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What work can robots do?

Published
September 30, 2026

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Acknowledgments

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Key findings

- We present a robot exposure index based on how well robots can perform job tasks today.
- Robots, which we define as autonomous physical machines that sense and act, can perform three-quarters of physical tasks in the US, making up 34% of working hours, but mostly in limited settings. Workers exposed to robots are more likely to be male, less educated, and lower paid. For example, driving and warehouse jobs are highly exposed to currently available robots; nursing and general repair jobs are not, since present-day robots can do little of their work even in highly controlled environments.
- Overall, about 80% of job tasks by working time are exposed to either robots or LLMs. Robots do work where LLMs cannot. The remaining unexposed work is highly interpersonal or requires physical skills that robots today don't have.
- While robots can do most physical work tasks today, they are much more expensive than human labor. Robots are cost-competitive for just 0.3% of job tasks. If robot price declines follow past trends, it will take 40 years for that share to reach 10%. Beyond price, factors including capabilities, preferences, and regulations pose further barriers to robot automation.
- Over the past 50 years, jobs more exposed to robots experienced greater declines in wages and employment than others. At the same time, job exposure has grown: each year, robots have become able to do about 2% of the physical work they previously couldn't.

Introduction

Advances in large language models have raised the possibility of automating large swaths of work. But many jobs are physical. AI's impact on the economy will in part depend on robotics.[1]

Predicting the pace of robot advances is difficult, but enumerating capabilities today, we argue, can give insight into the coming years. We develop a measure of job exposure to robots, using Claude to assess how well present-day robots can perform work tasks. A job is more exposed when robots can do more of its tasks in less controlled environments. A robot is cost-competitive when it can do the same task for cheaper than a human worker.

We find that robots can already perform 74% of physical tasks in the US, making up 34% of working hours. Robots and LLMs together expose all but one-fifth of employment.

But we also find significant barriers to adoption: most robots require highly structured environments, and are cost-competitive with people for just 0.3% of work. If robot price declines follow past trends, it will take 40 years for that share to reach just 10%. After cost, the main barrier is capability, such as the dexterity needed to untangle wires. Human preferences and regulations further limit robot adoption for a significant share of tasks.

Our core premise is that jobs are more likely to be impacted when robots can already do their work today. A backtest across 50 years validates this approach: from 1977 to today, jobs that were more exposed to existing robots experienced wage and employment declines in later decades.

If the past is any guide, taxi drivers and warehouse packers will see changes sooner than nurses and mechanics. We expect that physical work will first be automated where robots have a foothold today.

Robots today and tomorrow

Most robots today operate in controlled environments like factories. Robots usually need to be programmed to interact with the physical world, whereas humans can adapt to their work environments. This has been a major hurdle for commercially viable robots.[2] But AI helps robots interpret and respond to their surroundings, allowing warehouse robots and autonomous vehicles to operate alongside humans.[3]

Many observers expect AI to improve robot capabilities quickly.[4] Although spending on robots remains about 1% of total US equipment investment, business surveys suggest US robot adoption could nearly double within three years.[5] And firms are investing billions to develop AI-powered robots that match human physical abilities.[6]

It's difficult to predict exactly how these efforts will affect jobs and productivity. A *ranking* of occupations by current robot task coverage suggests where the impacts will appear first. Robots should affect jobs that they can already do before jobs they could do only with new technology and, in some cases, accommodating regulations. Current capabilities are also concrete and measurable, while forecasts of future capabilities must bet on which technologies will succeed.[7] Robots still in development support our focus on

current exposure: firms are testing humanoids in car factories and warehouses, structured environments where robots are already common.[8]

Measuring exposure

Our analyses use data from O*NET, a database of around 900 occupations linked with descriptions of around 19,000 job tasks. We identify a set of physical job tasks that we think could not be automated without robots. To do so, we have Claude score task descriptions on a rubric measuring physical, cognitive, and interpersonal work requirements.[9] The task "Dig trenches" is physical; so is "Teach dance students," though this also requires cognitive and interpersonal skills. While typists use their hands to "Compute and verify totals on report forms, requisitions, or bills, using adding machine or calculator," this task doesn't count. Appendix A gives details, and Appendix F lists our prompts.

Our task-level measure of robot exposure asks: can a robot today perform this task, and if so under what circumstances? We take robots to mean autonomous physical machines that sense and act, which includes car washes that scan cars to adjust sprayers and excludes teleoperated surgical machines fully controlled by a surgeon.[10] We measure degrees of exposure by the kind of work environment a robot needs to perform a task.[11]

Specifically, we sort tasks into four tiers of increasing exposure by where a robot can perform each task:

- E0: Robot cannot perform task.
- E1: Robot can perform task in a purpose-built robotic work environment, like a factory assembly line.
- E2: Robot can perform task in a structured human work facility, like a logistics warehouse.
- E3: Robot can perform task in an unstructured environment, like a city road.

Figure 1 also displays this rubric.

We think environmental control is a good measure of near-term automation risk. Because it's hard for robots to adapt to unpredictable environments, most deployed robots work in engineered environments, like those that spray paint cars on assembly lines. While these difficulties are thought to have

Task robot exposure rubric

Exposure	Robot can perform task in:
E0	Cannot perform task
E1	A purpose-built robotic work environment, like a factory assembly line
E2	A structured human work facility, like a logistics warehouse
E3	An unstructured environment, like a city road

Figure 1: Task robot exposure rubric
Notes: Job tasks identified as physical are rated on this robot exposure rubric. For example, the job task of unloading boxes from a truck at a warehouse is rated E2 if there's a warehouse robot that can do that task.

slowed physical automation in the past, AI-powered robots could better adapt to their environments.[12]

To determine exposure, we instruct Claude to search for specific robots relevant to each task and assess their capabilities and operating environments, quoting sources directly. We ask whether a robot could perform a task in versions of that task's typical work environment that are more or less structured. Getting robots to do seemingly simple tasks like loading a dishwasher requires many complex physical skills, so only demonstrated robot capabilities count.[13] Robots must also do a task similarly well to humans, factoring in reliability, error rates, and speed.

For instance, self-driving cars couldn't "Drive taxicabs or privately owned vehicles to transport passengers" on real roads in the early 2010s. But they did drive around mock towns built for testing, a step toward today's autonomous vehicles.[14] Our rubric would rate driving passengers at exposure level E1 at that time (robot can perform task in a purpose-built robotic work environment) and E3 today (in an unstructured environment).[15]

This rubric requires many judgment calls. The O*NET task statements are often terse, and omit details that may be easy for humans but hard for robots.[16] To describe work more concretely, we elicit detailed examples of how tasks are performed today, and how often these occur. Claude then scores exposure for these examples using web search to gauge robot capabilities. Cited sources

must show robot deployments, commercial sales, or demonstrations, and results are similar if we omit ratings relying on demonstrations. Task exposure is set by majority rule: the least structured environment in which robots can do at least half of a task's examples, weighted by time.[17]

Consider the task "Dig trenches." We first ask Claude to provide examples describing how workers perform this task today and how often. For example, Claude estimates that 25% of the time, this task requires "cutting a linear trench in open ground." Another 20% of the time, it requires "careful digging by hand around existing buried pipes, flowlines, cables and conduit." These activities require different sorts of physical abilities, like navigation and strength (linear trenches) compared to fine motor dexterity and perception (digging by hand around pipes).

Claude rates the first example at exposure E3, citing a control system that retrofits hydraulic excavators to autonomously dig trenches.[18] Robots today can't carefully dig around buried pipes, so the latter example is unexposed at E0. More examples for "Dig trenches" resemble careful digging than linear trenching, so overall this task is unexposed in our ratings.

Figure 2 gives examples of task ratings, along with fuller descriptions of each exposure tier from our exposure prompt and a robot cited to support each rating. We also calculate the share of physical tasks in each tier: here and throughout, each task is weighted by the number of workers who do it, and by the fraction of working time they spend on it, which we estimate with Claude.[19]

Tasks that robots can't do (E0) make up about a quarter of physical tasks by estimated working time. These tasks require physical skills that are hard for robots, like fine motor dexterity for "Bleach, dye, or tint hair, using applicator or brush" and strength, balance, and mobility for "Erect scaffolding or ladders for assembling structures above ground level."

Robots can do half of physical tasks in purpose-built environments but not in wider settings (E1). Food prep robots pack ready-to-eat meals on conveyor belts, and new models with AI can adjust to different ingredients, portions, and trays, so the task "Assemble meal trays with foods in accordance with patients' diets" is rated E1.

Example task exposure ratings

Robot can perform task in:	Share of physical tasks	Example occupation	Example task	Example of cited robot
E0 No environment No cited system could complete the instance even in a purpose-built setting.	26.3%	Hairdressers, hairstylists, and cosmetologists	Bleach, dye, or tint hair, using applicator or brush.	
		Carpenters	Erect scaffolding or ladders for assembling structures above ground level.	
E1 Purpose-built robotic work environment A setting built for the machine: fixtures hold each workpiece in a known position, conveyors present inputs one way, fences or light curtains keep people out. **Examples:** a fenced machine-tending cell, a bottling line, an automotive paint booth. **Mark of E1:** the setting is built around the machine, not around people.	49.8%	Food preparation workers	Assemble meal trays with foods in accordance with patients' diets.	Chef Robotics meal assembly robot
		Automotive service technicians and mechanics	Align vehicles' front ends.	Fori Automation robotic wheel alignment system
E2 Structured human work facility A setting built for human work and kept predictable: a fixed layout, standard equipment, and an institution that controls who and what is present. It may be indoor or outdoor. **Examples:** a hospital pharmacy, a hotel corridor, an airport concourse, a container port. **Mark of E2:** an institution controls the premises and keeps them to a working standard.	22.0%	Stockers and order fillers	Receive and count stock items, and record data manually or on computer.	Simbe Robotics shelf-scanning robot
		Pharmacy technicians	Deliver medications or pharmaceutical supplies to patients, nursing stations, or surgery.	Relay Robotics hospital delivery robot
E3 Unstructured environment A setting taken as found: the layout differs site to site, novel objects appear, and conditions are not kept to any standard. **Examples:** a private home, a construction site, a public sidewalk. **Mark of E3:** no institution controls the setting or keeps it to a working standard.	1.9%	Taxi drivers	Drive taxicabs or privately owned vehicles to transport passengers.	Waymo robotaxi
		Farmworkers and laborers, crop, nursery, and greenhouse	Operate tractors, tractor-drawn machinery, and self-propelled machinery to plow, harrow and fertilize soil, or to plant, cultivate, spray and harvest crops.	John Deere autonomous tractor

Figure 2: Example task exposure ratings
Notes: Levels of robot exposure are as described in the prompt we use to rate exposure with Claude. Exposure is rated for 7,594 job tasks classified as physical. Physical task shares in column 2 weight tasks by the fraction of time spent on each task in an occupation (estimated with Claude) and that occupation's employment (BLS, 2025). For example, the RelayRx robot delivers drugs in hospitals. Hospitals are structured human workplaces, so the task "Deliver medications or pharmaceutical supplies to patients, nursing stations, or surgery" is rated E2. Tasks rated E2 make up 22% of physical tasks by working time.

Another 22% of physical tasks can be done by robots in structured human workplaces (E2). Hospital delivery robots, for example, "Deliver medications or pharmaceutical supplies to patients, nursing stations, or surgery." Today's robots do only 2% of physical tasks in unstructured environments (E3). These often involve driving, done by autonomous cars, tractors, and other vehicles.[20]

Our accompanying data release contains Claude's reasoning and cited sources for all rated tasks. For example, Claude rates the task "Weld components in flat, vertical, or overhead positions" E1, and quotes an article about AI-powered robot welders: "Path Robotics said both of its welding cells can autonomously weld steel parts and are deployed in fabrication shops across the U.S. and Canada."[21]

We define a robot exposure index for jobs that averages a job's task exposure ratings on a 0–3 scale. This index rises with the share of exposed tasks and robot capabilities on those tasks, weighting tasks by estimated working time.

An ideal exposure index would perfectly predict robot automation in the coming years. Since we can't look forward in time, we instead try to validate our measure using historical data on jobs and task descriptions. We rate robot exposure in several years since 1977, and link exposure to changes in wages and employment. When a job was more exposed to robots, its wages and employment fell in later decades, even after accounting for industry trends and other potential confounders. These results, detailed in Appendix B, give us some confidence that our measure can predict future job disruption.

What work can robots do?

Figure 3 summarizes robot exposure across all job tasks in the US economy, weighting tasks by the estimated fraction of time spent per task for an occupation and that occupation's employment. Cognitive and interpersonal work makes up 54% of tasks by working time. The remaining 46% of tasks are physical. As a share of all tasks, around 12% cannot be done by any robot today (E0), 23% can be done by robots in specially built environments (E1), 10% in structured human workplaces (E2), and 1% in unstructured environments (E3). Counting any exposure level, 74% of physical work, or 34% of all work, can be done by robots in some circumstances.

Robots can do physical tasks in many parts of the economy. Autonomous mobile warehouse robots drive to loading docks and inside trailers. They use suction cups to grab packages and load them onto mobile conveyor belts.[22] Since these robots navigate structured human workplaces, many warehousing tasks are rated E2, like "Move freight, stock, or other materials to and from storage or production areas, loading docks, delivery vehicles, ships, or containers, by hand

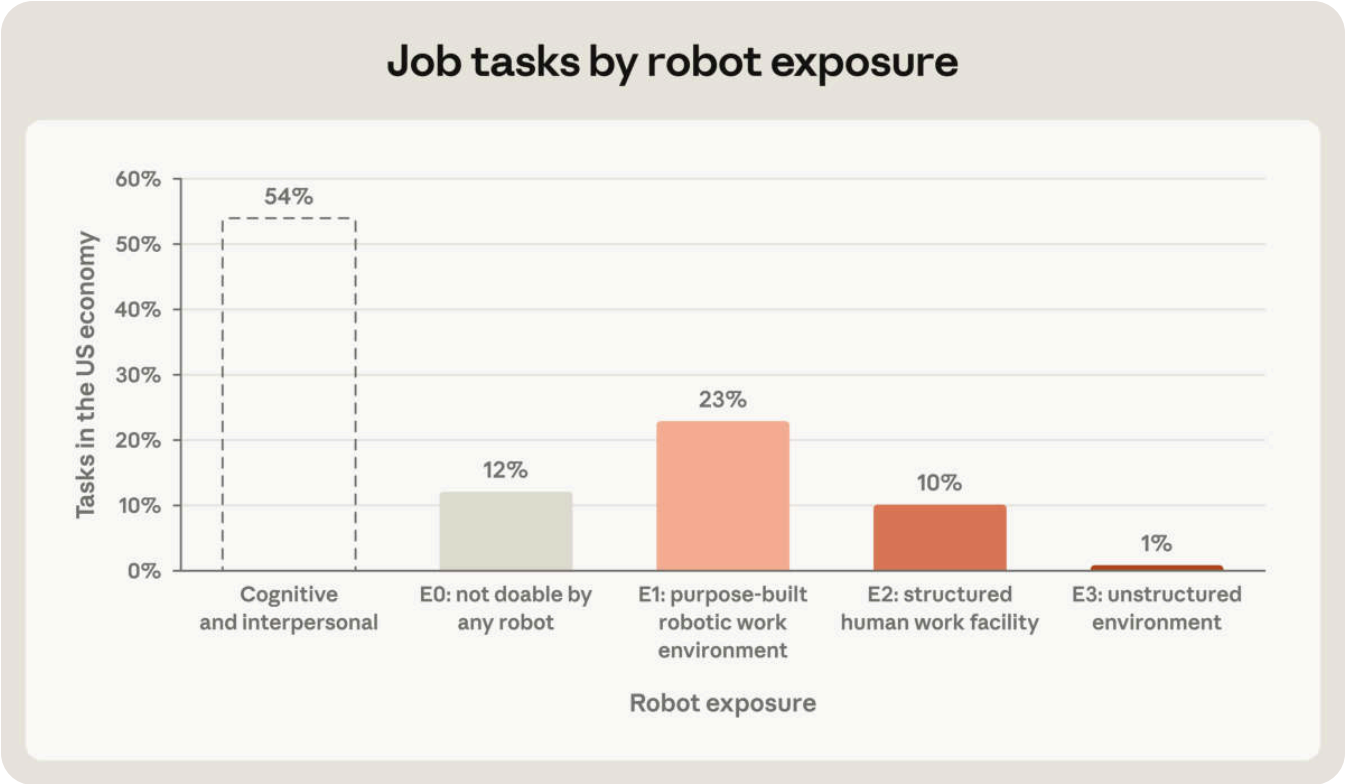

Figure 3: Job tasks by robot exposure
Notes: All job tasks are included. Tasks are weighted by the fraction of time an occupation spends on each task as well as that occupation's employment. Robot exposure is rated for tasks identified as physical. For example, 23% of worker time is spent on tasks that robots can do in a purpose-built environment. Example tasks by category: teaching classes, designing systems (Cognitive and interpersonal); taking people into custody, providing first aid (E0); dispensing medications, assembling electronics (E1); cleaning floors, moving warehouse goods (E2); regulating field irrigation, inspecting property from the air, and driving, which robots perform in unstructured environments (E3). Employment data come from the BLS (2025), and we use Claude to estimate occupation time on tasks.

or using trucks, tractors, or other equipment." Advances in navigation and handling have made robots like these common in logistics and transportation.[23]

Figure 4 shows the 10 most exposed occupations by our robot exposure index. Of these 10 occupations, 9 are vehicle operators. Robots cited for driving jobs include autonomous cars, tractors, trucks, and pavers. Taxi drivers lead exposure with an index of 2.2.[24] Since driving is most of the job, their median task by working time is exposed at E3, while auxiliary tasks like "Vacuum and clean interiors and wash and polish exteriors of automobiles" are doable by robots but in more structured settings than open roads. Autonomous vehicles have yet to upend driving jobs at scale, but their capabilities suggest that these jobs are at higher risk of automation than others.[25]

An occupation can cover many work settings. In the US, robots may only operate in some of these settings, while robots abroad sometimes cover all of

Most exposed occupations

Occupation	Exposure (0-3)	Employment (thousands)	Example exposed task	Example of cited system
Taxi drivers	2.2	41	E3 Drive taxicabs or privately owned vehicles to transport passengers.	Waymo robotaxi
Agricultural equipment operators	2.1	29	E3 Operate or tend equipment used in agricultural production, such as tractors, combines, and irrigation equipment.	John Deere autonomous tractor
Light truck drivers	2.1	983	E3 Drive vehicles with capacities under three tons to transport materials to and from specified destinations, such as railroad stations, plants, residences, offices, or within industrial yards.	Gatik autonomous box truck
Shuttle drivers and chauffeurs	2.0	249	E3 Drive shuttle busses, limousines, company cars, or privately owned vehicles to transport passengers.	Waymo robotaxi
Industrial truck and tractor operators	2.0	774	E2 Move levers or controls that operate lifting devices, such as forklifts, lift beams with swivel-hooks, hoists, or elevating platforms, to load, unload, transport, or stack material.	Fox Robotics autonomous forklift
Paving, surfacing, and tamping equipment operators	1.8	42	E3 Start machine, engage clutch, and push and move levers to guide machine along forms or guidelines and to control the operation of machine attachments.	XCMG unmanned paver and roller fleet
Refuse and recyclable material collectors	1.8	147	E3 Operate automated or semi-automated hoisting devices that raise refuse bins and dump contents into openings in truck bodies.	McNeilus automated side-loader refuse truck
Driver/sales workers	1.7	409	E3 Drive trucks to deliver such items as food, medical supplies, or newspapers.	Gatik autonomous box truck
Recycling and reclamation workers	1.7	1,475	E2 Sort materials, such as metals, glass, wood, paper or plastics, into appropriate containers for recycling.	AMP Robotics sorting robot
Excavating and loading machine and dragline operators, surface mining	1.6	34	E2 Move levers, depress foot pedals, and turn dials to operate power machinery, such as power shovels, stripping shovels, scraper loaders, or backhoes.	Sandvik AutoMine autonomous loader

Figure 4: Most exposed occupations
Notes: Exposure ranges from 0 (no task can be done by a robot) to 3 (every task can be done by a robot in an unstructured environment). Job exposure averages task exposure, weighting by time spent on each task. A highly exposed task is listed for each occupation along with a cited robot that can perform this task. The 10 most exposed occupations with at least 20,000 jobs are displayed. For example, averaging task exposure for shuttle drivers and chauffeurs gives an index of 2.0 out of 3. Claude cites Waymo autonomous vehicles as performing some of their tasks. Employment data from BLS (2025) sometimes combine several O*NET occupation titles; we split their employment equally, as for recycling and reclamation workers. We estimate task time requirements with Claude.

them. For example, stockers and order fillers do the task "Stock shelves, racks, cases, bins, and tables with new or transferred merchandise" in retail stores and in warehouses. In US warehouses, AI-powered robots with touch sensors

pick and stow merchandise.[26] In US retail, mobile robots scan for empty shelves, but must alert humans to restock them.[27] Robots in Japanese convenience stores restock fridges themselves.[28] Since stocker robots require items to be brought near them, this task is rated E1. We estimate that stockers spend 70% of their time on tasks rated E1 like this one, and another 16% on tasks rated E2. In total, they score 1.0 on the robot exposure index.

Jobs can be exposed to robots if many of their tasks are moderately exposed, or if some of their most time-intensive tasks are highly exposed. Compare tapers, who finish drywall and whose exposure index is 1.6, with recycling and reclamation workers, who sort recycling and whose exposure index is 1.7.

Tasks for tapers are split between unexposed and highly exposed. Workers building interior walls use paper tape and a paste called mud to smooth over seams, joints, and screws in drywall sheets. Mud and tape are messy materials, so robots cannot perform the task "Press paper tape over joints to embed tape into sealing compound and to seal joints." After the first tape coat dries, workers "Apply additional coats to fill in holes and make surfaces smooth." This task is rated E3: an autonomous drywall robot uses AI to scan walls, spray additional coats of sealant, and sand walls once dry.[29] Overall, by work time, 41% of tapers' tasks are exposed at E3, while robots cannot do another 26%.

In contrast, for recycling and reclamation workers, robots can perform over three-quarters of tasks by work time at level E2. Only 8% of their work time is unexposed. For example, robots with computer vision and suction grippers can do the task "Sort materials, such as metals, glass, wood, paper or plastics, into appropriate containers for recycling."[30] These robots stand in for workers picking recycling from conveyor belts, so this and other tasks are rated E2.

Robots are highly capable at specific tasks for tapers, while for recycling workers exposure is broader, but robots are less adaptable. Messy tasks for tapers may bottleneck automation. It's also possible that the largest recycling facilities use robots early, while smaller facilities adopt them later. Either way, robots seem likely to change both jobs if widely deployed.

Characteristics of exposed jobs

Having established our exposure measure, we now consider what exposure might imply for the labor market.

Figure 5 compares workers in the top quintile of the robot exposure index with unexposed workers, who make up another 20% or so of jobs. Data from the 2020–2024 American Community Survey show that highly exposed workers are 20 percentage points less likely to be female and 16 percentage points more likely to be Hispanic. These workers are also 55 percentage points less likely to hold a bachelor's degree or higher, earn around $30 less per hour, and face an unemployment rate more than twice as high.[31]

Occupational requirement statistics compiled by the Bureau of Labor Statistics also show that robot-exposed jobs are much more likely to require carrying weight and working in extreme heat or near hazardous contaminants. This exposure pattern is in many ways the opposite of what's typically found for LLMs.[32]

Robot and LLM exposure

We next analyze whether robots broaden job disruption risks beyond those from LLMs alone. Drawing on Eloundou et al. (2024) and Massenkoff and McCrory (2026), we compare two occupation exposure measures:

- LLM exposure: the share of job tasks for which an LLM could halve required time (called theoretical capability in our prior work).
- LLM and robot exposure: the share of job tasks exposed to either LLMs or robots, taking the higher of LLM exposure and E1+ robot exposure for each task.

Robot and LLM exposure ratings measure somewhat different concepts, but both indicate that technology could do much of a given task. While integrating LLMs and robots in actual jobs may present new challenges or enable new capabilities, these two measures provide initial insight into job exposure based on today's capabilities.

Figure 6 plots job exposure to LLMs alone (in blue) and to LLMs and robots (in orange), grouped by broad occupation category. Robots expose more and different kinds of jobs than LLMs alone. While less than 15% of transportation & moving tasks are exposed to LLMs alone, about 90% of these

Occupation characteristics by robot exposure

Category	Characteristic	Not exposed	Most exposed	Difference
Robot exposure	Robot exposure index (0–3)	0.0	1.3	+1.3
Demographics	Age	41.7	38.0	−3.7
	Female	51.2%	31.2%	−20.0 pp
	Hispanic	13.1%	29.6%	+16.5 pp
	White, non-Hispanic	63.3%	45.3%	−18.0 pp
	Black, non-Hispanic	10.0%	16.0%	+6.0 pp
	Asian, non-Hispanic	8.8%	4.3%	−4.5 pp
Education and licensing	Less than high school	1.8%	16.6%	+14.8 pp
	High school	11.9%	46.0%	+34.1 pp
	Some college	23.2%	29.0%	+5.8 pp
	Bachelor's degree or higher	63.2%	8.3%	−54.9 pp
	Requires license or certification	19.0%	13.3%	−5.7 pp
Labor market	Unemployment rate	2.2%	5.2%	+3.0 pp
	Hours per week	41.0	36.8	−4.2
	Hourly wage	$52.97	$22.88	−$30.09
	Union member	5.2%	10.2%	+5.0 pp
Physical demands	Share of workday standing	18.3%	79.1%	+60.8 pp
	Works in low postures	11.9%	85.5%	+73.6 pp
	Frequently lifts or carries some weight	3.5%	60.7%	+57.2 pp
Work environment	Works outdoors	13.5%	54.6%	+41.1 pp
	Exposed to extreme heat	0.3%	6.4%	+6.1 pp
	Exposed to hazardous contaminants	0.6%	6.5%	+5.9 pp

Figure 5: Occupation characteristics by robot exposure
Notes: The most exposed workers are those in the top quintile of the robot exposure index; unexposed workers have zero exposure and make up about another 20% of jobs. Demographics, education, and labor market data come from the 2020–2024 American Community Survey, save for union membership and licensing. Union membership comes from statistics tabulated by Hirsch et al. (2026) for the 2020–2024 Current Population Surveys. Licensing comes from the 2025 BLS Occupational Requirements Survey, as do physical demand and work environment variables (for some occupations, these come from the 2023 survey). Statistics are employment weighted.

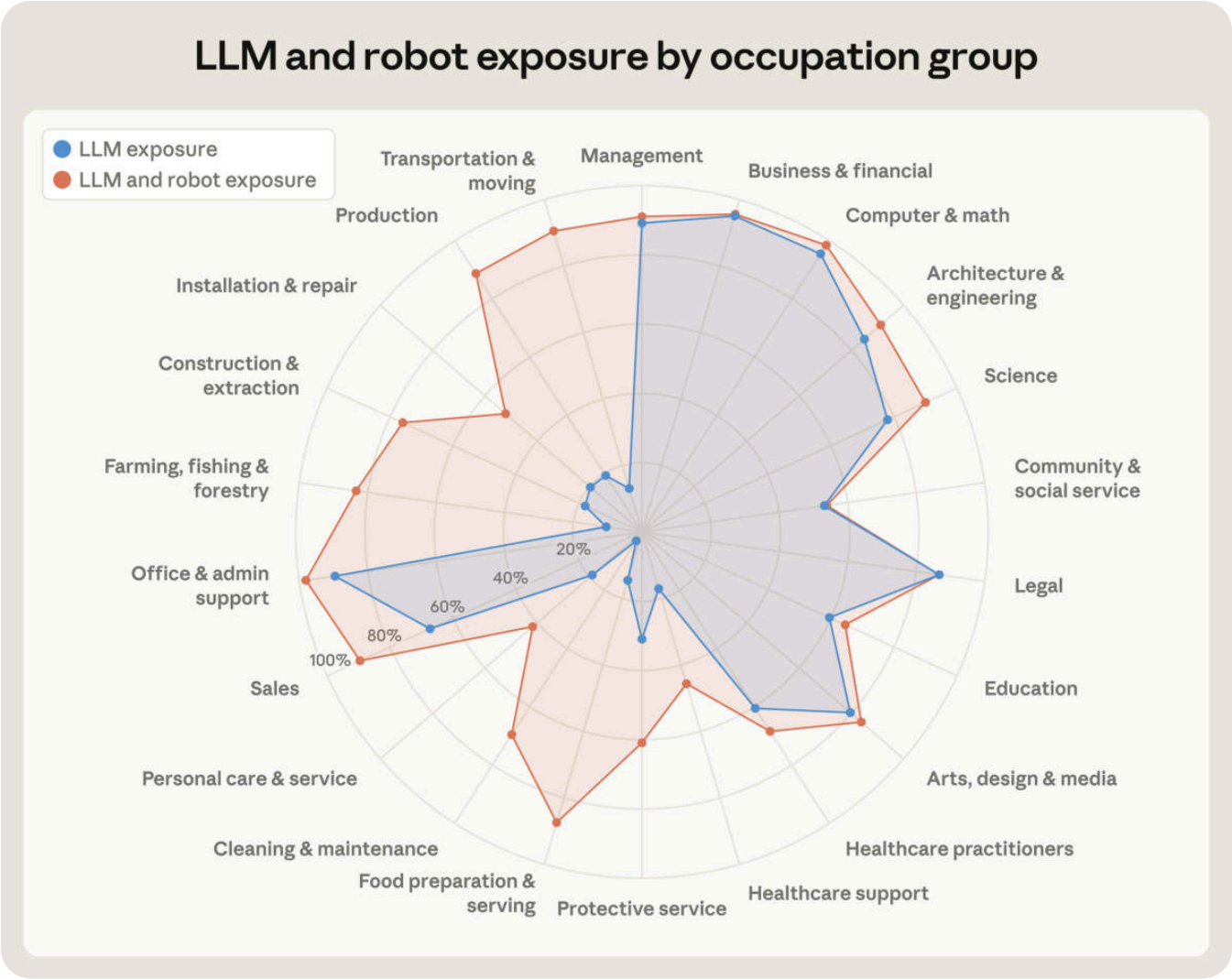

Figure 6: LLM and robot exposure by occupation group
Notes: LLM exposure is the share of tasks rated exposed in Eloundou et al. (2024) (positive β). Occupation exposure to LLMs and robots adds tasks rated at E1 or higher robot exposure. Occupation groups are 2-digit SOC codes, and group averages weight by task time shares and employment. In protective service occupations, for example, 31% of job tasks are exposed to LLMs, and 61% are exposed to LLMs or robots. Employment data come from BLS (2025). We estimate task time shares with Claude.

tasks are exposed with robots. Similarly, robots raise exposure in office & admin support jobs, which largely involve computer work and light physical tasks, to nearly 100%. Overall, around half of work is exposed to LLMs alone, but that rises to 81% when considering robots.

What work can't LLMs and robots do today? Consider personal care & service jobs, for which around 40% of tasks are exposed. In-person social interaction and physical contact with humans, which both LLMs and robots struggle with, are important for these jobs. This example suggests that highly interpersonal work, or work requiring delicate manipulation, may be less susceptible to

near-term automation.[33] Occupation groups like installation & repair, healthcare support, and community & social service fit this pattern too, with relatively low exposure. While LLMs and robots can't perform these tasks today, no occupation group overall is less than 40% exposed. And advances in technology may make possible new kinds of automation over time.

Unexposed tasks also help describe what could make work hard to automate. We group unexposed task statements that share similar text, and ask Claude to describe these (Appendix C.1). Tasks not exposed to LLMs or robots today tend to be hands-on and face-to-face, and are sometimes regulated. Healthcare tasks often combine these features, like "Administer medications to patients and monitor patients for reactions or side effects."

In Appendix C.2, we study which barriers may most prevent the automation of physical tasks. We ask Claude which barriers today would prevent robots from doing a significant share of each physical task, exposed or not, if unresolved. We group these into four categories: capabilities, human preferences, regulation, and cost. For tasks limited by capabilities, we have Claude pick the most important missing skill from manipulation, planning and reasoning, mobility and strength, and perception.

We find that capabilities and costs are the biggest impediments to robot adoption. Capabilities prevent adoption for around 70% of physical tasks. Manipulation capabilities stand out: half of physical tasks wouldn't be automated at scale unless robots become more adept at touching and handling objects. Shortcomings in planning and reasoning skills, which AI seems most likely to improve, limit robot automation for 8% of physical tasks. For nearly all tasks, costs would also need to fall.

Our estimates indicate that today's regulations wouldn't allow robots to perform 14% of physical tasks. Regulation matters for tasks in healthcare, protective service, and education, but less so for those in food preparation, cleaning, production, construction, repair, and material moving, which make up about half of physical work. Human preferences hold back robots for a quarter of tasks. That may be because people wouldn't trust a robot (to "Dress children and change diapers") or because they value social interaction (to "Greet guests, escort them to their seats, and present them with menus and wine lists").

If robot capabilities develop quickly, what do these results imply? Around 30% of physical tasks are limited either by preferences or by regulation. That would leave most physical work exposed if robots became capable and cost-effective, though the rest may become weak links that drag down aggregate productivity speedups. Uneven progress in capabilities could also slow adoption, if robots became smarter but still couldn't handle objects like humans. That said, better robots could also reduce resistance to automation, for example by assuaging safety concerns. We turn next to robot costs, the most common barrier in these estimates.

Robot costs and adoption

Though robots can perform most physical work today, it may not be economical for them to do so. Robots made with pricey hardware aren't as easily copied and distributed as software or LLMs. Compared to LLM exposure measures that assess capabilities but not costs, it's especially important to distinguish jobs exposed to cost-competitive robots.[34]

For every exposed task, we estimate the annual cost for robots to perform this task based on the specific robots cited in our task exposure measures. We prompt Claude to estimate costs using web search and the list of robots cited for each task. Automating an E1-exposed task could require redesigning workplaces to suit robots, while robots that do E3 tasks may use expensive sensors to navigate unstructured environments.

Estimates cover the full cost of deploying a robot to perform each task.[35] To make robot and labor costs comparable, we first ask Claude to estimate how much a human worker typically produces on a task in a year. Bakers who "Roll, knead, cut, or shape dough," for example, produce an estimated 180,000 shaped pieces per year. Claude then estimates what it would cost a robot to produce the same output. Because bakers do this task in different environments, Claude averages robot deployment costs across retail, mid-scale, and industrial bakeries. Fixed costs are annualized to reflect hardware lifespans and the time value of money.

Calculated this way, costs for robots to do a task can be compared to worker pay. We say a task is exposed to cost-competitive robots if its robot cost is less than its labor cost, calculated as the occupation's total compensation from the BLS scaled by the fraction of time spent on this task.[36] Standard economic

models predict that these tasks are automated, though given adoption frictions and cost uncertainties this measure is more suggestive.[37] See Appendix D.1 for details and a worked example of robot task costs.

Robots often perform multiple job tasks, but we estimate costs for individual tasks in an occupation. Simply adding up task costs may double count robots or undercount coordination costs in real deployments. We aggregate by occupation, providing Claude with task cost estimates and asking for a total cost, net of redundancies and new additions. We say that an occupation is exposed to cost-competitive robots if this total robot cost is less than its total compensation scaled by the fraction of time spent on tasks that robots can do.[38]

Figure 7 shows five highly physical jobs and cost estimates for robots to perform their exposed tasks. Packers and packagers are the largest occupation exposed to cost-competitive robots. Several robots are needed to do packers and packagers' tasks, including those that pack containers, move materials around warehouses, visually inspect goods, erect cardboard boxes, print and apply labels, and seal packages.[39] These robots are estimated to cost over $2 million to purchase and install, but replace the yearly work of around 14 workers. Fixed costs are spread over a roughly 10-year service life at an 8% cost of capital. Operating expenses, such as maintenance, part-time human supervision, and energy, bring annual costs to around $45,000 to replace one human worker per year. Since packers and packagers spend 97% of their time on tasks that robots can do and cost around $49,000, robots cost about $2,500 less per year to do that work.

The US currently employs around 560,000 packers and packagers. Firms face adoption frictions, like regulation or borrowing limits, and these cost estimates are approximate. For example, robotaxis are estimated to cost only around $7,000 more than taxi drivers, but face regulatory hurdles.[40] That said, automation risks are likely higher for physical jobs that cost-competitive robots can do. Employment for packers and packagers has fallen 22% since 2015. And the BLS projects this occupation will shed the 11th-most jobs of any occupation by 2035, behind only correctional officers and 9 sales and office occupations.[41]

For the other jobs shown in Figure 7, robots cost much more than humans even though they can do much of the work. In metalworking, robots with cameras and AI can weld autonomously.[42] But human welders perform many tasks that enable welding, like positioning large metal parts, climbing ladders to weld

Robot costs for physical occupations

	Occupation	Employment (thousands)	Median comp. ($ thousands per year)	Exposed tasks	Annual robot cost ($ thousands)			Example robot and upfront cost ($ thousands)
					Total	Fixed	Variable	
Cost-competitive	Packers and packagers, hand	560	$49.0	97%	$45.4	$22.2	$23.2	Douglas top-load case packer $160.0
Not cost-competitive	Taxi drivers	41	$56.8	89%	$57.8	$27.4	$30.4	Waymo robotaxi $135.0
	Dishwashers	477	$45.0	100%	$172.0	$97.9	$74.1	Armstrong Robotics dishwashing system $165.0
	Janitors and cleaners	2,210	$47.7	73%	$280.0	$143.7	$136.3	Somatic-class cleaning mobile manipulator $100.0
	Welders, cutters, solderers, and brazers	416	$73.4	90%	$334.6	$160.0	$174.6	Zeman steel-beam assembler line $2,700.0

Figure 7: Robot costs for physical occupations
Notes: Employment and total compensation use data from the BLS (OEWS 2025, ECEC 2026). Exposed tasks are the share of that occupation's tasks at exposure E1–E3, weighted by estimated time spent on each task. Claude estimates annual costs for robots to perform exposed tasks for each occupation. Costs include annualized fixed costs and variable costs. The final column lists one robot included in each cost estimate and its estimated purchase price.

hard-to-reach joints, checking quality, and grinding and finishing materials. Automating this work requires robots that together cost around five times more than human welders.

Dishwashers, along with janitors and cleaners, are paid $25,000 to $30,000 less than welders. But their robot analogs are still several times more expensive. Cleaning is hard to standardize and streamline, and robot cleaners are often slower than humans and limited to specific tasks.[43]

Figure 8 summarizes robot costs by plotting exposure to cost-competitive robots at hypothetical, uniform declines in robot costs. For example, if robots cost 20% less today, they would be cost-competitive for the physical work done by 2.8 million workers. These workers spend on average 42% of their time on work

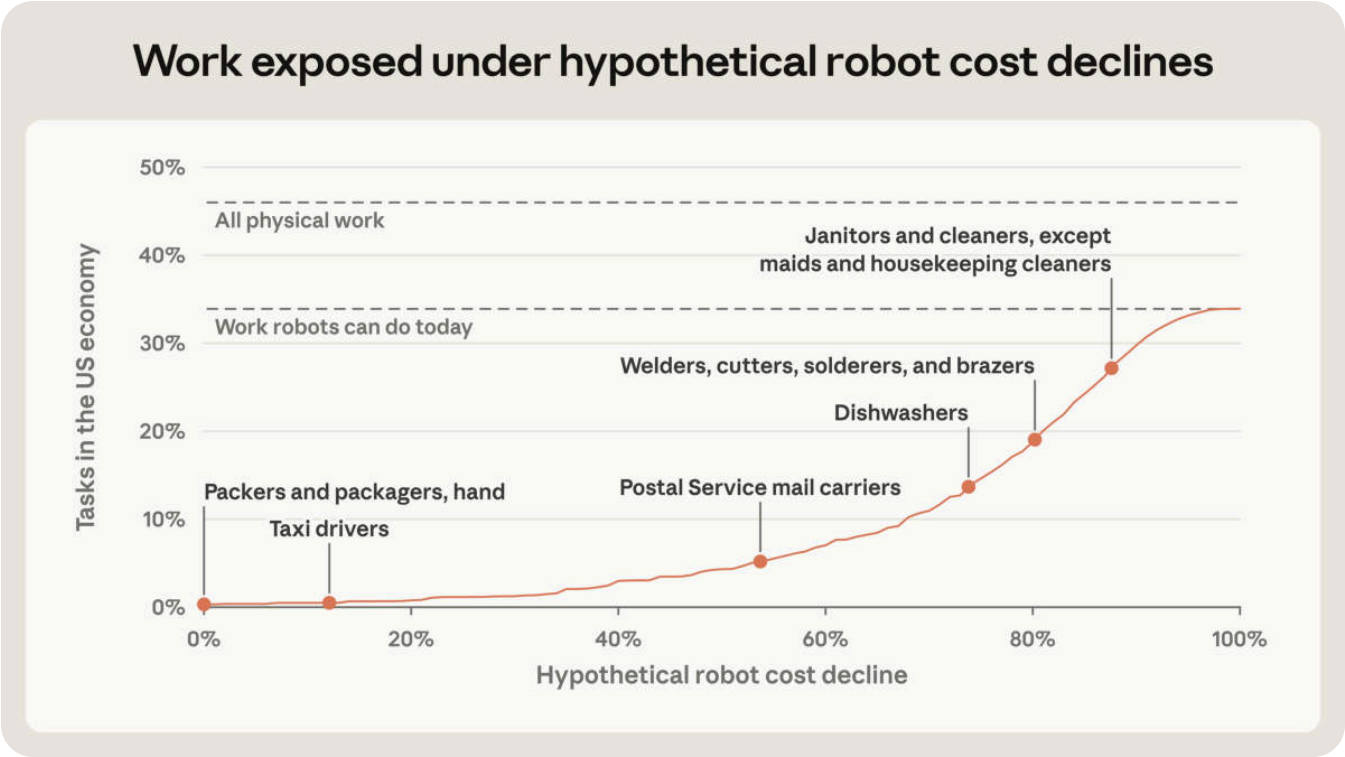

Figure 8: Work exposed under hypothetical robot cost declines
Notes: Calculated by comparing robot and labor costs. Labor costs are the fraction of time spent on exposed tasks multiplied by occupation total compensation. Given robot cost declines, the curve plots the share of all job tasks for which robots cost less than labor. Tasks are weighted by estimated time demands and occupation employment. Robot and labor costs are compared at six points in the worker pay distribution; see Appendix D.2 for details. Selected occupations are marked where their robot costs fall below their median labor cost. For example, robots do 94% of Postal Service mail carrier tasks. To match what workers produce in a year would cost $166,000 with robots. Median total compensation for Postal Service mail carriers is $82,000, so robots would be cost-competitive if cost declined 54% ($166,000·46% < $82,000·94%). Total compensation is calculated with data from the BLS (OEWS 2025, ECEC 2026).

exposed to robots, 0.8% of all working time in the economy. For reference, industry and government data suggest that robot prices have declined roughly 3% per year since the 1990s. At this rate, it would take around seven years to reach a 20% cost decline. Appendix E discusses historical robot price data in more detail.

Though robots can theoretically do tasks that add up to 34% of all work time, they are cost-competitive for just 0.3% today. Still, that includes roughly 300,000 workers for whom robots can do 95% of their tasks.[44] As Figure 7 suggested, robots today are cost-competitive or close to it for packers and packagers and taxi drivers, but far from it for most other jobs.

For robots to be cost-competitive for 10% of human work today, costs would need to decline about 70%. At a 3% decline per year, that would take around 40 years. That said, it's possible that new, more capable robots like humanoids or new manufacturing processes will drive down costs to automate human work.

Reports suggest that global production could scale quickly if there were intense demand for humanoids and other robots.[45]

Cost parity between humans and robots also needn't imply high unemployment or rapid economic growth. Tasks that workers still perform may become bottlenecks, and these robot cost estimates often include human supervisory, exception-handling, or repair work. As emphasized by Acemoglu and Restrepo (2019) and Jones and Tonetti (2026), automation boosts productivity only after machines are much cheaper than humans, rather than at cost parity.

We apply these cost estimates in two extensions. Appendix D.2 calculates an alternative occupation exposure measure that factors in both what robots can do and how cheaply they can do it. Accounting for cost produces a very similar ranking of jobs compared to our main, capabilities-focused measure (0.95 rank correlation).

Appendix E also presents stylized scenarios for robot adoption if robots become cheaper and more productive. The scenarios draw on episodes of innovation and adoption for industrial robots since the 1990s, as well as analyst forecasts for humanoids. We hold fixed tasks and wages and ask how soon historical rates of cost declines and capability gains would make robots cost-competitive.

To model how robots take on new work over time, we rate exposure for 1977 job tasks using today's robots, and compare with robot exposure as of 1977. In 1977, robots could not do 62% of physical tasks. Today's robots can do all but 24% of those same tasks. Over time, that means each year robots became able to do 2% of the tasks they previously could not (see Appendix B.4).

Adding in 3% cost declines per year, robots aren't cost-competitive for half of physical work today until 2085. But rapid advances in robotics may speed up these timelines. In a fast adoption scenario, where quality-adjusted costs fall up to four times faster and robots become able to do new tasks twice as fast, robots become cost-competitive for half of physical work by 2050. Automating 90% of physical work today still takes 53 years.

One caveat is that our scenarios apply the same cost decline or capability increase to every task, so tasks become cost-competitive at today's ranking of costs relative to worker pay. That ranking captures broad economic incentives, but robotics companies may also target certain capabilities first for other

reasons. Humanoid demonstrations sometimes showcase household chores, for example, while robot makers may prioritize factory work useful to their own operations, much as AI companies prioritized coding agents.[46]

Overall, robots would need to sustain record rates of price declines and quality improvements over the coming decades to enable rapid physical automation. Even so, job impacts are less certain with these cost projections, since they set aside forces like preferences and regulation as well as feedback effects like falling wages.

Discussion

We introduce a new measure of job exposure to robots. A job is exposed when robots can perform its tasks. Robots that work like humans count more toward exposure than those that require rebuilding the workplace, like factory robots.

We find that driving jobs are most exposed, due to autonomous vehicles. Most robots today aren't like driverless cars, and only operate in controlled environments. But robots could perform most physical work in some capacity, though they are several times more expensive than humans for the same jobs. Jobs exposed to robots are quite different from those exposed to LLMs. They pay less, and are more physically demanding.

We hope these measures help analyze physical automation as AI expands what robots can do. Exposure patterns today may inform which jobs more capable robots will disrupt tomorrow. And periodic updates to this work can track robot capabilities.

Our exposure scale is predicated on the idea that jobs are more at risk when today's robots already do them in some settings. We find that this way of assessing robots predicts historical labor market impacts. But AI-powered robots could leapfrog our scale and do work they cannot today, for example by learning to climb ladders or use their arms and grippers more deftly.

Much remains uncertain about how robots and AI could reshape the economy. Growth forecasts for AI often assume that physical bottlenecks, which robots could loosen, will drag down gains from automating cognitive work. We also have not considered how AI could affect physical work without robots, for example by better predicting when factory machines need maintenance. In the

nearer term, efforts to track AI's impacts could watch exposed occupations, like drivers and warehouse packers, for early signs of disruption. Further out, a key question is how work itself will change, perhaps becoming more social and interpersonal as robots and AI advance.

Appendix

Available here.

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[1] See for example Aghion et al. (2019), Davidson et al. (2026), and Jones and Tonetti (2026) on the role of weak links and complementarities in explosive economic growth scenarios. AI is often thought to affect digital work more than physical work; see for example Cazzaniga et al. (2024).

[2] See for example Autor (2015) on "environmental control" as a barrier to physical automation. See also Section 6 of Link et al. (2016). We discuss this point in more detail in "Measuring exposure."

[3] See Firoozi et al. (2025) on AI foundation models for robots. Rivière and Denain (2026) discuss robot capabilities afforded by AI. See Agaskar et al. (2025) and Hwang et al. (2025) on AI-powered robots in warehousing and driving. AI could also speed the pace of innovation in robotics; see Cockburn et al. (2019), Wang et al. (2023), and Davidson et al. (2026).

[4] See Baptista et al. (2026) and Goldman (2026) on a potential "ChatGPT moment" in robotics. See also forecasts from Morgan Stanley Research (2024) and McKinsey & Company (2026).

[5] Robot investment data from the 2022 Annual Capital Expenditures Survey (U.S. Census Bureau, 2024). Surveys of US executives in November 2025 from Yotzov et al. (2026) show that 13% of firms use robotics now while 22% expect to within three years of surveying, weighted by employment. Expected use is broadly similar in the United Kingdom, Germany, and Australia.

[6] See Robbins (2026) on investment in humanoid robotics startups and Ewing (2026) on efforts by large automakers to use humanoids.

[7] For example, some robots use cameras only while others use touch sensors. See Brooks (2025) on these approaches, as well as research on vision and tactile robots by Andrychowicz et al. (2020) and Suresh et al. (2024).

[8] See Counterpoint Research (2026) for a humanoid market overview; most humanoids today are used for entertainment and data collection. See BMW Group (2026) for a humanoid deployment in a car factory.

[9] Our taxonomy builds on a long tradition in labor economics and occupational analysis. The predecessor to O*NET, the Dictionary of Occupational Titles, categorized jobs by "Data/People/Things." See Fine (1955), Fine and Wiley (1971), Autor et al. (2003), Acemoglu and Autor (2011), and Deming (2017).

[10] Precise definitions of a robot vary. We describe robots in our exposure prompt (Appendix F.3), and rely on Claude to judge which machines meet this criterion. The International Organization for Standardization defines a robot as a "programmed actuated mechanism with a degree of autonomy to perform locomotion, manipulation or positioning" and autonomy as the "ability to perform intended tasks based on current state and sensing, without human intervention" (ISO 2021).

[11] Our focus on what today's robots can do is similar to Eloundou et al. (2024), who measure AI exposure by what tasks LLMs could speed up as of 2023. Other AI exposure measures are described in Massenkoff and McCrory (2026).

[12] See Autor (2015) on "environmental control" as a bottleneck to automation, and Autor et al. (2020) on how integration slows robot adoption. A report on the economic impacts of robotics for the National Institute of Standards and Technology highlights robot capabilities in unstructured environments; see Section 6 of Link et al. (2016). Kober et al. (2013), Ibarz et al. (2021), and Kim et al. (2025) discuss how robot

performance generalizes to new tasks and environments. See Firoozi et al. (2025) on robotic foundation models versus specialized robot control systems. For surveys on progress in robotic manipulation, see Kemp et al. (2007) and Kroemer et al. (2021). See Pumacay et al. (2024) for manipulation benchmarks. For an inventory of robot capabilities in complex environments, see Rivière and Denain (2026).

[13] Mason (2018) and Tedrake (2026), for example, discuss the complex skills robots need to manipulate objects.

[14] See for example Madrigal (2017) on a mock town at a former Air Force base and University of Michigan (2015) on Mcity, a similar facility.

[15] Our ratings indeed score this task E3 today and E1 in a version of our measure that rates exposure as of 2008 (Appendix B). As in our rubric, performance in unstructured environments factors into standards for autonomous vehicle performance; see SAE International (2021).

[16] Moravec (1988) notably makes this point. See also Polanyi (1966), applied to automation in Autor (2015).

[17] Appendix A.4 presents variants of our exposure measure; these produce a similar ranking of jobs by exposure.

[18] See the Built Robotics Exosystem (2026).

[19] Results are similar when also weighting across occupations by usual weekly hours from the 2020–2024 American Community Survey.

[20] Humans also work in controlled environments: tasks like "Deliver medications or pharmaceutical supplies to patients, nursing stations, or surgery" are done in hospitals and clinics. In Appendix A.4 we measure robot exposure by the gap between where robots can do a task and where humans do it. This produces nearly the same ranking of jobs by exposure.

[21] The Robot Report (2024).

[22] See the Boston Dynamics Stretch.

[23] See Pallottino (2026).

[24] Employment data in Figure 4 come from the BLS OEWS, so independent contractors for ride-sharing services are excluded from taxi driver employment.

[25] Early evidence suggests pay declines for drivers exposed to autonomous ride-hailing. See Gridwise (2025) and Yu et al. (2026).

[26] See Amazon's Vulcan robot.

[27] See the Badger Marty and the Simbe Tally.

[28] See the Telexistence TX SCARA.

[29] See the Canvas drywall robot.

[30] See the AMP Cortex (Waste360, 2023).

[31] Restricting to physical jobs (at least half physical by work time), exposed workers are still paid less, less educated, less often female, more often Hispanic, and more often unemployed, though most gaps are somewhat smaller.

[32] See for example Massenkoff and McCrory (2026).

[33] Deming (2017) and Frey and Osborne (2017).

[34] Analyses of automation and the labor market in the past few decades generally emphasize computers and software over physical automation. See for example Autor et al. (2003) on computerization and Acemoglu and Restrepo (2020) on the limited total impact of robots on US jobs so far. Svanberg et al. (2024) estimate costs to automate computer vision tasks.

[35] We instruct Claude to include costs of the robot itself, accessories, integration and installation, maintenance and service, software, energy and other operating inputs, oversight and operation, insurance, and end-of-life decommissioning, plus any other costs. Claude annualizes fixed costs with an estimated cost of capital.

[36] We estimate total compensation by multiplying BLS occupation wages by the ratio between total compensation and wages plus paid leave by occupation group in the BLS Employer Costs for Employee Compensation survey. Total compensation includes paid leave, supplemental pay, insurance, retirement and savings, and legally required employer payments like FICA and unemployment insurance.

[37] On automation in task models, see for example Zeira (1998), Acemoglu and Autor (2011), and Acemoglu and Restrepo (2018).

[38] In these comparisons, robots may be cheaper than workers but only do a few of their tasks. For example, archivists perform two physical tasks; their only robot-exposed one is "Preserve records, documents, and objects, copying records to film, videotape, audiotape, disk, or computer formats as necessary." We estimate that it costs $5,500 per year for robots to do this task. Archivists spend about 8% of their time on it, and their median total compensation is $85,000, so labor costs for this task are $6,800 per year. Robots are cost-competitive for this task, but automating one task is unlikely to displace archivists.

[39] Cited robots and systems include the Douglas top-load case packer (packing), Boston Dynamics' Stretch and Agility Robotics' Digit (material handling), machine-vision inspection stations (inspection), the Combi robotic random case erector (carton assembly), print-and-apply labelers (labeling), and the 3M-Matic random case sealer (sealing).

[40] See for example Honerkamp (2026) and Lung (2026).

[41] August 2026 forecasts from the BLS Employment Projections program, 2025–35, Table 1.6. Packers and packagers rank 11th in job loss, behind correctional officers and jailers and 9 sales and office occupations (the SOC "high-level aggregation" name for groups 41 and 43). Employment data from the BLS OEWS for 2015 and 2025.

[42] See for example the Path Robotics AW-3 autonomous welding cell.

[43] Though cleaning robots might work longer hours, they are up to 10 times slower than humans. See Rivière and Denain (2026).

[44] This figure includes tire builders and packers and packagers. In these occupations, at least 95% of tasks by work time are exposed to robots, and robot costs fall below total compensation for a share of workers.

[45] See Davidson and Hadshar (2025) and Denain and Rivière (2026).

[46] Compare LLM exposure in Eloundou et al. (2024) for computer programmers (25th most exposed by human raters, 6th by the LLM rater) and poets, lyricists and creative writers (11th by humans, 14th by the LLM). The two occupations were similarly exposed, but AI developers have since directed effort toward coding more than creative writing.

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Citation

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