

NSF/ASME Design Essay Competition 2025

**Looking to the Future: Will Your Best Partner Be a Robot?**



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## Abstract

This article focuses on the trend and path of robots and artificial intelligence driving the intelligent manufacturing industry. With the rapid changes in population and cost structure. Robot intelligence is becoming more and more important. In the face of the manufacturing industry in 2040, we have described the four core characteristics that the manufacturing industry should have in 2040: "robot secondary development capability", "AI integration capability", "efficient data collection and processing capability" and "supply chain dynamic adjustment capability". At the same time, this article also discusses the three major challenges of combining robots and AI in the manufacturing industry, namely robot environment understanding, trust and safety, and human-machine two-way learning and knowledge sharing. To conclude, we proposed six different dimensions to try to solve the above challenges from different dimensions such as dynamic control, environmental perception, LLM empowerment, knowledge sharing platform, industry basic model and self-learning mechanism, and proposed systematic solutions. Finally, the importance of talent reserves in promoting more efficient, safe and sustainable development of the manufacturing industry is explained.

## Introduction

The world's three major manufacturing entities have each proposed their own strategic plans for the manufacturing sector: China has "Made in China 2035[1]," Germany has the "National Industrial Strategy 2030 [2]," and the United States is promoting a manufacturing reshoring initiative [3]. These plans all underscore how much these major economic powers value the manufacturing industry. With the rapid advancement of robotics and AI technologies, the current manufacturing systems are progressively transformed[4]. As the digitalization of manufacturing approaches completion, the next breakthrough will be the move toward intelligent manufacturing. Some enterprises have already begun leveraging robots to enhance factory intelligence. For instance, Agility Robotics, based in Oregon, has launched a humanoid robot named "Digit," designed specifically for warehousing and logistics scenarios[5]. It is already deployed in the Spanx factory, where it handles repetitive physical labor tasks such as moving boxes, thereby helping to alleviate labor shortages. In China, SANY Heavy Industry's No.18 Smart Factory utilizes Automated Guided Vehicles and automated high-rise warehouses to realize autonomous material distribution [6]. Using IoT and other technologies, it collects and analyzes production data to optimize workflows, significantly boosting production efficiency. Smart robots have become a fiercely contested domain among developed nations. The fundamental driving force behind the push toward scalable and intelligent robotic technology stems from rapid changes in demographics and cost structures. In developed economies, the aging labor force and young people's reluctance to engage in repetitive, physically demanding, or hazardous jobs are becoming more pronounced [7]. In developing regions, where the demographic dividend is fading, rising wages and labor market volatility have made the "low-cost advantage" increasingly unsustainable[8]. Furthermore, industries such as consumer electronics and smart electric vehicles are accelerating their product update cycles. Finally,

dangerous or emission-prone processes—such as battery assembly, chemical coating, and heavy-duty handling—can be taken over by robots, thereby reducing occupational health risks.

The rapid development of AI has been demonstrated in many fields. In the product design phase, AI has already been applied to assist with design through topology optimization and material databases[9]. In the quality inspection stage, computer vision enables the detection of defective samples and assembly errors within milliseconds. For equipment maintenance, technologies such as digital twins have made predictive maintenance possible [10]. With the rapid development of large language models, communication between humans and robots is becoming increasingly seamless. So, a series of technological innovations is driving the manufacturing industry toward greater intelligence.

In my view, by 2040, an outstanding manufacturing enterprise will possess the following four characteristics: the capability for secondary development of robots, the ability to integrate artificial intelligence, robust data collection and processing capabilities, and the capacity for dynamic supply chain adjustment. However, achieving these four objectives still presents several challenges. These include how to enable robots to understand complex manufacturing environments; how to address issues of trust and safety in the process of human-robot collaboration; and how to realize bidirectional learning and knowledge sharing between humans and robots. Ensuring that robots can not only learn from humans' tacit knowledge and experience but also enhance workers' cognitive abilities in return.

### **Characteristics of the Manufacturing Industry in 2040**

Although many robotics companies have already released their latest humanoid robots, the field is still in its early stages. For example, the world's first humanoid robot half-marathon was held in Yizhuang, Beijing, China[11]. In Spartanburg, USA, the startup Figure 02 deployed its humanoid robot for the first time in a BMW factory, where it successfully completed assigned tasks[12]. Nevertheless, all of this is still in its infancy. In the era of Industry 4.0, the adoption of robots in manufacturing continues to increase year by year. At the same time, technologies such as digital twins, predictive analytics, and full-cycle management are being deeply integrated into production processes[13]. Moreover, efficient data collection and processing capabilities, along with the ability to dynamically adjust the supply chain, have become critical drivers of intelligent manufacturing. These advancements enable production enterprises to reduce costs and achieve rapid product delivery. Against this backdrop, robots are gradually becoming the bridge that connects the digital and physical worlds, serving as the key execution layer [14]. This shows that robots are no longer simply machines that execute programmed programs, but robots that can make autonomous decisions. Therefore, by the year 2040, an advanced high-tech manufacturing enterprise must possess the following capabilities throughout its production processes:

#### **1. Capability for Secondary Development of Robots**

This primarily refers to the ability to redevelop general-purpose robots so that they can more flexibly adapt to various manufacturing scenarios. This capability includes not only the rapid

replacement and upgrading of hardware modules but also the flexible programming and parameter optimization of software platforms to meet the requirements of specific processes and tasks. This is analogous to training a newly hired employee through pre-job onboarding.

## **2. Integration Capability of Artificial Intelligence**

The enterprise must be able to integrate various types of AI technologies, allowing each to handle the tasks it excels at. For instance, computer vision is well-suited for quality inspection and recognition tasks[15]. Reinforcement learning is appropriate for optimizing production processes[16], and LLMs are ideal for tasks involving text processing[17]. This ensures that the most suitable AI model is applied at each stage of the production process.

## **3. Data Collection and Processing Capability**

With the rapid advancement of artificial intelligence, obtaining superior models or enabling models to better understand the current production state requires enterprises to establish efficient mechanisms for data collection, filtering, and analysis. This includes deploying sensor technologies, implementing large-scale data storage systems, and ensuring real-time data stream processing. Such capabilities allow for the continuous acquisition of real-time data generated throughout the production process, which can then be used to train and improve AI models.

## **4. Dynamic Supply Chain Adjustment Capability**

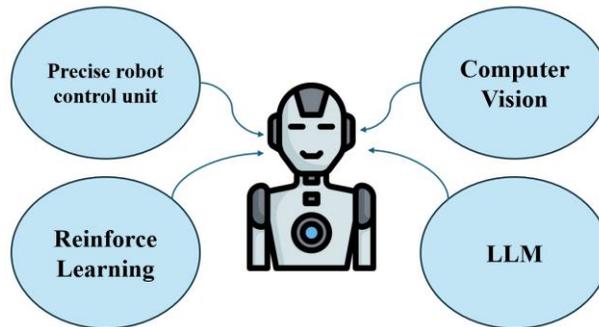
With ongoing geopolitical fluctuations, manufacturing enterprises must place greater emphasis on supply chain stability and market diversification. This includes achieving rapid multi-source switching and enabling localized manufacturing[18]. Such capabilities are essential to avoid production halts caused by geopolitical disruptions and to ensure continuity of operations and sustain competitive advantage.

## **Core Challenge: The Reshaping of Human-Robot Collaboration in Industrial Production**

According to a report by SNS Insider, the smart robot market is projected to grow at a compound annual growth rate of 26.63%, reaching USD 111.6 billion by 2032[19]. By then, many humanoid robots will enter the manufacturing sector, either replacing or augmenting human labor. This indicates that by 2040, the greatest challenge will no longer be whether robots can perform manufacturing tasks, but rather how industrial workers can effectively complement robots, how to build trust between workers and robots, and how to achieve co-evolution between humans and machines. The three key challenges are as follows:

**Challenge of enabling robots to understand complex manufacturing environments.** Robots must be equipped with artificial intelligence and computer vision to make dynamic decisions based on the real-world conditions of the factory. This means that robots must be able not only to operate under standardized production processes but also to analyze and adapt in real time to non-standard workflows and tasks. For example, robots must be capable of handling unexpected equipment or technical issues and recognizing different types of work. How to combine reinforcement learning and LLMs to enable robots to autonomously understand complex

manufacturing environments is also a major challenge in improving human-robot interaction efficiency.



**Figure 1:** Let robots integrate various artificial intelligence and dynamic models

**Challenge of Trust and Safety in Human-Robot Collaboration is a big issue.** In the process of human-robot interaction, how to make workers trust robots as they would their most reliable colleagues is a significant challenge. Furthermore, in terms of production safety, whether safety incidents may occur due to improper robot operations or inherent dynamic flaws is a matter that must be rigorously prevented.

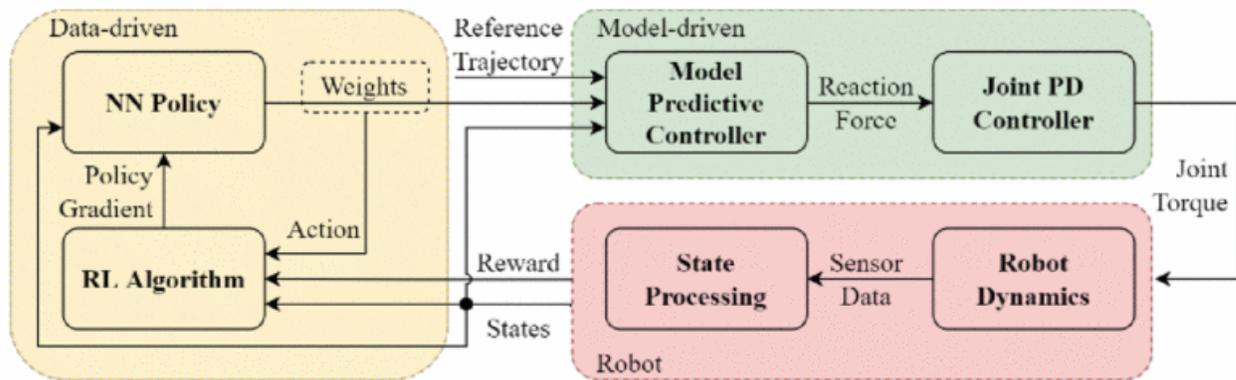
**Challenges in Enabling Robot Learning.** In the manufacturing environment of 2040, human-robot collaboration is no longer merely about task division or robot replacing labor but about achieving mutual learning between humans and robots. It is not just about letting robots understand humans, but also about humans understanding robots, so as to achieve a two-way improvement in the skills of humans and robots. Specifically, this means enabling robots to learn tacit knowledge and experience from humans, rather than simply learning through algorithms. It is necessary to develop knowledge-sharing platforms suitable for mutual communication between humans and robots, allowing tacit human knowledge to be made explicit for robotic learning. Then, through high-frequency practice, robots can continuously validate and optimize this knowledge to acquire the most effective practical experience. This, in turn, will further enhance the capabilities and efficiency of industrial workers. Achieving such human-robot co-evolution through this approach will become a key challenge and cornerstone of sustainable development in manufacturing.

### Strategic Solutions

To address the above challenges, we propose the following solutions:

**1. Enhancing the Kinematic Control Module of Robots:** With the rapid development of model predictive control (MPC) and reinforcement learning (RL), precise and safe kinematic control no longer relies on a single algorithm, but instead increasingly integrates multiple algorithms to control the robot. By combining multiple algorithms, the robot's locomotion becomes more robust. Each algorithm has its own unique purpose. For example, MPC can be used for multi-objective optimization over the entire process, integrating control objectives such as end-effector trajectory error, energy consumption, joint limits, and collision distances. It can also incorporate

constraints such as human activity zones, dynamic workpieces, minimum safety distances for collaborative robots, and velocity limits. RL, on the other hand, enhances the model's adaptability and assists MPC in making decisions under complex environmental conditions, thereby enabling more capable and flexible locomotion[20] [21].



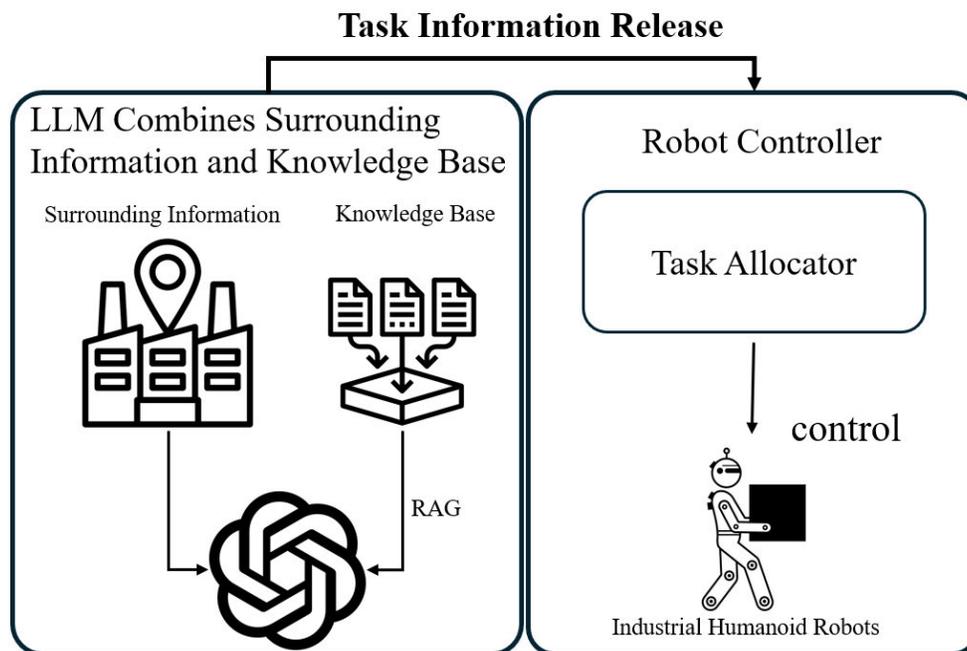
**Figure 2:** Schematic diagram of MPC with reinforcement learning[22]

**2. Enhancing the Environmental Perception Capabilities of Robots:** Robots must possess precise, efficient, and human-surpassing perception capabilities for complex factory environments. By integrating sensors such as 3D LiDAR, RGB-D cameras, and microphones, multi-sensor fusion can be achieved, enabling robots to possess human-like sensory capabilities[23], or even surpass them. Robots can perceive equipment conditions remotely and observe environments beyond their visual field through technologies such as IoT, thereby achieving rapid response. Specifically, 3D LiDAR provides high-precision point clouds, capable of generating centimeter-level three-dimensional geometric contours in real time within complex factory environments[24], which can be used for SLAM navigation and obstacle avoidance. RGB-D cameras supplement texture and depth information, and in combination with computer vision algorithms such as YOLO and U-Net, assist robots in recognition, surface defect detection, and grasping tasks[25]. Microphone arrays function as "industrial stethoscopes," capable of capturing abnormal bearing noises, air leakage, or collision sounds, providing acoustic features for early fault detection[26]. They can also capture human voices and, combined with LLMs, contribute to task planning[27].

Furthermore, robots can gain perception capabilities beyond those of humans' instance, perceiving areas outside the human field of vision by leveraging IoT technologies. Devices on the production line such as AGVs and PLC publish real-time status via MQTT[28]. External cameras and other devices located beyond the robot's visual field, combined with edge detection technologies and anomaly detection algorithms, can promptly assess the production line status and synchronize the information to the terminal robot. Through the above methods, robots can not only "see farther, hear more precisely, and detect faster," Using this way can significantly

improve production line stability, safety, and equipment availability, thus enabling human-robot collaboration that surpasses the boundaries of human sensory perception.

**3. Utilizing Large Language Models to Achieve Robot Intelligence:** As the capabilities of large language models in understanding, reasoning, and generalization continue to improve, deeply integrating them with robotic systems can enable robots to possess more advanced natural language processing abilities, laying the foundation for thinking like humans in the future. By introducing LLMs, robots can not only comprehend complex task instructions expressed in natural language by humans, but also, after fine-tuning, autonomously perform task decomposition[29], plan generation, and control strategy design, thereby achieving a leap from “understanding human speech” to “executing practical actions.” Combined with Retrieval-Augmented Generation (RAG) technology[30], LLMs can access external knowledge bases such as operation manuals, production documents, and process specifications in real time, dynamically acquiring contextual information, effectively reducing hallucination generation, and improving task accuracy and knowledge timeliness, see figure 3.

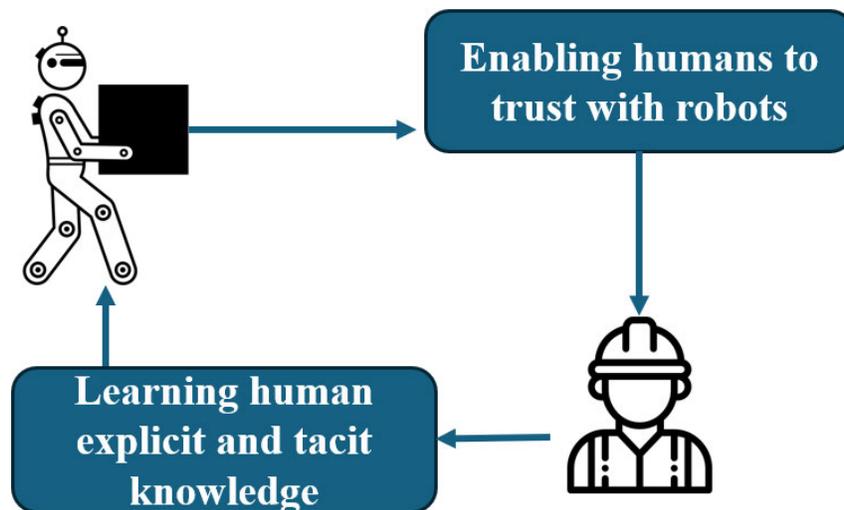


**Figure 3:** Integrating LLMs with robotic systems enables robots to understand tasks through command, enhanced by RAG to improve accuracy and reduce hallucinations.

This enables robots to possess knowledge retrieval and real-time reasoning capabilities oriented toward dynamic environments. By integrating perception systems and control systems with LLMs, robots can achieve embodied intelligence[31]. LLMs interpret and parse tasks, execute specific actions through connections with control systems, and receive feedback, thus realizing closed-loop control of language-perception-action. Through the introduction of LLMs, robotic systems will no longer be limited to simple tasks like picking up the apple but will be able to

autonomously plan and become capable of addressing the intelligent manufacturing challenges of 2040.

**4. Promoting a Knowledge-Sharing Platform Between Robots and Humans:** In order to make workers trust robots more and make them believe in the safety of robots, it is necessary to build a platform for robots and humans to share knowledge. This will allow humans to deeply understand the decision-making mechanism of robots, and in turn allow robots to learn human knowledge systems and behavior patterns. As Thomas Hobbes stated in Chapter 13 Of the Natural Condition of Mankind as concerning their Felicity, and Misery in Leviathan: “Man does not trust others because, in the natural condition, he lives under uncertainty and mutual distrust.” This viewpoint similarly applies to the relationship between humans and machines’ distrust of robots does not originate from technical flaws themselves, but rather from their inability to see and understand how robots think and act[32]. To eliminate humans' distrust toward humanoid robots, it is necessary for them to understand how robots make decisions. Moreover, robot decisions should resemble those of humans. Robots must not only learn to explicit human knowledge but also tacit knowledge. Explicit knowledge refers to knowledge that can be clearly articulated, systematically encoded, and conveyed through language, diagrams, manuals, or digital models, for example: equipment operation procedures, product assembly drawings, task allocation instructions, and visual recognition models. This type of knowledge constitutes the core of the robot’s current “task execution capability.”



**Figure 4:** The process of mutual learning between robots and humans

Tacit knowledge, on the other hand, is more subtle, experience-based, and difficult to formalize. It is often embodied in human intuition, motion fine-tuning, experience-based responses, and situational understanding. For instance, a skilled worker naturally controls the force and angle when tightening a screw, yet this behavior is difficult to describe with precise parameters. Or in collaborative scenarios, interpreting whether a colleague is ready for the next operation through body language, this kind of “tacit coordination” also falls under tacit knowledge. Therefore,

robots must gradually learn tacit knowledge in addition to mastering explicit knowledge. Through this cycle, people will trust robots more and be more willing to work alongside them. See figure 4.

By constructing a human-robot knowledge sharing platform, robots can gradually acquire tacit knowledge through video acquisition data learning, imitation learning, multimodal perception, and human feedback mechanisms, and convert it into executable strategies via embodied intelligence. This platform should also feature bidirectional transparency. On the one hand, robots should clearly display their current states, intentions, and reasoning processes to workers; on the other hand, through continuous data collection of human interaction patterns and natural language communication, the platform's human tacit knowledge base can be continuously optimized for robot learning. Using this way, I believe AI with robots are no longer "black box". This forms the foundation for building a safe, controllable, and highly trusted human-robot collaboration system, and is a prerequisite for humanoid robots to truly deliver value in the manufacturing environment of 2040.

**5. AI Models Based on the Manufacturing Industry:** To achieve the four points mentioned above in the manufacturing industry in 2040, the manufacturing sector must develop its own foundational AI model system. This involves building its own database for AI training. A full life-cycle intelligent model tailored to manufacturing needs to be established. Since different AI models have their own characteristics, each stage of production requires its own specialized AI model[33]. Multiple AI models should be integrated through a Modal Fusion to achieve multimodal detection and anomaly-linked alerts across "vision, sound, and measurement." The goal is to construct an intelligent model ecosystem that spans design, production, quality inspection, and maintenance, making multimodal AI the central perception and decision-making hub of the intelligent factory of 2040.

## **6. Solving the Problem of Robot Self-Learning Capability**

For manufacturing in 2040, the self-learning capability of robots remains an unresolved challenge. A mechanism for autonomous knowledge updating and performance improvement is required. Given the fast-paced product iteration cycles in manufacturing, especially in consumer electronics and the automotive sectors, where updates may occur on a monthly rather than yearly basis[34], robots' self-learning capabilities are particularly critical. Therefore, establishing a comprehensive robot self-learning system is a key support for achieving manufacturing goals in 2040.

First, we need to automatically establish a mechanism for data acquisition and ensure that the data is stored in a consistent format. This data will span multiple dimensions, such as operational processes, yield rates, and voice recordings. In this way, high-quality data can be obtained for subsequent model training.

Furthermore, we need to establish a mechanism for continuous knowledge updating and classification. Imagine if a robot has learned how to install the cover of device A, and later it

needs to install the cover of device B using the same method. Do we need to retrain the robot from scratch? To address this issue, we need to construct a skill graph. When a new task arises, the robot can first match similar skills within the graph and then perform fine-tuning to achieve transfer and adaptation, significantly improving learning efficiency.

Finally, to ensure that the new knowledge and strategies acquired during the robot's self-learning process are executable and safe on actual production lines, they must be validated using digital twins. Whenever a robot completes a task transfer, parameter adjustment, or strategy update in the Skill Graph, the corresponding skill must first be simulated in its digital twin production unit[35]. This validates the stability and execution precision of the skill under different scenarios, working conditions, and abnormal disturbances[36]. Through this process, the system can expand from single-point knowledge learning to multi-scenario generalization, while significantly reducing the safety risks and cost pressures associated with trial and error on real production lines.

### **Conclusion**

As 2040 approaches, I believe that with the development of AI and the advancement of robot dynamics, robots combined with AI technology will bring revolutionary changes to the manufacturing industry. This transformation is not only caused by the advancement of science and technology, but also social factors. I believe that robots with AI can change this situation, and in the future, robots will not only do some repetitive mechanical work that has been pre-edited by code but also use artificial intelligence to achieve collaboration with humans, thereby improving the work ability of workers. Enabling robots to autonomously understand and adapt to complex production environments is the direction that all major excellent manufacturing industries need to work hard on, and this challenge is huge. This is not just a breakthrough in one field but requires exploration and research in multiple fields. In summary, in order to become an excellent manufacturing company in 2040, at least it must have integrated optimization of robot technology, artificial intelligence technology and data processing technology. As long as the company actively reserves relevant technology and talents and keeps up with the pace of the times, I believe that it will be able to obtain more efficient production efficiency, produce better products, and thus gain more market share. Although the above technologies seem out of reach for most companies, I believe that with the continuous development of technology, just like personal computers, from tools that can only be used in high-end laboratories to personal computers have become a part of people's lives. Therefore, as long as companies have careful planning, they will be able to successfully cope with the above challenges and set a benchmark for the global manufacturing industry.

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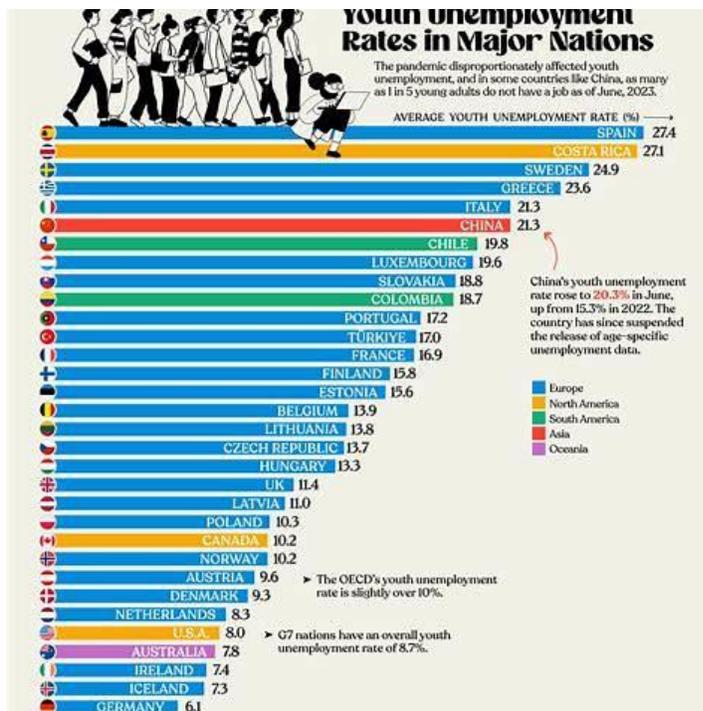
## Appendix

The two versions of LLM used are GPT o3 and GPT 4o. As a non-native English speaker, I used English and Chinese as the languages for the prompts. I use AI to assist me with translation and grammar correction. I also use AI for information retrieval and to help with creating visualizations. All AI-generated texts are for reference only, and only translated texts are chosen for direct use. All the content retrieved by AI has been double checked by me again.

In terms of hallucinations, my experience is that many answers generated by LLMs cannot withstand close scrutiny. This is especially true for highly specialized questions, where the model often produces responses that appear highly convincing but fall apart upon deeper analysis. For prompts, I prefer to input all the materials I have to see if the summary and answer of LLM are consistent with what I imagined. I used LLM to help me quickly read the design essays of previous years. I think this is a good method to help me quickly understand the structure and ideas of other people's articles. When searching for information, LLM will give me some information that I didn't know before, but some of the information is fictitious. I can't find the source of the information when I double check, which is something to pay attention to. The following are the raw outputs.

Me: Please find me a chart that shows trends in young labor in developed countries.

ChatGPT :



Certainly! Here's a chart illustrating youth unemployment rates in major developed countries, based on data from the OECD and China's National Bureau of Statistics as of June 2023:

---

 Youth Unemployment Rates in Major Nations (June 2023)

Country	Youth Unemployment Rate (%)
Spain	27.4
Costa Rica	27.1
Sweden	24.9
Greece	21.3
Italy	21.3
China	19.6
Chile	19.5
Lithuania	19.2
Slovakia	18.0
Colombia	17.9
Portugal	17.2
France	16.6
Finland	15.8
Israel	15.6
Luxembourg	15.0
United States	14.3
Mexico	14.0
Italy	13.8
Czech Republic	13.5
Hungary	13.0
United Kingdom	12.6

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Country	Youth Unemployment Rate (%)
Poland	12.4
Canada	11.3
Norway	10.2
Austria	9.5
Netherlands	8.3
Denmark	7.4
Australia	7.1
Ireland	6.4
Iceland	6.3
Germany	6.1

*Note: Youth refers to individuals aged 15–24.* [ResearchGate+21OECD+21norvanreports.com+21](#)

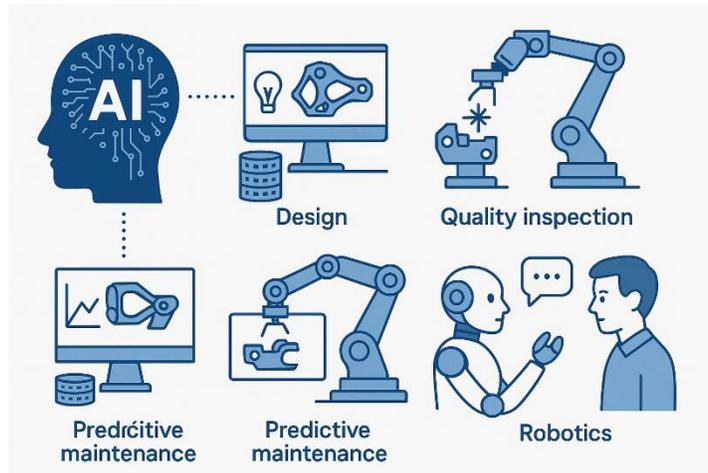
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This chart highlights the varying levels of youth unemployment across developed nations, with countries like Spain and Costa Rica experiencing higher rates, while Germany and Iceland have comparatively lower rates.

For more detailed information and visual representations, you can refer to the full article here: [Charted: Youth Unemployment in the OECD and China. Telegraph](#)

If you need further insights or data on specific countries or trends, feel free to ask!

Me: The rapid progress of artificial intelligence is injecting "cognitive and decision-making brain" into the above-mentioned robots and manufacturing ecosystem. In the product design stage, AI has realized assisted design through topology optimization and material database. In the quality inspection link, computer vision and assembly errors can be found for defective samples at the millisecond level. Predictive maintenance can be achieved by combining technologies such as digital twins in equipment maintenance. With the rapid development of LLM, communication between humans and robots will become more and more smooth. In summary, a series of technological innovations are driving us towards a more intelligent manufacturing direction. Draw a schematic diagram required in a PPT based on this description.



ChatGPT :

Me: 机器人每年会增加多少 预测数值?

ChatGPT :

近年来，全球机器人数量持续增长，尤其是在工业和服务领域。以下是一些关键数据和预测，帮助您了解机器人每年增加的趋势：[世界知识产权组织](#)

### 工业机器人增长趋势

- 根据国际机器人联合会（IFR）的《2024年世界机器人报告》，截至2023年底，全球工厂中运行的工业机器人数量达到4,281,585台，同比增长10%。[世界知识产权组织+5IFR International Federation of Robotics+5 维基百科+5](#)
- 2023年，全球工业机器人年安装量为541,302台，连续第三年超过50万台。[中国政府网+3 世界知识产权组织+3IFR International Federation of Robotics+3](#)
- 预计到2026年，全球每年将安装约70万台工业机器人，显示出持续增长的趋势。[维基百科+2 世界知识产权组织+2 维基百科+2](#)

### 智能机器人市场增长

- 2023年，全球智能机器人市场规模为136.32亿美元，预计到2032年将达到646.08亿美元，预测期内（2024-2032年）的复合年增长率为19.51%。[Fortune Business Insights+4Straits Research+4Mordor Intelligence+4](#)
- 这一增长主要受到人工智能技术进步和各行业对自动化需求增加的推动。[Statzon](#)

## 🔍 仿人机器人未来展望

- 摩根士丹利预测，到 2050 年，仿人机器人市场年收入将达到 4.7 万亿美元，累计销量超过 10 亿台。 [Investors Business Daily](#)
- 特斯拉计划在 2025 年生产数千台仿人机器人，并在随后几年大幅增加产量。 [barrons.com](#)
- 埃隆·马斯克预测，到 2040 年，仿人机器人数量将超过全球人口。 [news.com.au+2](#)  
[澳大利亚人+2 国际电子商情+2](#)

## 📊 总结

类型	当前数量/市场规模	年增长趋势
工业机器人	2023 年全球运行数量约 428 万台	年增长率约 10%，预计 2026 年年安装量达 70 万台
智能机器人市场	2023 年市场规模约 136 亿美元	2024-2032 年复合年增长率约 19.5%
仿人机器人	2050 年预测销量超 10 亿台	未来 25 年内年销量将显著增长

总体来看，机器人技术正迅速发展，预计未来几年将继续保持强劲的增长势头。

Me:

需要英文文献

ChatGPT :

Here are key English-language sources and forecasts regarding the annual growth of robots across various sectors:

## 🤖 Industrial Robots

- Annual Installations: In 2023, global installations of industrial robots reached 541,302 units, marking the third consecutive year with over half a million units installed. [Statzon](#)
  - Operational Stock: The total number of industrial robots in operation worldwide was approximately 4.28 million units in 2023, a 10% increase from the previous year. [Statzon](#)
  - Regional Insights:
    - Asia: Accounted for 70% of all new robot installations in 2023.
    - Europe: Saw a 9% increase in installations, reaching a new high of 92,393 units.
    - Americas: Maintained a robust installation rate of over 50,000 units for the third consecutive year. [Statzon](#)
- 

### Smart Robots (AI-Enabled)

- Market Size: Valued at USD 13.39 billion in 2023, the smart robot market is projected to reach USD 111.6 billion by 2032. [MAXIMIZE MARKET RESEARCH+4SNS Insider+4EIN Presswire+4](#)
  - Growth Rate: Expected to grow at a compound annual growth rate (CAGR) of 26.63% from 2024 to 2032. [EIN Presswire+1GlobeNewswire+1](#)
  - Key Drivers: Advancements in AI, increased automation across industries, and rising demand for robotics in sectors like healthcare, automotive, and consumer goods. [GlobeNewswire](#)
- 

### Humanoid Robots

- Market Forecast: Morgan Stanley projects that the global humanoid robot market could generate \$4.7 trillion annually by 2050, with over 1 billion units in operation by then. [superhuman.ai+5Investors Business Daily+5 特斯拉塔+5](#)
- Adoption Timeline:
  - 2030: Estimated cumulative sales of 900,000 humanoid robots.
  - 2040: Projected sales of 134 million units.
  - 2050: Expected to reach 1.02 billion units. [Investors Business Daily](#)
- Applications: Initial adoption in industrial and logistics sectors, expanding to household and eldercare applications over the next decade. [Investors Business Daily+1Investing.com+1](#)

## Summary Table

Robot Type	2023 Data / Forecasts	Growth Rate / CAGR	Key Sources
Industrial Robots	541,302 units installed; 4.28 million in use	10% annual increase	IFR World Robotics Report 2024
Smart Robots	\$13.39B market size in 2023	26.63% CAGR (2024–2032)	SNS Insider Report
Humanoid Robots	\$4.7T projected market by 2050; 1B units	Significant growth through 2050	Morgan Stanley, Investor's Business Daily

If you need further details or access to specific reports, feel free to ask!

Me: 特朗普 的制造业回流计划叫什么？

ChatGPT :

特朗普的制造业回流计划并没有一个官方的专属名称，但通常被称为“制造业回流”（Reshoring）或“让美国制造业再次伟大”（Make American Manufacturing Great Again），是其“美国优先”（America First）政策的核心组成部分。[腾讯新闻+1](#) [观察者网+1](#)

在 2025 年，特朗普政府推动制造业回流的主要措施包括：

- 高额关税：对从中国等国家进口的商品征收高达 60% 的关税，旨在迫使企业将生产线迁回美国。[观察者网+4](#) [腾讯新闻+4](#) [新浪财经+4](#)
- 税收优惠：提议将在美国本土生产的企业的公司税率从 21% 降至 15%，以激励企业在美国投资建厂。[新浪财经+4](#) [AP News+4](#) [Gryphon Citadel+4](#)
- 设立制造业特区：计划在联邦土地上建立“超低税收和监管”的制造业特区，为在美国生产的企业提供更多优惠。[POLITICO+1](#) [Reuters+1](#)
- 任命制造业大使：任命专门的“制造业大使”，负责游说全球制造商将工厂迁至美国。[Goover+2](#) [POLITICO+2](#) [Reuters+2](#)

此外，特朗普还强调通过减少监管、降低能源成本等手段，吸引企业回流美国。

[Centurion Publishing+1](#) [观察者网+1](#)

虽然这些政策在短期内吸引了一些企业的投资承诺，但也引发了对消费者成本上升和全球供应链稳定性的担忧。

综上所述，特朗普的制造业回流计划并没有一个特定的官方名称，但其核心目标是通过一系列政策手段，推动制造业回归美国本土。[Robotics & Automation News+1 新浪财经+1](#)

Me:

给我找一些现在工厂智能化 和引入机器人的 案例。

ChatGPT 说:





以下是当前工厂智能化和引入机器人技术的几个典型案例，涵盖了从传统制造业到新兴高科技企业的实践：[物联网智库+1Reuters+1](#)

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## CN 中国案例

### 1. 三一重工 18 号智能工厂

三一重工的 18 号厂房是亚洲最大的单体智能制造工厂，建筑面积达 10 万平方米。该工厂实现了从产品设计、工艺规划到生产交付的全流程数字化和自动化：[物联网智库](#)

- 部署了自动化立体仓库和 AGV（自动导引车）系统，实现物料的自动配送。
- 集成了 MES（制造执行系统）和 ERP 系统，实现订单到生产的无缝衔接。
- 通过工业物联网（IoT）技术，采集和分析生产数据，优化生产流程。[澎湃新闻+2](#)  
[物联网智库+2 中国 AGV+2 商业新知+1 物联网智库+1](#)

改造后，工厂的生产效率提高了 24%，生产周期缩短了 28%，不良品率下降了 14%。[物联网智库](#)

## 2. 美的集团 智能精益工厂

美的集团在其苏州分厂引入了智能化系统，实现了人机协作的高效生产：[中国 AGV+1moma-hz.com+1](#)

- 采用 24 台码垛机器人和 AGV 系统，实现了多品类产品的混流运输。
- 建立了智能立体仓库，入库能力达到每小时 3600 台，日入库量可达 4.5 万台。
- 通过智能仓储系统，节省了 85% 的占地面积，年运营成本降低约 500 万元。[中国 AGV+1 物联网智库+1](#)

此外，美的还通过收购德国库卡公司，进一步提升了其在工业机器人领域的技术实力。[中国 AGV](#)

## 3. 中国 AI 驱动的人形机器人制造

中国正在积极推进 AI 驱动的人形机器人在制造业的应用：[Reuters](#)

- 初创公司如 AgiBot 和 Unitree 正在开发具备自主感知和决策能力的人形机器人。
- 政府投入超过 200 亿美元支持该领域的发展，包括设立 1370 亿美元的专项基金。
- 目标是到 2030 年将人形机器人的生产成本从目前的约 3.5 万美元降低到 1.7 万美元。[中国 AGV+2Reuters+2 虎嗅+2](#)

这些机器人被视为解决劳动力短缺和提高制造业自动化水平的关键。[Reuters](#)

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## 其他国家案例

### 4. 通用汽车 上海金桥工厂

通用汽车在上海的金桥工厂被誉为中国最先进的制造工厂之一：[澎湃新闻](#)

- 工厂内部署了 386 台机器人，主要负责焊接等重复性高的工作。
- 尽管自动化程度高，但仍保留了少量工人进行管理和维护。
- 每天可生产约 80 台凯迪拉克汽车。[澎湃新闻](#)

该工厂展示了高度自动化与人工协作的制造模式。

## 5. 京东“亚洲一号”无人仓

京东在上海建立的“亚洲一号”无人仓是其物流自动化的代表作：[澎湃新闻](#)

- 仓库内部署了大量 AGV 和机器人，实现了从订单处理到包裹分拣的全流程自动化。
- 在“双 11”等购物节期间，处理订单的能力大幅提升，有效应对高峰期的物流压力。

该项目展示了电商平台在物流领域的智能化升级。

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如果您对某个行业或具体技术（如 AGV、MES 系统、AI 视觉识别等）感兴趣，我可以为您提供更详细的案例分析或技术解析。

Me:

美国当地呢？

ChatGPT :





以下是一些美国本土制造业在智能化和引入机器人方面的典型案例，涵盖了从传统制造到物流、食品加工等多个领域：

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### 1. Agility Robotics 的人形机器人“Digit”投入实际生产

位于俄勒冈州的 Agility Robotics 推出了人形机器人“Digit”，专为仓储和物流场景设计。2024 年，Digit 已在佐治亚州的 Spanx 工厂投入使用，负责将箱子搬运到传送带上。Agility 采用“机器人即服务”（RaaS）模式，客户按月支付费用，涵盖机器人本体、工作单元和操作软件。该公司还与亚马逊合作，在其仓库中部署 Digit，以缓解劳动力短缺问题。 [维基百科+1Business Insider+1Business Insider](#)

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## 2. 亚马逊的“Vulcan”机器人具备触觉能力

2025 年，亚马逊在德国的“Delivering the Future”活动中展示了名为“Vulcan”的机器人，该机器人具备触觉能力，能够处理约 75% 的仓库物品。Vulcan 利用人工智能识别并通过触觉操控物体，超越了依赖吸力和视觉的现有机器人系统。它可以在不同的货架层级存放物品，减少了人类工人的体力负担。 [卫报+1news+1](#)

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## 3. Rumiano Cheese 公司引入 Formic 的机器人服务

加州的 Rumiano Cheese 公司在应对特朗普政府新关税政策带来的成本上升和供应链不确定性时，选择引入 Formic 提供的机器人服务。Formic 提供“机器人即服务”模式，客户无需前期投资即可部署机器人。截至 2025 年初，Formic 的机器人已在美国 100 多家工厂中部署，处理超过 12 亿件产品，客户使用率在 1 月至 2 月间增长了 17%。 [Business Insider](#)

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## 4. 美国工厂机器人部署创历史新高

根据国际机器人联合会（IFR）2024 年 9 月的报告，美国工厂中的工业机器人数量达到 381,964 台，同比增长 12%。2023 年，美国共安装了 44,303 台工业机器人，主要集中在汽车和电子电气行业。 [techb2b.com+2IFR International Federation of Robotics+2todaymedicaldevelopments.com+2IFR International Federation of Robotics](#)

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## 5. AI 与机器人结合实现预测性维护

美国制造商越来越多地利用人工智能和机器人技术进行预测性和处方性维护，以减少设备故障带来的损失。例如，Aquant 和 Gecko Robotics 等初创公司开发了基于人工智能的平台和检查机器人，帮助可口可乐和西门子能源等公司减少停机时间并优化维护工作。 [Business Insider](#)

如果您对某个行业或具体技术（如协作机器人、AGV 系统、AI 视觉识别等）感兴趣，我可以为您提供更详细的案例分析或技术解析。

Me: what is Embodied Intelligence

ChatGPT :

Embodied Intelligence is a concept in robotics, artificial intelligence (AI), and cognitive science that refers to intelligence that emerges from the interaction between an agent's body, brain, and its environment. Rather than viewing intelligence as something purely computational or brain-based, embodied intelligence emphasizes that physical form (the body) and real-world interaction are essential to intelligent behavior.

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Key Ideas Behind Embodied Intelligence:

1. Intelligence is not just in the brain (or code):
    - The body contributes to cognition—shape, sensors, actuators, and morphology all influence behavior.
    - For example, a gecko's ability to climb is not just about control algorithms but about the physics of its toes.
  2. Sensorimotor coupling:
    - Intelligent agents perceive the environment and act upon it in a tightly coupled loop.
    - Action and perception are inseparable in real-time interaction.
  3. Situatedness:
    - Intelligent behavior is context-dependent. A robot's "smart" response depends on its physical setting.
  4. Learning by doing:
    - Embodied agents learn not through abstract data alone but by exploring, failing, and adapting within a physical (or simulated physical) world.
- 

In Robotics:

- A robot with embodied intelligence learns to walk, manipulate objects, or collaborate with humans by relying on its sensors, motors, and body dynamics.
- Famous examples include:
  - Boston Dynamics robots (e.g., Spot, Atlas)
  - Soft robotics
  - Legged robots that learn balance and locomotion via reinforcement learning

#### Contrast with Traditional AI:

Traditional AI	Embodied Intelligence
Symbolic/logical reasoning	Physical interaction and adaptation
Disembodied (just software)	Grounded in a physical body
Pre-programmed responses	Adaptive, learned behaviors
Often static datasets	Real-time, dynamic sensory input

#### Related Concepts:

- Morphological computation: Using the body's shape to simplify control (e.g., passive walkers).
- Embodied cognition: In psychology, the idea that the mind is shaped by the body's interactions.

Would you like a real-world robotics example or how it relates to AI training strategies like reinforcement learning?

Me: 根据这个描述 给我绘制一个 ppt 当中的示意图。对于 2040 制造业，机器人的自主学习能力也是一个有待解决的问题。需要一个自主的知识更新和性能提升的机制。制造业作为一个产品更新迭代速度快尤其在消费电子、汽车等领域，产品更新周期可能以月计，而非年计，为了适应这快节奏的时代，机器人的自我学习能力显的尤为突出。因此，建立一套完整的机器人自我学习体系，是实现制造业 2040 的关键支撑。首先，机器人学习的第一步是数据获取机制的自动化与结构化。要让机器人“看懂”生产过程，就需要从视觉、力觉、语音、操作记录等多个维度持续采集原始数据，并且为了之后的稳定训练，

需要将采集的数据自动结构化，可用于直接拿去训练。更进一步，还需构建一个知识持续更新机制。机器人学习不能停留在一次性任务，而应具备“任务迁移能力”与“知识复用能力”。例如，学会了安装盖子之后，不仅仅可以安装一种盖子，也可以安装类似这一类的盖子。这需要在后端建立一个机器人技能库，每个技能节点记录其学习来源、适用条件、成功率及人类反馈，这一 Skill Graph 可以与机器人与人类知识共享平台结合。新任务到来时，机器人可先在图中匹配相似技能，再通过微调进行迁移适配，大幅提高学习效率。最后，为确保机器人自我学习过程中所获得的新知识、新策略在真实产线上具备可执行性与安全性需要结合 digital twins 来验证更新的知识体系能否真实有效，每当机器人在技能库中完成一次任务迁移、参数微调或策略更新后，首先需将该技能在其对应的虚拟孪生生产单元中进行仿真测试，验证其在不同场景、不同工况、不同异常扰动下的表现稳定性与执行精度。通过这一过程，系统可实现从单点知识学习向多场景泛化能力的扩展，同时也极大降低了“在真实产线试错”的安全风险与成本压力。

### ChatGPT

