

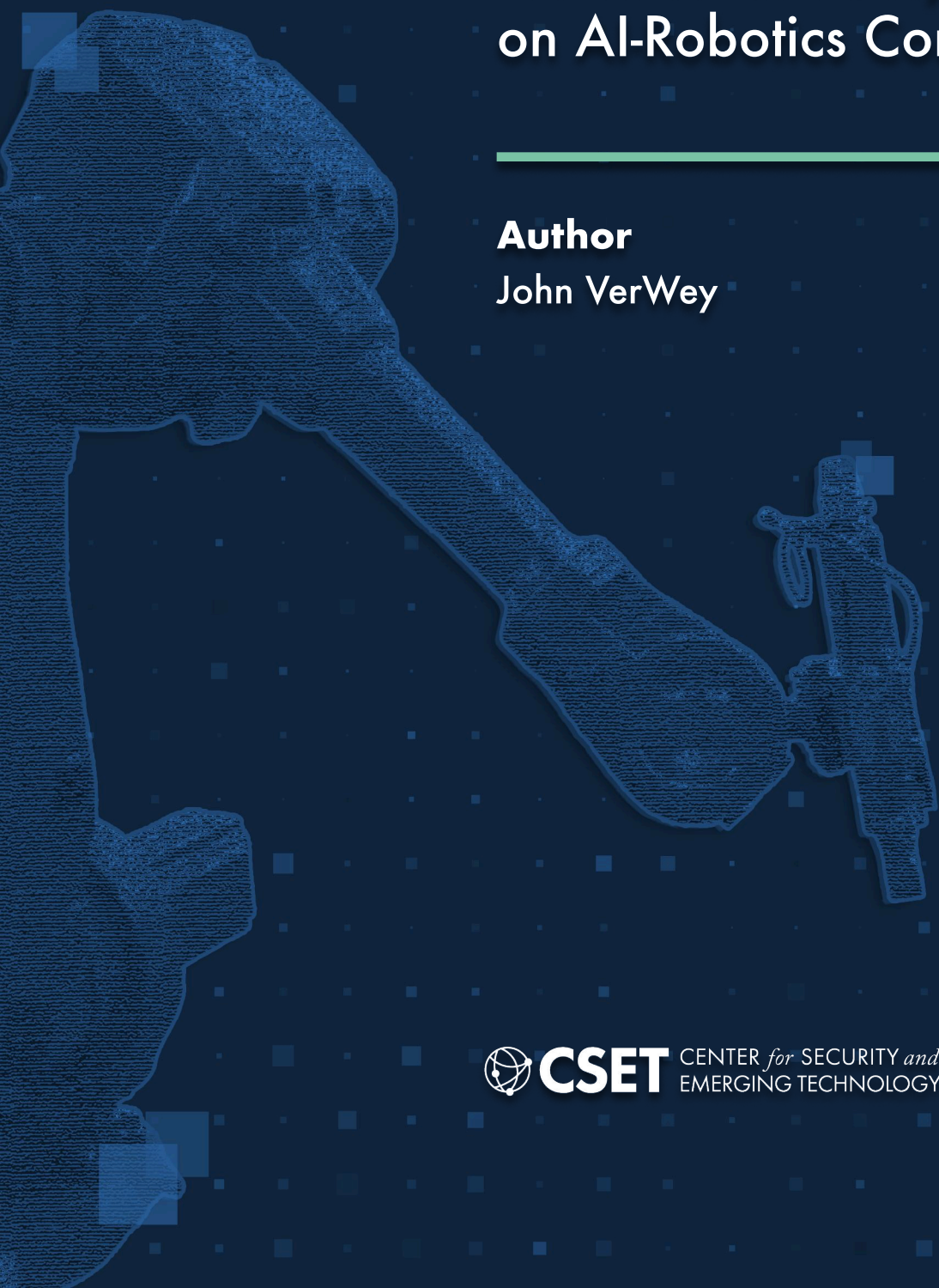
Issue Brief

Physical AI

A Primer for Policymakers
on AI-Robotics Convergence

Author

John VerWey



Executive Summary

While the world has focused its attention for the last three years on generative artificial intelligence, chatbots, and new model releases coming from frontier AI labs, a quieter revolution is taking place that many believe represents the next stage in AI development: the arrival of Physical AI. Like the iPhone's introduction in 2007, AlexNet's victory in the 2012 ImageNet competition, and ChatGPT's release in 2022, analysts and industry representatives believe a similar breakthrough is imminent.

Physical AI “lets autonomous systems like robots, self-driving cars, and smart spaces perceive, understand, and perform complex actions in the real (physical) world.”¹ NVIDIA has declared “in the near future, everything that moves, or that monitors things that move, will be autonomous robotic systems.”² OpenAI reportedly re-opened its robotics division in early 2025 to capitalize on the convergence of AI and robotics, while startups from Shanghai to Silicon Valley building the “brains” of robots are raising hundreds of millions of dollars.³ Electric vehicle makers Tesla and XPeng are racing to develop humanoid robots of their own.⁴ Meanwhile Amazon, which reports having one million robots in operation today, believes “Physical AI is about to change everything for robotics [including] autonomy, manipulation, sortation, and computer vision.”⁵ Adding to this enthusiasm, analysts at Morgan Stanley assert the market for humanoid robots will grow from tens of millions of dollars today to reach \$5 trillion by 2050.⁶

Yet the convergence of AI and robotics is so new that the field lacks a shared name, to say nothing of a mature technology stack. Some companies call this convergence “embodied AI” while others prefer “physical AI,” “embodied machine intelligence,” or “generative physical AI.”⁷ It is not at all clear if the hype around AI progress can translate into robots finding their way through the physical world: autonomous three-dimensional navigation of dynamic environments requires a mature software, hardware, and data ecosystem that simply does not exist at scale today. NVIDIA states part of the problem plainly: “Large language models are one-dimensional, able to predict the next token, in modes like letters or words. Image- and video-generation models are two-dimensional, able to predict the next pixel. None of these models can understand or interpret the 3D world.”⁸

The primary challenges facing Physical AI are the same ones that have troubled the robotics industry for generations: technology barriers and economic barriers. Parts of the robotics supply chain remain in their industrial infancy, key hardware technology breakthroughs remain elusive, and even recent advances are not ready for scalable manufacturing. Batteries, motors, sensors, and actuators evolve far more slowly than

algorithms and software, and scalable manufacturing requires large amounts of patient capital. In addition, much of the supply chain for robotics components is commoditized, and the relatively slim margins dissuade innovative startups from competing with established incumbents. Adding to these challenges, each robotics company is pursuing its own unique approach, meaning the supply chain of components and parts remains largely non-standardized, hampering scalability and adding cost. The gap between impressive demonstrations in controlled environments and the promise of millions of affordable robots acting independently as they navigate the world is enormous.

The focus of this paper is on characterizing the convergence of Physical AI and robotics, its underlying supply chain, and identifying competitive advantages as well as constraints. This paper provides background on the technology and describes the ecosystem and supply chain of hardware and software suppliers supporting the technology. It then characterizes competitiveness worldwide using bibliometrics, patents, investment data, and industry reports to determine firm leadership, constraints, and breakthroughs across the technology ecosystem from AI foundation models and software to hardware component and robot manufacturers as well as end users. It concludes with a summary of drivers and positive trends, as well as constraints and limiting trends with an eye towards opportunities policymakers interested in promoting the tech industry's next breakthrough moment can consider.

This paper builds on previous CSET research looking at the robotics patent landscape to characterize competitiveness using CSET's [Map of Science](#) and separate research that proposed a methodology for identifying and characterizing an emerging technology.⁹ It concludes by introducing a template that could be used by policymakers interested in global competitiveness assessment of other emerging technologies.

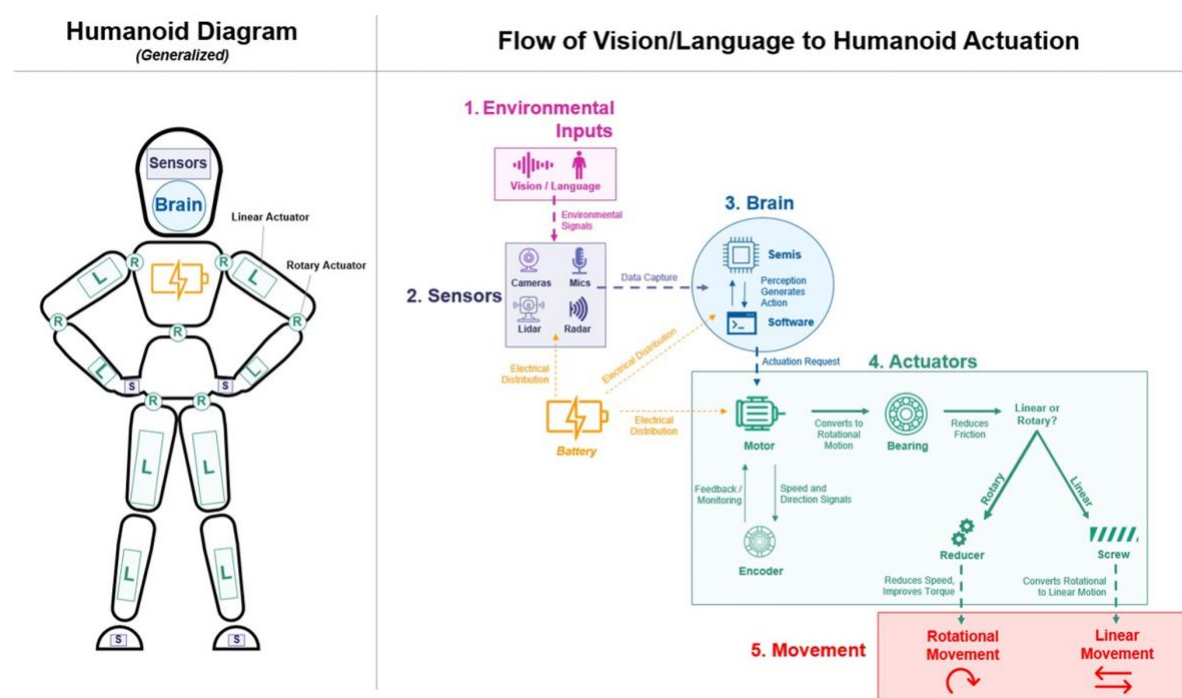
Table of Contents

Executive Summary.....	1
Introduction.....	4
Scoping and Defining the AI-Robotics Supply Chain.....	7
Manifesting Physical AI: Describing The Robotics Hardware Supply Chain.....	7
Building Sentient Silicon: AI Advances and the Robotics Software Supply Chain	12
Competitiveness Assessment: AI-Robotics Convergence.....	15
Innovation Ecosystem Mapping: AI-Robotics Research, Patents, and Investment	15
ETO Research Almanac: Publications and Patents	15
ETO Country Activity Tracker: Investment Data	17
Characterizing Relative National Standing: AI-Robotics Market Analysis.....	18
AI-Robotics Foundation Models and the Software Ecosystem.....	19
Robotics Hardware Components	23
Robot Manufacturers	25
Robot Deployment and End Users	26
Conclusion: Technology Trends Assessment.....	29
Author.....	31
Acknowledgments.....	31
Appendix 1. Template for Technology Competitiveness Assessment:	
Technical Level-Setting	32
Endnotes.....	35

Introduction

Physical AI equips autonomous machines with cognitive reasoning and spatial knowledge, enabling them to learn from their interactions and respond in real time.* These autonomous machines take many different forms, and the field is emerging in near real time such that the final, optimal form(s) Physical AI takes may not yet be invented. Current enthusiasm for Physical AI primarily centers on integration with robotics. In general, humanoid, industrial, and autonomous mobile robots (AMRs) are emerging as leading instantiations of Physical AI.¹⁰ These robots rely on a technology ecosystem to support their “brain” (simulation and vision software, data science, semiconductors, and AI models (including LLMs and multimodal foundation models)) as well as their “body” (sensors, batteries, (more) semiconductors, actuators, and other physical hardware).¹¹

Figure 1: Notional Hardware Inputs for a Humanoid Robot



Source: Morgan Stanley Research.¹²

* This definition is derived from: https://www.cadence.com/en_US/home/explore/physical-ai.html. The terms Physical AI and Embodied AI are closely related and frequently used interchangeably. Physical AI typically refers to AI systems that can perceive, reason about, and interact with the physical world. Embodied AI usually refers more specifically to AI systems that have a physical form or “body” that allows them to directly experience and interact with the world. The key difference is that physical AI is a broader concept that includes AI systems that reason about or affect the physical world.

Robots that assist with everything from factory automation to hazardous work environments have been a dream for decades. This dream has repeatedly run into the reality that core hardware and software innovations underlying the robotics ecosystem have matured at different times. Until recently, collecting the data and compute necessary to train robot systems in simulated environments was expensive, training robots in the real world took too long, and simulation-based training resulted in robots ill-equipped for real-world settings.¹³ Adding to these challenges, no standard bill of materials to build robots exists, making for multiple heterogeneous ecosystems of components and suppliers, each pursuing their own preferred solution.

A recent convergence of AI advances and improvements in the underlying hardware supply chain that supports robotics accounts for the growing sense that a breakthrough in Physical AI is imminent. This change in sentiment has encouraged large investments to accelerate AI and robotics convergence, both within large public companies and the venture capital and startup communities.¹⁴ The sum of these advances suggest the emergence of a positive feedback loop whereby better AI models improve robot capabilities, improved prospects for deployment of AI-empowered robots attracts investment, increased investment allows startups and established firms to mature and scale hardware production, and better hardware allows for improved data collection that can feed back in to enhanced AI improvements that optimize robot performance. In theory, this feedback loop promises a new scaling law similar to Moore's Law in the semiconductor industry: consistent improvement in robot capability and performance at steady to declining costs.¹⁵

Policymaker interest in AI and AI applications remain high. This interest is motivated by economic and social factors as well as national security. Within the context of Physical AI, AI-robotics convergence offers a potential solution to looming labor shortages, especially in manufacturing, logistics, and healthcare industries. Likewise, the economic appeal of a robot workforce that can work continuously and consistently with a level of precision that exceeds human ability holds clear economic appeal for manufacturers. Additionally, robots can work in dangerous environments unsafe for humans, promising to reduce the thousands of fatal occupational injuries that happen in the United States alone annually.¹⁶ Finally, military interest in robotic applications has persisted for decades and remains high, particularly in the United States and China.¹⁷

Yet despite the favorable convergence of AI-driven breakthroughs and intense public interest, the robotics revolution has not arrived on time, and further delays seem inevitable. New industrial robot installations declined worldwide from 2023-24 in spite of hoped-for progress that automation would alleviate impending manufacturing

labor shortages in the U.S., China, and elsewhere.¹⁸ Industrial robots well-suited to work with solid physical objects (boxes, car parts, consumer electronics) fail spectacularly when presented with soft and stretchy objects common in textile manufacturing.¹⁹ Humanoid robots in 2026 can complete half marathons, dance in festivals, and walk with a human-like gait, but they struggle to independently navigate down a street, cannot handle tasks requiring dexterity, and rarely exceed human performance in warehouse settings.²⁰ Robots continue to do best when designed, trained, and deployed for discrete tasks and fail when forced to adapt. It is not clear how much the introduction of AI can and will resolve these persistent challenges.

Against the backdrop of these technical headwinds, economic competition over AI in general is adding urgency to AI-robotics progress specifically. Chinese firms are leveraging a diverse, flexible, and scalable manufacturing base to take the lead in the supply of key robotics hardware components, developing a wide variety of robots domestically, and leading the world in robot installations. U.S. firms like NVIDIA and Meta are releasing open-source AI-robotics models in the hopes that they can seed an innovation ecosystem with their preferred software (much like NVIDIA accomplished with its GPUs and CUDA toolkit), and U.S. investment in robotics startups is surging. Firms in Asia and Europe control the supply of key hardware components and software and, in some cases, continue to enjoy first-mover advantages as robotics end users.

This paper begins by mapping the robotics supply chain that supports Physical AI. “Manifesting Physical AI” and “Building Sentient Silicon” describe the hardware and software supply chains underlying AI-robotics convergence and summarize recent breakthroughs. Next, the paper presents a competitiveness assessment of AI-robotics convergence from two perspectives. First, using resources from CSET’s [Emerging Technology Observatory](#), bibliometrics, investment data, and patent filings are analyzed to identify countries and companies leading in AI-robotics convergence.²¹ Second, the specific segments of the supply chain introduced earlier are evaluated with an eye toward company- and country-level leadership. This section expands on a 2024 RAND methodology and combines it with previous CSET research as well as CSET bibliometric resources to quantitatively and qualitatively assess leadership, breakthroughs, roadblocks and signals of Physical AI emergence.²²

Scoping and Defining the AI-Robotics Supply Chain

This section presents the basic industry mapping of the Physical AI ecosystem, focusing on hardware and software in particular. The first section (“Manifesting Physical AI”) defines what a robot is (and is not), introduces the different forms robots currently take, describes the core hardware subcomponents on which all different varieties of robots rely, and summarizes recent component breakthroughs that have contributed to the current enthusiasm around AI and robotics. The second section (“Building Sentient Silicon”) describes the various instantiations of software that support AI-robotics convergence. It describes breakthroughs in large language models, multimodal models, reinforcement learning, and simulation-to-reality transfer that have contributed to the current enthusiasm for AI. In addition, it describes the various layers of compute underlying these software advances (a key enabling part of this supply chain) as well as the role of real-world and synthetic data and robotics simulation and operating system software.

Manifesting Physical AI: Describing the Robotics Hardware Supply Chain

The leading international robotics association defines a robot as “an actuated mechanism programmable in two or more axes with a degree of autonomy, moving within its environment, to perform intended tasks.”²³ Helpfully, it also explains specifically what they do not consider a robot: software, drones, voice assistants, autonomous cars, ATMs, and smart washing machines are not considered robots.* In the context of Physical AI, robots are often thought of as autonomous mobile robots (AMRs), manipulator arms or humanoids.²⁴ There are dozens of other types of robots, including quadruped (dog-like) robots, medical robots (designed to assist with surgery, for example), and collaborative robots (or “cobots,”) that work with a human-in-the-loop, typically in industrial environments. In general, all robots typically consist of five core hardware systems:

- **Structural components** provide the physical framework, support, and protection for all other systems. For humanoid robots, as the name implies, these structural components are anthropomorphic and generally are designed to provide joint, weight distribution, movement, and manipulation that mimics human form.
- **Actuation systems** generate and control physical movement. For industrial robotics, these systems rely on precision motors that can operate repeatedly at




* There is room for disagreement about what constitutes a robot based upon this definition, but for the sake of accurately representing the data IFR collects, this paper uses the IFR definition when referring to statistics on robotics adoption cited in subsequent sections.

high speeds, manipulating heavy loads. For humanoid robots, these systems can require more precision and less load-bearing ability.

- **Power systems** provide and distribute energy to all systems. Industrial robots are usually connected to a fixed power supply, while humanoid robots and AMRs rely on batteries.
- **Computing systems** process sensor data and control robot behavior, with humanoid robots having the most complex compute stack and industrial robots among the least compute-intensive.
- **Sensor systems** perceive the environment in which the robot operates as well as its internal state and include cameras, sensors for depth perception, torque/force, joint position, and LiDAR.

The robotics hardware supply chain suffers from a lack of standardization, which hampers economies of scale for component suppliers who are instead forced to supply hundreds or thousands (at most) of different products to meet demand. This in turn limits the component supplier margins and their ability to reinvest in future advances. As Table 1 shows, while all robots share these five types of components in general, the specification to which each of these components is rated, their operating environment, and intended end use necessitate a high level of customization. Additionally, more complex robots inherently require more materials, gears, mechanisms, and compute, all of which drive up costs.

Table 1: Hardware Bill of Materials for Three Types of Physical AI-Powered Robots


	Humanoid Robot	Industrial Robot	Autonomous Mobile Robot
Example			
Physical Structure	<ul style="list-style-type: none">○ Full-body frame with ~20-30 degrees of freedom○ Anthropomorphic proportions and joint designs○ Lightweight materials (carbon fiber, aluminum alloys)	<ul style="list-style-type: none">○ Heavy-duty fixed base○ Rigid arm links (4-7 segments)○ Industrial steel, aluminum	<ul style="list-style-type: none">○ Wheeled-base platform○ Payload structure○ Protective bumpers/housing
Actuators	<ul style="list-style-type: none">○ 20-30+ high-performance electric motors/actuators○ Custom gearboxes with high torque density○ Specialized joint mechanisms (series elastic, direct drive)	<ul style="list-style-type: none">○ 6-7 high-precision servo motors○ Industrial gearboxes○ Braking systems	<ul style="list-style-type: none">○ 2-4 drive motors with wheels○ Optional lift mechanism
Power	<ul style="list-style-type: none">○ High-density battery packs (2-4 kWh typical)○ Power distribution system	<ul style="list-style-type: none">○ Fixed power supply (typically no battery)	<ul style="list-style-type: none">○ Battery pack (1-3 kWh typical)

	<ul style="list-style-type: none"> ○ Thermal management system 	<ul style="list-style-type: none"> ○ Electrical cabinet 	<ul style="list-style-type: none"> ○ Charging interface
Compute	<ul style="list-style-type: none"> ○ High-performance onboard computer (often multiple) ○ GPU/TPU for AI inference ○ Multiple microcontrollers for low-level control 	<ul style="list-style-type: none"> ○ Industrial controller ○ Safety PLC ○ Teach pendant interface 	<ul style="list-style-type: none"> ○ Navigation computer ○ Motor controllers ○ Fleet management interface
Sensors	<ul style="list-style-type: none"> ○ Stereo/depth cameras (2-4) ○ Force/torque sensors at key joints ○ IMUs for balance ○ Tactile sensors for hands/grippers ○ Microphones for audio input 	<ul style="list-style-type: none"> ○ Encoders at each joint ○ Limited external sensing ○ Optional vision system for guidance 	<ul style="list-style-type: none"> ○ LiDAR for navigation (1-2 units) ○ Cameras for object detection ○ Proximity sensors ○ Wheel encoders
Cost Range	\$50-\$500k	\$20-150k	\$15-80k

Source: For the complete list of data sources for this table, please refer to the endnote.²⁵

The technology for each of these hardware components matured at different times, though recent breakthroughs across the hardware stack are adding to industry and investor enthusiasm (Table 2). Actuators have gotten more powerful and accurate, sensors are decreasing in cost and increasing in quality, commercial off-the-shelf microelectronics contain more than enough compute for most current robots, and battery technology continues to improve. Recent research from financial analysts suggests that for humanoid robots, only certain sensors (6D torque sensors, tactile sensors) and actuating components (planetary roller screws) currently lack mass producibility such that they present a bottleneck to overall humanoid robotics manufacturing scaling.²⁶

Table 2: Breakthroughs and Advances Hardware for Physical AI and Leading Component Suppliers

<p>Improved Actuators: More power-dense, responsive, and affordable electric motors and hydraulic systems.</p>	<p style="text-align: center;">COMPONENT SUPPLIERS & INTEGRATORS</p> 
<p>Sensor Technology: Better cameras, depth sensors, tactile sensors, and inertial measurement units (IMUs) at lower costs.</p>	
<p>Compute Integration: More powerful onboard computing enabling real-time decision-making.</p>	
<p>Battery Technology: Improvements in energy density are making longer operation times practical, especially for humanoid robots and AMRs.</p>	
<p>Materials Science: Advanced lightweight, strong materials for robot construction.</p>	

Source: For the complete list of data sources for this table, please refer to the endnote.²⁷

This is an optimistic view of the hardware supply chain. Other recent research has observed that imitation of hand-like movements and dexterous manipulation in humanoid robots remains quite difficult due to both hardware and software constraints.²⁸ More generally, the highest-performing robots continue to be those whose hardware and software stack is optimized for specific tasks such as sorting boxes or moving pallets in a warehouse. Generalizable AI-powered robots capable of, for example, working on an automotive assembly line in one moment and pivoting to sort through a bucket of hundreds of mismatched screws the next, remain aspirational. These constraints will be discussed in greater detail below.

Building Sentient Silicon: AI Advances and the Robotics Software Supply Chain

At the same time the hardware stack has matured, recent advances in AI have changed how robots are trained, how they learn, how they interpret real-world feedback, and the sources of data on which robots can “learn,” adding to overall enthusiasm that AI is accelerating the arrival of a breakthrough moment for robotics. As NVIDIA’s CEO recently put it, “we need to build the AI to build the robots.”²⁹ Specifically, advances in Large Language Models, Multimodal Foundation Models, Reinforcement Learning (RL), and Simulation-to-Reality (Sim2Real) Transfer suggest that robotic reasoning, perception, skill acquisition, and training are poised for categorical improvement. The software supply chain that supports robotics development lacks clear definition and theoretically could extend all the way upstream to the instruction set architectures and electronic design automation tools used by chip designers to optimize the performance of compute for robotics. This section takes a narrower view and focuses on the specific AI algorithmic breakthroughs that have occurred recently to support AI-robotics convergence as well as the underlying layer of compute that enables these breakthroughs.

Within the context of robotics software for training and inference, LLMs provide high-level reasoning, multimodal models handle perception and object understanding, RL enables skill acquisition, and sim2real makes training feasible at scale (Table 3).³⁰ Together, they create a technical ecosystem where robots can understand what humans want (LLMs), perceive the relevant aspects of their environment (multimodal models), learn how to accomplish tasks efficiently (RL), and do so using relatively inexpensive simulated data (sim2real) instead of expensive real-world training. As successive breakthroughs have occurred in recent years across each of these areas, researchers believe the day is fast approaching when general-purpose Physical AI systems may finally be commercially viable across multiple domains rather than just in structured industrial settings.

Table 3: Breakthroughs and Advances in Software/Algorithms for Physical AI³¹

<p>Large Language Models (LLMs): Successive generations of LLMs demonstrated that foundation models could serve as reasoning engines for robots, enabling them to understand verbal human instructions in real time, decompose complex tasks into simpler steps, and adapt plans when encountering obstacles.</p>
<p>Multimodal Foundation Models: Systems that integrate vision, language, and reasoning provide a more holistic understanding of physical environments. These models enable robots to see objects, understand what they are, reason about their properties, and manipulate them appropriately. For example, a robot can visually identify an unfamiliar tool, understand its purpose from its visual features, and determine how to use it—all without prior specific training on that exact tool.</p>
<p>Reinforcement Learning: Modern RL (e.g., offline RL, model-based RL) approaches can learn from diverse datasets of robot experiences and use predictive models to imagine outcomes before taking actions, reducing the amount of real-world data needed for robots to master skills like manipulation and locomotion.</p>
<p>Sim-to-real transfer: Better simulation tools and transfer learning techniques bridged the gap between simulated training and real-world deployment, addressing a fundamental economic challenge in robotics: the cost and time required to collect real-world training data. By shifting most training to simulation, developers can iterate quickly, test in diverse scenarios, and train data-hungry deep learning models without the constraints of physical training environments.</p>

Source: For the complete list of data sources for this table, please refer to the endnote.³²

Importantly, all of the aforementioned advances are contingent on an increasingly mature supply chain of compute (including GPUs, CPUs, and MCUs, among many other kinds) on which this software runs. In essence, the software stack relies on one computer to train the AI, one computer to deploy the AI, and another computer to serve as a digital twin (where the AI can go to practice/employ its training).³³ While this is a simplistic representation of the resources required, it illustrates the three key domains in the software supply chain and how interconnected they are:

- **Compute for Training:** For training, cutting-edge AI models leverage distributed computing clusters with thousands of specialized accelerators (e.g., NVIDIA GPUs and custom ASICs like Alphabet's TPUs) that enable efficient processing of petabytes of multimodal data using techniques like model parallelism and pipeline parallelism.
- **Compute for Inference:** Deployment on robotics platforms employs a heterogeneous computing architecture with energy-efficient edge processors (like NVIDIA Jetson Orin or other specialized AI accelerators) that handle real-time inference, sensor fusion, and control loops within power and thermal constraints while maintaining low latency for safety-critical operations.
- **Compute for Mod/Sim:** Meanwhile, digital twin environments rely on high-performance compute clusters that simulate physics, sensor data, and environmental interactions with increasing fidelity using specialized middleware that bridges the simulation-reality gap, enabling reinforcement learning algorithms to train robots in accelerated virtual environments before transferring policies to physical robots through sim-to-real techniques.

In addition to this AI-centric part of the software supply chain, there is also a separate and distinctive ecosystem of developers and vendors that provide robot-specific software for operating systems, modeling and simulation, computer-aided engineering, and data management solutions (including reality capture and synthetic data generation). To the extent there is overlap with ongoing Physical AI developments, this ecosystem and leading vendors will be discussed in the following section assessing competitiveness.

Competitiveness Assessment: AI-Robotics Convergence

This section provides a competitiveness assessment of AI-robotics convergence. Methodologically, it borrows from prior CSET research focusing on mapping the supply chains of emerging technologies as well as research from RAND Corporation on Net Technical Assessment and, separately, analytic approaches for conducting comparative technology assessments.³⁴ The focus of this section is to conduct what RAND refers to as “technical level-setting,” the first step of a net technical assessment. This consists of scoping a set of technologies, assessing the technologies’ technical state of the art and trends, and capturing relative national standing.³⁵ The goal of this section is to provide an analytic baseline for the technology area. In support of this goal, a template is provided in Appendix 1 which summarizes each of the elements.

Innovation Ecosystem Mapping: AI-Robotics Research, Patents, and Investment

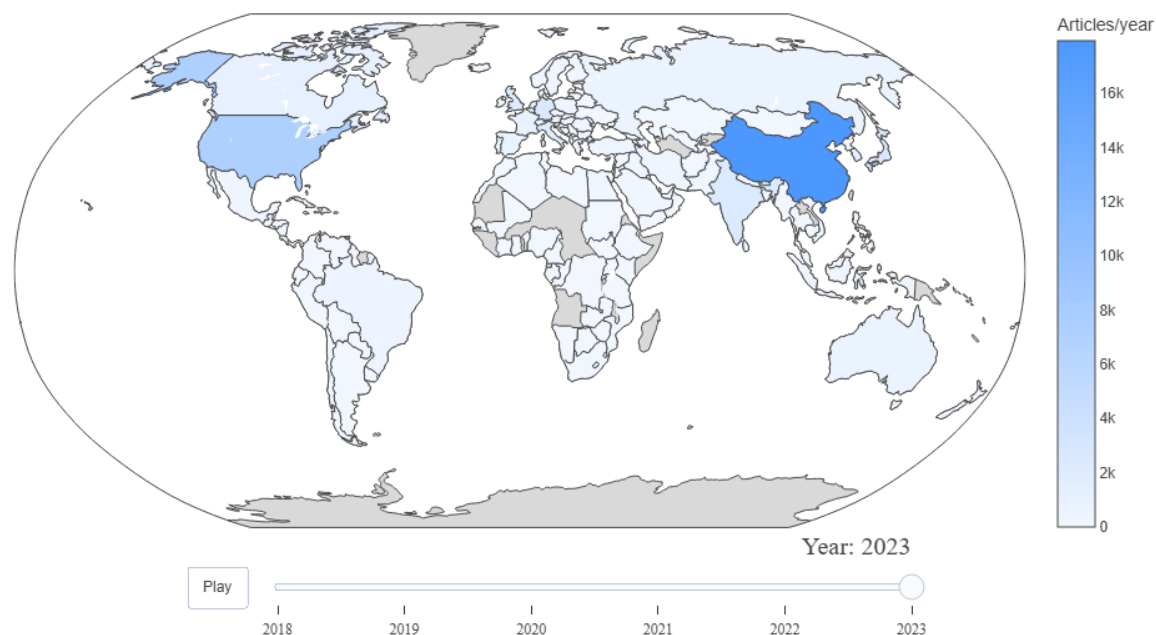
Based on bibliometric, patent, and investment activity described below, China maintains a quantitative lead in AI-robotics research output annually, but researchers in the United States maintain an edge in terms of highly cited work (a proxy for interest and impact). Chinese affiliates maintain a clear advantage in terms of robotics patenting activities, but prior research from CSET calls into question the quality of this patent activity. More recent research by financial analysts also suggests firms outside China lead in patenting activity in specific sub-markets of robotics. Finally, U.S. startups and publicly traded firms lead in terms of investment measured by deal count and dollar value. This lead appears stable in recent years, though there is notable AI-robotics investment activity occurring among Chinese firms as well. For all of this data, there is a lag period (for example, patent filings can take years to be reported, and recent publications that may prove to be high-impact have yet to register in terms of citation intensity).

ETO Research Almanac: Publications and Patents

According to CSET’s Emerging Technology Observatory [Research Almanac](#), from 2018 to 2023, 14% of all AI articles focused on robotics.³⁶ Roughly 258,000 robotics articles were released between 2018 and 2023, with a 47% growth rate in articles published during that five-year period. China (28%), the United States (16%), and Japan (7%) led the world in number of articles published during this time period (Figure 2), though U.S. research is more heavily cited per article (~19 citations on average) compared with Chinese research (10 citations) and Japanese research (6 citations). Nevertheless, the most productive academic research organizations during this time period were nearly all Chinese (7 of the top 10, as measured by publications). The opposite is true in terms

of industry-affiliated publications however, where no Chinese firms are listed in the top 10 and instead companies like Google and NVIDIA (United States) as well as Robert Bosch (Germany), Honda (Japan), and Samsung (South Korea) lead.

Figure 2: Robotics-affiliated Articles Published by Country, 2023



Source: CSET ETO Research Almanac.

Quantitative metrics on the AI-robotics patenting landscape paint a muddled picture of competitiveness and come with necessary caveats. This is primarily because there are differences in how patent data is counted (by individual patent vs. patent family) and reported (by filing date vs. date granted), which make comparisons between companies and countries challenging. Previous CSET research into the AI-robotics patent landscape found that Chinese robotics patent growth significantly outpaced the rest of the world from 2015 to 2019 but there are lingering questions about the quality of these patents.³⁷ This research further found that China's leading patent filers during this time period were university affiliates (accounting for 92% of all robotics patent filings) and the vast majority of Chinese robotics patents were not filed for use outside the country.³⁸

More recent research from financial analysts at Bank of America suggests that U.S. firms lead in this space, finding that the largest share of robotics-related patent filings in the technology industry in Q4 2023 was in the US with 34%, followed by China (24%) and Japan (5%).³⁹ Additional research by PitchBook, a venture capital monitoring data service, looked more specifically at humanoid and warehouse robotics

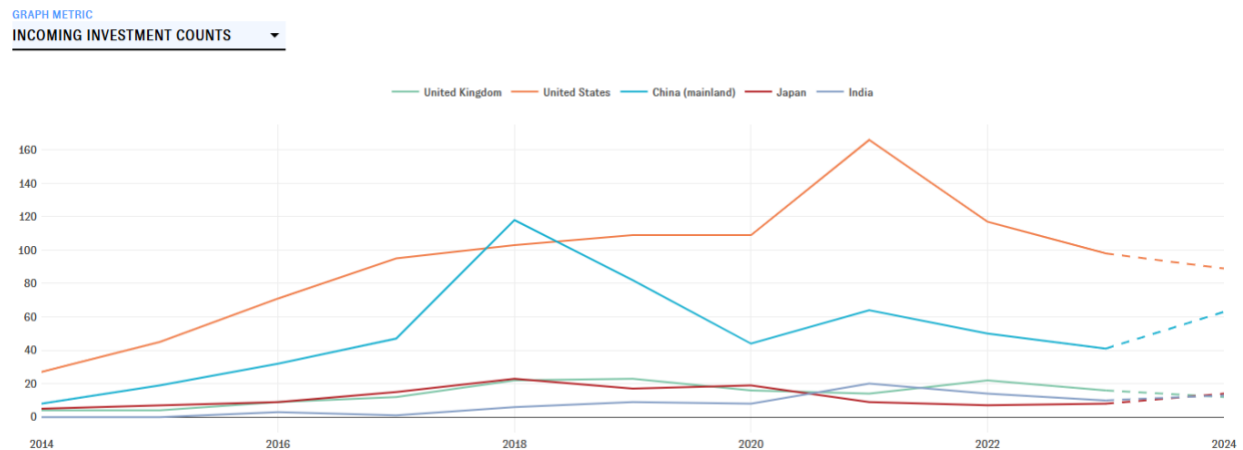
competitiveness and patents. Among humanoid robotics companies, UBTECH (China, 609 active patents) and Boston Dynamics (U.S., 455 active patents) have more patents than all the other firms in the top 10 combined.⁴⁰ When evaluating warehouse robotics companies by active patent filings a similar “best and the rest” story emerges: Mitsubishi Logisnext (Japan, 1,598 patents), AutoStore (Norway, 654 patents), and Berkshire Grey (U.S., 597 patents) have more patents than all the other firms in the top-10 combined.⁴¹ In general, the patent data on robotics aligns with the findings described on publication data (above) and investment data (below): firms in the United States and China are most active, with notable participation from entities in Europe and Asia.

ETO Country Activity Tracker: Investment Data

In the past decade, the five countries home to the most companies receiving one or more robotics investments are the United States (327 companies), China (263 companies), the United Kingdom (60 companies), Japan (47 companies), and India (44 companies).⁴² Leading robotics firms receiving investment in the United States include Boston Dynamics, Figure, Skydio, Rokid, Physical Intelligence, and Bright Machines. In China, leading investment recipients include MEGVII, Terminus Technologies, and MegaRobo. The U.S. and Chinese robotics startup ecosystems have seen a growing number of investments in recent years, a sign of investor enthusiasm, while investments in Japanese, Indian, and British robotics startups remain relatively low but stable (Figure 3). This data from CSET’s ETO [Country Activity Tracker](#) generally aligns with recent industry research, which estimated that of the ~\$100 billion invested in robotics since 2018, roughly 75% of investment flows to robotics startups in either the United States or China (50% and 24%, respectively).*

* Note that this number is likely inflated due to an over-inclusive methodology that “includes announced and completed VC deals with exposure to robotics *theme* [emphasis added],” which is not defined and may include things like autonomous vehicles. The challenge of finding rigorous, well-defined data on robotics-specific investment is also discussed in the following “market analysis” section.

Figure 3: Changes in Robotics-Affiliated Deal Counts Among Leading Countries, 2014-2023



Source: CSET ETO Country Activity Tracker: Artificial Intelligence.

Underneath these top-line investment numbers, investor enthusiasm appears to be concentrated in specific sub-markets of robotics. According to data from PitchBook, companies involved in humanoid and warehouse robotics have raised a cumulative ~\$25 billion in the past five years. Interestingly, while advances in humanoid robots garner headlines and front page news, the vast majority of this funding (\$20.5 billion) has been directed to startups developing warehouse robotics that leverage AI/ML advances to provide automated material handling and order fulfillment systems that optimize otherwise labor-intensive tasks such as picking, sorting, and inventory management within logistics facilities.⁴³ During this same period of time, PitchBook data shows that companies operating in the humanoid robotics market raised far less, roughly ~\$4.6 billion.⁴⁴ As discussed below, this disparity is striking given the enthusiasm gap today: all of the marketing for Physical AI talks about humanoid robots, but the vast majority of recent investment is directed to less exciting, but far more practical, industrial robots.

Characterizing Relative National Standing: AI-Robotics Market Analysis

The worldwide AI robotics market was valued at \$20-\$23 billion in 2025.⁴⁵ In the next ~10-year period, however, industry analysts expect this market will reach, or exceed, \$100 billion in value.⁴⁶ Analysts at Goldman Sachs recently forecast that the total addressable market specifically for humanoid robots will grow from \$6 billion today to \$38 billion in 2035, while analysts at Morgan Stanley are even more optimistic, asserting the market will reach \$5 trillion by 2050.⁴⁷

These market numbers are speculative and lack definitional clarity. The “AI Robotics market” is poorly defined and can refer to everything from autonomous mobile robots like those currently in use by Amazon to the industrial robots used by automotive manufacturers. Scalable manufacturing of humanoid robots faces myriad technical obstacles, some of which were discussed above. Much of this market’s forecast growth is contingent on unit costs going down as manufacturing economies of scale are achieved (“the robots start to build robots”) and performance and reliability increases dramatically as hardware and software improve. These breakthroughs are by no means guaranteed.

Additionally, numbers cited by analysts and firms lack clarity and cannot be independently verified. Some companies consider warehouse robots a form of industrial robots and report numbers accordingly. Others maintain different definitions, leading to over- (or under-) counting total deployment numbers. Relatedly, the numbers that are reported by firms are often speculative, and it is difficult to determine the validity of the claims without genuine on-the-ground investigation. For example, in 2011 Foxconn announced a program to deploy 1 million robots in its factories by 2014.⁴⁸ By 2016 it had only managed to deploy 40,000, and more recent numbers are lacking.⁴⁹ Similarly, companies like Siemens (Germany) and JD.com (China) have announced the creation of “dark” factories that are fully automated and can function without human intervention, but it is unclear how robot-dense these facilities are, if they are comparable, and by what metrics to compare them. The sections below present reported numbers at face value, with these caveats in mind.

While the overall size of the AI-robotics market and its growth rate remain speculative, many firms are actively investing in this market to maintain or establish leading positions. This section summarizes leadership in the AI-robotics market according to supply chain segment, focusing on (1) AI foundation models and software (2) hardware components and subsystems (3) robot manufacturers and (4) robot deployment and end users. Importantly, within each of these categories there are firms which specialize in serving one or more sub-market for robotics (e.g., motors specifically for industrial robots or software specifically for humanoid robots).

AI-Robotics Foundation Models and the Software Ecosystem

The AI-robotics software ecosystem is currently dominated by a handful of tech giants, several notable startups, and “traditional” robotics firms focused on supplying specialized software for robotics operating systems, as well as simulation and programming environments.⁵⁰ Few of these firms report public numbers on the value

of their AI-robotics investments to date, however, all have publicized their work in the space extensively.

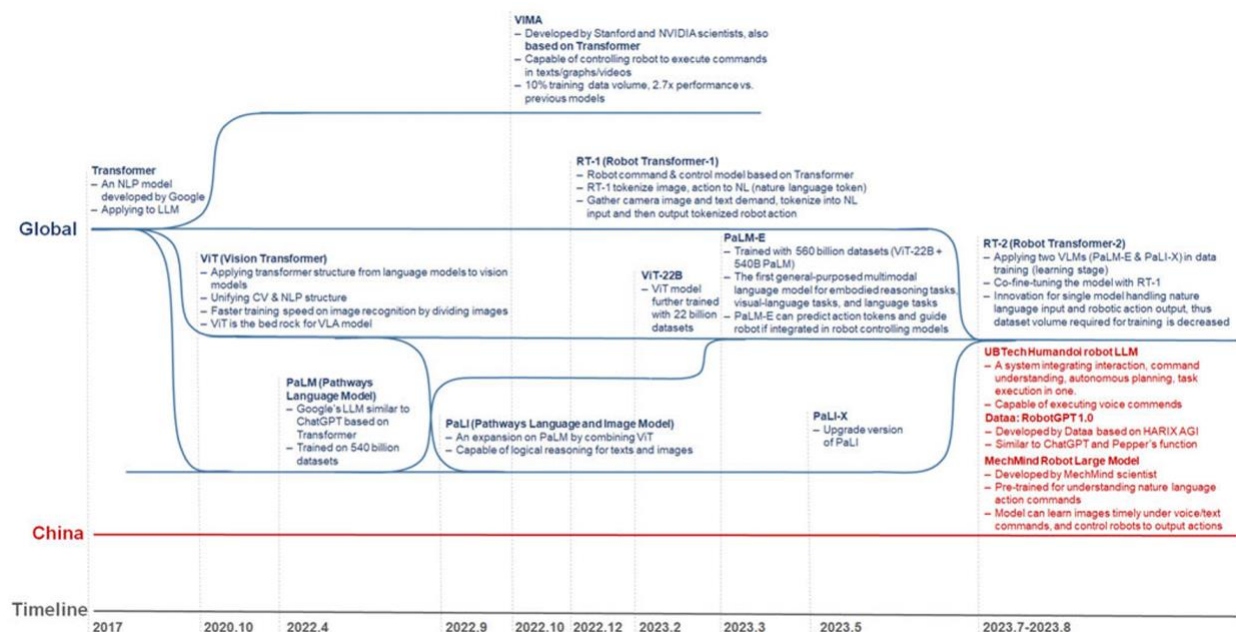
U.S. firms enjoyed a first mover advantage in robotic LLM development and have leveraged that lead to iterate and achieve subsequent breakthroughs. Early efforts by Alphabet include PaLM-E, ViT, PaLI, and RT, a family of vision-language-action (VLA) models were among the earliest well-funded examples to leverage breakthroughs in AI for robotics applications.⁵¹ Through its DeepMind subsidiary, Alphabet more recently introduced a family of models under the Gemini Robotics umbrella, notably Gemini Robotics-ER (Embodied Reasoning), which focuses on giving robots stronger spatial and physical reasoning capabilities.⁵² NVIDIA (U.S.) has aggressively courted robotics developers with its GR00T (Generalist Robot 00 Technology) foundation model family, Isaac robotics platform, and its recently-introduced Cosmos “world foundation model.”⁵³ It also maintains partnerships with dozens of startups and large technology firms across the Physical AI supply chain to integrate its products with developers.⁵⁴ Microsoft (U.S.) has leveraged its close collaboration with OpenAI to introduce ChatGPT for robotics and established partnerships with humanoid robotics startups like Sanctuary AI and Figure AI, whose humanoid robots use Azure-based training systems.⁵⁵ Meta (U.S.) is applying its Llama large language models to robotics control through a new division in its Reality Labs unit focused on humanoid robots.

Outside of the tech giants, several U.S. startups developing foundational models for robotics have raised significant funding in the last 18 months. Skild AI and Physical Intelligence raised \$300 million and \$400 million, respectively, in 2024, with Skild AI raising another \$500 million in a follow-on round in 2025.⁵⁶ Covariant, a developer of models with a focus on warehouse operations, was acquired by Amazon Robotics in September 2024.⁵⁷ More recently, in early 2025, Field AI raised \$100 million, and Boston Dynamic’s AI Institute announced a partnership focused on advancing reinforcement learning for humanoid applications.⁵⁸

A similar dynamic is emerging in China, as large technology conglomerates and startups have begun to introduce domestically-developed models optimized for robotics applications in recent years (Figure 4). Some of these models have been introduced by vertically integrated firms, that are simultaneously also attempting to build physical robots (e.g., UBTech). In other instances, Chinese-developed LLMs like DeepSeek R1 are being leveraged to assess their ability to train robots in basic tasks like playing checkers.⁵⁹ Chinese startups like AgiBot that specialize in robotics model development and development of robotics datasets have entered this market since 2023 as well.⁶⁰

Outside of the United States and China, Europe's leading frontier AI company, the French startup and LLM developer Mistral AI, has partnered with HuggingFace to sponsor robotics hackathons that offer teams the opportunity to build real-world models to train and manipulate HuggingFace-developed robotic arms.⁶¹ South Korean robotics foundational model startup RLWRLD also recently closed a seed round valuing it at \$15 million.⁶²

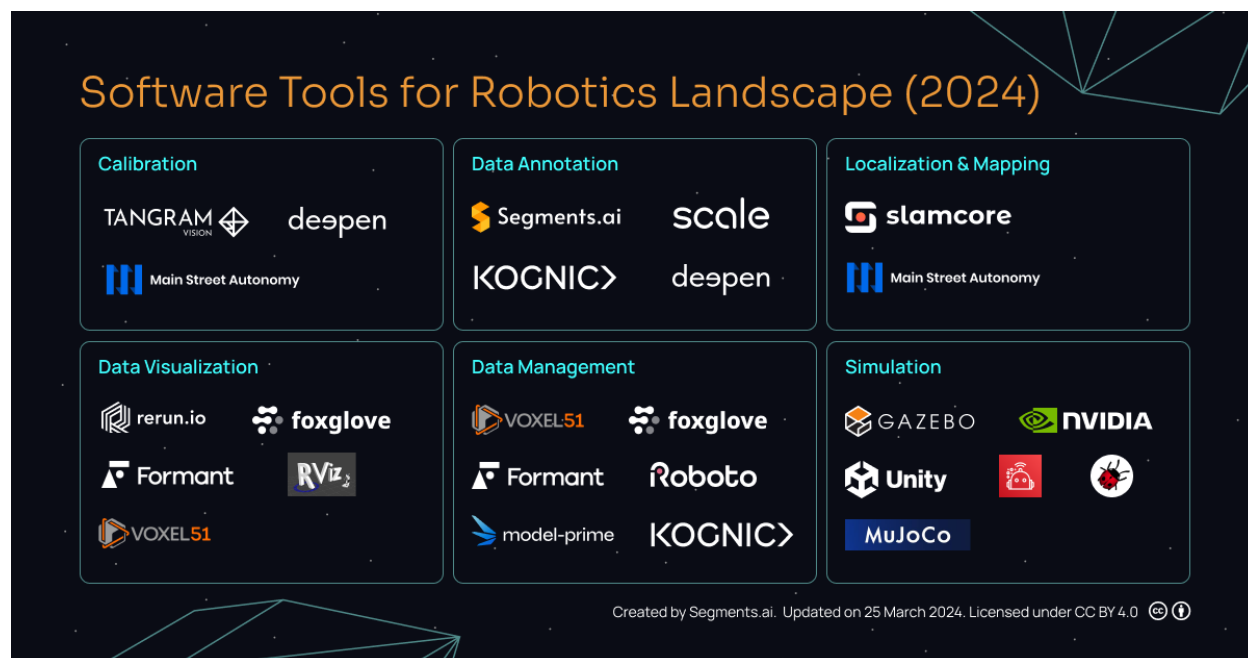
Figure 4: Robotic LLM Development, 2017-23



Source: "Global Automation Humanoid Robot: The AI accelerant" (Goldman Sachs, January 8, 2024), <http://www.goldmansachs.com/pdfs/insights/pages/gs-research/global-automation-humanoid-robot-the-ai-accelerant/report.pdf>.

Separate from the AI-Robotics foundational models being developed, there is also a robust ecosystem of software suppliers. This ecosystem is divided into firms supplying robotics operating systems and firms providing simulation software. In the latter category, leading suppliers like ABB (Switzerland), FANUC (Japan), and KUKA (Germany, now owned by China) all offer comprehensive simulation and programming environments for their industrial robots, allowing users to program and configure their systems before deployment. This part of the software supply chain is generally company-proprietary and business-to-business in nature (original equipment manufacturer (OEM) to customer) and has limited overlap with current enthusiasm for Physical AI. These suppliers are perhaps best understood as systems engineering automation providers, as opposed to the firms supplying Physical AI solutions.

Figure 5: Robotics Software Segments (Excluding Foundation Model Providers), 2024



Source: Tobias Cornille, “Software Tools For Robotics Landscape (2024)”, Segments.ai (blog), March 21, 2024, <https://segments.ai/blog/software-tools-for-robotics-landscape/>.

As Figure 5 also shows, the final important components of the software ecosystem related to AI-robotics convergence involve the collection, generation, annotation, visualization, and management of the data used to train robots and the modeling and simulation environments. Within this ecosystem, the key barrier to developing reliable digital twin environments (where an AI-powered robot can “practice” what it has been taught) is the necessity of adequately collecting and annotating real-world data. Simply put, data suitable for sim2real is expensive to collect, difficult to organize, and in some cases simply does not exist.⁶³ Leading companies are investing to get around this problem, as are several startups. In general, approaches fall into two camps: accelerating “reality capture” and accelerating synthetic data generation. Reality capture refers to the process of scanning a physical environment, digitally representing that environment, and optimizing it for training/mod-sim purposes.⁶⁴ Synthetic data generation, as the name suggests, skips the process of rendering a physical environment and instead creates a digital one from scratch. Advances in AI have aided companies developing both approaches. In general, AI is making object identification, segmentation, and 3D reconstruction processes easier for reality capture, while the promise of AI and synthetic data has been well understood for several years.⁶⁵ The major players in electronic design automation (Cadence, Siemens (Mentor Graphics), and Synopsys, which also owns Ansys) have all announced recent modelling and simulation environments optimized for Physical AI that rely on these advances.

Similarly, several startups are developing reality capture and robotics simulation software including Hexagon, Luma AI, and MetAI. Finally, several smaller firms retain a loyal following among researchers and hobbyists due to their long-standing commitment to free and open-source software (e.g., Gazebo).⁶⁶

Robotics Hardware Components

The robotics hardware components ecosystem, especially the ecosystem of suppliers that can deliver components at scale cost-competitively (Figure 6), is largely controlled by firms in Asia and Europe. Several recent reports cover this market in detail.⁶⁷ This section summarizes these reports, focusing specifically on firms that control one or more chokepoint technology that could help or hinder AI-robotics convergence. There is no one country with a vertically integrated robotics supply chain, and interdependence is high.

Robotics-specific hardware demand is rarely sufficient for firms to establish a business line, meaning nearly all suppliers serve multiple end-use markets (e.g., automotive, aerospace). Japanese and German component suppliers maintain notable market share, though there are also competitive suppliers in the United States, Europe, and China. This supply chain has many “hidden giants” that control one or more key parts of the market as well as COTS suppliers who offer best-in-class products. In both cases, suppliers rarely produce products solely for the robotics end-use market, though they will optimize products for specific use cases if demand is sufficient.*

In the former category, Japanese firms like Harmonic Drive Systems, Nabtesco, Nidec, and Sumitomo Heavy Industries offer precision mechanical gears, motors, and actuators that facilitate robotic joint movements and maintain high market share worldwide.⁶⁸ Notably, Harmonic Drive Systems controls 80% of the market for the precision gears it produces.⁶⁹ In Europe, German firms like Bosch Rexroth Festo, SEW-Eurodrive, SCHUNK, and Schmalz offer robotics components for “end effectors” (gripping), motors, and actuators.⁷⁰ German firms are particularly competitive in the supply of end-effectors (for dexterous manipulation), a key technical challenge that has yet to be fully addressed for humanoid adoption.⁷¹

In the latter category, many firms offer commercial off-the-shelf (COTS) products at competitive prices with performance characteristics that make them suitable for robotics applications. For many robotics manufacturers, access to CATL’s (China)

* For example, ST Micro will not create an entirely new chip architecture for robotics users, but it will tweak existing products for robotics use cases: <https://www.therobotreport.com/stmicroelectronics-boosts-ai-edge-npu-accelerated-microcontroller/>.

batteries, Sony's (Japan) cameras, and NXP's (Netherlands) microcontrollers is sufficient. This reliance on COTS parts comes with trade-offs, however. Each robotics company is cobbling together their own unique bill of materials, meaning suppliers cannot rely on large orders necessarily. If demand shifts in their core markets (e.g., aerospace), they are likely to prioritize production volume for these customers at the expense of the high-mix, low-volume components required by robot manufacturers. In addition to this economic challenge, these COTS hardware solutions are frequently “good enough,” but not necessarily technically optimal. Hardware optimized for robotics applications is costly to develop and difficult to scale. And, once integrated into actual robots, characterizing why the hardware failed (fatigue, environment, tolerance) makes for a slow and expensive cycle of iteration. Other industries have accelerated these cycles of “downtime” by creating service and support businesses, but that generally does not yet exist in robotics at scale.

Figure 6: Humanoid Robot Component Suppliers (Publicly Traded)

Body						
Actuators & Actuator Parts		Sensors	Batteries	Semis (Analog)	Body, Wiring, Thermal	Diversified Automation
Bearings	Complete Actuators	Radar & Lidar			Aluminum Castings	
NSK TIMKEN SCHAEFFLER	IRCC SHUANGLIN Regal Rexnord	MAGNA TEL EGYPT TECHNOLOGIES Valeo	EVE Energy SAMSUNG SDI LG Energy Solution	ALLEGRO ANALOG DEVICES Infineon NXP	MAGNA XUSHENG	Honeywell Rockwell Automation
Screws	Motors	Magnetic	CATL	RENEASAS onsemi	Wires & Connectors	SIEMENS
NSK SKF HIWIN	INOVANCE Regal Rexnord Nidec Leadshine ZHAOWEI ESTUN	Melexis ALLEGRO Force & Torque Novanta KOLB SONY		Melexis TEXAS INSTRUMENTS	Amphenol TE APTIV Thermal	FOXCONN
Gears / Reducers	Encoders	Cameras & Vision Sensors				
HIWIN Nabtesco ZD Regal Rexnord	Nidec Novanta Sensata Rare-Earths / Magnets Lynas MP MATERIALS JL MAG	TEL EGYPT TECHNOLOGIES HEXAGON SONY robosense onsemi KEYENCE				

Source: See footnote for complete sourcing information: Adam Jonas et al., “The Humanoid 100.”*

Market analysis of international hardware component suppliers for robotics likely overstates their competitiveness in China. Though the headlines claim 75% of China's robotics components are supplied by international firms, Chinese robot manufacturers likely prefer to partner directly with Chinese robot component suppliers, many of whom are (1) not publicly traded and (2) not offering their products internationally and thus are not widely covered outside the country.⁷² It is likely also the case that

* Complete Source: Adam Jonas, William J. Tackett, Sheng Zhong et al., “The Humanoid 100: Mapping the Humanoid Robot Value Chain” (Morgan Stanley, February 6, 2025), https://advisor.morganstanley.com/john.howard/documents/field/ij/john-howard/The_Humanoid_100_-_Mapping_the_Humanoid_Robot_Value_Chain.pdf.

internationally competitive firms that have factories in-country are producing products for domestic consumption (such as Nabtesco), and it is unclear whether this market analysis considers this international or domestic supply.⁷³ Several Chinese firms are establishing genuine domestic market share, including Leaderdrive, HSOAR Group Robotics, and ZD Drive.⁷⁴

Robot Manufacturers

The robot manufacturing landscape features startups as well as established industry leaders spread across several key countries. This section focuses specifically on relative national competitiveness in three types of robots that are seeing the greatest interest in Physical AI integration: humanoid robots, industrial robots, and autonomous mobile robots.

The humanoid robotics manufacturing landscape is diverse, with at least 38 companies developing 47 different robots listed as under development, according to one source.⁷⁵ There are no “incumbent” humanoid manufacturers today (unlike other robotics sub-markets), and all the firms mentioned below, with the exception of Boston Dynamics, entered the market in the last 5-10 years. The largest and most well-funded U.S.-based developers of humanoid robots include Boston Dynamics* (Atlas), Tesla (Optimus), Agility Robotics (Digit), Apptронik (Apollo), and Figure AI (Figure 02). China has at least twice as many firms as the United States pursuing humanoid robotics development, including Unitree (H1 and G1 models), UBTECH (Walker series), Xiaomi (CyberOne), EngineAI (PM01), and Fourier (GR-1). Outside of the United States and China, there are also firms in Japan (Kawasaki), South Korea (Rainbow Robotics), and Canada (Sanctuary AI) with at least one humanoid in development.

Industrial robotics continues to be dominated by the so-called “Big Four”: ABB (Switzerland), FANUC and Yaskawa (Japan), and KUKA (Germany, now China).⁷⁶ While these four firms are estimated to control 75% of the global market for industrial robots, there are also notable suppliers in Europe (Comau and Staubli) and Japan (Epson, Kawasaki, Mitsubishi).⁷⁷ China has several publicly traded industrial robot manufacturers, including Siasun Robotics, Efort [sic], and Etsun Automation.⁷⁸

At the same time, the warehouse robotics market continues to grow worldwide at a scale and speed that exceeds other industry adoption. Amazon, which acquired Kiva Systems in 2012 to enter the warehouse robotics market, reports having one million autonomous mobile robots in its factories.⁷⁹ These robots consist of everything from

* Note: now owned by Hyundai (South Korea), though its operations remain in the United States.

AMRs capable of moving pallets around a warehouse to “pick and place” arm-like robots that can sort boxes for transport. Other notable suppliers include Geek+ (China), Daifuku (Japan), EK Robotics (Germany), and Balyo (France, publicly traded and majority-owned by SoftBank (Japan)).⁸⁰

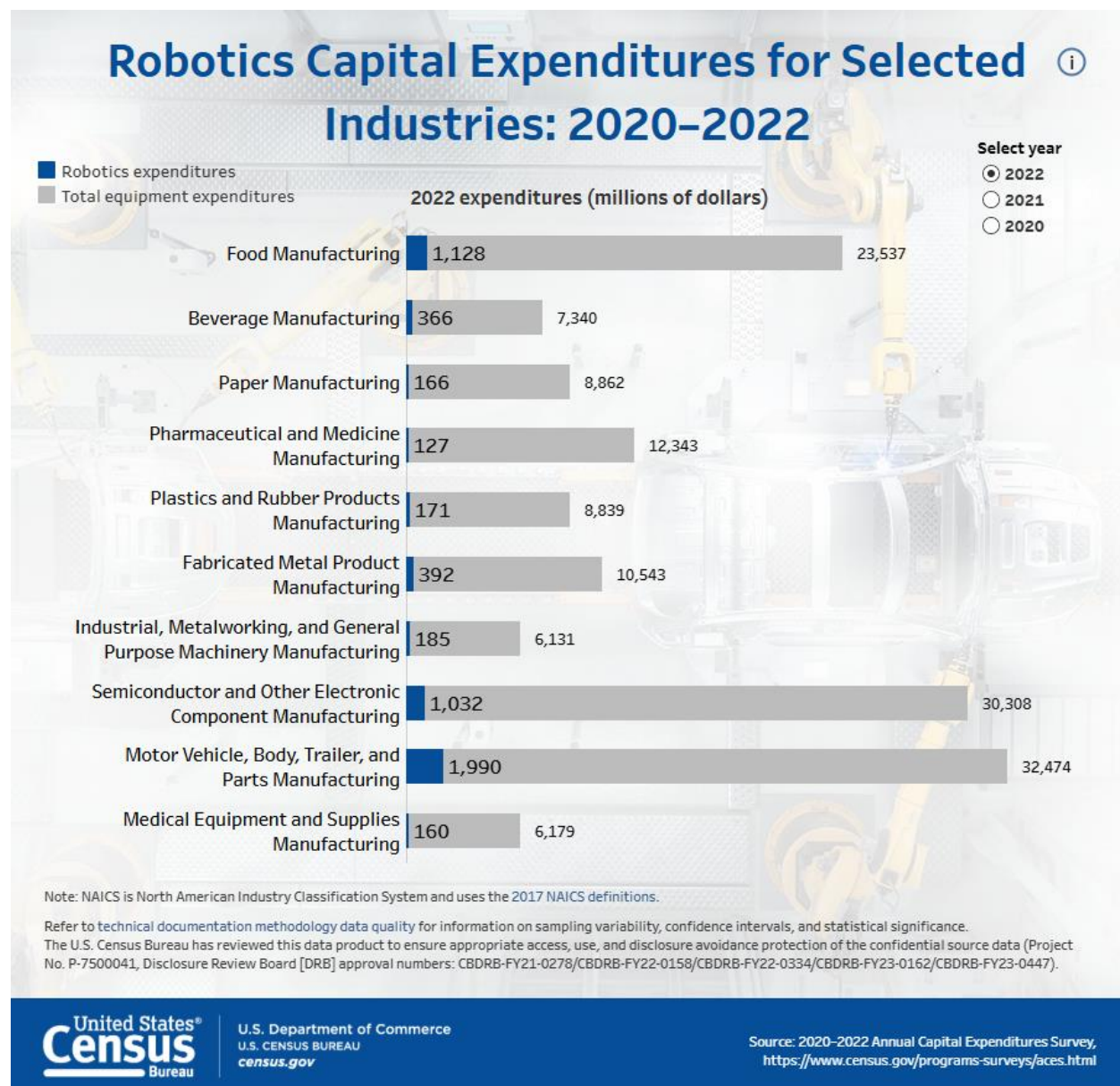
Finally, specialized robotics applications for hospital and medical environments are also seeing increased development. In the U.S., firms such as Intuitive Surgical with its da Vinci system have been commercializing human-in-the-loop surgical robots, while in China, firms like Fourier are manufacturing robots for medical rehabilitation.⁸¹

Robot Deployment and End Users

While humanoid robots get the headlines, the actual deployment numbers by volume are dominated by industrial robots, and, interestingly, the leading deployer of robots per capita is a country not mentioned to this point: South Korea.⁸² Robots are most frequently installed by automotive, aerospace, electronics, and food manufacturing OEMs.

The industrial robotics sector remains the most mature segment of the robot market, with automotive manufacturing still leading global deployment. This is true in the United States (Figure 7) as well as in Europe and Asia. Japan's Toyota and Germany's Volkswagen Group consistently rank among the highest-density robot users, while South Korea maintains the world's highest robot density at 1,000 industrial robots per 10,000 manufacturing employees (with Singapore coming in second).⁸³ China has rapidly emerged as the largest overall market by volume, installing nearly 290,000 industrial robots annually—more than Japan, the United States, South Korea, and Germany combined.⁸⁴ These same trends of adoption are true for AMRs as well, with the United States and Europe leading in installations to date, while Chinese firms see the highest growth rate in installations in recent years.

Figure 7: U.S. Robotics CapEx by Industry, 2020-22



Source: United States Census Bureau, “Robotics Capital Expenditures for Selected Industries: 2020-2022,” April 23, 2024, <https://www.census.gov/library/visualizations/interactive/robotic-capital-expenditures-for-selected-industries-2020-2022.html>.

The humanoid robotics sector remains largely in the experimental phase, with total shipments in the hundreds compared with the hundreds of thousands of industrial robots and AMRs mentioned above. Japan leads in research and development, with Honda's ASIMO pioneering the field and newer platforms from SoftBank Robotics gaining traction in customer service roles. Hospitals in Japan have been early adopters of humanoid assistants for patient monitoring and basic care tasks. In Europe,

automotive manufacturers, including BMW and Audi, are piloting limited humanoid robot deployments for specific assembly tasks. Figure AI, the U.S. developer of humanoid robots, announced a successful test with BMW in 2024.⁸⁵ China has made humanoid robotics a national priority, with companies like UBTECH deploying service robots in retail, hospitality, and healthcare settings. Despite the attention humanoids receive, they currently represent a small fraction (likely less than 1%) of the total robotics market by revenue.

Conclusion: Technology Trends Assessment

Interest in AI-robotics convergence is spiking according to nearly every metric. AI-robotics-affiliated publications, patents, and investment activity have all surged in recent years. This interest is global, as is the AI-robotics supply chain. Leading U.S. AI developers are betting that they can leverage their lead in foundational and multimodal models to corner the next innovation ecosystem. It is not at all clear that the Physical AI ecosystem will evolve along the same lines, however. AI model developers in China and Europe are pursuing their preferred approaches as well, in partnership with robotics OEMs and end-users and occasionally with government support. All of these developers have, for the time being, voiced their support for open-source solutions. As robotics applications mature, whether this commitment to open source remains will be a clear signal to watch. Likewise, a clear signal of unresolvable technical headwinds will be these firms' exiting the market and/or cutting their discretionary CapEx currently directed towards robotics.

Hardware is hard. Nowhere does that remain truer and relevant for Physical AI than at the subcomponent level. While the performance of custom and COTS components has dramatically improved in recent years, economic and technical obstacles remain. Expensive and time-consuming cycles of hardware iteration sharply contrast with the cycles enjoyed by robotics software developers. Incumbents matter tremendously, as well. Hidden giants in Japan, Germany, and elsewhere control key chokepoints in the component ecosystem. Their high market share has resulted in excellent products and performance, but costs remain stubbornly high, and the volume of production for key components will need to expand greatly to meet forecasted demand. A loss of incumbent market share to ascendant new-entrants, as well as breakthroughs in remaining technical obstacles (especially end-effectors capable of dexterous manipulation), and standardization of the robotics component supply chain would signal change is coming.

In spite of these headwinds, robotics OEMs are proliferating, and robotics end-user installations per year continue to grow. South Korea and Singapore lead the world in per capita robot adoption not because of government directives, but instead because of economic imperatives. Similar interest in the U.S. and European automotive industries in robotics is spiking as anticipated labor shortages and high wages threaten margins. While industry enthusiasm for humanoids grows, the actual dollars and unit installations consist of industrial robots and AMRs. The pace, depth, and breadth of robotics adoption across industry will be dictated by cost: if an affordable humanoid robot capable of exceeding human performance arrives in the next 10 years, it will be a

welcome surprise. For that to happen, major breakthroughs in synthetic data, hardware components, and standardization will need to occur.

The policy agenda around robotics is immature compared to other emerging technologies like semiconductors, AI, and quantum, where substantial research has mapped the key players, their comparative advantages, chokepoints, and supply chains. The robotics supply chain also lacks robust datasets that provide signals on supply, demand, production, consumption, and the intensity of robotics adoption (by country, by industry, by factory). As a result, the few data providers today, such as IFR and financial analyst reports, play a disproportionate role in shaping discourse. There is a need for a policy research agenda that develops mature analysis to cut through the hype, identify genuine advances, and characterize the potential depth of robotics adoption across economies.

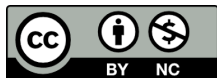
Finally, from a national security perspective, a research agenda to address the gap between physical intelligence and dexterous intelligence is critical. This gap is particularly problematic in the aerospace and defense sectors, where high-mix, low-volume manufacturing lines necessitate regular re-tooling and adoption of automated solutions is more difficult. Physical intelligence (spatial awareness for pick, move, and place-capable robots) is not enough in environments that require dexterous intelligence (insertion, threading, force feedback). Policies that address (in particular) the acute lack of quality tactile sensors, kinematics, and real-world data would facilitate the development and adoption of robotics in these key sectors.

Author

John VerWey is a non-resident research fellow at CSET and an advisor at Pacific Northwest National Laboratory.

Acknowledgments

For feedback and assistance, the author would like to thank Igor Mikolic-Torreira, Lauren Lassiter, Aaron Prather, Esube Bekele, Catherine Aiken, Matt Mahoney, Sara Abdulla, Shelton Fitch, Owen Daniels, Kevin McGinnis, and Taylore Roth.



© 2026 by the Center for Security and Emerging Technology. This work is licensed under a Creative Commons Attribution-Non Commercial 4.0 International License.

To view a copy of this license, visit <https://creativecommons.org/licenses/by-nc/4.0/>.

Document Identifier: doi: 10.51593/20250023

Appendix 1. Template for Technology Competitiveness Assessment: Technical Level-Setting

	Key Competitiveness Questions	Key Metrics
Scope (Define) the Technology and its Ecosystem <i>Basic Industry/Supply Chain Mapping</i>	<ul style="list-style-type: none"> ○ What are the key constituent parts of the technology ecosystem? ○ What hardware, software, data, and talent is this technology contingent on? ○ How does this technology “stack”? ○ How does this technology's supply chain compare with and integrate with other supply chains? ○ Which underlying supply chains are “critical” to this technologies' development? ○ What are the enabling tools and technologies on which this technology relies? 	<p>Map the supply chain:</p> <ul style="list-style-type: none"> ○ Key Products ○ Key Services
Assessment of Country-Level Activity and Capacity <i>Map the Innovation Ecosystem</i>	<ul style="list-style-type: none"> ○ Where is the best/most advanced research being conducted and by whom? ○ Which academics, companies, and countries are engaged in R&D of a particular technology ○ Where are leading researchers employed and located? ○ What are the primary avenues for collaboration between researchers? ○ Where is the leading research published, presented and standardized? What metrics can be used to capture expertise and enthusiasm in this field? 	<p>Analyze Bibliometrics/Scientometrics:</p> <ul style="list-style-type: none"> ○ Publication intensity ○ Citation intensity ○ Network density (co-authorship) ○ Patent filings ○ Quality-adjusted patents ○ Investment data (mergers, acquisitions, venture capital)

Capture Relative National Standing <i>Detailed Market Analysis and Current SoTA</i>	<ul style="list-style-type: none"> ○ Who are the current leading actors? ○ Which firms are the leading suppliers of a particular product or service? ○ Do any choke points (e.g., single, sole-source suppliers) exist in terms of technology or companies; what vulnerabilities exist ○ What constitutes "state of the art" (SoTA) across different parts of the ecosystem and which firms are operating at SoTA? ○ How does the domestic industry compare to the international industry? ○ What domestic sectoral capabilities exist; what capabilities exist overseas? ○ Can domestic production meet domestic demand and, if not, how severe is international reliance? 	<p>Map the suppliers:</p> <ul style="list-style-type: none"> ○ Identify firms that provide key products, services ○ Identify monopolistic global actors, without whom the broader ecosystem would collapse
Assess Technologies' Trends <i>Opportunity Analysis</i>	<ul style="list-style-type: none"> ○ Are there roadblocks (e.g., regulatory, technical) that will affect the pace of innovation? ○ What is the pace of progress, path to commercialization, and timeline? ○ What are policymakers doing to protect and promote a given technology's development? ○ What other options do they have? ○ What barriers to entry exist, is there potential for new entrants, and, if so, under what circumstances? 	

- | | | |
|--|--|--|
| | <ul style="list-style-type: none">○ Who are the ultimate customers for this technology (were it to “emerge”)?○ What factors will dictate the speed and scale of adoption? | |
|--|--|--|

Endnotes

¹ “What is Physical AI?” NVIDIA, <https://www.nvidia.com/en-us/glossary/generative-physical-ai/>.

² Madison Huang, “What is NVIDIA’s Three-Computer Solution for Robotics?” NVIDIA (blog), August 8, 2025, <https://blogs.nvidia.com/blog/three-computers-robotics/>.

³ Michael J. de la Merced, “Physical Intelligence, a Robot A.I. Specialist, Raises Millions From Bezos,” *The New York Times*, November 4, 2024, <https://www.nytimes.com/2024/11/04/business/dealbook/physical-intelligence-robot-ai.html>; Amanda Greenwood, “OpenAI’s secret robot plans revealed,” *The AI Report*, January 13, 2025, <https://www.theaireport.ai/articles/openais-secret-robot-plans-revealed>; “Chinese embodied AI startup TARS raises \$120m in angel funding,” *Tech In Asia*, March 25 2025, <https://www.techinasia.com/news/chinese-embodied-ai-startup-tars-raises-120m-in-angel-funding>.

⁴ Tom Carter, “Tesla’s Chinese EV competitors are racing to build their own Optimus rivals,” *Business Insider*, November 2024, <https://www.businessinsider.com/tesla-chinese-ev-competitors-build-optimus-rivals-2024-11>; Aditi Bharade & Cheryl Teh, “China’s spring festival celebration featured a fleet of dancing robots that flexed the country’s advancements in robotics,” *Yahoo!Tech*, January 29, 2025, <https://tech.yahoo.com/science/articles/chinas-spring-festival-celebration-featured-101336663.html>; Jack Ewing, “Elon Musk Shows Off Tesla ‘Robotaxi’ That Drives Itself,” *The New York Times*, October 10, 2024, <https://www.nytimes.com/2024/10/10/business/tesla-robotaxi-elon-musk.html>.

⁵ “Amazon VP shares his approach to the future of robotics innovation,” Amazon, April 10, 2025, <https://www.aboutamazon.com/news/operations/amazon-robotics-culture>; Scott Dresser, “Amazon launches a new AI foundation model to power its robotic fleet and deploys its 1 millionth robot,” Amazon Robotics, June 30, 2025, <https://www.aboutamazon.com/news/operations/amazon-million-robots-ai-foundation-model>.

⁶ Pia Singh, “Morgan Stanley says humanoid robots will be a \$5 trillion market by 2050. How to play it,” CNBC, April 29, 2025, <https://www.cnbc.com/2025/04/29/how-to-play-a-5-trillion-market-for-humanoid-robots-by-2050.html>.

⁷ The trend that appears to have gotten the most traction in the past year, as measured by Google Search, is “Physical AI.” See: “Search: Interest in Physical AI, Embodied AI, and Related Terms,” Google Trends, [https://trends.google.com/trends/explore?geo=US&q=physical ai,embodied ai,embodied machine intelligence,generative physical ai&hl=en-US](https://trends.google.com/trends/explore?geo=US&q=physical%20ai,embodied%20ai,embodied%20machine%20intelligence,generative%20physical%20ai&hl=en-US).

⁸ Huang, “What is NVIDIA’s Three-Computer Solution?”

⁹ Sara Abdulla, “China’s Robotics Patent Landscape,” Center for Security and Emerging Technology, August 2021, <https://cset.georgetown.edu/publication/chinas-robotics-patent-landscape/>.

¹⁰ There are dozens of other types of robots, including quadruped (dog-like) robots, medical robots (designed to assist with surgery, for example), and collaborative robots (or “cobots,”) that work with a human-in-the-loop, typically in industrial environments.

¹¹ Adam Jonas, William J. Tackett, Sheng Zhong et al., “The Humanoid 100: Mapping the Humanoid Robot Value Chain” (Morgan Stanley, February 6, 2025),

https://advisor.morganstanley.com/john.howard/documents/field/j/jo/john-howard/The_Humanoid_100_-_Mapping_the_Humanoid_Robot_Value_Chain.pdf.

¹² Jonas et al., “The Humanoid 100.”

¹³ Jack Clark, “Import AI 364: Robot scaling laws; human-level LLM forecasting; and Claude 3,” Import AI (Substack), March 11, 2024, <https://importai.substack.com/p/import-ai-364-robot-scaling-laws>.

¹⁴ Sunny Cheung, “The PRC’s Robotics Industry – Sunny Cheung’s Testimony Before the U.S.-China Economic and Security Review Commission” (The Jamestown Foundation, March 19, 2025), <https://jamestown.org/program/testimony-before-the-u-s-china-economic-and-security-review-commissions-hearing-made-in-china-2025-who-is-winning/>.

¹⁵ Jack Clark, “Import AI 364.”; “Cramming More Components onto Integrated Circuits: Moore’s Law,” Intel, <https://www.intel.com/content/www/us/en/history/virtual-vault/articles/moores-law.html>.

¹⁶ U.S. Bureau of Labor Statistics, *Census of Fatal Occupational Injuries Summary, 2023* (Washington, DC: Department of Labor, 2024), <https://www.bls.gov/news.release/cfoi.nr0.htm>.

¹⁷ “Memos to the President – National Robotics Strategy” (Special Competitive Studies Project, February 2025), <http://www.scsp.ai/wp-content/uploads/2025/02/Robotics-Memo.pdf>; Jonathan Ray, Katie Atha, Edward Francis et al., *China’s Industrial and Military Robotics Development* (Washington, DC: U.S.-China Economic and Security Review Commission, October 2016), <https://www.uscc.gov/research/chinas-industrial-and-military-robotics-development>; U.S. Department of Defense Manufacturing Technology Program, *Shaping a Responsible and Secure Future with Robotics and Autonomous Systems* (Washington, DC: National Defense University, January 23, 2023), <https://www.dodmantech.mil/News/News-Display/Article/3976457/shaping-a-responsible-and-security-future-with-robotics-and-autonomous-systems/>.

¹⁸ International Federation of Robotics, “World Robotics Press Conference 2024,” https://ifr.org/img/worldrobotics/Press_Conference_2024.pdf; William Langley and Haohsiang Ko, “China is Suffering its Own ‘China Shock,’” *Financial Times*, March 25, 2025, <https://www.ft.com/content/7640fe64-006a-4d46-9564-cbb2bd89ebd4>; Peter Eavis, “Robots Struggle to Match Warehouse Workers on ‘Really Hard’ Jobs,” *The New York Times*, November 19, 2024, <https://www.nytimes.com/2024/11/19/business/robots-warehouses-amazon.html>.

¹⁹ Jon Emont, “Why It’s So Difficult for Robots to Make Your Nike Sneakers,” *Wall Street Journal*, April 21, 2025, <https://www.wsj.com/economy/trade/why-its-so-difficult-for-robots-to-make-your-nike-sneakers-47b882b5>.

²⁰ Android SLTD (@androidstld), “Optimus, the Humanoid Tesla robot, walking test,” YouTube Short, April 3, 2025, <https://www.youtube.com/shorts/iIWApHz8ags>; Leia Wang and Zilan Qian, “China’s Humanoid Marathon Signals a New Kind of AI Race,” *The Diplomat*, April 21, 2025, <https://thediplomat.com/2025/04/chinas-humanoid-marathon-signals-a-new-kind-of-ai-race/>; Eavis, “Robots Struggle to Match Warehouse Workers.”; Jack Clark, “Import AI 412: Amazon’s Sorting Robot,” Import AI (Substack), May 12, 2025 <https://importai.substack.com/p/import-ai-412-amazons-sorting-robot>; Brian Potter, “Robot Dexterity Still Seems Hard,” *Construction Physics*, April 24, 2025, <https://www.construction-physics.com/p/robot-dexterity-still-seems-hard>.

²¹ “ETO About Page,” Emerging Technology Observatory (ETO), <https://eto.tech/>.

²² Sarah Harting, Daniel Gonzales, Michael J. Mazarr, and Jon Schmid, “Comparative Analysis of U.S. and PRC Efforts to Advance Critical Military Technology” (RAND Corporation, January 2, 2024), https://www.rand.org/pubs/research_reports/RRA2197-1.html.

²³ International Organization for Standardization, ISO 8373: Robots and Robotic Devices—Vocabulary, 2nd ed. (Geneva: ISO, 2012), <https://www.iso.org/obp/ui/-iso:std:iso:8373:ed-2:v1:en>; The IFR also explicitly states what a robot is not: software, drones, voice assistants, autonomous cars, nor ATMs, smart washing machines, etc., See: International Federation of Robotics, “World Robotics Press Conference 2024.”

²⁴ Madison Huang, “What is NVIDIA’s Three-Computer Solution for Robotics?” NVIDIA (blog), August 8, 2025, <https://blogs.nvidia.com/blog/three-computers-robotics/>.

²⁵ Motion Lab, University of Illinois, “Anatomy of a Robot,” <https://motion.cs.illinois.edu/RoboticSystems/AnatomyOfARobot.html>; Tesla, “AI,” <https://www.tesla.com/AI>; KUKA, “Industrial Robots,” KUKA Robotics Systems, <https://www.kuka.com/en-us/products/robotics-systems/industrial-robots>; Amazon, “Amazon Robotics: Autonomous Robot Proteus for Warehouse Packages,” About Amazon News, <https://www.aboutamazon.com/news/operations/amazon-robotics-autonomous-robot-proteus-warehouse-packages>; Ravi Rao, “Robotic Actuators: A Comprehensive Guide to Types, Design, and Emerging Trends,” Wevolver, December 4, 2023, <https://www.wevolver.com/article/robotic-actuators-the-muscle-power-of-industry-40>; Pablo Segura, Odette Lobato-Calleros, Alejandro Ramírez-Serrano, and Isidro Soria, “Human-robot collaborative systems: Structural components for current manufacturing applications,” *Advances in Industrial and Manufacturing Engineering* 3 (November 2021), <https://www.sciencedirect.com/science/article/pii/S2666912921000301> - sec1; Standard Bots, “The key 7 components of a robot and how they work,” Standard Bots (blog), September 10, 2025, <https://standardbots.com/blog/what-are-the-main-components-of-a-robot>; Umar Waseem, “Understanding AMR Robots: A Comprehensive Guide,” Wevolver, October 24, 2023, <https://www.wevolver.com/article/understanding-amr-robots-a-comprehensive-guide>; Sofiyan Isaac, “Cost of Autonomous Mobile Robots (AMR) 2025,” QViro (blog), April 2, 2024, <https://qviro.com/blog/cost-of-autonomous-mobile-robots/>; Sofiyan Isaac, “How Much Does a Humanoid Robot Cost?” QViro (blog), May 3, 2024, <https://qviro.com/blog/how-much-does-a-humanoid-robot-cost/>; Standard Bots, “How much do robots cost? 2025 price breakdown,” Standard Bots (blog), August 7, 2025, <https://standardbots.com/blog/how-much-do-robots-cost?>; Dylan Patel, Reyk Knuhtsen, Jeremie Eliahou Ontiveros et al., “America Is Missing the New Labor Economy - Robotics Part 1,” SemiAnalysis, March 11, 2025, <https://semianalysis.com/2025/03/11/america-is-missing-the-new-labor-economy-robotics-part-1/>; KUKA, “SmartPad Robot Teach Pendant,” KUKA Robot Controllers, <https://www.kuka.com/en-us/products/robotics-systems/robot-controllers/smartpad-robot-teach-pendant>.

²⁶ “Global Automation Humanoid Robot: The AI accelerant” (Goldman Sachs, January 8, 2024), <http://www.goldmansachs.com/pdfs/insights/pages/gs-research/global-automation-humanoid-robot-the-ai-accelerant/report.pdf>.

²⁷ Author’s compilation and International Federation of Robotics, “World Robotics Press Conference 2024,” https://ifr.org/img/worldrobotics/Press_Conference_2024.pdf; Joe Ryu and Quintet AI, “The

Physical AI Revolution Part II: Dawn of the True Robotics Industry,” The Edge of Automation, February 26, 2025, [https://www.edgeofautomation.com/p/the-physical-ai-revolution-part-ii - %E2%80%9C%E2%80%A2-whats-different-now-gearing-up-for-transformation](https://www.edgeofautomation.com/p/the-physical-ai-revolution-part-ii-%E2%80%93-%E2%80%9C%E2%80%A2-whats-different-now-gearing-up-for-transformation); Joe Ryu and Quintet AI, “The Physical AI Revolution Part I: The Long Road to Humanoid Robotics,” The Edge of Automation, February 5, 2025, https://www.edgeofautomation.com/p/the-physical-ai-revolution-part-1_.

²⁸ Toru Lin, Kartik Sachdev, Linxi Fan et al., “Sim-to-Real Reinforcement Learning for Vision-Based Dexterous Manipulation on Humanoids,” arXiv preprint arXiv:2502.20396 (2025), <https://arxiv.org/abs/2502.20396>; Potter, “Robot Dexterity Still Seems Hard.”

²⁹ Tiffany Janzen (@tiffintech), “NVIDIA CEO Jensen Huang on Robotics, AI, and the Next Big Emerging Technologies,” YouTube video (beginning at 1:10), https://www.youtube.com/watch?v=Z_DR1_zhmCU.

³⁰ Roya Firoozi, Johnathan Tucker, Mac Schwager et al., “Foundation models in robotics: Applications, challenges, and the future,” *The International Journal of Robotics Research* 44, no. 5 (2024): 701-739, <https://journals.sagepub.com/doi/abs/10.1177/02783649241281508>.

³⁰ Fanlong Zeng, Wensheng Gan, Yongheng Wang et al., “Large Language Models for Robotics: A Survey,” arXiv preprint arXiv:2311.07226 (2023), <https://arxiv.org/abs/2311.07226>; Firoozi et al., “Foundation models in robotics.”; Jens Kober, J. Andrew Bagnell, and Jan Peters, “Reinforcement Learning in Robotics: A Survey,” *The International Journal of Robotics Research* 32, no. 11 (2013), https://www.ri.cmu.edu/pub_files/2013/7/Kober_IJRR_2013.pdf; Sebastian Höfer, Kostas Bekris, Ankur Handa et al., “Sim2Real in Robotics and Automation: Applications and Challenges,” *IEEE Transactions on Automation Science and Engineering* 18, no. 2 (2021), https://dspace.mit.edu/bitstream/handle/1721.1/138850/2021-04-Sim2Real_T-ASE.pdf; Wenshuai Zhao, Jorge Peña Queralta, and Tomi Westerlund, “Sim-to-Real Transfer in Deep Reinforcement Learning for Robotics: a Survey,” arXiv preprint arXiv:2009.13303 (2020), <https://arxiv.org/abs/2009.13303>.

³² Author's compilation and Joe Ryu and Quintet AI, "The Physical AI Revolution Part II: Dawn of the True Robotics Industry," The Edge of Automation, February 26, 2025, [https://www.edgeofautomation.com/p/the-physical-ai-revolution-part-ii - %E2%9C%8Civ-whats-different-now-gearing-up-for-transformation](https://www.edgeofautomation.com/p/the-physical-ai-revolution-part-ii-%E2%80%A2-%E2%9C%8Civ-whats-different-now-gearing-up-for-transformation); Joe Ryu and Quintet AI, "The Physical AI Revolution Part I: The Long Road to Humanoid Robotics," The Edge of Automation, February 5, 2025, <https://www.edgeofautomation.com/p/the-physical-ai-revolution-part-1>.

³³ This was recently summarized by Nvidia's CEO in a keynote address: Sean Kinney, "NVIDIA takes on physical AI for automotive, industrial and robotics," *RCR Wireless News*, January 12, 2025, <https://www.rcrwireless.com/20250112/ai-ml/nvidia-takes-on-physical-ai-for-automotive-industrial-robotics>.

³⁴ Sarah Harting, Daniel Gonzales, Michael J. Mazarr, and Jon Schmid, “Comparative Analysis of U.S. and PRC Efforts to Advance Critical Military Technology” (RAND Corporation, January 2, 2024), https://www.rand.org/pubs/research_reports/RRA2197-1.html; Jon Schmid, Chad J. R. Ohlandt, and Shawn Cochran, “Net Technical Assessment” (RAND Corporation, May 28, 2024), https://www.rand.org/pubs/research_reports/RRA1350-1.html; John VerWey, “Through a Glass, Darkly: Mapping Emerging Technologies and Their Supply Chains,” Center for Security and Emerging

Technology, August 2023, <https://cset.georgetown.edu/publication/through-a-glass-darkly-mapping-emerging-technologies-and-their-supply-chains/>.

³⁵ Schmid et al., “Net Technical Assessment.”

³⁶ The data cited in this section is derived from the ETO Research Almanac. Reported figures were pulled in July 2025. An archived version of the site from that time is available at <https://almanac.eto.tech/topics/robotics/archive/2025-01-06/>. The current ETO Research Almanac contains updated data so estimates and figures may vary. For additional information on how ETO defines robotics research, see: “CSET Merged Academic Corpus,” Emerging Technology Observatory, <https://eto.tech/dataset-docs/mac/#ai-ai-subfields-and-cybersecurity>.

³⁷ Sara M. Abdulla, “China’s Robotics Patent Landscape,” Center for Security and Emerging Technology, August 2021, 5, 9, <https://cset.georgetown.edu/wp-content/uploads/CSET-Chinas-Robotics-Patent-Landscape.pdf>.

³⁸ Sara M. Abdulla, “China’s Robotics Patent Landscape,” 6, 10.

³⁹ “Next-Gen Tech: Robots” (Bank of America Institute, 2024), <https://institute.bankofamerica.com/content/dam/transformation/next-gen-tech-robots.pdf>

⁴⁰ PitchBook Emerging Space Brief, Humanoid Robotics, January 12, 2024. (7)

⁴¹ PitchBook Emerging Space Brief, Warehouse Robotics, January 7, 2025. (8)

⁴² The data cited in this section is derived from the ETO Country Activity Tracker. Reported figures were pulled in July 2025. An archived version of the site from that time is available at: https://cset.georgetown.edu/wp-content/uploads/Country-Activity-Tracker-CAT-Artificial-Intelligence_Archived-09.25.2025-7.pdf. The current site contains updated data so estimates and figures on the current CAT dashboard vary.

⁴³ Pitchbook Emerging Space Brief, Warehouse Robotics, January 7, 2025. (4)

⁴⁴ Pitchbook Emerging Space Brief, Humanoid Robotics, January 12, 2024. (5) NOTE: in a sign of how quickly this industry is moving, there were major humanoid investments throughout 2024 and 2025 not captured in the PitchBook report, for example: “Humanoid Funding Rounds in 2025,” Humanoid Robotics Technology, <https://humanoidroboticstechnology.com/articles/humanoid-funding-rounds-in-2025/>.

⁴⁵ Statista, “AI Robotics - Worldwide,” <https://www.statista.com/outlook/tmo/artificial-intelligence/ai-robotics/worldwide>; Precedence Research, “Artificial Intelligence Robots Market Size Worth \$124.26 Billion by 2034,” Globe Newswire, October 22, 2024, <https://www.globenewswire.com/news-release/2024/10/22/2967253/0/en/Artificial-Intelligence-Robots-Market-Size-to-Worth-USD-124-26-Bn-by-2034.html>; Yogesh Shinde, “AI Robots: Transforming Industries with Smart Robotic Solutions,” Robotics Tomorrow, August 23, 2024, <https://www.roboticstomorrow.com/story/2024/08/ai-robots-transforming-industries-with-smart-robotic-solutions/23005/>.

⁴⁶ Statista, “AI Robotics – Worldwide.”; Precedence Research, “Artificial Intelligence Robots Market Size Worth \$124.26 Billion by 2034.”; Yogesh Shinde, “AI Robots Transforming Industries.”

⁴⁷ “Global Automation Humanoid Robot: The AI accelerant” (Goldman Sachs, January 8, 2024), <http://www.goldmansachs.com/pdfs/insights/pages/gs-research/global-automation-humanoid-robot-the-ai-accelerant/report.pdf>; Pia Singh, “Morgan Stanley says humanoid robots will be a \$5 trillion market by 2050. How to play it,” CNBC, April 29, 2025, <https://www.cnbc.com/2025/04/29/how-to-play-a-5-trillion-market-for-humanoid-robots-by-2050.html>.

⁴⁸ Lee Chyen Yee and Clare Jim, “Foxconn to rely more on robots; could use 1 million in 3 years,” Reuters, August 1, 2011, <https://www.reuters.com/article/technology/foxconn-to-rely-more-on-robots-could-use-1-million-in-3-years-idUSTRE77016B/>.

⁴⁹ Brian Wang, “Foxconn reaches 40,000 robots of original 1 million robot automation goal,” Next Big Future, October 13, 2016, <https://www.nextbigfuture.com/2016/10/foxconn-reaches-40000-robots-of.html>.

⁵⁰ See Appendix 1 for an indicative list of firms.

⁵¹ Yevgen Chebotar and Tianhe Yu, “RT-2: New model translates vision and language into action,” Google DeepMind, July 28, 2023, <https://deepmind.google/discover/blog/rt-2-new-model-translates-vision-and-language-into-action/>; “Embodied AI” – Google’s PaLM-E allows robot control with natural commands,” Ars Technica, March 7, 2023, <https://arstechnica.com/civis/threads/embodied-ai---google-s-palm-e-allows-robot-control-with-natural-commands.1490504/>; “Google’s new PaLI-3 vision-language model,” AI Breakfast, October 25, 2023, <https://aibreakfast.beehiiv.com/p/googles-new-pali3-vision-language-model>.

⁵² Carolina Parada, “Gemini Robotics brings AI into the physical world,” Google DeepMind, <https://deepmind.google/discover/blog/gemini-robotics-brings-ai-into-the-physical-world/>; Joel Meares, “How we built the new family of Gemini Robotics models, Google (blog), <https://blog.google/products/gemini/how-we-built-gemini-robotics/>.

⁵³ NVIDIA Newsroom, “NVIDIA Isaac GR00T-N1 – the World’s First Open Humanoid Robot Foundation Model – and the Simulation Frameworks to Speed Robot Development,” NVIDIA, March 18, 2025, <https://nvidianews.nvidia.com/news/nvidia-isaac-gr00t-n1-open-humanoid-robot-foundation-model-simulation-frameworks>; Larry Dignan, “NVIDIA’s model parade: Llama Nemotron, Cosmos additions, Isaac GROOT N1,” Constellation Research, March 18, 2025, <https://www.constellationnr.com/blog-news/insights/nvidias-model-parade-llama-nemotron-cosmos-additions-isaac-groot-n1>.

⁵⁴ NVIDIA (@nvidia), “NVIDIA CEO Jensen Huang Keynote at CES 2025,” YouTube video (beginning at 1:04:25), <https://www.youtube.com/watch?v=k82RwXqZHY8>.

⁵⁵ Sai Vemprala, Rogerio Bonatti, Arthur Buckner, and Ashish Kapoor, “ChatGPT for Robotics: Design Principles and Model Abilities,” Microsoft, February 20, 2023, <https://www.microsoft.com/en-us/research/articles/chatgpt-for-robotics/>; Scarlett Evans, “Microsoft, Sanctuary AI Team to Advance General Purpose Robots,” IoT World Today, May 3, 2024, <https://www.iotworldtoday.com/robotics/microsoft-sanctuary-ai-team-to-advance-general-purpose-robots>; Harshita Mary Varghese and Krystal Hu, “Robotics Startup Figure Raises \$675 Million from

Microsoft, NVIDIA, and Other Big Tech Firms,” Reuters, February 29, 2024, <https://www.reuters.com/technology/robotics-startup-figure-raises-675-mln-microsoft-nvidia-other-big-techs-2024-02-29/>.

⁵⁶ Marina Temkin, “SoftBank to invest \$500M in robotics startup Skild AI,” TechCrunch, January 28, 2025, <https://techcrunch.com/2025/01/28/softbank-to-invest-500m-in-robotics-startup-skildai/>.

⁵⁷ “RFM-1,” Covariant, <https://covariant.ai/rfm/>.

⁵⁸ “Boston Dynamics and the Robotics & AI Institute Partner to Advance Humanoid Robots Through Reinforcement Learning,” Boston Dynamics, February 5, 2025, <https://bostondynamics.com/news/boston-dynamics-and-the-robotics-ai-institute-partner/>; Ayushman Ojha, “NVIDIA-Backed Field AI in Talks to Raise Funds at \$2 Billion Valuation,” Investing.com, February 18, 2025, <https://www.investing.com/news/stock-market-news/nvidiabacked-field-ai-in-talks-to-raise-funds-at-2-bn-valuation-the-information-3876127> (note: \$100mil investment reported in PitchBook, public link lacking).

⁵⁹ Cody Reading, Sarthak Das, Magnus Dierking et al., “Deepseek R1 Robotic Reasoning with Checkers,” Hugging Face (blog), March 5, 2025, <https://huggingface.co/blog/codyreading/deepseek-checkers>.

⁶⁰ “AgiBot GO-1: The Evolution of Generalist Embodied Foundation Model from VLA to ViLLA,” Agibot World, March 10, 2025, <https://agibot-world.com/blog/go1>; The Robot Report Staff, “Agibot releases humanoid manipulation dataset to enable large-scale learning,” The Robot Report, December 30, 2024, <https://www.therobotreport.com/agibot-releases-humanoid-manipulation-dataset-to-enable-large-scale-learning/>.

⁶¹ “Mistral AI Robotics Hackathon,” Lu.ma, archived April 17, 2025, <https://web.archive.org/web/20250417223238/https://lu.ma/roboticshack>.

⁶² The Robot Report Staff, “Physical AI startup RLWRLD brings in \$15M,” The Robot Report, April 16, 2025, <https://www.therobotreport.com/physical-ai-startup-rlwrl-d-brings-in-15m/>.

⁶³ Brian Albright, “The Promise of Synthetic Data,” Digital Engineering 24/7, February 11, 2025, <https://www.digitalengineering247.com/article/the-promise-of-synthetic-data/simulate>.

⁶⁴ Paul Logan and Elijah Gray, “Accelerating Reality Capture Workflows with AI and NVIDIA RTX GPUs,” NVIDIA Developer (blog), October 7, 2024, <https://developer.nvidia.com/blog/accelerating-reality-capture-workflows-with-ai-and-nvidia-rtx-gpus/>.

⁶⁵ Logan and Gray, “Accelerating Reality Capture Workflows.”; Brian Eastwood, “What Is Synthetic Data and How Can It Help Competitively?” MIT Sloan School of Management, January 23, 2023, <https://mitsloan.mit.edu/ideas-made-to-matter/what-synthetic-data-and-how-can-it-help-you-competitively>.

⁶⁶ Formant Accounts, “Best Robot Simulators,” Formant (blog), August 23, 2023, <https://formant.io/blog/best-robot-simulators/>; “Gazebo Robotics Simulator,” Gazebo, <https://gazebo.org/>.

⁶⁷ For example: Sunny Cheung, “Testimony Before the U.S.-China Economic and Security Review Commission’s hearing ‘Made in China 2025—Who Is Winning?’” (The Jamestown Foundation, February 6, 2025), https://www.uscc.gov/sites/default/files/2025-02/Sunny_Cheung_Testimony.pdf.

⁶⁸ “Robot Gear Works Under the Hood Is All Japanese,” Asian Robotics Review, <https://asianroboticsreview.com/home224-html>.

⁶⁹ Cheung, “Testimony to the U.S.-China Economic and Security Review Commission.”

⁷⁰ “SEW Eurodrive,” The Mobile Robot Directory, Manufacturer, <https://www.mobile-robots.com/manufacturer/sew-eurodrive/>; “Festo Corporation,” Automation World, Company Profile, <https://www.automationworld.com/home/company/13321766/festo-corporation>; “Industrial Automation,” Bosch Rexroth, <https://www.boschrexroth.com/en/de/industrial-automation/>; “Robot End Effector Market,” Markets and Markets, Market Reports, March 2023, <https://www.marketsandmarkets.com/Market-Reports/robot-end-effector-market-251736819.html>.

⁷¹ Markets and Markets, “Robot End Effector Market.”; Brian Potter, “Robot Dexterity Still Seems Hard,” Construction Physics, April 24, 2025, <https://www.construction-physics.com/p/robot-dexterity-still-seems-hard>.

⁷² Dylan Patel, Reyk Knuhtsen, Jeremie Eliahou Ontiveros et al., “America Is Missing The New Labor Economy: Robotics Part 1,” SemiAnalysis, March 11, 2025, <https://semianalysis.com/2025/03/11/america-is-missing-the-new-labor-economy-robotics-part-1/>; “Under the Hood: China’s Robot Parts Industry,” Asian Robotics Review, <https://asianroboticsreview.com/home414-html>.

⁷³ “U.S. Scrutiny Over China’s Robots,” Asian Robotics Review, <https://asianroboticsreview.com/home510-html>.

⁷⁴ Asian Robotics Review, “Under the Hood”; Cheung, “Testimony to the U.S.-China Economic and Security Review Commission”; “About Leaderdrive,” Leaderdrive, <https://www.leaderdrive.com/>.

⁷⁵ Aaron Saunders, Per Ivar Selvaag, Rob Knight et al., “The Humanoid Robot Market 2025/2026,” Humanoid.Guide, <https://humanoid.guide/>.

⁷⁶ “Robots for manufacturers: 2025 guide to cost, ROI, and use cases,” Standard Bots (blog), [https://standardbots.com/blog/robots-for-manufacturers-a-guide-:-:~:text=Who are the big four,bigger isn't always better](https://standardbots.com/blog/robots-for-manufacturers-a-guide-:-:~:text=Who%20are%20the%20big%20four,bigger%20isn't%20always%20better); Patel et al., “America Is Missing The New Labor Economy.”

⁷⁷ “10 Industrial Robot Companies That Lead the Industry,” Association for Advancing Automation, <https://www.automate.org/robotics/news/10-industrial-robot-companies-that-lead-the-industry>.

⁷⁸ Asian Robotics Review, “Under the Hood.”

⁷⁹ Caleb Naysmith, “Amazon Grows to Over 750,000 Robots As World’s Second-Largest Private Employer Replaces Over 100,000 Humans,” Yahoo!Finance, April 11, 2024, <https://finance.yahoo.com/news/amazon-grows-over-750-000-153000967.html>; Scott Dresser, “Amazon launches a new AI foundation model to power its robotic fleet and deploys its 1 millionth

robot,” Amazon Robotics, June 30, 2025, <https://www.aboutamazon.com/news/operations/amazon-million-robots-ai-foundation-model>.

⁸⁰ Brianna Wessling, “SoftBank makes offer to acquire Balyo shares” The Robot Report, June 16, 2023, <https://www.therobotreport.com/softbank-makes-offer-to-acquire-balyo-shares/>; “Autonomous Mobile Robots Market Size, Share and Trends, 2025 To 2030,” Markets and Markets, Market Reports, December 2024, <https://www.marketsandmarkets.com/Market-Reports/autonomous-mobile-robots-market-107280537.html>; Aaron MC Nicholas, “Geeking Out Over Warehouse Robots,” The Wire China, June 2, 2024, <https://www.thewirechina.com/2024/06/02/geeking-out-over-warehouse-robots-chinese-company-geekplus/>; “Balyo Stock Quote,” Yahoo!Finance, <https://finance.yahoo.com/quote/BALYO.PA?guccounter=1>.

⁸¹ Arendse Huld, “Investing in the Future: Opportunities in China’s Humanoid Robotics and Embodied AI Industry,” China Briefing, April 7, 2025, <https://www.china-briefing.com/news/chinese-humanoid-robot-market-opportunities/>; “Da Vinci Robotic Surgery System,” Intuitive Surgical, <https://www.intuitive.com/en-us/patients/da-vinci-robotic-surgery>.

⁸² The reason for South Korea’s leading position in robotics adoption stems from several factors: a major push for automation from OEMs seeking productivity gains, interest/first-mover advantages from the chaebol’s beginning decades ago, and government policies to encourage robotics development/adoption as a means of mitigating rapid population aging and persistently low birth rates. See: Sarah Rudge, “One in Ten Workers in South Korea is a Robot,” Manufacturing Today, September 4, 2024, <https://manufacturing-today.com/news/one-in-ten-workers-in-south-korea-is-a-robot/>.

⁸³ Bao Tran, “Top Countries Automating Fastest: Global Robotics Map,” PatentPC, September 14, 2025, <https://patentpc.com/blog/top-countries-automating-fastest-global-robotics-map>.

⁸⁴ International Federation of Robotics, “World Robotics Press Conference 2024,” https://ifr.org/img/worldrobotics/Press_Conference_2024.pdf.

⁸⁵ “Successful test of humanoid robots at BMW Group Plant Spartanburg,” BMW Group, Press Release, June 8, 2024, <https://www.press.bmwgroup.com/global/article/detail/T0444265EN/successful-test-of-humanoid-robots-at-bmw-group-plant-spartanburg?language=en>.