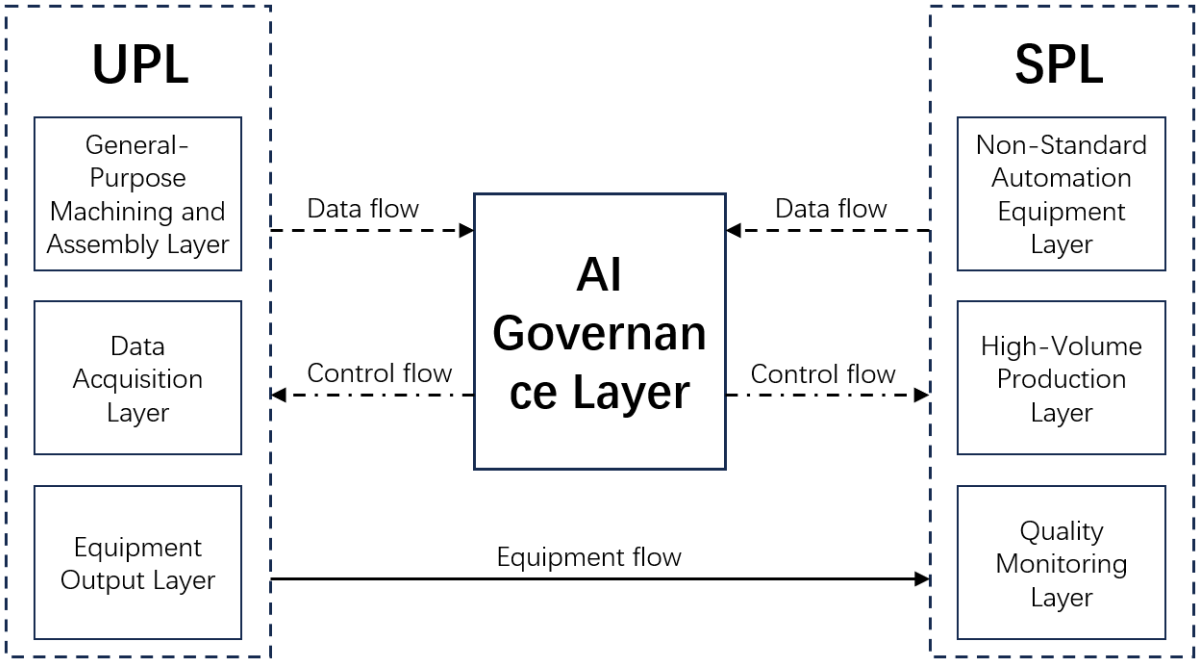

Figure 1: Schematic diagram of the UPL/SPL dual-track architecture

3.3 Universal Production Line (UPL): The Capability Kernel of Equipment-Producing-Equipment

Functional positioning: UPL is the "capability kernel" of AI-AGF, undertaking two core tasks: (1) manufacturing the production equipment needed for the factory's own operation

("equipment producing equipment"); (2) product prototyping and small-batch trial production. UPL consists of assembly lines, numerous industrial manipulators, and multi-degree-of-freedom robots. Its production line is relatively fixed and tends toward general-purpose design. The product prototyping stage not only completes manufacturing but, more importantly, collects in real time the operational parameters, material states, equipment loads, and takt time data for each process step and injects them into the AI training database. These data subsequently become the "raw material" for AI to plan the standard production line. Zhang Dang et al. [17] proposed a data-knowledge hybrid-driven intelligent control framework that can provide technical reference for data acquisition and knowledge accumulation in UPL. In the taxonomy of manufacturing systems, UPL belongs to the category of general-purpose manufacturing units under unified scheduling by the AI governance layer. Its process switching and parameter optimization are autonomously completed by AI in a closed loop, achieving response speed and optimization granularity unattainable by manual scheduling.

UPL manufacturing capability boundary: covers (i) mechanical structural parts and fixtures produced via standard machining processes (turning, milling, drilling, grinding, laser cutting, 3D printing, etc.); (ii) sensor/actuator integration modules with standard electrical interfaces; (iii) non-standard automated stations assemblable by general-purpose manipulators. Excludes (a) optical inspection modules dependent on specialized optical coating or ultra-precision lithography; (b) special material joining equipment for high-power laser/electron beam welding; (c) sensor chips involving chemical etching or semiconductor doping. The boundary is not fixed—it iteratively expands as UPL's processing capabilities advance. The AI governance layer dynamically assesses the "self-supply feasibility" of each non-standard component during planning and generates an external procurement list.

3.4 Standard Production Line (SPL): The Main Body of High-Volume Efficient Production

Functional positioning: SPL is the "production main body" of AI-AGF, consisting of assembly lines, numerous non-standard automated specialized equipment, and several industrial manipulators. The key difference from UPL lies in the process implementation method: in UPL, processes are executed by general-purpose manipulators; in SPL, they are executed by non-standard equipment purpose-built by UPL for that specific product. The essence is cost optimization—the extreme optimization of non-standard equipment for a

single process step far surpasses the "general-purpose but lacking specialized efficiency" of general-purpose manipulators. SPL possesses dynamic reconfigurability—after AI plans the production line topology based on prototyping data, robots carry out the assembly.

Physical reconfiguration proceeds in four steps: (i) **Topology computation**—AI generates the physical layout topology of the production line based on the process diagram; (ii) **Module calibration**—unified physical interface standards, robot vision-guided positioning to pre-calibrated grid nodes; (iii) **Automatic calibration**—digital twin virtual co-commissioning to match takt times and material timing, with real-time micro-adjustments after physical operation; (iv) **Modular stepwise switching**—AI generates a minimal-downtime plan, dividing the production line into independently stoppable modules for step-by-step reorganization. The industrial feasibility of the above workflow depends on the degree of physical interface standardization—when all non-standard equipment follows the same specification for external dimensions, mounting hole positions, and electrical interfaces, robots can reassemble production lines like "LEGO blocks." The review by Mayer et al. [16] showed that digital twins can shorten reconfiguration cycles, and the multi-agent framework of Todescato et al. [15] further complements the autonomous reconfiguration picture. SPL's dynamic reconfigurability distinguishes it from traditional dedicated production lines—in the latter, hardware is tied to the product life cycle, and product iteration means production line obsolescence; SPL achieves the unification of "specialized efficiency" and "generalized flexibility."

3.5 Complete Production Workflow Under Dual-Track Synergy

UPL and SPL collaboratively form a five-step closed loop: (1) UPL prototypes and collects data; (2) AI determines the equipment list and layout; (3) UPL manufactures non-standard equipment; (4) robots assemble SPL and conduct virtual commissioning; (5) SPL operates at full speed, with AI continuously optimizing.

Footnote 1: A thought experiment using the smartwatch as an example (author's estimation based on industry data for consumer electronics ODM new product introduction cycles, average non-standard equipment delivery cycles, and the compression ratio of digital twin virtual commissioning time): Under the traditional model, from prototyping to mass production takes approximately 8 months (equipment outsourced design 2 months → manufacturing 3 months → production line setup and commissioning 2 months → trial production and ramp-up 1 month). Under the AI-AGF closed loop, four processes are highly

parallelized and, under ideal conditions, can potentially be compressed to one-third to one-quarter of the traditional model (approximately 2–3 months).

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4 AI-AGF Launch Pathway

4.1 Transition Medium: Natural Language Script-Based Motion Control Platform

The core challenge in transitioning from human-led to AI-led operations lies in bridging the two paradigms. This paper envisions the **Natural Language Script-based Motion Control Platform** (currently implemented in Chinese) as the transition medium, with its design grounded in two core judgments. **First**, natural language scripts allow engineers to directly describe control logic in their native language—large language models natively output natural language reasoning, and scripting languages happen to be the optimal bridging format between natural language and control commands. The author team uses Chinese as the current implementation language, but the design logic of the framework is language-independent; any natural language can serve as the representation layer for scripts. Even process engineers without programming expertise can quickly understand, modify, and verify control logic written in their native language. **Second**, research such as IMR-LLM [18] has already demonstrated that large language models can decompose natural language manufacturing tasks into process steps and generate control code. The concise, interpretable, and easily debuggable nature of scripting languages makes AI output inherently reviewable and modifiable by engineers, forming a bidirectional readable interaction interface during the "human-AI co-governance" stage.

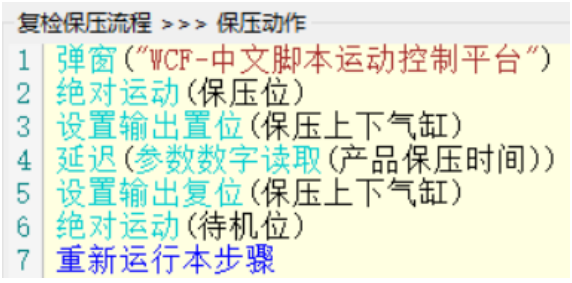

Figure 2: Chinese-Language Scripting Motion Control Platform

Basic working principle of the natural language script platform. The platform encapsulates a natural language semantic interpretation layer (currently implemented in Chinese: Chinese-Language Scripting Motion Control Platform), translating process

descriptions into axis control commands, thereby unifying control precision with natural language readability.

Why choose a script platform over traditional PLC/G-code. There exists a semantic gap between the expression paradigms of PLC (ladder diagram/structured text) and G-code on one hand, and the natural-language-to-code generation paradigm of large language models on the other. The natural language script platform switches control logic to "natural language description of process motions," which falls precisely within the high-density region of large language model output distributions—this is the fundamental reason why IMR-LLM [18] can generate natural language control scripts with a high pass rate. The engineering practice of the natural language script platform described in this paper (currently implemented in Chinese: Chinese-Language Scripting Motion Control Platform) originates from the author team and awaits subsequent systematic validation.

4.2 Four-Stage Transition from "Human" to "AI"

The following time estimates are based on three references: the historical extrapolation cycle required for industrial AI such as IMR-LLM [18] to transition from laboratory to production environment verification; recorded implementation cycles of comparable manufacturing system transformation projects (e.g., FANUC progressive automation production lines); and current maturity assessments of AI capabilities in industrial scenarios (see §1.3 for details). All stage milestones are verifiable quantitative indicators; actual progression pace will vary by industry characteristics and enterprise scale.

Stage 1: Establishing the Baseline—Injecting "Human" Knowledge into "AI"

Inject the manufacturing knowledge accumulated by human engineers into the AI training dataset, covering equipment design drawings, BOMs, technical specification sheets, and natural language script motion control programs. Zheng Pai et al.'s [19] "mutual cognition" concept provides theoretical guidance for this step. **Milestone**: AI can autonomously generate correct control scripts for at least 80% of standard production scenarios, and the equipment knowledge base covers all registered equipment.

Stage 2: AI Initiates, Humans Review—The "Human-AI Co-Governance" Model

AI leads proposal generation, with engineers transitioning from "executors" to "reviewers." AI autonomously completes equipment conceptual design, control script writing, and production line layout planning; engineers review AI output and provide feedback for

iteration. Tao Jiaqi et al.'s [20] manufacturing domain knowledge graph provides reasoning and compliance-checking capabilities for this stage. **Milestone**: The direct approval rate of AI proposals by engineers reaches over 85%, with zero production accidents caused by AI design defects for three consecutive months.

Stage 3: AI Leads—Gradually Reducing Human Intervention

Engineers consciously reduce intervention in AI decisions, with trust built on two dimensions: AI performance validation and explainability. Qiao Fei et al.'s [21] multi-level human-centric integration framework provides theoretical support for this stage. **Milestone**: Engineer intervention rate falls below 5%, and AI decision rejection rate falls below 15%.

Stage 4: Entering AI Autonomous Governance—An Autonomous Closed Loop of Continuous Optimization

Grant AI full production system authority to autonomously complete the perception → decision-making → execution closed loop without human intervention and exercise autonomous governance. Wang Junliang et al. [22] pointed out that the continuous optimization closed loop supported by manufacturing big data enables AI-AGF to achieve efficiency improvements independent of external experts. Jiang Zhoumingju et al.'s [6] Industry 5.0 additive manufacturing framework provides a reference for this stage. **Milestone**: The prototyping-to-mass-production closed loop is completed for six consecutive months without human intervention, with key KPIs reaching or exceeding the best levels achieved by human management in the same industry.

Quantitative thresholds reference the historical extrapolation of IMR-LLM laboratory pass rates, comparable manufacturing system transformation cycles, and industry baselines for autonomous system takeover rates.

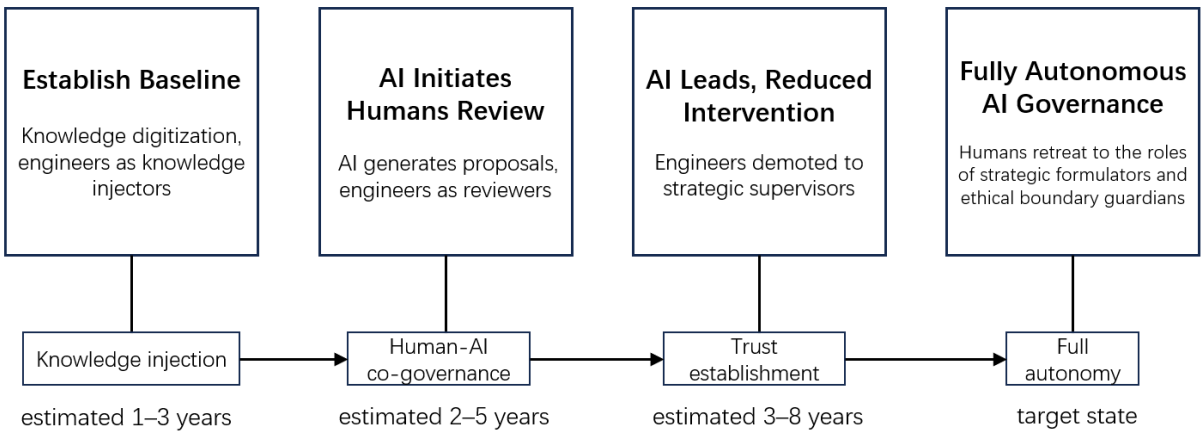

Figure 3: Four-stage transition roadmap

5 Summary and Outlook

5.1 Review of Core Contributions

The core contributions of this paper can be summarized at three progressive levels. (1) Conceptual layer: proposing the AI-AGF concept, unifying autonomy and governance as inseparable dimensions in manufacturing systems research, filling the governance gap in existing paradigms. (2) Architectural layer: designing the UPL/SPL dual-track architecture and the four-dimensional governance framework, advancing manufacturing governance from asset-centric to governance-centric, and establishing systematic dialogue with IEC 62264, RAMI 4.0, and ISO 55000. (3) Pathway layer: designing a four-stage progressive roadmap mediated by the Natural Language Script-based Motion Control Platform, with verifiable quantitative milestones at each stage, situating AI-AGF within the real-world industrial context through the five-dilemma framework.

5.2 Uncertainties, Bottlenecks, and Risks

The proposal of the AI-AGF concept is based on reasonable technological extrapolation, but its multiple uncertainties and bottlenecks must be squarely acknowledged.

Technological uncertainties and safety vulnerabilities: The reliability and explainability of large AI models in industrial scenarios have yet to be verified—whether IMR-LLM [18] can be successfully migrated from the laboratory to real factory settings remains unknown. When AI is granted comprehensive autonomous authority, it introduces a risk chain of "cyberattack → decision tampering → physical anomaly → safety incident." The four-dimensional governance framework can mitigate this to some extent (rule governance mandates compliance checking; risk governance enables degraded operation), but the industrial-grade integration of zero-trust architectures, AI robustness verification, and intrusion detection [13][14] remains an engineering challenge yet to be overcome.

Should the reliability of large AI models consistently fail to cross the Stage 3 threshold, AI-AGF would degrade to enhanced automation (see §5.4 for details).

Organizational and economic feasibility bottlenecks: The identity transition of engineers from "executors" to "reviewers" entails a shift in authority and sense of achievement.

Frontline personnel's trust-building toward AI and management's oversight of "black-box AI" both require institutional and temporal absorption.

Construction costs and return cycles. Preliminary estimates suggest that the incremental investment for AI-AGF is approximately 1.5–2 times the cost of the traditional model, with a return cycle of approximately 3–5 years after 2–3 product iteration cycles (pending empirical validation). Uncertainties stem primarily from the rate of decline in AI infrastructure prices and the speed of adoption of this script platform.

Short-Term and Medium-Term Research Pathways

Short-term (1–3 years): Extend the core production system governance framework to supporting subsystems such as ERP/MES/warehousing and logistics, verifying the transferability of the four-dimensional governance logic. **Medium-term (3–8 years)**: Complete the engineering implementation of the four sub-modules of the governance framework—KPI linkage matrix, complete rule base, decision classification table, and degradation strategy map [23]—and complete stress testing in simulation environments. The above roadmap broadly aligns temporally with the first two stages of the four-stage launch pathway and can provide methodological reserves for subsequent advancement.

5.3 From Predicament to Pathway: Prospective Outlook for AI-AGF

The fivefold predicament described in §2.1 collectively points to a single crux: the capability boundary of the traditional manufacturing model can no longer cover the complexity of the current industrial environment. AI-AGF provides differentiated, structured responses—not claiming to solve all problems, but clearly specifying the response mode and capability boundary for each predicament.

Demand side: The dual-track closed loop compresses the prototyping-to-mass-production cycle to 20%–25% of the traditional model, enabling factories to rapidly switch production within limited opportunity windows to capture fragmented orders and gain differentiated competitiveness amid declining order volumes.

Cost side: The equipment self-supply closed loop frees factories from dependency on the pricing power of external non-standard equipment suppliers. AI continuously optimizes energy consumption and material utilization rates, squeezing out profit margins at the edge where production costs approach or exceed revenue thresholds.

Supply chain: The equipment self-supply closed loop directly provides immunity against external dependency risks in critical equipment segments. Raw material supply disruptions lie beyond AI-AGF's current capability boundary and must be progressively addressed after extending the governance framework to the full-system supply chain as outlined in the research pathway in §5.2.

Labor force: AI autonomous decision-making substitutes for the execution-level labor gap. The four-dimensional governance framework liberates humans from "micro-level decision-makers" to "macro-level objective setters"—this is AI-AGF's most direct and complete response dimension.

K-shaped divergence: AI-AGF provides a clear transformation track from "relying on scale and low cost" to "relying on AI and autonomous governance"—not telling factories which market domain to choose, but providing a systematic solution for factories that have already chosen a growth track to cross the capability chasm.

The alleviation of predicaments is accompanied by the introduction of new forms of risk. While the equipment self-supply closed loop provides immunity against external supply chain risks, it creates a governance blind spot unique to AI-AGF: when equipment manufactured by UPL is deployed in SPL production, equipment performance defects propagate internally within the factory through the "self-supply chain" in a closed loop. This closed-loop propagation bypasses the quality arbitration mechanism of external suppliers in traditional supply chains—which is rendered completely ineffective within this closed loop. To address this, the rule governance layer within the four-dimensional governance framework must include an "independent audit loop"—with external evaluation nodes periodically verifying the quality independence of the equipment self-supply chain, severing cascading feedback pathways.

Industrial and societal impact: AI-AGF will reduce the number of directly employed workers in manufacturing while simultaneously creating new positions such as AI trainers and governance auditors. Governance mechanisms must embed diverse objectives such as social responsibility and environmental sustainability during the design phase. Entrepreneurs providing product designs alone can have AI-AGF complete the journey from prototyping to mass production—this can be seen as a critical descent of cloud manufacturing from the information layer to the physical layer.

AI-AGF is a redefinition of the essence of manufacturing—manufacturing evolves from an artisanal skill exclusive to humans into a governance practice co-constructed by humans and AI. Faced with the ongoing deepening of the five structural predicaments, direction is no longer optional.

5.4 Research Limitations and Regression Pathways

Research limitations. This paper is a prospective review and does not involve experimental validation or simulation. The time estimates and threshold settings of the four-stage roadmap are based on historical data extrapolation and industry experience reference; their applicability across different industries and factory scales awaits empirical verification. The physical reconfiguration mechanism of the dual-track architecture and the manufacturing capability boundary of UPL remain at the level of conceptual description, lacking prototype validation. The main limitations of this study include: (1) argumentative force relies on logical coherence and literature support, without having undergone stress testing in real factory environments; (2) the quantitative thresholds of the four-stage milestones reference historical cycle extrapolation from comparable systems, with insufficient discussion of applicability differences across industries; (3) the reliability of large AI models in industrial scenarios constitutes the underlying assumption of the entire conceptual framework—if this assumption does not hold, AI-AGF faces the wholesale erosion of its conceptual foundation.

Counterfactual regression pathway. Among the above limitations, the most destructive scenario is that the reliability of large AI models in industrial scenarios consistently fails to cross the Stage 3 threshold. Under this regression pathway, although AI-AGF fails to achieve fully autonomous governance, its upfront investments—knowledge digitization, the natural language script platform, and the engineer review mechanism—could still significantly elevate the factory's automation level. What is lost, however, are the four most essential system-level synergies (design feedback closed loop, cross-production-line globally optimal scheduling, cross-product knowledge transfer, and equipment supply chain immunity), with the system essentially regressing to the existing mainstream paradigm of "AI-assisted + human decision-making." The candid presentation of this regression pathway is not a self-negation of the paper's core thesis but a fundamental observance of academic honesty: acknowledging the real-world ceilings that theoretical constructs may encounter.

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Wei Jili Input Method Software(韦季李输入法软件): V1.0 [CP]. Registration No.: 2026SR0058599, 2026-01-09.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.