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How and when will AI impact the economy: Evidence from China[1]

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Key points

- This brief contributes to the current literature on AI exposure of jobs by considering cost curves of AI execution to estimate the timeline of AI adoption in China until 2050 using industry reports and sectoral employment and wage data from the National Bureau of Statistics of China.
- To analyse the economic impact of AI, it breaks down job tasks into a set of well-defined, complementary, and combinable set of basic tasks, categorized by intelligence types.
- For each basic task, it compares the current wage level with the expected evolution of the costs of AI to carry out each task to assess when it is economically profitable to replace a basic task with a machine.
- The study reveals that basic tasks with lower AI execution costs, such as strength, auditory, visual, numerical, and text information processing tasks, are likely to be replaced first. Meanwhile, tasks such as solution generation, management, and care and nursing are less likely to be substituted in the short term, and humans will predominantly engage in jobs involving these basic tasks.
- This approach provides policymakers, researchers, and business managers with a quantitative framework to estimate the economic impacts of AI, deepening the understanding of AI advancements and offering references for economic policies, academic research, and business strategies.

Introduction

The recent breakthroughs, represented by transformer technologies, have sparked a new wave of enthusiasm for AI, prompting renewed interest in its economic implications. Currently, popular estimation methods evaluate AI's economic impact from a task-based perspective. Autor (2003) was among the first to use this approach to measure the economic impact of computer technology. Acemoglu (2024) applied this task-based analysis framework, to estimate the impact of AI on productivity. By measuring AI's impact on task

[1] This research brief is based on Chapter 3, "Basic-Tasks and AI Economic Impact Analysis," from the report collection "AI Economics" by China International Capital Corporation (CICC) Global Institute. The original Chinese report is available at: https://cgi.cicc.com/zh_CN/2024-ai. Published June 28, 2024. The authors would like to thank Caroline Fredrickson and Sher Verick for helpful comments.

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productivity, it is possible to estimate AI's influence on occupational and overall economic productivity. Similar methodologies are employed by institutions like Goldman Sachs (2023) and McKinsey (2023a), which break down production activities into job tasks and business functions to evaluate AI's impact on production efficiency.

One challenge in task-based analysis is identifying an appropriate task classification for studying AI's economic impact. Traditional automation studies focus on specific tasks within particular scenarios, but researchers could face thousands of tasks, with new tasks emerging and old ones disappearing, creating complexity in quantitative analysis. Alternative approaches have been used to identify tasks at the occupational level, including the use of specialized surveys such as O*NET[2] (Felten et al., 2018), World Bank's STEP survey[3] (Carbonero et al., 2023) or the description available within labour force surveys (Berg et al., 2023).

Although the task categories, such as those available in O*NET provide a useful classification, they remain incomplete — working activities may overlap each other. For example, differentiating between "Working with Computers" and "Processing Information" can sometimes be challenging. Consequently, if we attempt to estimate each activity's contribution to job output, we may encounter difficulties. Hence, for quantitative analysis, developing a classification approach that reduces complexity while still enabling clear estimation of each task's contribution is essential.

Transformer-based AI technologies exhibit general capabilities in task execution, fundamentally differing from prior computerization and automation. Unlike traditional systems that require programming for each scenario-specific task, modern AI can effectively perform tasks, even those not included in the training data. Once AI develops intelligence in a specific area, it can achieve human-level performance across diverse scenarios. Therefore, it is only necessary to classify tasks according to the intelligence of AI, instead of classifying every task in each scenario separately as before, which is also the biggest difference between our classification methods and those in other studies.

Given AI's nature as a data-driven technology, its level of intelligence naturally depends on the volume of training data available in specific domains. For instance, abundant data typically exists in language, numerical information, video, and audio processing, whereas data for movement and physical interactions are relatively limited yet highly feasible for future collection. Conversely, data related to emotional processes and interpersonal relationships developed through long-term interactions may be exceedingly scarce and challenging to gather. Therefore, AI tasks can be classified based on the varying difficulty levels of information collection and processing across domains. Moreover, to delineate clearly defined task boundaries that facilitate the estimation of their contributions to output, we have adopted a top-down classification method.

This method accurately describes how AI and humans divide labour at different levels of intelligence. It simplifies task classification, making the estimation of AI's economic impact more feasible. The results also help governments, businesses, and individuals better understand AI's progress and provide valuable references for economic policies, academic research, and business strategies. The remainder of this brief outlines the key elements of this method and presents estimation results using the data from China as an example. Given the importance of China in the global

[2] A database that provides information on occupations in the US.

[3] Skills towards Employment and Productivity, a database collected by the World Bank that provides information on skills by occupations in a selected number of developing countries.

market for AI investment, the estimates presented in this brief are likely to be relevant for other countries as well (Ernst and Saurabh, 2021).

Methodology: Framework and Data

Taxonomy of Basic-Tasks

Building on the framework by Fernandez-Macias and Bisello (2022), our taxonomy categorizes task elements based on categories of intelligence, which can be further divided according to the type of information to be processed and the complexity of its handling (see figure 1). At the highest level, when an agent performs a task independently, all inputs and outputs of information occur solely through the agent itself. However, when social interactions are involved, communication of information between multiple agents may occur. Accordingly, work tasks can be divided into two primary categories: Individual tasks and social tasks. Individual tasks refer to tasks that can be completed independently without interacting with others, while social tasks are those that require interaction.

Individual tasks can be further divided into physical tasks and intellectual tasks. This concept aligns with classifications found in the psychological literature, where intelligence can be categorized into concrete intelligence, abstract intelligence, and social intelligence, respectively. These different forms of intelligence correspond to humans' ability to understand and manipulate physical objects, comprehend and operate linguistic and mathematical symbols, and engage in social interactions (Thorndike, 1920).

Physical tasks can be further divided based on spatial relationships into strength, dexterity, and spatial navigation tasks. Intellectual tasks can be subdivided, based on the type of thinking required, information processing tasks (fast thinking) and problem-solving tasks (slow thinking).

Based on whether the information being processed is encoded, information processing tasks are further categorized into four types: Visual, auditory, text, and numerical information. Problem-solving tasks are further divided into two types: Problem exploration and evaluation, and solution generation and execution. These can be divided further into four categories: Information collection and retrieval tasks, conceptualization and abstraction tasks, solution generation, and planning and execution.

For social tasks, based on the complexity of the type of interpersonal interaction, they can be divided into dominant tasks and supportive tasks, which are further categorized into five types: Sales, persuasion and induction; management and supervision; service and reception; teaching, training and tutoring; and care and nursing.

Splitting basic tasks according to types of intelligence may not be the only approach – other classification methods have the potential to do this as well – but what is important is the idea of classifying the tasks. Its advantage is evident: this classification ensures that the basic tasks do not overlap in functionality. From an economic perspective, we have eliminated the substitutive relationships among the 16 basic tasks while retaining their complementarity, thus forming a set of basis vectors that can combine to represent the entire task space for work. This is significant for understanding how AI integrates into human production activities and its impact on employment.

▶ Table 1: Basic tasks by type of intelligence

Dimension				Basic-tasks	Explanation	AI tools
Individual tasks	Physical tasks	Fixed site		**Strength**	Refers to tasks that are accomplished purely by muscular force, e.g., lifting heavy objects, swinging a hammer, etc.	Robots or Machines driven by general AI.
				Dexterity	Involves precise movements of the hands or fingers, using the hands and arms to manipulate materials or objects, and, as technology advances, also includes the manipulation of various types of equipment to accomplish tasks with materials and objects, such as welding, carving, spinning, weaving, cooking, cleaning, etc.	Robots or Machines driven by general AI, especially humanoid robots.
		Position movement		**Spatial navigation**	Includes moving objects or one's position in unstructured or changing space and finding appropriate routes in the presence of other objects or buildings, e.g., walking, driving, transporting objects, etc.	Robots or vehicles driven by autopilot.
	Intellectual tasks	Information processing	Noncoded information	**Processing visual information**	Acquiring and understanding noncoded information through vision, and making judgements and outputs, e.g., face recognition, judging object types, judging image and video content, tracing images, drawing images, etc.	Tools like OpenCV, DALL·E and Midjourney.
				Processing auditory information	Acquiring and understanding non-codified information through hearing, and making judgements and outputs, e.g., determining the source and type of sound, imitating vocalizations, etc.	Tools like OpenAI's Whisper, ElevenLabs and 15.ai.
			Encoded information	**Processing text information**	Processing of verbal and written information, generally comprehending the content of the input information or outputting it according to the given content requirements, e.g., basic reading, writing, listening, or reading aloud	Tools like ChatGPT.
				Processing numerical information	Be able to use mathematical tools such as existing formulas, theorems, algorithms, or statistical methods to compute, record, or present numbers, e.g., prepare graphs and charts of numbers, use mathematical formulas to compute data, use statistical tools to determine trends and distributions of data, etc.	Tools like IBM Watson Analytics.
		Problem solving	Problem exploration and evaluation	**Information collection and retrieval**	Finding, locating and accessing information needed to make decisions or solve problems (mainly refers to the thinking process), e.g., questionnaires, searching databases, reviewing literature, retrieving audio and video, etc.	Techniques related to slow thinking, such as Chain-of-Thought. OpenAI's Deep Research could be a prototype.
				Conceptualization and abstraction	Use of acquired information, combined with the ability to conceptualize, learn, and abstract, to make assessments based on certain norms and values, e.g., problem categorization, attribution analysis, etc.	
			Solution generation and execution	**Solution generation**	Generate new ideas and methods with a rational structure and model based on the problem to be solved, e.g., artistic design, new product ideas, marketing strategies, etc.	Techniques related to specific expertise and slow-thinking. Producing deliverable results without process monitoring. AI agent could be a prototype.
				Planning and execution	Involves the steps required for an organization to effectively implement a solution to a problem, with a high degree of logic and big picture thinking, e.g., developing a strategic plan, writing an academic article, proving a theorem or law, producing an engineering guide, planning an itinerary, etc.	
Social tasks	Dominant tasks			**Sales, persuasion, and induction**	Inducing others to do something or buy goods or services, as well as various types of negotiations and debates, such as: selling products or services, negotiating contract terms, persuading customers to pay, persuading stakeholders to cooperate, conducting seminars, etc.	Requiring the establishment of long-term relationships and more complex emotional interactions, which may be difficult for AI to achieve.
				Management and supervision	Managing or supervising the behaviour of others, e.g., monitoring project progress, assigning tasks to team members, reviewing employee performance and providing feedback, coordinating inter-team or inter-individual cooperation, resolving employee conflicts, etc.	
	Supportive tasks			**Service and reception**	Responding to or fulfilling requests from customers, leaders, and coworkers, e.g., answering customer inquiries, ordering and serving food, handling customer complaints, guiding tour groups, reporting on work, etc.	The requirements for interpersonal relationship building and emotional interaction are weaker than the dominant task. Tools like customer service chatbots, Duolingo and Character.ai could be a prototype.
				Teaching, training, and tutoring	Transferring knowledge or helping others to improve their skills, e.g., job skills training, coaching team members to improve sales skills, general education, vocational training, etc.	
				Care and nursing	Providing personal assistance, medical care, emotional support, etc., to others, such as co-workers, customers, or patients, to meet the welfare needs of others, e.g., assisting an elderly customer with purchasing goods, ensuring the health of a patient, organizing a charity or philanthropic event, etc.	

Data source: Fernández-Macías & Bisello (2022), CICC Global Institute

Quantitative Analysis Framework

The total human working time equates to the time spent completing various basic tasks. The improvement in current AI capabilities means AI can perform an increasing number of basic-tasks at human-equivalent levels. Therefore, knowing how many basic tasks AI can execute allows us to estimate the economic and social implications of AI on labour demand and on the structure of production across geographies, sectors and occupations.

Similar to previous general-purpose technologies (Jovanovic et al., 2005), AI influences the economy through three steps: R&D, absorption, and growth. Under the basic task framework, these steps can be described as follows: First, AI R&D departments advance technology to expand the range of executable basic-tasks while reducing AI execution costs. Second, when the cost of using AI to perform a particular basic task falls significantly below human labour costs, businesses adopt AI. Finally, as AI costs continue to decline, cheaper AI solutions are deployed to execute more basic tasks. This allows investment in more production factors under constant total costs, resulting in higher outputs and economic growth.

The quantitative model is based on profit-maximizing firms, using AI cost changes for each basic-task to estimate AI's annual economic impact. The basic tasks, in complementary form, constitute labour as a factor of production, which combines with capital to generate industry outputs. The outputs of various industries collectively form GDP (Nordhaus, 2008; Acemoglu, 2024).[4] The decision on whether a basic task should be executed by AI or human labour depends on the costs.

Data

For the estimation model, data on value-added, employment, and capital inputs, was obtained from yearbooks or statistical agencies' websites. Two key datasets that critically affect estimation results are: (1) The future cost trends of AI for each basic task, and (2) the distribution of basic tasks across industries.[5]

Regarding the first dataset, we referenced AI forecast published by institutions such as Stanford HAI (2024) and the World Economic Forum (2023), as well as a survey by Grace et al. (2024), which collected predictions from thousands of AI experts about the future development of AI technology. Using these references, we estimated the approximate number of years until which AI will achieve technical feasibility for each basic task.[6] Based on trends in AI costs, computational power, and energy prices, we projected the costs for all technically feasible basic tasks up to 2050.[7]

While AI may achieve significantly higher output per unit of time, we evaluate AI costs based on the equivalent cost for AI to complete the same workload that a human worker would accomplish. Furthermore, AI may encounter the "Solow Productivity Paradox" whereby productivity gains only show up much later

[4] For each industry, we use the CES function to estimate the relationship between basic-tasks and total labour factor inputs, where the substitution elasticity coefficient between basic-tasks is set to 0.5, according to Acemoglu (2024). For capital and labour factors, we use the Cobb-Douglas function to estimate the relationship between labour factors, capital factors, and industry output. Considering the possibility of "Baumol's cost disease", for the long-term estimation of industry output to GDP, we use the CES function to estimate the long-term relationship between industry output and GDP from the perspective of the aggregate demand function, where the elasticity of substitution between industries is set to 0.7 (Nordhaus, 2008).

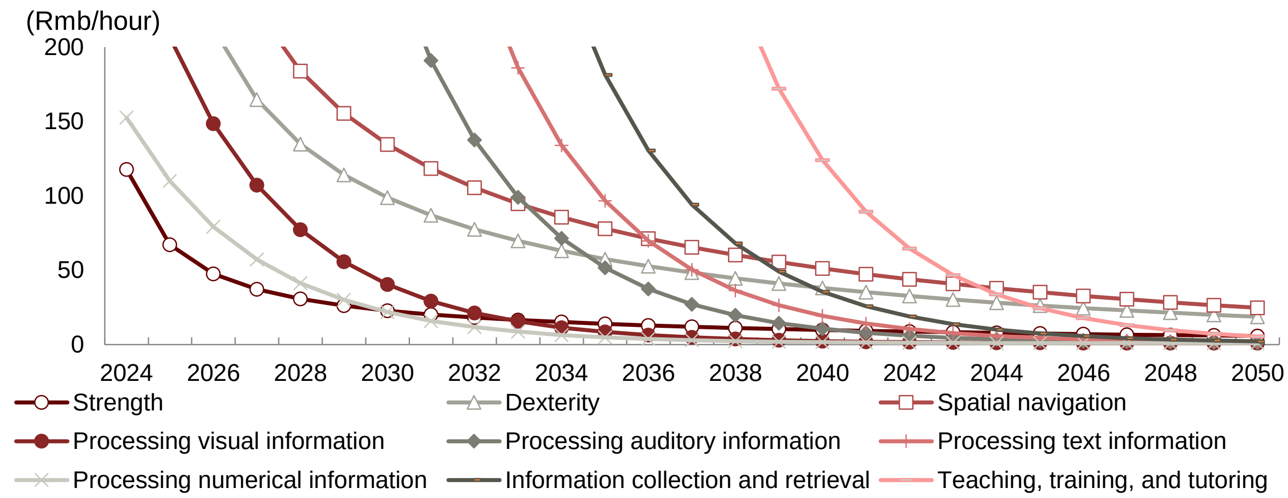
[5] As Acemoglu (2024) noted, obtaining precise estimates for these datasets is impossible, but we endeavor to produce robust approximations.

[6] Based on the reported performance trends of different AI tools or applications, we match them with the basic-tasks to estimate roughly the years that are technically feasible.

[7] For physical tasks, which involve physical interaction, costs were primarily benchmarked against humanoid robots, while intellectual and social tasks were benchmarked against AI software services. Sources from Epoch AI (2024), Artificial Analysis (2024), Ark-invest (2019), McKinsey (2023b), Mecademic (2024) and Change Discussion (2024). See endnote for detailed citation information.

than when new technologies are being introduced. We estimate that a lag of approximately 2–4 years could occur between the successful research and development of AI technology and its full deployment. Additionally, AI deployment may require complementary expenditures, such as initial investments in specialized equipment (e.g., servers), as well as subsequent costs associated with maintenance, personnel training, data processing, and application adaptation. In our estimation of AI basic-task cost curves, we have incorporated deployment costs and deployment time lags to calculate realistic cost curves across different basic tasks at the point of actual deployment (see Figure 1).

▶ **Figure 1: Expected cost curves for AI performing various basic-tasks in deployment**



Note: The figure shows relative costs, that is, considering one hour of human workload and converting it into the cost for AI to perform that workload. The cost curves are based on global expert estimates, with values converted into RMB per hour.

Data source: Epoch AI (2024), Artificial Analysis (2024), Ark-invest (2019), McKinsey (2023b), Mecademic (2024), Change Discussion (2024), CICC Global Institute

Basic tasks represent a new classification framework, hence no existing statistical data is available. Therefore, to construct our second dataset, we used a survey method to obtain industry-level data for China. The survey was designed in a scoring format, with a total of 100 points distributed according to the proportion of time spent on each basic task within a given industry's total working hours. The questionnaire was sent to industry analysts at CICC, covering hundreds of listed companies across 19 industries. Table 2 illustrates the distribution of the time required to complete basic tasks across industries, providing insights into the production characteristics of each sector. [8]

Each number represents the share of total working hours spent on each of the basic tasks, adding up to the total hours work in each industry horizontally. Note that attribution across basic tasks is based on its predominance in each occupation. For instance, in health care, only 6.5 per cent of time is spent on actual care as defined in table 1. This has to do with the fact that actual nursing staff represents only between a third and two fifth of total employment and often spend a considerable amount of their time on non-care related activities such as planning, or compliance.

[8] The industry classification in this article uses the major industry categories in the "Industrial Classification for National Economic Activities (GB/T 4754-2017)". For ease of presentation and understanding, some industry names have been adjusted or simplified. The manufacturing industry is split into light manufacturing, resource processing, and equipment manufacturing.

▶ Table 2: Time share of basic-tasks in production activities of various industries

Industry	Strength	Numerical information processing	Visual information processing	Dexterity	Spatial navigation	Auditory information processing	Text information processing	Information collection and retrieval	Teaching, training, and tutoring	Service and reception	Planning and execution	Conceptual-ization and abstraction	Solution generation	Sales, persuasion, and induction	Management and supervision	Care and nursing
Financial	1.7	3.8	3.1	5.8	7.3	0.7	3.9	4.1	9.2	9.9	5.3	5.7	7.6	17.4	9.4	5.1
Information services	2.4	6.3	6.1	8.5	4.6	1.5	6.1	4.9	4.1	12.8	5.9	3.7	8.7	10.8	11.3	2.4
Mining	22.0	2.5	2.6	20.3	14.6	0.5	1.2	2.7	1.7	2.8	3.0	2.4	2.5	11.6	9.0	0.7
Real estate	2.4	6.0	4.0	8.0	2.4	4.0	6.0	6.0	4.0	7.4	9.4	6.0	9.4	7.0	10.0	8.0
Leasing and business services	1.1	4.9	5.1	5.1	4.2	4.7	4.9	4.9	5.2	9.9	5.2	5.0	5.0	19.9	10.3	4.9
Water, electricity, heating, and gas supply	3.1	9.4	4.1	11.6	7.5	0.6	8.8	6.1	6.0	6.8	5.3	6.7	5.6	8.4	5.9	4.2
Medical and health	2.2	6.5	6.5	6.5	5.4	1.6	6.5	7.6	7.6	8.6	7.6	5.4	6.5	7.6	7.6	6.5
Resource processing	24.9	8.4	5.5	14.9	5.8	1.4	3.4	2.7	3.2	3.7	4.3	1.6	2.3	11.2	5.5	1.3
Cultural, sports, and entertainment	5.5	2.8	2.8	6.7	8.4	2.1	3.8	2.5	7.1	17.6	2.8	2.8	2.2	17.4	10.1	5.7
Education	3.0	5.0	4.0	10.0	7.0	1.0	5.0	6.0	15.0	5.0	4.0	7.0	8.0	7.0	8.0	5.0
Equipment manufacturing	5.3	6.5	3.2	12.8	6.6	1.5	4.8	5.4	5.7	9.3	7.1	2.7	6.0	10.9	7.5	4.8
Transportation and logistics	14.2	0.1	2.3	1.4	61.8	2.0	1.5	0.5	1.1	1.1	4.8	0.3	0.2	2.3	5.4	1.0
Construction	21.7	0.9	0.6	14.0	0.4	0.6	0.9	0.9	13.4	1.1	14.2	0.9	5.6	1.0	22.8	1.2
Agriculture, forestry, animal husbandry, and fishery	27.5	0.6	1.9	45.1	12.1	0.9	0.8	0.6	3.8	1.1	0.7	0.8	0.7	1.0	1.2	0.9
Wholesale and retail	8.7	1.7	1.1	3.6	6.4	0.8	1.3	1.3	3.6	12.8	2.4	1.8	1.0	40.8	10.0	2.8
Residential services	12.5	0.2	1.6	21.1	3.8	0.5	0.4	0.9	5.1	27.1	5.5	1.9	1.5	12.3	4.0	1.6
Light manufacturing	8.3	1.5	2.0	28.8	7.5	1.0	2.8	2.0	2.4	7.2	2.7	2.5	4.0	16.6	8.1	2.4
Water conservancy and environmental protection	3.6	5.8	3.9	21.6	9.4	0.6	7.7	4.3	6.4	3.5	3.3	10.2	5.0	4.8	6.7	3.2
Accommodation and catering	6.7	0.5	1.1	10.0	5.6	2.1	1.1	1.1	5.0	37.7	1.2	1.1	3.0	13.9	5.0	5.0

Note: The industries on the left side of the chart are arranged from high to low according to the average hourly labour cost in 2023[9], and the basic-tasks on the top of the chart are ranked by the year of technically feasibility from the earliest to the latest. The data units in the chart are percentages, which are estimated based on the actual situation in 2024.
Data source: CICC Global Institute, CICC Research Department, National Bureau of Statistics of China

Findings and possible applications

Based on the cost curve of AI performing basic-tasks and the distribution of basic-tasks across industries, we can roughly outline the timeline of AI absorption within various industries under the assumption that the structure of basic-tasks remains unchanged.[10] The speed of AI absorption in different industries depends on two factors: First, the wage levels in an industry—industries with higher wages are more likely to absorb AI with other conditions being equal; second, the proportion of basic-tasks in an industry's time distribution that can be performed by AI at a relatively low cost—the higher the proportion, the faster the absorption of AI. By comparing the wage levels in different industries with the cost of AI performing basic tasks, we can estimate the extent of AI absorption in various industries over time.[11] The results are shown in Table 3. Given the lack of sectoral data on AI absorption, the table assumes that all industries started absorption only in 2024.

[9] The labour costs of various industries are calculated through the "Labour Remuneration" item in the "China Input-Output Table (2020)", which reflects the total cost of labour for producers. The labour costs in 2023 are calculated according to the economic growth rate, which may be different from the per capita wage based on worker income.

[10] Although we have considered the endogenous shift of industrial share with the introduction of AI, the data in this presentation are projections of economic activity based on existing trends and may fluctuate in the future due to factors such as policy changes, differences in statistical measurements, and technology that does not meet or exceeds expectations, thereby posing the risk of overestimation or underestimation.

[11] That is, using the initial (2024) time share structure for each type of basic-task as a baseline, the proportion of total time spent on basic-tasks performed by the AI in each year.

▶ Table 3: Timeline for the absorption of AI in various industries

Industry	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036	2037	2038	2039	2040	2041	2042	2043	2044	2045	2046	2047	2048	2049	2050
Financial	0.0	1.7	5.5	5.5	8.6	8.6	14.4	14.4	14.4	22.4	22.4	26.4	26.4	30.5	30.5	30.5	30.5	39.7	39.7	39.7	39.7	39.7	39.7	39.7	39.7	39.7	39.7
Information services	0.0	2.4	8.7	8.7	14.8	14.8	14.8	14.8	23.3	23.3	24.8	29.4	35.5	35.5	40.4	40.4	40.4	40.4	44.5	44.5	44.5	44.5	44.5	44.5	44.5	44.5	44.5
Mining	0.0	22.0	24.4	24.4	27.1	27.1	27.1	27.1	47.4	47.4	47.9	62.5	63.7	63.7	66.4	66.4	66.4	66.4	68.0	68.0	68.0	68.0	68.0	68.0	68.0	68.0	68.0
Real estate	0.0	2.4	2.4	8.4	8.4	12.4	12.4	12.4	12.4	20.4	20.4	24.4	30.4	32.8	38.8	38.8	38.8	38.8	42.8	42.8	42.8	42.8	42.8	42.8	42.8	42.8	42.8
Leasing and business services	0.0	0.0	1.1	6.0	6.0	11.1	11.1	11.1	11.1	11.1	16.1	20.8	20.8	25.7	29.9	34.7	34.7	34.7	39.9	39.9	39.9	39.9	39.9	39.9	39.9	39.9	39.9
Water, electricity, heating, and gas supply	0.0	0.0	3.1	12.5	12.5	16.5	16.5	16.5	16.5	16.5	16.5	28.7	28.7	37.5	45.0	51.1	51.1	51.1	51.1	57.1	57.1	57.1	57.1	57.1	57.1	57.1	57.1
Medical and health	0.0	0.0	2.2	8.6	8.6	15.1	15.1	15.1	15.1	15.1	15.1	23.2	23.2	29.7	29.7	42.7	42.7	42.7	42.7	50.3	50.3	50.3	50.3	50.3	50.3	50.3	50.3
Resource processing	0.0	0.0	24.9	24.9	33.4	33.4	38.8	38.8	38.8	38.8	38.8	38.8	40.2	55.1	58.5	61.3	61.3	67.1	67.1	70.2	70.2	70.2	70.2	70.2	70.2	70.2	70.2
Cultural, sports, and entertainment	0.0	0.0	5.5	5.5	8.2	8.2	11.0	11.0	11.0	11.0	11.0	11.0	13.1	19.8	23.6	26.0	26.0	34.4	34.4	41.5	41.5	41.5	41.5	41.5	41.5	41.5	41.5
Education	0.0	0.0	3.0	3.0	8.0	8.0	12.0	12.0	12.0	12.0	12.0	12.0	13.0	13.0	28.0	28.0	34.0	41.0	41.0	56.0	56.0	56.0	56.0	56.0	56.0	56.0	56.0
Equipment manufacturing	0.0	0.0	0.0	0.0	5.3	11.8	11.8	15.0	15.0	15.0	15.0	15.0	15.0	16.5	16.5	21.2	21.2	26.6	39.4	39.4	39.4	45.1	51.7	51.7	51.7	51.7	51.7
Transportation and logistics	0.0	0.0	0.0	0.0	14.2	14.3	14.3	16.6	16.6	16.6	16.6	16.6	16.6	18.7	18.7	20.2	20.2	20.7	20.7	22.0	22.0	23.1	23.1	84.9	84.9	84.9	84.9
Construction	0.0	0.0	0.0	0.0	0.0	21.7	22.6	23.2	23.2	23.2	23.2	23.2	23.2	23.8	23.8	24.6	24.6	25.5	25.5	25.5	39.5	52.9	52.9	52.9	53.3	53.3	53.3
Agriculture, forestry, animal husbandry, and fishery	0.0	0.0	0.0	0.0	0.0	27.5	28.1	28.1	30.0	30.0	30.0	30.0	30.0	30.0	31.0	31.8	31.8	32.4	32.4	32.4	32.4	81.3	81.3	81.3	81.3	81.3	93.4
Wholesale and retail	0.0	0.0	0.0	0.0	0.0	0.0	10.4	10.4	11.4	11.4	11.4	11.4	11.4	11.4	12.2	12.2	13.5	14.8	14.8	14.8	14.8	18.3	21.9	21.9	21.9	21.9	28.3
Residential services	0.0	0.0	0.0	0.0	0.0	0.0	12.7	12.7	14.3	14.3	14.3	14.3	14.3	14.3	14.8	14.8	15.3	16.1	16.1	16.1	16.1	21.3	42.4	42.4	42.4	42.4	46.2
Light manufacturing	0.0	0.0	0.0	0.0	0.0	0.0	9.8	9.8	11.9	11.9	11.9	11.9	11.9	11.9	12.9	12.9	15.7	15.7	17.8	17.8	17.8	17.8	20.2	20.2	49.0	49.0	49.0
Water conservancy and environmental protection	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.8	9.5	13.4	13.4	13.4	13.4	13.4	14.1	14.1	21.8	21.8	26.1	26.1	26.1	26.1	32.5	32.5	32.5	54.1	54.1
Accommodation and catering	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.5	1.5	1.5	1.5	8.2	8.2	8.2	10.3	10.3	11.4	11.4	12.5	12.5	12.5	12.5	17.5	17.5	17.5

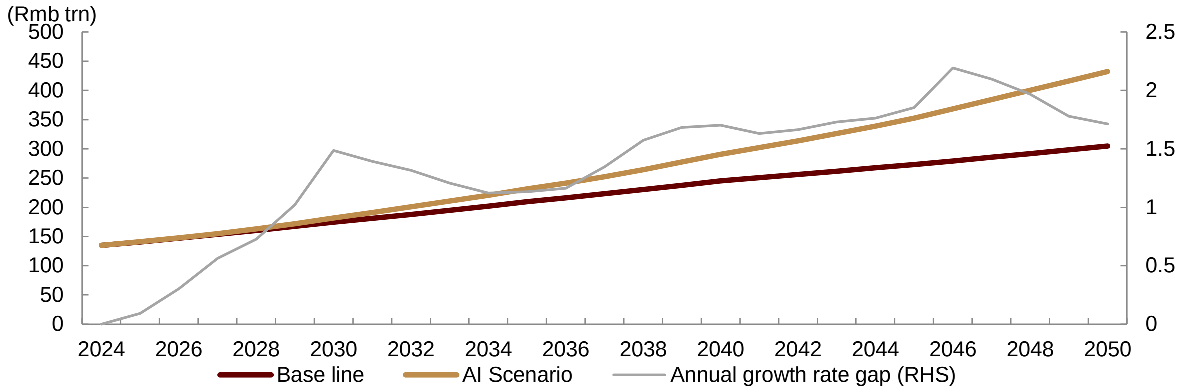
Note: The data in the chart is the percentage of time spent on basic-tasks performed by AI during each year. The specific calculation method is a comparison of the AI deployment cost of basic-tasks and the labour cost level of each industry year by year based on the analyst's estimate of the time share of different basic-tasks in each industry. If the AI deployment cost of a certain type of basic-task is lower than the labour cost, then this type of basic-task will be performed by AI.

Data source: CICC Global Institute, CICC Research Department, National Bureau of Statistics of China, "China Input-Output Table (2020)", "China Population Census Yearbook (2020)"

Based on the production structure of various industries and the timeline for AI absorption with basic-tasks, we can estimate AI's impact on China's gross domestic product (Figure 2).[12] We project that the additional GDP growth brought by AI in China will reach approximately Rmb7.1trn by 2030, Rmb21.8trn by 2035, and Rmb127.4trn by 2050. Figure 2 also illustrates the potential effects of AI on China's GDP growth rate. Initially, due to relatively low absorption levels of AI in various industries, AI's contribution to China's economic growth rate will be relatively low. However, as industries increase their absorption of AI, its positive impact on GDP growth will become more pronounced. If industries reach saturation in their absorption of AI, productivity gains resulting from AI may gradually diminish.

[12] The benchmark GDP growth rate forecast comes from an ECB report written by Al-Haschimi & Spital (2024).

▶ **Figure 2: Additional GDP growth from AI**

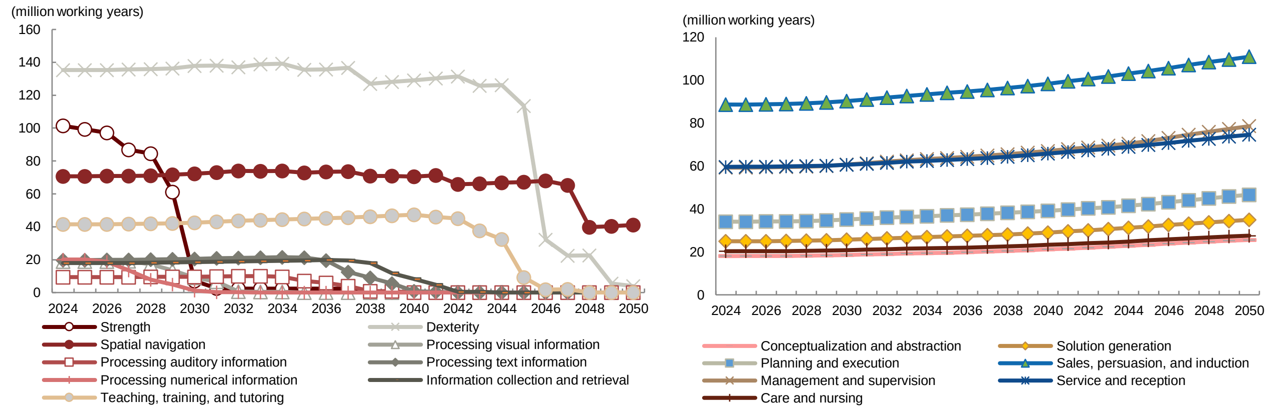


Note: The left axis shows GDP for each year, and the right axis shows the difference in annual GDP growth rates between the two scenarios.

Data source: CICC Global Institute, CICC Research Department, National Bureau of Statistics of China, "China Input-Output Table (2020)", "China Population Census Yearbook (2020)"

AI may lead to a divergence in demand for human labour across different basic tasks and a transformation of the human task structure. For basic tasks that can be performed by AI, once AI costs fall below human labour costs, AI will likely gain a comparative advantage over humans in such tasks and increasingly take over this category of task. We assume that in a specific industry, once AI costs fall below those of human labour for a particular basic-task, AI will be used exclusively for that task. For basic tasks that are difficult or costly for AI to perform, human labour retains a comparative advantage, and AI serves as an enabler for these tasks, which will need more human workers. With the continuous advancement of AI and its absorption into the economy, humans and AI will collabourate based on different basic tasks. The left panel of Figure 3 shows the basic tasks that AI is expected to begin replacing humans with by 2050; the demand for human labour in these tasks will gradually approach zero as AI costs decrease. The right panel includes basic tasks that are more difficult for AI to replace by 2050, where demand for human labour will continue to grow. In the future, humans may increasingly engage in tasks that are harder for AI to perform, such as complex problem-solving and social interaction tasks.

▶ **Figure 3: The impact of AI on human labour demand for different types of basic-tasks**



Note: The chart shows the changes in total labour demand for various basic-tasks across the whole economy. The vertical axis represents labour demand for various basic-tasks. Each working year is the equivalent workload of a worker based on 49 hours per week and 52 weeks per year.

Data source: CICC Global Institute, CICC Research Department, National Bureau of Statistics of China, "China Input-Output Table (2020)", "China Population Census Yearbook (2020)"

▶ Policy implications

Based on the basic-task framework, we estimated AI's economic impact on China until 2050. Since the cost of implementing AI may converge globally, this method also has the potential to be applied on a global scale. Based on China's results, this analysis generates rich policy implications.

Firstly, during the integration of AI into economic activities, the phenomenon of the "Solow productivity paradox" may emerge. Scale effects within a country in the AI sector can be highly significant. Internal scale effects within research and development departments, for instance, can effectively reduce the costs of AI R&D, while external scale effects may accelerate reductions in AI deployment costs.

Secondly, AI's impact on the labour market has dual characteristics. AI does not merely empower or substitute human labour in a unidirectional manner. Instead, humans will increasingly concentrate in sectors characterized by intensive research and social interactions. Conversely, tasks involving physical strength or those lacking complex reasoning, innovation, or social attributes are more likely to be replaced by AI-driven robots.

Finally, since AI's development has multifaceted impacts on different population groups, social policies will need to anticipate differential impacts. On the one hand, AI will boost the overall social output, laying a material foundation for improving overall social welfare . On the other hand, without protective social policies, the large-scale deployment of AI could widen income disparities, thereby reducing aggregate social demand and lowering potential economic growth rates.

The basic task taxonomy and data for estimation in this study still need to be improved, and some surveys and interviews will be conducted in the future to further improve it.

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