



New-generation artificial intelligence boosts product forward design capability in manufacturing industry

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Product forward design is generally posited as an essential pathway for surmounting bottlenecks in technological innovation and augmenting the core capabilities of the manufacturing industry. Bolstered by knowledge engineering, new-generation intelligent products are distinguished by the salient attributes of self-sensing, self-adaptation, self-learning, and self-decision-making. These advancements are propelling mechanical design to evolve from a traditional paradigm rooted in single-discipline expertise, empirical heuristics, and function-satisfaction orientation, toward a sophisticated framework that features multidisciplinary coupling, collaborative architecture-knowledge driving, and integrated lifecycle-wide optimization—from which defining characteristics including innovativeness, customizability, intelligence, virtuality, sustainability, optimality, and human-machine collaboration distinctly emerge. This perspective hereby explores the conceptual essence of product forward design, elaborates on the enabling role of frontier artificial intelligence technologies thereof, and underscores their typical application scenarios in high-end equipment, where these intelligent capabilities substantively drive breakthroughs in performance and adaptive functionality.

PRODUCT FORWARD DESIGN PARADIGM

Forward design is a theory-guided, internally consistent process from requirements to conceptual design and then to detailed design. It is related to, but distinct from, function-behavior-state (FBS) design, set-based design, and generative design: FBS design provides requirement-to-structure reasoning, set-based design supports parallel exploration of alternatives, and generative design produces candidate geometries under predefined objectives and constraints. Forward design further innovatively integrates these ideas into a requirement-driven, knowledge-guided, and verification-closed-loop workflow.

Based on the previous publications involving expert systems,¹⁻³ digital twins,^{4,5} knowledge particle navigation,⁶ intelligent design,⁷ within this continuous process, numerous interdependent capabilities organize the transition from intention to artifact (Figure 1). They encompass conceptual creation, progressive scheme refinement, requirement-responsive functional design, motion-based mechanism design, recursively modular structural design, top-down assembly design, error-feedback accuracy design, coupled performance design, integrated process design and knowledge-engineered design architectures. These capabilities are primarily embodied in the systematic support provided by foundational mechanical-engineering software systems for design, process planning, assembly, and knowledge resources.

Mechanical engineering is generally evolving toward green, intelligent, integrated, extreme, and service-oriented development, as represented by new-generation intelligent products and equipment. Supported by knowledge engineering, based on which systems exhibit self-sensing, self-adaptation, self-learning, and self-decision-making capabilities, their design tasks now extend beyond geometry, materials, and structural parameters to the coordi-

nated construction of knowledge distillation, sensing mechanisms, control logic, manufacturing processes, service modes, and data-feedback loops. Accordingly, forward design is shifting from a single-discipline, experience-driven, and function-satisfaction-oriented paradigm toward multidisciplinary coupling, architecture-knowledge co-driven design, and lifecycle-wide integrated optimization, featuring innovativeness, customizability, intelligence, virtuality, sustainability, optimality, and human-machine collaboration, thereby boosting product capability.

FRONTIER ARTIFICIAL INTELLIGENCE FOR MECHANICAL DESIGN

Driven by the Internet, big data, cloud computing, as well as artificial intelligence (AI), knowledge bases, metadata repositories, and architecture repositories are becoming strategic resources rather than optional accessories for mechanical design. The deep integration of metadata, architectures, and knowledge boosts various AI architectures which can be utilized in the forward design paradigm.

(1) Generative Cognition reframes mechanical design as concurrent intent interpretation and candidate synthesis that displaces post hoc verification. In this regard, large language models (LLMs) furnish knowledge understanding, semantic interaction, and reasoning assistance.^{8,9} The Transformer architecture underpins in-context learning, chain-of-thought reasoning, and natural language interaction. Representative applications cover requirement parsing, standards retrieval, document generation, process knowledge question answering, and cross-software workflow orchestration. Multimodal models fuse drawings, 3D models, simulation results, and sensor data, supporting CAD/CAE/CAM operations that include model generation, parameter adjustment, and simulation setup. Generative adversarial networks (GANs)¹⁰ and diffusion models¹¹ learn complex engineering distributions from which candidates are synthesized under stated objectives and constraints. Adversarial training with progressive morphology generation consolidates robustness and expands conceptual creation, requirement-responsive functional design, and knowledge-engineered architectures.

(2) Multi-Agent Collaboration partitions complex mechanical design among interacting roles whose intermediate results undergo reciprocal evaluation.^{12,13} Agentic artificial intelligence, model context protocol interfaces, and AI scientist workflows further structure this collaboration. Concept generation, simulation verification, manufacturability analysis, and allied subtasks can proceed in parallel under mutual critique that curtails subjective unsupported claims. Multi-agent systems (MASSs) allocate these domain-specific responsibilities and reconcile outputs across software boundaries, sustaining progressive scheme refinement, coupled performance design, integrated process design, and knowledge-engineered design architectures without collapsing the process into a single opaque generator. In AI-enabled forward design, the resulting trajectories remain attributable to declared roles and checks rather than to an unexamined end-to-end proposal whose governing assumptions remain concealed from review.

(3) Embodied Physicalization relocates artificial intelligence from software

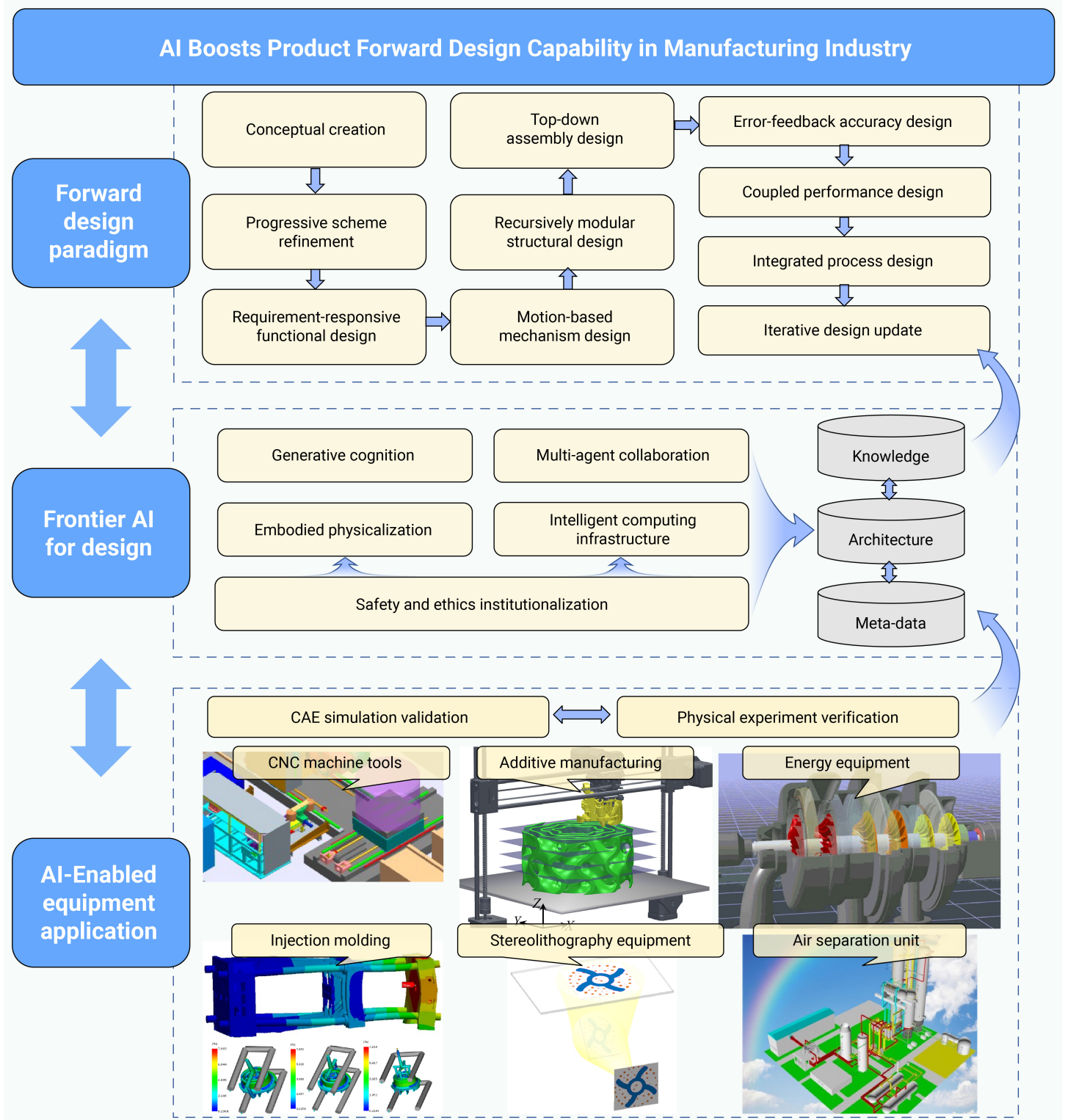


Figure 1. AI boosts product forward design capability in manufacturing industry

procedures onto physical equipment, where perception, manipulation, and feedback are acquired through environmental interaction.¹⁴ Embodied intelligence, humanoid robots, digital twins, and physics-informed neural networks instantiate this physical agenda. Vision language action (VLA) models couple visual perception, language instructions, and action execution into a closed loop that runs from task understanding and state estimation to motion control. VLA pipelines demonstrated in robotic 3D grasping already exhibit autonomous perception and manipulation in manufacturing settings.¹⁵ Embodied physicalization anchors motion-based mechanism design, error-feedback accuracy design, robotic assembly verification, and integrated

process design, subjecting design intent to the conditions under which geometry, actuation, sensing, and disturbance finally meet on the manufacturing shop floor.

(4) Computing Infrastructure constitutes the search, simulation, and decision substrate of forward design through metaheuristics, learning-based surrogates, reinforcement learning, and digital twins. Metaheuristics conduct global search, constraint handling, and multi-objective trade-offs among performance, manufacturability, reliability, and cost in high-dimensional nonlinear spaces.⁵ Machine-learning surrogates, neural operators, physics-informed neural networks, and reduced-order models accelerate finite-

element analysis, computational fluid dynamics, multibody dynamics, thermal analysis, and related evaluations.¹⁶ Reinforcement learning further supports sequential decision-making, adaptive process-parameter adjustment, and complex system control.¹⁷ Moreover, digital twins extend the same substrate to real-time monitoring, performance prediction, and closed-loop optimization across the product lifecycle,^{18,19} underwriting coupled performance design, accuracy design, scheme refinement, process design, and lifecycle-wide knowledge-engineered architectures.

(5) Safety and Ethics Institutionalization constitutes the universal acceptance and accountability regime of AI-enabled forward design. Its scope covers uncertainty quantification, physics-based simulation, human-in-the-loop review, experimental testing, and certification-oriented validation ahead of deployment on high-end equipment. Institutional mechanisms address geometric integrity, safety margins, manufacturability, and standards compliance, together with controls on unsupported claims in terminology, design rules, and similar-component recommendations under weak knowledge grounding. It further encompasses evidence-linked revision pathways for requirements, architectures, and process plans under extreme loads or long service cycles, where attendant risk modes include structural failure, fatigue, thermal instability, vibration, leakage, and process accidents in service.

AI-ENABLED EQUIPMENT APPLICATIONS

New-generation artificial intelligence is accelerating the development of forward design capability for computer numerical control (CNC) equipment, driving a paradigm shift in equipment design from experience-based modification, prototype testing, and repeated iteration toward forward demand-driven, architecture-supported, data-closed-loop, and intelligence-enabled optimization. AI integrates design knowledge, mechanistic models, simulation data, and operational data to support requirement analysis, knowledge reuse, concept generation, performance prediction, simulation verification, and process optimization, thereby improving design efficiency, solution innovativeness, and overall performance.

In typical equipment applications, AI is being progressively embedded into key design stages. For CNC machine tools, AI can support overall structural layout optimization, dynamic characteristic analysis of spindle and feed systems, thermal error modeling and compensation, machining chatter prediction, tool wear identification, and adaptive optimization of process parameters, thereby supporting the design of high-precision and high-stability machine tools. Illustratively, physics-informed neural networks can be employed for machine error compensation, reducing the mean absolute positioning error from 12.35 μm to 2.43 μm and the maximum residual error from 31.47 μm to 8.67 μm , achieving a positioning accuracy index of $\pm 2.8 \mu\text{m}$, which comfortably meets the $\pm 5 \mu\text{m}$ tolerance required for high-end aerospace machining.²⁰

In additive/subtractive hybrid manufacturing, 3D printing (3DP), metal laser manufacturing, and stereolithography equipment, AI could be applied to forming process prediction, defect identification, residual stress and deformation control, parameter optimization, and quality regulation. One representative application involves the deployment of generative adversarial networks to predict and homogenize optical tomography images and the resulting microstructure during laser powder bed fusion of alloys, which reduced the standard deviation of the thermal signals by over 25% and promoted the transformation of the microstructure toward a more uniform equiaxed grain structure.²¹

In energy equipment, AI can support the design of wind power, photovoltaic, energy storage, hydrogen energy, and key manufacturing equipment for new energy vehicles, enabling the coordinated optimization of aerodynamic shape design, thermal management design, flow-field structure optimization, and reliability analysis. A typical application lies in compressor blade aerodynamic design, where diffusion-model-based generative design can explore blade stacking configurations, potentially improving the total-to-total isentropic efficiency of the compressor from 80.5% to 81.2%.²²

In air separation units (ASUs), AI can be used for process system design, heat exchanger structural optimization, column parameter matching, energy consumption analysis, and operating strategy optimization, thereby improving the energy efficiency, safety, and stability of large-scale process equipment. For flexible air separation units, the pressure-driven digital twin model

is validated for full-range operation including shutdown and cold restart, reaching the target oxygen purity within 1.5 h and steady state after approximately 33.3 h.²³

In injection molding equipment, AI can be integrated into mold design, melt flow analysis, molding defect prediction, cooling system optimization, and adaptive adjustment of process parameters, improving molding quality and process stability. When combined with generative design and 3D topology optimization, AI further supports the forward design of 3DP lightweight components, complex flow channels and lattice structures. In flow-channel design, graph neural networks can encode the connectivity of flow-channel networks and enable topology-aware flow-path optimization, potentially reducing pressure drop by 10–30% under identical flow-rate constraints.²⁴

Although significant progress has been made, AI still faces arduous challenges in mechanical design:

(1) Limited 3D spatial understanding and geometric reasoning. Most AI architectures are trained primarily on 2D images and text, lacking inductive biases for explainable 3D structures, engineering drawings, assembly relationships, and physical constraints. This limits their ability to form operable and verifiable geometric understanding, constraining applications in complex component modeling, assembly constraint recognition, and structural performance reasoning.

(2) Insufficient engineering data infrastructure and knowledge standardization. Mechanical engineering metadata are often scattered across design, simulation, manufacturing, testing, and service systems, with inconsistent formats, incomplete metadata, uneven quality, and limited semantic annotations. These issues hinder the construction of high-quality knowledge bases, metadata, and architecture repositories for forward design. Future work should focus on standardized metadata, knowledge granulation, product architecture ontologies, geometry-material-process-performance mappings, quality-controlled datasets, and traceable simulation-experiment-service correlations.

(3) Hallucinations under semantic ambiguity and similar engineering tasks. LLMs or GANs typically generate outputs probabilistically rather than through deterministic knowledge retrieval and logical reasoning, making them prone to factual errors in technical terminology, design standards, process rules, and similar-component tasks. Such risks become more pronounced when requirements are ambiguous, component functions are similar, or knowledge grounding and verification mechanisms are insufficient.

(4) Dependence on rigorous engineering verification. AI-generated 3D structures may contain non-manifold surfaces, self-intersections, or missing features, requiring geometric repair, feature simplification, mesh generation, and validation before CAD/CAE integration, which may introduce additional errors.

(5) AI safety and trustworthy deployment in high-end equipment. AI-generated mechanical designs may pose risks when physical constraints, safety margins, manufacturability, and standard compliance are insufficiently considered. For equipment, e.g., CNC machine tools and ASUs, under extreme or long-cycle conditions, unsafe outputs may cause structural failure, fatigue damage, thermal instability, vibration, leakage, or process accidents. Thus, AI outputs should be treated as candidate solutions and verified through uncertainty quantification, physics-based simulation, human-in-the-loop review, experimental testing, and certification-oriented validation before deployment.

In summary, future AI-enabled forward design should go beyond improving generative capability to strengthen 3D geometric reasoning, engineering knowledge constraints, physical consistency discrimination, and verifiable closed-loop design. Meanwhile, manufacturing should balance open collaboration and academic exchange with industrial security, technological self-reliance, and supply chain resilience.

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AUTHOR CONTRIBUTIONS

J.T. supervised and reviewed this work. M.C, C.C drafted the manuscript and produced figure. J.X. conceptualized, edited and finalized the manuscript. All authors contributed to the manuscript and approved the final version.

DECLARATION OF INTERESTS

Jianrong Tan is the Editor-in-Chief of *AI Plus* and was blinded from reviewing or making final decisions on the manuscript. Peer review was handled independently of this member and their research group. The other authors declare no conflicts of interest.