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Productivity Dynamics of Artificial Intelligence Adoption: An Analysis of the Machinery Industry

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This study documents the adoption of AI in the workplace and its impact on productivity among workers in the Japanese machinery industry. At the end of 2025, 34% of workers use AI in their jobs, with R&D accounting for the largest proportion of AI-utilized jobs. Among AI users, the mean share of tasks using AI, efficiency gains, and resulting productivity effects are 12%, 20%, and 4%, respectively. Most workers use AI for only a small fraction of their overall job tasks. The productivity effect is larger for continuous AI users than for new AI users, suggesting selection and learning effects of AI adoption. The use of AI at work is projected to increase labor productivity in the industry by 0.3–0.4 percentage points annually over the next several years. If the use of AI in R&D activities improves the efficiency of R&D investment, it is likely to generate productivity gains that extend beyond simple labor-saving effects. Finally, more than 80% of workers hold positive views toward expanding the use of AI in the workplace, with stronger support among those already using AI and those facing severe labor shortages.

Keywords

artificial intelligence, machinery industry, productivity

JEL Classification

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Abstract

This study documents the adoption of AI in the workplace and its impact on productivity among workers in the Japanese machinery industry. At the end of 2025, 34% of workers use AI in their jobs, with R&D accounting for the largest proportion of AI-utilized jobs. Among AI users, the mean share of tasks using AI, efficiency gains, and resulting productivity effects are 12%, 20%, and 4%, respectively. Most workers use AI for only a small fraction of their overall job tasks. The productivity effect is larger for continuous AI users than for new AI users, suggesting selection and learning effects of AI adoption. The use of AI at work is projected to increase labor productivity in the industry by 0.3–0.4 percentage points annually over the next several years. If the use of AI in R&D activities improves the efficiency of R&D investment, it is likely to generate productivity gains that extend beyond simple labor-saving effects. Finally, more than 80% of workers hold positive views toward expanding the use of AI in the workplace, with stronger support among those already using AI and those facing severe labor shortages.

Keywords: artificial intelligence; machinery industry; productivity

JEL Codes: J24; L60; O33

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1. Introduction

Automation technologies such as artificial intelligence (AI) and robotics are expected to raise potential growth rates and help alleviate severe labor shortages. Among automation technologies, many studies have quantified the productivity impact of industrial robots (e.g., Graetz and Michaels, 2018; Kromann *et al*., 2020; Cette *et al*., 2021; Dauth *et al*., 2021; Adachi *et al*., 2024).[1] However, over the past years, generative AI has spread rapidly and is now used for a wide range of tasks, including document preparation, image processing, and customer support service. Against this backdrop, economic research on the impact of AI on productivity is advancing rapidly.

Existing empirical studies can be classified into three strands. First, studies using randomized field experiments to identify the causal effects of AI on worker productivity for specific tasks (e.g., Noy and Zhang, 2023; Brynjolfsson *et al*., 2025; Kanazawa *et al*., 2025; Cui *et al*., 2026; Dell'Acqua *et al*., 2026). Second, several studies estimate AI's macroeconomic impacts by building on these micro-level findings (e.g., Aghion and Bunel, 2024; Filippucci *et al*., 2024; Acemoglu, 2025; Misch *et al*., 2025). Third, some studies examine efficiency gains from AI in work tasks using worker survey data (e.g., Morikawa, 2024; Humlum and Vestergaard, 2025; Bick *et al*., 2026). Although all three strands find that AI utilization enhances productivity, the estimated magnitudes vary widely, and substantial uncertainty remains regarding the future productivity effects of AI.[2]

This study presents evidence on the actual use of AI among workers in the Japanese machinery industry, based on panel surveys conducted in 2024 and 2025, and quantitatively estimates its impact on productivity. This study can be positioned in the

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[1] For a survey of recent economic research on the productivity effects of automation technologies, see Restrepo (2024).

[2] In addition to the three strands of studies, McElheran *et al*. (2025) examine the impact of AI using survey data from manufacturing establishments and present evidence of the productivity J-curve.

third strand of the empirical research mentioned above. The machinery industry examined in this study is a leading industry in Japan that has long utilized automation technologies, particularly industrial robots, and is also actively pursuing the adoption of AI. The 2025 survey tracks respondents from the 2024 survey, enabling observation of changes over time. This study contributes to the literature by using worker-level panel data to reveal the dynamics of AI's productivity impacts.

The main findings of this study are as follows. First, 34% of workers use AI in their jobs, more than double the share observed one year earlier, with R&D accounting for the largest proportion of AI-utilized tasks. Second, among AI users, the mean share of tasks using AI, efficiency gains, and resulting productivity effects are approximately 12%, 20%, and 4%, respectively. Third, with a few exceptions, workers use AI for only a small fraction of their overall job tasks, limiting the magnitude of productivity gains. Fourth, the use of AI at work is projected to increase overall labor productivity in the industry by approximately 0.3–0.4 percentage points annually over the next several years. Fifth, more than 80% of workers hold positive views toward expanding the use of AI and robots in the workplace, with stronger support among those already using AI and those facing severe labor shortages.

The remainder of this paper is structured as follows. Section 2 describes the panel survey used in this study. Section 3 reports findings on the use of AI in the workplace and its productivity effects. Section 4 presents workers' views regarding the expansion of automation technologies in the workplace. Section 5 concludes the paper by summarizing the main findings, and discussing the study's limitations and directions for future research.

2. Survey design

The data used in this study were drawn from the "Survey on Current Working Conditions and Outlook" conducted by the Japan Society for the Promotion of Machine Industry in 2024 and 2025. The author created the survey questionnaire and contracted Rakuten Insight Inc., a subsidiary of Rakuten, Inc.—one of the largest online retailers in Japan—

to implement it. The first survey was conducted in November 2024 with working individuals aged 20 years and older, drawn from a pool of more than 2 million registered individuals. A follow-up survey was conducted in November 2025 targeting machinery industry workers (2,312 individuals) who had responded to the November 2024 survey. The machinery industry includes the "manufacture of general-purpose, production, and business machinery," "manufacture of electronic components and devices," "manufacture of electrical machinery," "manufacture of information and communication equipment," and "manufacture of transportation machinery." The panel dataset used in the analysis consisted of 1,609 individuals who were working in the machinery industry at the time of the November 2025 follow-up survey.[3]

The composition of respondents by gender, age group, and industry in 2025 is presented in **Appendix Table A1**. Compared to the distribution of machinery industry workers in the 2022 Employment Status Survey (ESS) conducted by the Statistics Bureau of Japan, Ministry of Internal Affairs and Communications, a representative official survey of the Japanese labor market in five-years interval, the proportion of female respondents in our sample is lower, and the age distribution is skewed toward older workers. By industry, the share of electric machinery is relatively high, whereas the share of general-purpose, production, and business machinery is relatively low. Consequently, the sample composition differs from that of the ESS in terms of gender, age group, and industry.

To mitigate potential biases arising from these differences, this study applied weight adjustments to align the sample with the ESS's distribution of employed individuals by gender, age group, and industry sector, thereby ensuring that the results are representative of the Japanese machinery industry. Specifically, weights were calculated as the ratio of the number of employed individuals in the ESS to the number of survey respondents in each cell, defined by gender, age group (six categories from 20–29 to 70 years and older), and industry (five machinery industries).

[3] Among the 1,838 respondents who were working at that time, those in industries other than the machinery industry were removed from the dataset.

Although the survey covers a wide range of topics, this study primarily focuses on questions related to the use of AI and its effects. The main AI-related questions include: (1) current use of AI at work and expectations regarding future use; (2) the proportion of work tasks performed using AI; (3) subjective assessments of efficiency gains from AI use; and (4) the specific tasks for which AI is used. Additionally, (5) respondents were asked whether they believed the use of AI and robots in the workplace should be expanded in the future. The exact wording of the questions and the available response options are described in the following sections, in conjunction with the presentation of the tabulation and estimation results.

The survey also collected detailed information on respondents' characteristics, including educational attainment (seven categories), employment type (10 categories, such as full-time regular employment, part-time employment, and self-employment), industry in which they work (five machinery industry categories), occupation (13 categories, such as managerial, professional/technical, clerical, and sales positions), firm size (13 categories), tenure (measured in years and months), weekly working hours (12 categories), annual earnings from work (18 categories), and the presence of a labor union at the workplace. For the multiple-choice questions, the response options were generally designed to be consistent with those used in the ESS.[4]

When response options included a large number of categories, some were consolidated in the analysis to avoid excessive complication. For example, firm size was grouped into three categories: fewer than 20 employees, 20–299 employees, and 300 or more employees.[5] Educational attainment was consolidated into five categories, ranging from high school or below to graduate school. Annual income from work was grouped into three broad categories: less than JPY 5 million, JPY 5 million to JPY 9.99 million, and JPY 10 million or more. Additionally, when weekly working hours and annual income

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[4] The top annual income bracket (JPY 15 million or higher) in the ESS was divided into three categories (JPY 15–17.49 million, JPY 17.5–19.99 million, and JPY 20 million or higher).

[5] In addition to these three firm size categories, "government agencies" was an option.

were used as continuous variables in the regression analyses, the median value of each category was log-transformed.[6]

3. Use of AI and its impacts on productivity

The specific question regarding the use of AI at work was: “We would like to ask you about your use of Artificial Intelligence (AI) including generative AI.” The four choices were: (1) “I currently use AI at work,” (2) “I do not currently use AI at work, but I think I will within five years,” (3) “I do not currently use AI at work, but I think I will in more than five years,” and (4) “I do not use AI at work and do not think I will in the future.”

As explained in the previous section, the tabulation and regression results reported below are weighted to match the employment composition by gender × age × industry in the ESS, thereby ensuring the representativeness of the Japanese machinery industry workforce. According to the tabulation results, the share of workers using AI in the workplace (*AI user*) in 2025 was 34.2%, more than double the 14.4% observed in 2024. Respondents who reported not currently using AI at work but expected to do so within the next five years account for 18.5% of the sample, while those who expected to adopt AI in more than five years account for 19.8%. Taken together, these “potential AI users” represent 38.3% of the machinery industry workforce.[7] Examining transitions in AI use at work, 12.3% of respondents used AI in both 2024 and 2025, whereas 21.9% began using AI for the first time during the past year. A small share of respondents (2.5%) used AI in 2024 but no longer did so in 2025.

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[6] For weekly working hours, “less than 15 hours” is treated as 13 hours and “75 hours or more” is treated as 80.5 hours. For annual income from work, “less than JPY 5 million” is treated as JPY 2.5 million and “JPY 20 million yen or higher” is treated as JPY 21.25 million.

[7] In the 2024 survey, the second and third response options were not separated, and the percentage of potential AI users was 46.3%.

Even when AI is used at work, it is rarely applied to all tasks; in most cases, it is used only for a subset of tasks. The survey question on the proportion of tasks performed using AI (*AI_Taskshare*) asked: "What percentage of your overall tasks are performed using AI?" Respondents were required to provide a specific numerical value expressed as a percentage.[8] According to the tabulation results, the mean values were 12.1% for 2024 and 11.5% for 2025 (see column (1), **Table 1**).

Table 1. AI users, task share of AI, efficiency gains, and productivity effects (%).

	(1) *All AI user*		(2) *Continuous AI user*		(3) *New AI user*
	2024	2025	2024	2025	2025
AI_Taskshare	12.1	11.5	13.3	17.6	8.1
	(15.2)	(13.1)	(16.3)	(16.2)	(9.4)
AI_Efficiency	21.0	18.8	21.1	25.6	14.9
	(20.3)	(18.3)	(20.5)	(22.1)	(14.5)
AI_Productivity	4.6	3.4	5.3	6.0	1.9
	(10.0)	(7.0)	(10.9)	(8.9)	(5.1)

The figures are the weighted mean values with standard deviations in parentheses.

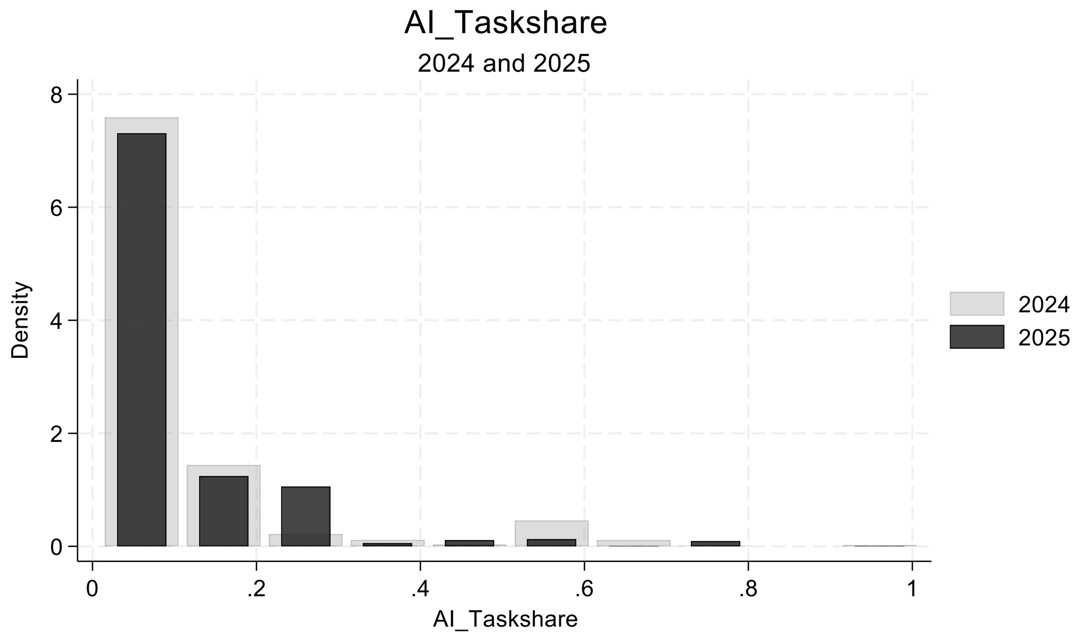
However, among workers who continued using AI in both 2024 and 2025, the mean *AI_Taskshare* increased by 4.3 percentage points, from 13.3% to 17.6% (see column (2), **Table 1**). By contrast, the mean *AI_Taskshare* among workers who newly adopted AI in 2025 was 8.1% (column (3)), which is far lower than that of continuing users, indicating that new adopters pull down the overall mean in 2025. The mean *AI_Taskshare* in 2024 for workers who used AI in 2024 but not in 2025 was 6.9%, suggesting that some workers with relatively low AI usage intensity discontinued their use.

The figures reported above were the mean values for AI users; however, the distribution was highly dispersed. The median *AI_Taskshare* was 10% in 2024 and 5% in 2025. **Figure 1** illustrates the distribution of *AI_Taskshare*, showing that a large proportion of AI users reported an *AI_Taskshare* of 10% or less (81.3% in 2024 and 76.7% in 2025). These results indicate that, even among those who use AI at work, the vast majority of

[8] The lower and upper bounds of the response were set at 1% and 100%, respectively.

workers apply it only to a limited set of tasks—such as document preparation or image processing— whereas only a small fraction use AI intensively. This pattern is unsurprising, given that even relatively routine clerical jobs involve a wide range of activities, including meetings and coordination with internal staff and external organizations. Although the potential displacement of white-collar jobs due to the proliferation of AI is widely debated, the current evidence suggests that such concerns remain premature.

Figure 1. Distribution of tasks performed using AI.



The question on efficiency gains from AI (*AI_Efficiency*) asked: "How much more efficient do you feel your tasks are when using AI compared with not using AI?" Responses were presented as specific percentages. The lower bound of the response was set at 0% (if the respondent believed that AI use had no effect on work efficiency), and the upper bound was set at 100% to avoid extreme responses. Because only a small share of AI users (0.7% in 2024 and 1.3% in 2025) reported 100%, any potential downward bias resulting from the upper bound is likely to be limited.[9] The mean efficiency gain was 21.0% in 2024 and 18.8% in 2025 (see **Table 1**), although the dispersion was large, with medians of 15% in 2024 and 10% in 2025.

Among those who continued using AI in both 2024 and 2025, the mean efficiency gain increased by 4.5 percentage points, from 21.1% to 25.6% (column (2), **Table 1**). By contrast, the mean efficiency gain for individuals who newly adopted AI in 2025 was 14.9% (column (3), **Table 1**). As with the AI task share, these new users pull down the 2025 overall average. The mean efficiency gain in 2024 for individuals who used AI in 2024 but discontinued its use in 2025 was 20.8%, which is comparable to that of continuing users.

The worker-level productivity effect (*AI_Productivity*) is calculated for AI users as *AI_Taskshare* multiplied by *AI_Efficiency*. For example, if a worker uses AI for 10% of their tasks and the efficiency gain from AI is 30%, their overall labor productivity is 3% higher than it would be without AI. The estimated mean productivity effects were 4.6% in 2024 and 3.4% in 2025 (column (1), **Table 1**). Although the decline in the mean productivity effect may appear surprising, it reflects the influx of new AI users in 2025, many of whom have relatively small AI task shares and efficiency gains, thereby lowering the average for all AI users. The distribution was highly dispersed, and the median productivity effect was 1.0% for both 2024 and 2025. Only 14.3% of AI users in the 2024 survey and 8.1% in the 2025 survey reported productivity effects of 10% or more.

For those who continued using AI in 2024 and 2025, the mean productivity effect increased by 0.7 percentage points, from 5.3% to 6.0% (column (2), **Table 1**). Meanwhile, the mean productivity effect for those who newly adopted AI in 2025 was 1.9% (column (3), **Table 1**), significantly lower than that of continued users.[10] The mean productivity

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9 Regarding lower bound, only a small number of respondents answered zero: 5.3% in 2024 and 4.2% in 2025.

10 Even after controlling for gender, age, educational attainment, firm size, employment type, union membership, working hours, and annual income, the productivity effect for new AI users remained significantly lower (a 3.4% difference).

effect in 2024 for individuals who used AI in 2024 but not in 2025 was 1.7%, which is substantially lower than that for continuing AI users. These findings suggest the presence of two mechanisms in the process of increasing AI utilization at work: (1) a selection effect and (2) a learning effect. Individuals engaged in tasks for which AI has a larger impact are more likely to adopt AI earlier (selection effect) and, through accumulated experience, either expand its use to a broader set of tasks or achieve greater efficiency gains (learning effect).

The figures reported above pertain only to workers who use AI in their jobs. When the impact on labor productivity is calculated for the entire industry, including workers who do not use AI, labor productivity in 2025 is estimated to be 1.1% higher than that in a counterfactual scenario without AI. Given that the corresponding figure for 2024 was 0.7%, AI utilization increased labor productivity in the machinery industry by 0.4 percentage points over the past year. Decomposition of this increase shows that more than 80% of the productivity gain is attributable to an increase in the proportion of AI users. Because the share of AI users was relatively low in 2024, the contribution from the extensive margin dominated over the past year. Going forward, as AI adoption becomes more widespread, the contribution from the intensive margin is expected to grow.

Among potential AI users, 18.5% reported that they expected to start using AI within the next five years. If all these individuals adopt AI for work and experience productivity gains comparable to those of current AI users (3.4%), labor productivity would increase by approximately 0.12 percentage points per year over the next five years. However, given the aforementioned selection and learning effects, this estimate is likely to be an upper bound. Assuming that potential AI users achieve productivity gains at the mean of new AI users (1.9%), the estimated annual increase falls to 0.07 percentage points. By contrast, productivity gains among existing AI users increased by 0.7% over the past year. If *AI_Taskshare* and *AI_efficiency* among these users continue to expand linearly, labor productivity would rise by an additional 0.25 percentage points per year ([6.0% - 5.3%] * 34.2% ≈ 0.25%). Combining both extensive and intensive margins, AI could raise overall labor productivity in the machinery industry by approximately 0.3–0.4 percentage points per year. However, this estimate is based on only two survey waves and should be interpreted as a mechanical calculation that relies heavily on the assumption of linear trends and workers' subjective assessments.

Table 2. Worker characteristics and AI usage and its effects.

	(1) *AI User*			(2) *AI Taskshare*			(3) *AI Efficiency*			(4) *AI Productivity*		
Female	-0.005	(0.004)		0.059	(0.003)	***	0.070	(0.004)	***	0.045	(0.002)	***
Age 20-29	-0.048	(0.005)	***	0.039	(0.003)	***	0.022	(0.005)	***	0.015	(0.002)	***
30-39	0.096	(0.005)	***	-0.005	(0.003)	*	0.011	(0.004)	***	-0.004	(0.002)	**
40-49	0.065	(0.004)	***	-0.014	(0.003)	***	0.019	(0.004)	***	-0.007	(0.001)	***
60-69	0.014	(0.006)	**	0.042	(0.004)	***	0.041	(0.006)	***	0.034	(0.003)	***
Vocational school	-0.014	(0.007)	*	0.034	(0.005)	***	0.041	(0.008)	***	0.013	(0.002)	***
Junior college	-0.025	(0.008)	***	-0.006	(0.004)		-0.012	(0.006)	*	-0.012	(0.002)	***
4-year university	0.033	(0.004)	***	0.034	(0.002)	***	0.058	(0.004)	***	0.018	(0.001)	***
Graduate school	0.014	(0.005)	***	0.018	(0.003)	***	0.000	(0.004)		0.003	(0.002)	
20-299 employees	0.015	(0.013)		0.050	(0.005)	***	0.114	(0.015)	***	0.027	(0.003)	***
300 employees or more	0.088	(0.010)	***	0.117	(0.006)	***	0.166	(0.015)	***	0.061	(0.003)	***
Labor union	0.047	(0.004)	***	-0.085	(0.004)	***	-0.111	(0.005)	***	-0.053	(0.002)	***
ln working hours	0.011	(0.005)	**	0.019	(0.003)	***	-0.013	(0.004)	***	0.009	(0.001)	***
ln annual income	0.142	(0.005)	***	0.025	(0.002)	***	-0.006	(0.003)	**	0.014	(0.001)	***
Year 2025	0.207	(0.004)	***	0.003	(0.003)		-0.013	(0.004)	***	-0.006	(0.002)	***
Pseudo R^2, R^2	0.2015			0.1444			0.1094			0.1851		

Probit estimation (column (1)) and OLS estimations (columns (2) – (4)). Robust standard errors are reported in parentheses. ***: p<0.01, **: p<0.05, *: p<0.10. R^2 in column (1) is pseudo R^2. The reference categories for the dummy variables are male, age 50–59, high school education or less, firm size of 19 employees or fewer, and workplaces without labor unions. While not reported in the table, occupation dummies are included in the estimations.

Table 2 reports the results of a pooled estimation using data from the 2024 and 2025 surveys to examine AI usage, the share of tasks performed using AI, efficiency gains, and productivity effects as functions of individual characteristics. As in the previous analysis, observations are weighted by gender × age group × industry. The reference category for the dummy variables is male; individuals in their 50s; those with a high school education or less; employees at firms with 19 or fewer workers; and employees at workplaces without labor unions. The results indicate that individuals in their 30s and 40s, those with higher levels of education, employees at unionized workplaces, and individuals with higher annual incomes are more likely to use AI in their work (column (1), **Table 2**).

AI_Taskshare, *AI_Efficiency*, and *AI_Productivity* are higher among females, individuals in their 20s, vocational school and four-year university graduates, and employees at larger firms (columns (2) – (4), **Table 2**).

The survey also inquired about specific jobs that utilized AI. The question was: "In what types of jobs do you use AI? Please select all that apply." Nine job categories were specified: "research and development (R&D)," "production management," "marketing," "procurement," "customer management/customer support," "human resources management," "accounting," "legal affairs/compliance," and "other." The tabulation result from the 2025 survey, AI utilization was heavily concentrated in R&D (40.4%), followed by marketing (19.5%), production management (19.0%), and human resources management (13.9%) (see **Table 3**).

Table 3. Specific jobs utilizing AI.

Jobs	Percentage
Research and development	40.4
Production management	19.0
Marketing	19.5
Procurement	4.8
Customer management/support	8.0
Human resources management	13.9
Accounting	4.4
Legal affairs/compliance	7.4
Other	13.6

The question is a multiple-choice format.

If the use of AI in R&D activities improves the efficiency of R&D investment, it is likely to generate productivity gains that extend beyond simple labor-saving effects (e.g., Aghion *et al*., 2019; Jones, 2022, 2024; Baily *et al*., 2026; Bianchini *et al*., 2026). In the machinery industry, the ratio of R&D expenditure to nominal value added is approximately 20%.[11] Assuming a rate of return on R&D investment of 30%[12], if AI utilization increases this return rate by 20% (= 6 percentage points), it would result in a 1.2 percentage points increase in the annual productivity growth rate.[13] Although this is a mechanical calculation intended to illustrate the potential quantitative impact, productivity gains arising from improved R&D efficiency may exceed the direct productivity effects arising from labor-saving discussed above.

4. Workers' view on the expanding use of automation technologies

This section presents the results of the 2025 survey on respondents' views regarding the future use of AI and robots in the workplace. The specific question asked was: "Do you think the use of artificial intelligence (AI) and robots should be increased in your workplace?" The response options were: "Should be significantly increased," "Should be increased," and "Should not be increased."[14] According to the tabulation results (see **Table 4**), 12.8% of respondents believed that automation should be significantly increased, 68.7% believed it should be increased, and 18.5% believed it should not be increased. Thus, more than 80% of respondents expressed a positive view toward expanding the use of automation technologies. **Table 4** also reports the results for a

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[11] Calculated using research expenditures from the "Survey of Research and Development" (Statistics Bureau of Japan, Ministry of Internal Affairs and Communications) and nominal value added (GDP) by economic activity from the "National Accounts" (Cabinet Office).

[12] The simple average of past studies cited in Hall *et al*. (2010), a representative survey on the return on investment in R&D, is 36%.

[13] According to the standard approach to quantify the productivity effects of R&D, the impact on macroeconomic productivity growth is approximated as the ratio of R&D investment to GDP multiplied by the rate of return on R&D investment.

[14] This question was not included in the 2024 survey.

subsample of workers who currently use AI in their jobs. These AI users, particularly continuous AI users, tend to be more supportive of further automation, with approximately 90% expressing favorable views. Taken together, these findings suggest that concerns about AI-induced job losses are currently limited among workers in the machinery industry.

Table 4. Views on the future use of AI and robots in the workplace (%).

	Should be significantly increased	Should be increased	Should not be increased
All respondents	12.8	68.7	18.5
AI users	17.9	73.9	8.2
Continuous AI user	23.2	70.3	6.5
New AI user	14.9	76.0	9.2
Severe labor shortage	28.3	61.0	10.8
Slight labor shortage	11.1	71.3	17.6
No labor shortage	10.0	66.0	23.9

The row labeled "No labor shortage" includes "surplus of labor."

Appendix Table A2 reports the results of an ordered probit estimation in which the dependent variable captures views toward expanding automation technologies (3 = should be significantly increased; 2 = should be increased; 1 = should not be increased). Various individual characteristics are included as explanatory variables. The results indicate that males, employees of larger firms, and individuals with higher annual income tend to hold more favorable views toward expanding the use of automation technologies (column (1) of **Table A2**). Additionally, after controlling for individual characteristics, workers who use AI in their jobs are significantly more positive about further expanding automation technologies.

As discussed earlier, even among workers who use AI in their jobs, the share of tasks performed using AI remains small. In other words, aside from a limited number of exceptional cases, automation technologies are applied only to a narrow subset of the diverse tasks that workers perform. This pattern suggests that the time saved through streamlining tasks is being reallocated to other activities, implying that automation technologies currently function primarily as complements to workers, rather than substitutes.[15]

The positive views toward the use of automation technologies may be related to Japan's severe labor shortages. To explore this possibility, we examined the relationship between perceived labor shortages in the workplace and views toward automation technologies. The survey question on labor shortages was phrased as follows: "Japan's labor shortage is becoming severe. How is it in your workplace?" The four response options were: "severe labor shortage," "slight labor shortage," "no labor shortage," and "surplus of labor." According to the 2025 survey, 11.8% of respondents reported a severe labor shortage, and 61.1% reported a slight labor shortage in their workplace. Together, these responses accounted for nearly 80% of the workforce, indicating a widespread perception of labor shortages.[16]

The cross-tabulation of views toward expanding automation technologies by perceived labor shortages is reported in the lower rows of **Table 4**. A stronger perception of labor shortages in the workplace is associated with a more favorable view toward expanding the use of automation technologies. This systematic relationship persists in an ordered probit estimation that controls for a range of individual characteristics (column (2) of **Table A2**). Although this evidence is cross-sectional and, therefore, cannot be interpreted causally, the observed relationship suggests that a further intensification of labor shortages could accelerate the adoption of automation technologies, including AI.

5. Conclusion

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[15] Engberg *et al*. (2025) demonstrate that increased exposure to automation technologies (AI and robots) among German workers is leading to changes in task composition within occupations. The results of the current study are consistent with their finding.

[16] In the 2024 survey, 13.6% reported severe labor shortages and 62.5% reported slight labor shortages.

This study examines the dynamics of AI utilization and its productivity effects using panel data from the 2024 and 2025 surveys of workers in the Japanese machinery industry. By focusing on a sample of workers who responded to both surveys, the analysis enables longitudinal comparisons that are unaffected by compositional changes. The key findings are summarized as follows.

First, the share of workers using AI in their jobs more than doubled over the past year, reaching approximately 34%. Moreover, an equal or larger share of workers can be regarded as potential AI users who expect to begin using AI in the future.

Second, among AI users, the mean share of tasks performed using AI is approximately 12%, and the associated efficiency gains are approximately 20%, with no significant change observed over the past year. However, focusing on workers who continued to use AI across both survey waves reveals increases in both AI task share and efficiency gains, suggesting the presence of learning effects. At the same time, dispersion across individuals is substantial. Except for a small number of workers, AI currently accounts for only a limited fraction of overall work tasks, and the resulting efficiency gains remain modest.

Third, by 2025, the impact of AI adoption on the level of labor productivity in the machinery industry—including workers who do not yet use AI—is estimated to be approximately 1.1% relative to a counterfactual scenario without AI, up from 0.7% in 2024. The additional productivity effect from potential AI users who begin using AI at work is estimated at approximately 0.1 percentage points per year over the next five years. Meanwhile, both the AI task share and efficiency gains among existing AI users have been increasing. If these trends continue linearly, they are expected to raise labor productivity by approximately 0.2–0.3 percentage points per year. Taken together, AI use in the workplace is estimated to increase labor productivity in the machinery industry by roughly 0.3–0.4 percentage points annually over the next several years. Moreover, because R&D accounts for the largest share of AI-utilizing tasks, improvements in R&D investment efficiency could generate even larger productivity effects.

Fourth, workers in the machinery industry hold strongly positive views on the expanded use of AI and robots in the workplace. This tendency is particularly pronounced among workers who already use AI in their jobs and those who perceive severe labor shortages in their workplaces. Currently, expectations that automation will help alleviate labor shortages appear to outweigh concerns about worker displacement by automation technologies.

However, the survey used in this study is limited to workers in the machinery industry, and the sample size is relatively small. Consequently, the findings cannot be generalized to the entire Japanese economy. Additionally, the estimated effects of automation technologies on task efficiency are based on respondents' subjective assessments. It should also be noted that the data constitute a balanced panel of machinery industry workers observed in both 2024 and 2025, and therefore do not include individuals who lost their jobs or entered the labor force during this period.

The use of AI in the workplace is expanding rapidly, and its technical characteristics and scope of application are evolving. Accordingly, continuous monitoring of actual AI usage and its effects is warranted.

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Appendix Tables

Table A1. Composition of respondents by gender, age, and industry (%).

Worker characterstics	Percentage	ESS in 2022
Male	92.9	76.3
Female	7.1	23.7
Age 20-29	0.9	15.5
30-39	5.1	21.2
40-49	20.5	25.8
50-59	43.6	25.7
60-69	28.0	9.2
70 or older	1.9	2.5
General-purpose, production, and business machinery	12.7	35.2
Electronic components and devices	20.0	16.0
Electrical machinery	32.8	14.2
Information and communication equipment	4.4	5.2
Transportation machinery	30.2	29.4

The numbers and percentages refer to the 2025 survey. “ESS” denotes the Employment Status Survey.

Table A2. Worker characteristics and views on the expanding use of AI and robots.

	(1)			(2)		
Female	-0.258	(0.015)	***	-0.231	(0.015)	***
Age 20-29	0.225	(0.018)	***	0.297	(0.018)	***
30-39	-0.102	(0.021)	***	-0.059	(0.021)	***
40-49	0.014	(0.018)		0.020	(0.018)	
60-69	-0.155	(0.023)	***	-0.101	(0.023)	***
70 or older	0.226	(0.040)	***	0.350	(0.041)	***
Vocational school	0.393	(0.031)	***	0.370	(0.031)	***
Junior college	-0.082	(0.030)	***	-0.205	(0.029)	***
4-year university	0.242	(0.016)	***	0.164	(0.016)	***
Graduate school	0.395	(0.018)	***	0.345	(0.019)	***
20-299 employees	0.453	(0.036)	***	0.474	(0.037)	***
300 employees or more	0.789	(0.038)	***	0.873	(0.039)	***
Government agencies	1.495	(0.039)	***	0.951	(0.046)	***
Labor union	0.007	(0.039)		0.045	(0.018)	**
ln working hours	0.030	(0.018)		0.057	(0.021)	***
ln annual income	0.302	(0.020)	***	0.282	(0.013)	***
AI user	0.286	(0.013)	***	0.292	(0.014)	***
Serious labor shortage				0.674	(0.026)	***
Slight labor shortage				0.176	(0.017)	***
Surplus of labor				-0.128	(0.034)	***
Pseudo R^2	0.0963			0.1114		

Ordered probit estimation results with robust standard errors are in parentheses. ***: p<0.01, **: p<0.05. The reference categories for the dummy variables are male, age 50–59, high school education or less, firm size of 19 employees or fewer, workplaces without labor unions, and no labor shortage. While not reported in the table, occupation dummies are included in the estimations.