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Generative AI and Employment in Japan

— How to ensure young people develop skills —

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⟨Summary⟩

◆ Generative AI (hereinafter, "GenAI"), the prime example of which is ChatGPT, has become capable of performing tasks such as drafting documents, organizing data, and handling routine responses in place of humans. These tasks have traditionally been entry-level duties that enable young people who have just entered the workforce to learn the basics of work. In the U.S., the employment of young workers for entry-level tasks is visibly declining due to the impact of GenAI. Meanwhile, employment for veteran workers remains stable, and it has been noted that GenAI is bringing about a "seniority-biased technological change."

◆ In Japan, labor shortages caused by the declining birthrate and aging population, as well as employment practices such as emphasis on a sense of belonging to an organization (below, "membership-based employment") and the simultaneous hiring of new graduates, are serving as cushions, making it unlikely that unemployment among young workers will surge as it has in the U.S. But what is concerning in Japan is not the possibility of a reduction in the number of jobs, but rather the problem of young people getting older without being able to develop vocational skills.

◆ Japan's membership-based employment has developed human resources through a process in which workers begin with simple tasks, grow through on-the-job training (OJT), and are gradually entrusted with more important work. If GenAI takes over the starting point of this process, the development mechanism is in danger of collapsing from within. There is a risk that time will pass without young people being able to acquire the skills that would normally be picked up gradually through OJT, i.e., practical training in the workplace, and a "generation that was able to get jobs, but could not learn about work" may emerge. This problem will only become apparent five to ten years from now, when the cohort that joined companies during the proliferation of GenAI become managers responsible for business

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decisions. Measures must be taken now before it becomes too late.

- There is a notion that companies should take responsibility for training young people, but that cannot solve this problem. First, in a society where the declining birthrate means that young people are scarce, training them increases their value, making it easy for them to switch employers. As a result, companies are reluctant to invest in training young people. Second, even if the quality of experience declines, it is unlikely that this will be reflected in numerical indicators, delaying recognition of the problem. Third, amid intense competition with rivals, investment in training tends to be pushed back. The upshot is that society as a whole is in danger of falling into a vicious cycle in which investment in training young people keeps decreasing.

- Policies to prevent such an "experience gap" from developing can be grouped into three categories: (1) expand fiscal and institutional support for companies that invest in training young people in parallel with the introduction of GenAI, and establish pre-employment training opportunities at universities and colleges of technology; (2) require disclosure of investment in human capital so that companies do not stop "investing in people" in favor of short-term profits, thereby allowing market discipline to function; and (3) build data foundations, including national statistics, to continuously monitor and visualize the impact of GenAI on entry-level tasks and experience accumulation for young people across society.

- Japan's so-called "Employment Ice Age" was a period in which employment opportunities themselves disappeared. But what is coming next is a problem of employment quality, namely a "generation that was able to get jobs, but was unable to acquire skills." To avert such a situation, it is necessary for the public and private sectors to work together and take action now.

- **This is an English version of “生成 AI と日本の雇用— 若年層の技能形成をどう確保するか —” in JRI Review (The original version is available at https://www.jri.co.jp/MediaLibrary/file/report/jrireview/pdf/16641.pdf)**

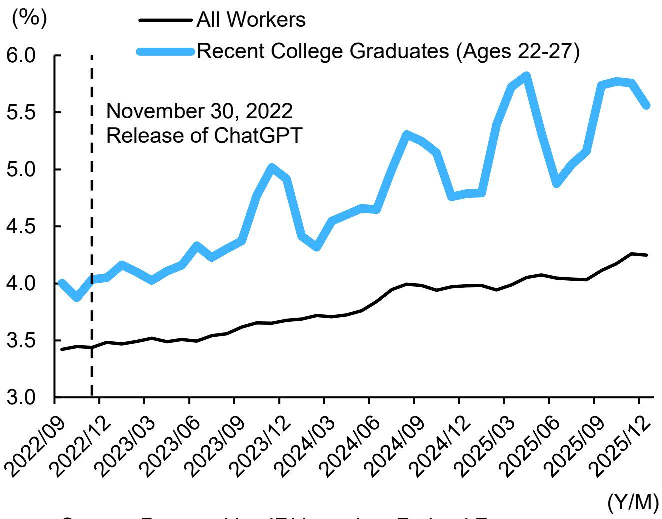
1. Introduction

Since OpenAI released ChatGPT to the public in November 2022[1] , generative AI (hereinafter, "GenAI") has rapidly permeated society (Chatterji, et al. [2025]). As of 2025, large language models (LLMs) such as Anthropic's Claude, Google's Gemini, xAI's Grok, and Meta's Llama are becoming more advanced with each release, and are now able not only to generate and summarize text but also to complete or assist with a wide range of intellectual tasks, including coding and data analysis. Furthermore, image and video generation models are now provided on the same platforms as the LLMs, further expanding the scope of use.

The impact of GenAI on the labor market is already becoming visible in the U.S. In 2025 alone, layoffs at tech companies reached an estimated 120,000 to 250,000 people[2] , and according to Challenger, et al. [2026a], employers themselves cited AI as the reason for 54,836 of those layoffs[3] . Major companies such as Microsoft, Salesforce, and Amazon have expanded AI investment while simultaneously making large workforce reductions, and these two developments are not contradictory, but rather, two sides of the same coin. In other words, as GenAI replaces humans for tasks, the feeling that the organization is overstaffed grows, and the need for hiring declines. Within this structural change, the group under the most pressure are those standing at the entrance to the labor market. Companies, by coupling budget constraints with GenAI use, are cutting recruitment of new graduates and entry-level personnel, creating a situation in which labor supply-demand balance for young people is apt to deteriorate.

"The Labor Market for Recent College Graduates" from the Federal Reserve Bank of New York tracked the employment environment for college graduates aged 22 to 27 (early career graduates), and found that their unemployment rate rose from 4.0% in September 2022 to 5.6% in December 2025, an increase of about 1.6 percentage points. During the same period, the unemployment rate for all workers rose from 3.4% to 4.2%, an increase of only about 0.8 percentage points (Figure 1). In addition, regarding hiring decisions for new graduates and young people, 37% of respondents to a survey said they would prefer to have robots or AI do the work instead of hiring recent college graduates (Workplace Intelligence [2025])[4] .

Figure 1. U.S. Uunemployment Rates for Recent College Graduates



Source: Prepared by JRI based on Federal Reserve Bank of New York, "The Labor Market for Recent College Graduates"

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1 Released to the public as a research preview.
2 Figure differs depending on the statistics. As discussed later, these sorts of figures need to be treated only as estimates.
3 The figure for layoffs due to AI is based on reasons cited by companies, and caution is required because there is potential for so-called "AI-washing," as discussed later.
4 A survey conducted by Workplace Intelligence targeting hiring managers at U.S. companies.

In response to these overseas developments, this question has arisen: "Will GenAI also take jobs from young people in Japan?" The hypothesis of this paper is that Japan is unlikely to experience a sudden shock in terms of youth unemployment of the like seen overseas. However, this does not mean that no problems will arise. In Japan, rather than unemployment, what is expected to become visible is an "experience gap" resulting from the disappearance of entry-level tasks. As GenAI replaces tasks that young people have traditionally handled, such as drafting, proofreading, and summarizing documents, conducting preliminary research, preparing simple analytical reports, organizing data, handling routine responses, and scheduling, opportunities for skill development through OJT will diminish, creating the risk that managers of the future will assume their posts without an understanding of frontline operations.

The question addressed in this paper is how Japan, while utilizing GenAI amid labor shortages, can secure opportunities for young people to gain experience and develop skills. Below, Chapter 2 presents the characteristics of GenAI and its impact on work, and Chapter 3 reviews research from the U.S., where impacts have already become visible. Chapter 4 looks at how GenAI enhances the productivity of new employees yet hinders training. Chapter 5 analyzes the context specific to Japan, and Chapter 6 suggests policy directions.

2. What does GenAI change?

(1) Characteristics of GenAI: ease of deployment and integration into work

What differentiates GenAI from previous automation technologies is its ease of adoption and the breadth of its applications. Whereas applications for industrial robots and RPA (robotic process automation) technology were limited to specific production lines or routine data processing, it is possible to start using GenAI immediately via the cloud, and users do not need to invest in hardware. In addition, because users interact with it in natural language, they can employ it for tasks even if they lack programming knowledge. This "low entry barrier" is what has enabled its rapid adoption in white-collar work.

The Organisation for Economic Co-operation and Development (OECD) estimates that about one-quarter (approximately 26%) of workers in member countries are already in situations where their tasks can be performed wholly or partially by GenAI, and that as software integrating the technology proliferates, the share of highly exposed workers could exceed 70% in some regions (OECD [2024]). A report published by the International Labour Organization (ILO) in May 2025 concludes that one in four workers across the world have some degree of GenAI exposure, but that because of the need for human input, most jobs will be transformed rather than made redundant (Gmyrek, et al. [2025]). GenAI is particularly strong in intellectual tasks centered on language and information processing. For this reason, it may bring major changes to fields such as education, IT, finance, and services, which were previously considered to be less affected by automation.

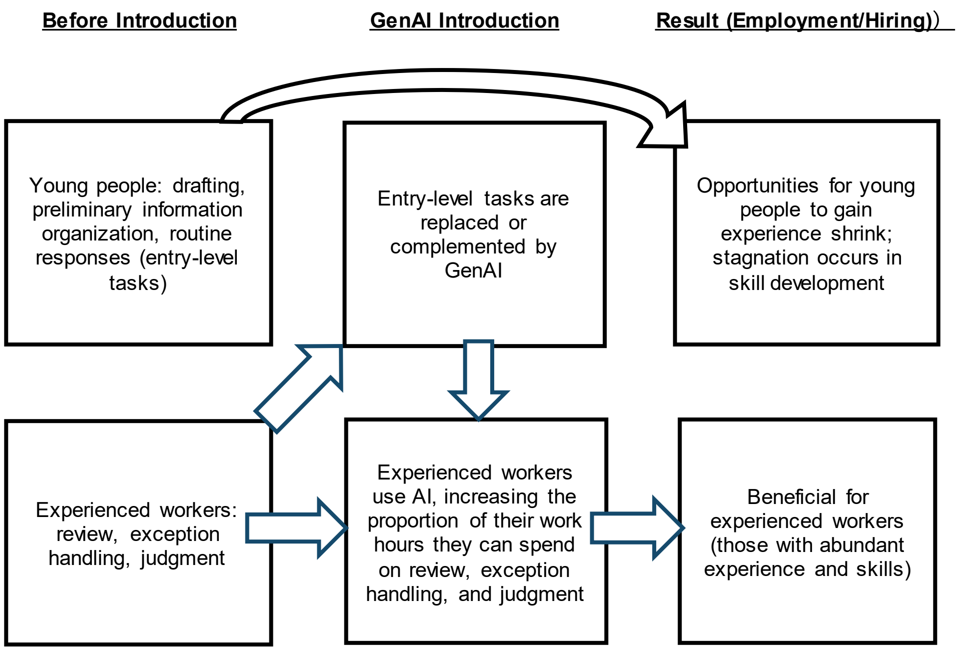
(2) Breaking down work: tasks that are replaced and tasks that remain

To accurately understand the impact of GenAI, analysis must be conducted at the task level rather than the job level. This perspective was originally presented in machine learning research (Brynjolfsson & Mitchell [2017]) and has been carried over into studies on GenAI. A single job is actually a bundle of multiple tasks, and some are easy for GenAI to perform while others are not. GenAI cannot replace, or even complement, everything. Only certain tasks can be automated, and given their relationship with the remaining tasks, the impact on employment does not fit into a simple "replacement" narrative.

Specifically, tasks that GenAI can easily handle or assist with include drafting, proofreading, and summarizing documents, conducting preliminary research, preparing simple analytical reports, organizing data, handling routine responses, and scheduling. These are tasks for which inputs and evaluation criteria can be defined relatively clearly, making it easy to integrate GenAI into practical operations. On the other hand, tasks that are difficult for GenAI to cope with include decision-making that involves defining goals, handling exceptions, interviewing witnesses and formulating strategies in legal proceedings, and performing reviews or quality control where there must be accountability for the basis of judgments.

What requires attention here is that many of the tasks that can be easily handed off to GenAI are precisely those entry-level tasks that have long been assigned to new employees and young people. Put another way, the proliferation of GenAI has the effect of reducing the steps that young people ought to be taking at the early stage of their careers (Figure 2). And as will be discussed later, U.S. research is beginning to support this hypothesis.

Figure 2. Decline in entry-level tasks due to GenAI and its impact



Source: Prepared by JRI based on Brynjolfsson, et al. [2025], etc.

3. U.S. research: decline in entry-level tasks and advantages for experienced workers

Before examining the research from the U.S., where the impacts of GenAI have already become visible, it is useful to classify the pathways through which GenAI affects employment into two categories. The first is "actual substitution," a pathway whereby specific tasks actually disappear or shrink significantly due to the introduction of GenAI. The second is "anticipatory substitution," a pathway whereby companies preemptively restrict hiring or restructure their organizations based on the expectation that GenAI may substitute for tasks in the future (Brüll, et al. [2025]). In addition, "exogenous macroeconomic factors" caused by phenomena such as monetary tightening and the reconsideration of investments that occurred during the same period as the diffusion of GenAI can sometimes also be explained as being due to AI (Restrepo [2023]). However, it is difficult to completely separate the two GenAI-related pathways from exogenous macroeconomic factors.

(1) Relative contraction of employment for young people

Using payroll records from ADP, one of the largest payroll processing companies in the U.S. (ADP provides services to companies employing more than 25 million workers in the U.S.), Brynjolfsson, et al. [2025] estimated changes in employment by occupation and age following the diffusion of GenAI based on monthly records for the period January 2021 to July 2025. To measure occupational sensitivity to GenAI, they combined the GPT-4 β index of Eloundou, et al. [2023] with the Anthropic Economic Index based on Claude conversation data (Handa, et al. [2025]) to analyze occupational GenAI sensitivity and age-specific employment dynamics.

Their main findings were as follows: In occupations highly exposed to GenAI, such as software developers and customer service representatives, the number of employed young people (ages 22–25) declined by about 6% from the end of 2022 to July 2025. Furthermore, even with analysis that eliminated firm-level shocks, the slump in employment among young people was concentrated in occupations highly exposed to GenAI, and employment in the most exposed occupations was 12–13% lower relative to the least exposed occupations. For other age groups, this difference was small. In the same highly exposed occupations, the number of employed experienced workers aged 30 and above increased by 6–9%, widening the employment gap between age groups. Meanwhile, in occupations less exposed to GenAI, employment increased overall, including for young people, indicating that employment deterioration is occurring only in highly exposed occupations.

Atkinson & Yamco [2026] confirmed similar patterns using the Current Population Survey (CPS) and report that the main cause of the decline in the employment share of young people is not an increase in layoffs, but "lower inflow," i.e., fewer people who were not working going straight into employment without experiencing unemployment. The main cause is presumably curtailment of recruitment, i.e., "anticipatory substitution."

(2) Seniority-biased technological change

Hosseini & Lichtinger [2025] used U.S. résumé data and job posting data (approximately 62 million individuals and 285,000 firms) to examine how the adoption of GenAI affects the employment composition of young people and experienced workers within firms. From the first quarter of 2023, after ChatGPT was released as a research preview (November 30, 2022), there was a rapid deterioration in the number of employed young people at companies that adopted GenAI compared with non-adopting firms, and the relative decline reached about 9% after six quarters. In contrast, the number of employed experienced workers continued to grow more strongly at adopting firms than at non-adopting firms, and no clear structural break in around 2023 was observed. Furthermore, comparing the balance of young people and experienced workers within the same company, until the end of 2022 there was no major difference in the trends at adopting and non-adopting firms. However, from 2023 onward, employment of young people at adopting firms began to deteriorate rapidly relative to experienced workers, and compared with non-adopting firms, the gap widened to about 10% after six quarters. The main cause of this decline was not increased layoffs or voluntary departures, but slower hiring, i.e., "anticipatory substitution."

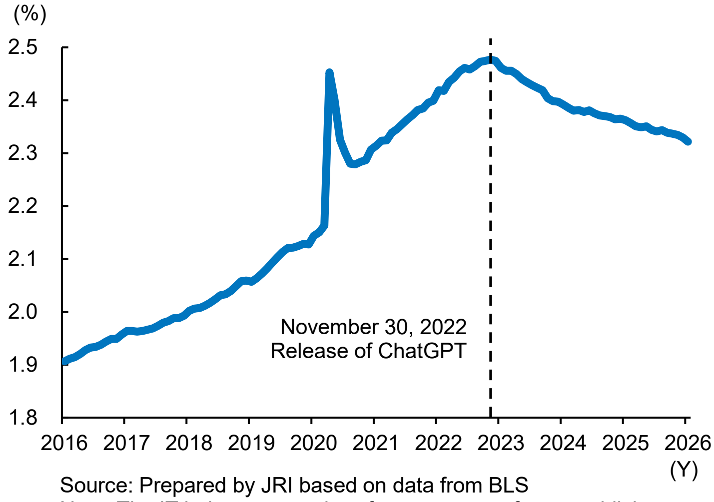
The study suggests that the proliferation of GenAI is bringing about "seniority-biased technological change." The authors contend that early-career experience forms the basis for lifetime wage growth and promotions, so any reduction in opportunities to gain experience at the career-entry stage may have long-term effects on wage growth and generate disparities.

Whereas the previously dominant "skill-biased technological change" increased demand for highly educated and highly skilled labor (Autor, et al. [1998]), the studies discussed above collectively indicate that GenAI, depending on how it is deployed, may relatively advantage experienced workers with many years behind them. This is likely because experienced workers excel at tasks that are difficult for GenAI to perform or assist with, such as decision-making and exception handling.

(3) Evidence in official statistics and trends in the U.S. tech industry

The next three figures, which are based on official statistics, show that changes in employment in tandem with GenAI diffusion are already emerging in some areas. First, the share of total employment accounted for by tech-related sectors, as defined in the Bureau of Labor Statistics' Current Employment Statistics (CES), continues to decline (Figure 3).

Figure 3. Share of IT industry Employment in Total U.S. Non-farm Employment

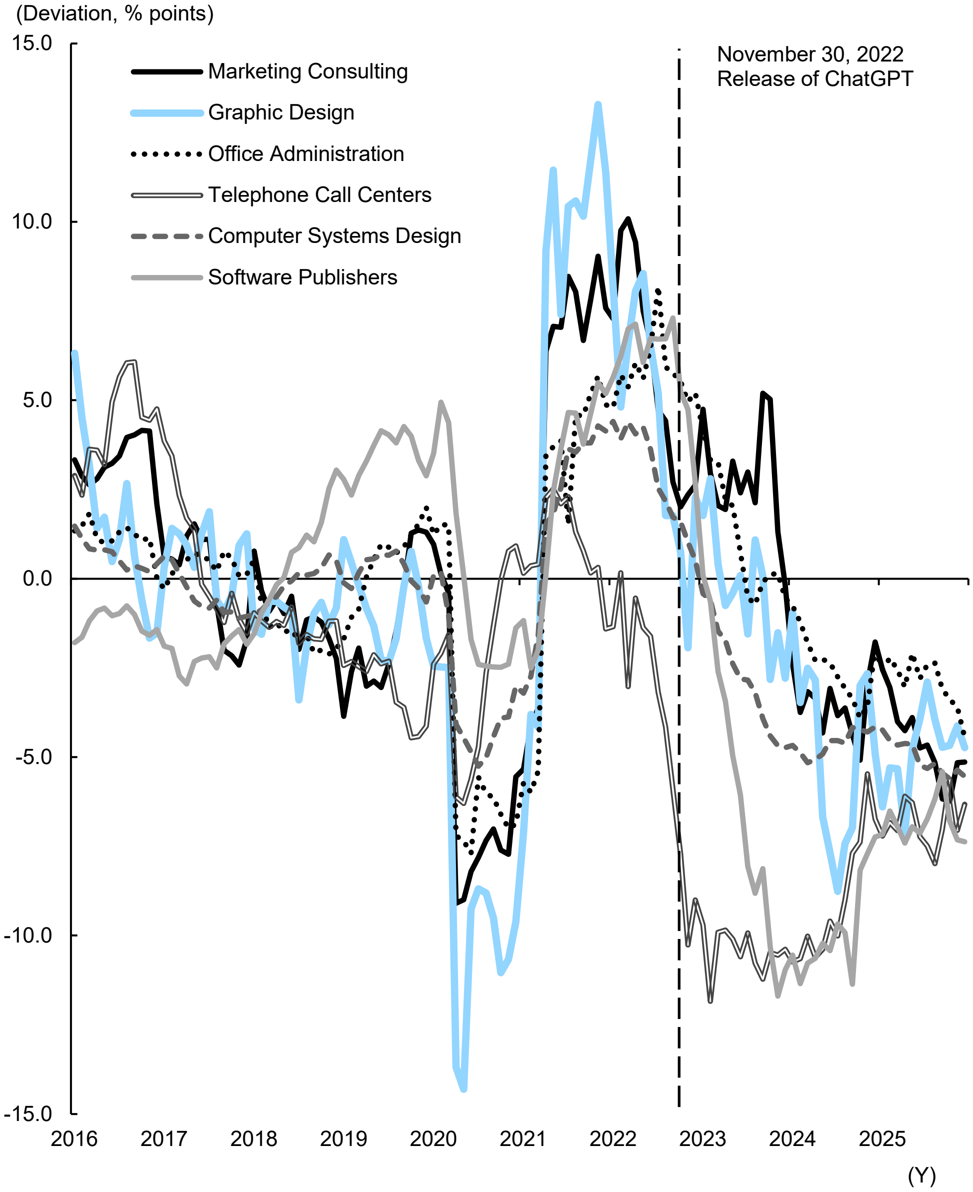


Source: Prepared by JRI based on data from BLS
Note: The IT industry comprises four sectors: software publishers; computing infrastructure providers, data processing, web hosting, and related services; web search portals and all other information services; and computer systems design and related services.

Second, in areas such as marketing consulting, graphic design, office administration, and call centers, year-on-year employment growth has consistently been below the 2015–2019 trend, and similar downward deviations can be observed for software publishers and systems design (Figure 4).

Morita [2026] provides analysis consistent with Figure 4, showing that the employment indices for the "information" and "administrative support services" sectors have continuously declined since the release of ChatGPT.

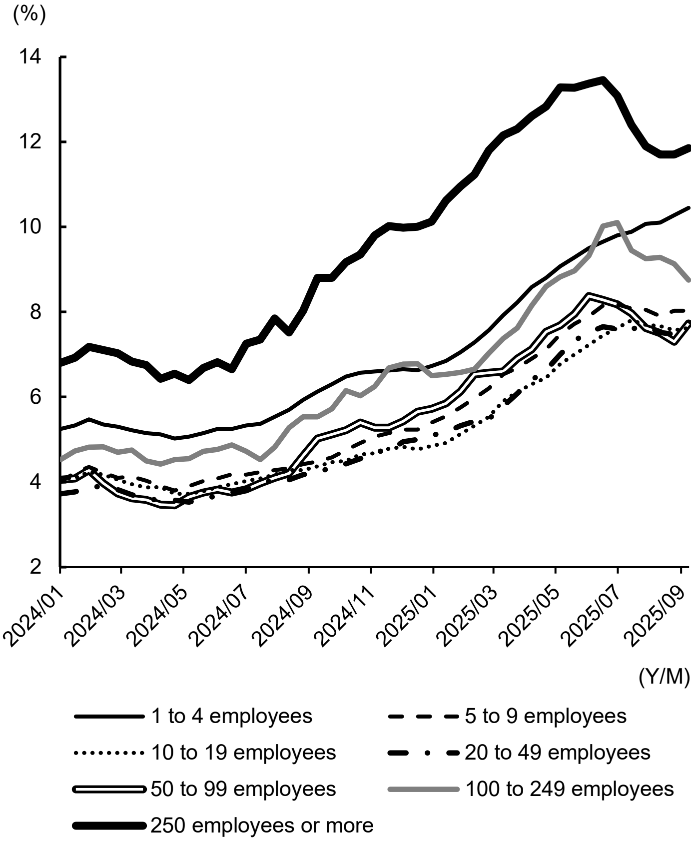
Figure 4. Deviation of Year-on-year Employment Growth from The 2015–2019 trend



Source: Prepared by JRI based on data from BLS

Third, the Census Bureau's "Business Trends and Outlook Survey" shows that although rates of AI use have risen more quickly at larger firms, as of mid-2025, the rate remains only slightly above 10% at companies employing 250 or more people, and is generally in the single-digit range at firms in other size categories, indicating that diffusion is still in progress (Figure 5). Taken together, these findings suggest that the recent softening in employment is likely concentrated in areas where AI deployment has advanced, and that as adoption spreads, there is potential for the impact to propagate and expand.

Figure 5. AI Adoption Rates by Firm Workforce Size



Source: Prepared by JRI based on data from the Census Bureau
Note: Proportions of firms answering "yes" to the question: "In the last two weeks, did this business use Artificial Intelligence (AI) in producing goods or services? (Examples of AI: machine learning, natural language processing, virtual agents, voice recognition, etc.)." Six-survey moving averages. Surveys are conducted approximately every two weeks.

However, data on the scale of layoffs in the tech industry varies greatly depending on how data collectors define layoffs and the scope of their data collection. For example, in 2025 TrueUp reported that there had been approximately 246,000 layoffs, while Layoffs.fyi reported a figure of about 124,000, so the numbers must be treated as estimates. In addition, data on the scale of workforce reductions attributed to AI is based on the number of cases where the companies themselves cited AI as a reason when announcing their layoff plans. Because firms may have incentives to discuss AI in ways that are positively received by the market, it is possible that reductions caused by "exogenous macroeconomic factors" are instead described as being driven by "AI," a possibility referred to as "AI-washing" (Rogelberg [2026], Challenger, et al. [2026b]). For example, workforce reductions in the tech industry since 2022 also reflect cyclical factors such as retreat from the hiring expansion that had occurred during the COVID-19 pandemic. Therefore, it is inappropriate to conclude that "AI stole jobs" without separating out such exogenous factors, as doing so risks both overestimation and underestimation.

4. Results on the ground: productivity gains for new employees but limits to learning

(1) Productivity gains for new employees through GenAI

It is not the case that GenAI only poses a threat. For young people with limited experience, GenAI can serve as a powerful support tool. Brynjolfsson, Li, & Raymond [2023] report that incorporating conversational AI into customer support operations improved productivity by increasing the number of issues resolved per hour and shortening the average time spent dealing with each issue. Notably, the effects of GenAI introduction were large for less experienced and lower-skill workers, while for experienced workers the effects were small or, in some cases, resulted in slightly lower call quality. By presenting past responses and best practices in real time and imparting knowledge that includes tacit elements, GenAI makes it easier even for new employees to provide services at a certain standard. As a result, overall workplace productivity can be raised.

Otake [2026] argues that there were once high entry barriers to intellectual work, such as the language ability and stamina needed to read large volumes of previous research and the long training periods needed to learn norms and methods, and that young people in those days trained themselves for their jobs by "carefully adhering to existing frameworks while making small modifications." GenAI, however, has eliminated these entry barriers at a stroke, he argues. Noy & Zhang [2023] obtained similar findings from an online experiment involving intermediate-level professional writing tasks. In the group using ChatGPT, average completion time fell by 40% and output quality improved by 18%. Moreover, participants with lower writing ability saw larger improvements when using ChatGPT, narrowing quality differences among the participants. Even new employees or personnel with limited experience may be able to produce output of a certain standard in a short time, and this can be seen as productivity improvement brought about by GenAI.

(2) Apparent proficiency and challenges for training

However, improvement in the quality of output does not necessarily mean that the person actually understands the task. GenAI is good at "producing correct answers," but it does not automatically provide, step by step, the reasons why an answer is correct or the background and context that make a judgment appropriate. If young people routinely submit GenAI output as is and obtain approval for it from their supervisors, they accumulate "results" without experiencing skill development. As a consequence, they do not develop the ability to make judgments and handle exceptions, creating a distortion in training design in which young workers appear more proficient without actually developing the underlying judgment and problem-solving skills. This tendency is related to current patterns of GenAI use. According to Handa, et al. [2025], who analyzed Anthropic conversation data, about 51% of GenAI use cases involve GenAI substituting for humans in the performance of tasks, with complementary use accounting for only 49%. Although not all tasks can be handled completely by GenAI, the fact that substitutional use accounts for more than half of the use cases is in line with this paper's concern about the decline in entry-level tasks that young people ought to be performing.

This phenomenon is also observed in educational settings. At universities, the use of GenAI in writing graduation theses is spreading. Although text and answers that appear fine on the surface can be produced quickly, this apparent proficiency may weaken the consolidation of understanding and thinking processes, hollowing out the intellectual foundation (Freeman [2025]). Similarly, in companies, if more young people can produce the "finished output" without going through dull but essential tasks such as drafting documents, organizing data, and handling routine responses, their ability to handle exceptions, infer context, and inherit organizational tacit knowledge will stagnate (Kosmyna, et al. [2025]). Otake [2026] raises the important concern that instead of waiting for young workers to develop their abilities before evaluating them, the proliferation of GenAI has increased the number of situations in which they are judged from the start on whether they "possess the essence," creating conditions that may be extremely disadvantageous for them.

The problem is that if the effects of GenAI introduction are measured only with short-term KPIs such as reductions in labor hours or increases in volume handled, it becomes difficult to see the impact on long-term productivity, including skill acquisition and the development of thinking and judgment abilities (OECD [2025a]). As will be discussed in Chapters 5 and 6, when outcomes of GenAI introduction are measured using indicators such as "issues resolved per hour," there is a risk that the perspective of quality of human resource development will be omitted in evaluation design.

5. Japan's distinctive problem: not "unlikely to occur" but "occurring in a different way"

The overseas studies presented in Chapter 3 were all conducted in labor markets premised on job-based employment. The reason the same youth unemployment shock is unlikely to occur in Japan is that three structural conditions function as cushions against such a shock: the delayed introduction of GenAI, the practices of membership-based employment and the simultaneous hiring of new graduates, and labor shortages accompanying the declining birthrate and aging population. However, "unlikely to occur" does not mean "no problem exists." These cushions protect the number of jobs, but they do not protect the quality of jobs.

(1) International gaps in GenAI utilization

As a premise, Japan lags far behind countries such as the U.S. in the use of GenAI. According to an international comparison survey by the Ministry of Internal Affairs and Communications, as of FY2024, 81.2% of individuals in China had used GenAI services, and the figures were 68.8% in the U.S. and 59.2% in Germany, but just 26.7% in Japan (Figure 6). The picture is similar for the proportions of companies using GenAI in

Figure 6. Experience using GenAI services

(%)

	Using (have used in the past)	Not using (have not used in the past)
Japan (FY2024 survey)	26.7	73.3
(FY2023 survey)	9.1	90.9
U.S. (FY2024 survey)	68.8	31.2
(FY2023 survey)	46.3	53.7
Germany (FY2024 survey)	59.2	40.8
(FY2023 survey)	34.6	65.4
China (FY2024 survey)	81.2	18.8
(FY2023 survey)	56.3	43.7

Source: Ministry of Internal Affairs and Communications (2025), "Survey on trends in research and development of the latest information and communication technologies and digital utilization in Japan and abroad" business operations, with figures of 90.6% in the U.S., 95.8% in China, and 90.3% in Germany, compared with 55.2% in Japan (Figure 7). There are also big gaps in the depth of GenAI deployment at the firm level. According to estimates by Filippucci, et al. [2025], the share of companies that have fully integrated GenAI into core operations is only 1.9% in Japan, less than one-third the figure for the U.S. (6.1%), and the lowest among the G7 countries.

Figure 7. Proportions of companies using GenAI in business operations

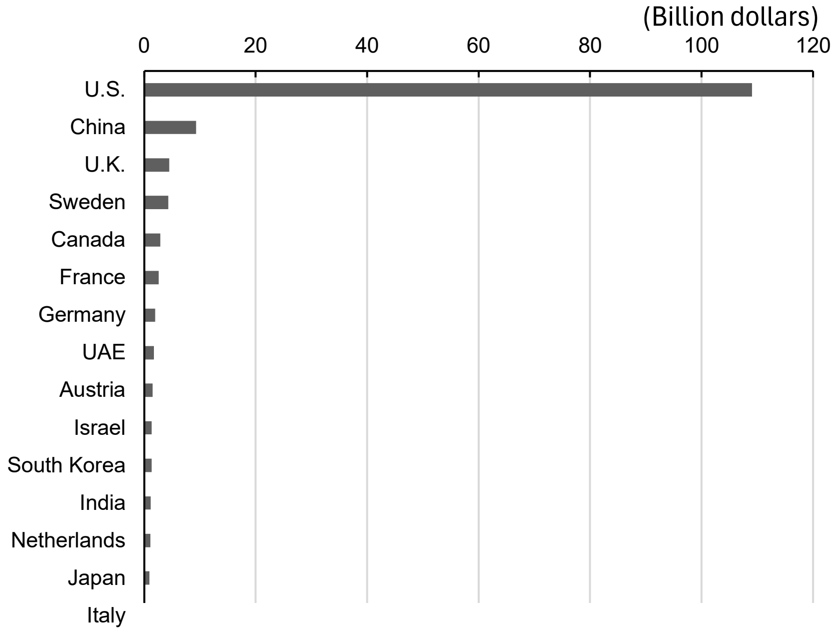
(%)

	Using for at least one task	No. of respondents	Proportion using for at least one task
Japan	244	442	55.2
U.S.	279	308	90.6
Germany	269	298	90.3
China	296	309	95.8

Source: Ministry of Internal Affairs and Communications (2025), "Survey on trends in research and development of the latest information and communication technologies and digital utilization in Japan and abroad"

Looking at private-sector investment in AI, the U.S. leads overwhelmingly with approximately $109.1 billion as of 2024, followed by China at about $9.3 billion and the U.K. at about $4.5 billion. Japan ranks 14th at around $0.9 billion, lagging behind such countries as South Korea (about $1.3 billion, 11th) and the United Arab Emirates (about $1.8 billion, 8th) (Figure 8). This delay in introduction itself can be seen as one reason that the rapid impact on youth employment observed in the U.S. is less likely to occur in Japan.

Figure 8. Private-sector Investment in AI by Country



Source: Prepared by JRI based on Stanford Institute for Human-Centered Artificial Intelligence AI Index Steering Committee [2025]
Note: 2024.

(2) Membership-based employment and simultaneous new-graduate hiring

An essential concept for understanding Japan's employment system is "membership-based" employment, a term proposed by Hamaguchi [2013]. In a membership-based system, job duties are not specified in the employment contract; instead, employees are hired first as members of the organization, and specific duties are assigned later at the employer's discretion. By contrast, in the job-based systems common overseas, employment is tied to a clearly defined set of tasks, making it easier for recruitment and wages to be structured around the duties involved (Hamaguchi [2022]). This difference affects routes into employment and the design of training. In Japan, a typical career path has been regarded as moving into stable employment upon graduation and then developing job performance capabilities through long-term in-company training and flexible job rotation (JILPT [2022]). Moreover, because job duties are not contractually specified, it is difficult to set wages strictly on the basis of job content, which tends to align well with seniority-based pay structures linked to years of service and age (Hamaguchi [2022]).

Under this system, Japanese companies have tended to emphasize aptitude and general abilities rather than uniformly demanding immediate job-readiness from new employees, because the assumption is that training will take place after assignment (Figure 9). In a questionnaire survey it conducted on expectations for recruitment and university reform in 2022, Keidanren (Japan Business Federation) found that the attributes most expected of university graduates were broad knowledge and education beyond the humanities-science divide (84.7%), initiative (84.0%), and teamwork, leadership, and cooperativeness (76.9%), indicating an orientation toward future potential. By contrast, in the "Job Outlook 2024" survey conducted by NACE in the U.S., problem-solving skills ranked first, with other competencies including written and verbal communication skills, strong work ethic, technical skills, and analytical/quantitative skills also being high up the list.

Figure 9. Differences in attributes sought in job candidates in Japan and the U.S.

	Japan		U.S.
1	Broad knowledge and education beyond the humanities-science divide	1	Problem-solving skills
2	Initiative	2	Ability to work in a team
3	Problem-setting and -solving skills	3	Communication skills (written)
4	Teamwork, leadership, and cooperativeness	4	Strong work ethic
5	Basic knowledge in field of major	5	Flexibility/adaptability
6	Logical thinking	6	Communication skills (verbal)
7	Specialized knowledge in field of major	7	Technical skills
8	Ability to execute	8	Analytical/quantitative skills
9	Creativity	9	Initiative
10	Ability to continue learning	10	Detail-oriented

Source: Prepared by JRI based on Keidanren [2022] and National Association of Colleges and Employers [2023]
Note: Japanese figures combine "attributes particularly expected," "abilities particularly expected," and "knowledge particularly expected."

This difference directly shapes hiring logic. In countries with job-based employment, hiring tends to be conducted on the premise of specific positions (Hamaguchi [2022]). If GenAI becomes capable of performing a given task, the need for positions designed around that task diminishes, and at minimum, motivation to recruit for that position weakens. Large Japanese companies operate differently. They hire new graduates all at once at the start of the fiscal year and then assign them duties while training them and rotating them through different jobs (Hamaguchi [2022]). Under this system, the disappearance of a particular task is unlikely to immediately translate into a one-to-one reduction in recruitment on the grounds that "no one is required for that role because it is gone."

However, even if hiring levels are maintained, if entry-level tasks are hollowed out by GenAI, the step-by-step human resource development chain that underpins the functioning of membership-based employment in practice, i.e., "entry-level tasks → OJT → job rotation," could break down from within. This qualitative risk is examined in detail in (4).

(3) Structural condition of labor shortages amid a declining birthrate and aging population

The most significant structural condition shaping Japan's job market is labor shortages amid the country's declining birthrate and aging population. At the Jackson Hole Symposium in August 2025, Bank of Japan Governor Kazuo Ueda highlighted the fact that Japan's total fertility rate had fallen to 1.15 in 2024, and that the working-age population (ages 15–64) had already peaked in 1995. He stated, "The youth unemployment rate, which in some countries seems to be affected by AI adoption, is at a 30-year low in Japan" (Ueda [2025]).

Indeed, Japan's unemployment rate for young people (ages 15–24) was 2.4% as of December 2025, significantly lower than the figures for the U.S. (10.4%) and the EU (14.7%) for the same age range (OECD [2026]). As for China, meanwhile, the published youth unemployment rate is for ages 16–24 (excluding students), and according to the National Bureau of Statistics of China, it was 16.5% in December 2025.

In the Bank of Japan's Tankan (December 2025 survey), the employment conditions DI (all industries, all company sizes) was minus 38, indicating that labor shortages are perceived to be severe. Therefore, at least from a macro perspective, companies have relatively little incentive to make large-scale reductions in their workforces, including for young people[5].

However, discussions on whether "Japan is unique" require a careful distinction to be made between demographic factors and institutional factors. Population decline and aging are not unique to Japan, as many developed countries face similar challenges, including South Korea (total fertility rate: 0.75 in 2024), Italy (1.18 in 2024), and Germany (1.35 in 2024). In fact, among advanced economies, the U.S. still continues to see population growth and leads in AI investment and development, placing it in a distinct position. That said, membership-based employment is particularly prevalent in Japan, and the country's combination of demographic and institutional factors may put Japan in a distinctive position[6].

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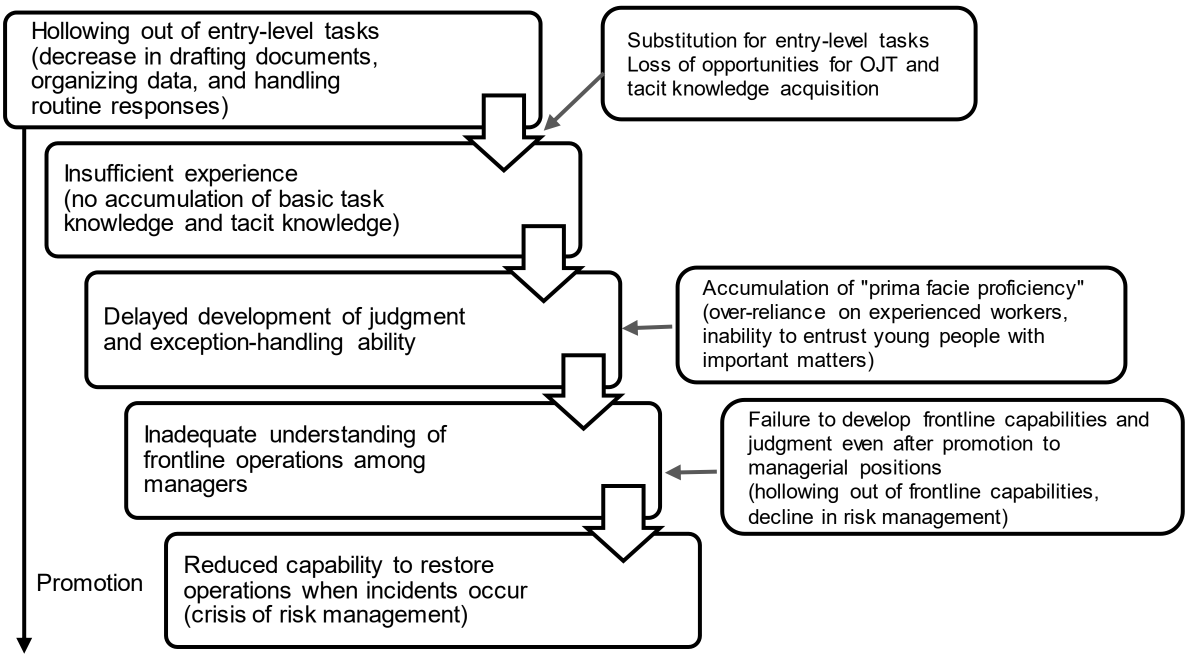
[5] However, labor shortages are worse in non-manufacturing for all company sizes, where the DI stands at minus 46, compared with minus 25 for manufacturing.
[6] Seniority-based wages are also observed in South Korea (OECD [2018]).

(4) Mechanism through which the experience gap gradually widens

The fact that job duties are not pre-determined at the time of hiring is not the only defining feature of membership-based employment. At its heart is the process by which companies adapt employees to the organization along a step-by-step developmental path, i.e., "entry-level tasks → OJT → job rotation." Assigning new graduates to entry-level tasks such as drafting documents, organizing data, and handling routine responses in their first one to three years is not intended to maximize productivity immediately. Rather, it is designed to help them learn the structure of work through direct experience and absorb the organization's tacit knowledge. The shared organizational language formed through this process, which includes document conventions, ways of reading information, and patterns for exception handling, becomes the foundation for later productivity growth and promotion.

However, when GenAI substitutes for entry-level tasks, this starting point for human resource development is eroded. If GenAI hollows out entry-level tasks, an "experience gap" between experienced workers and young people will gradually emerge later through the mechanism illustrated below, potentially harming the organization (Figure 10).

Figure 10. Mechanism Through Which An "Experience Gap" Emerges



Source: Prepared by JRI based on various materials

First, there will be a weakening of the foundation for OJT (Kosugi [2018]). The pathway of gaining an understanding of the overall nature of work by drafting documents, organizing data, and handling routine responses, as well as learning about the form that work takes through supervisor feedback, will become narrower. If GenAI is assigned these tasks, output will be produced, but the learning that takes place from performing the process will be lost. Young people will become the "first approvers" of GenAI output rather than "producers" of output. Repeated approval without experience of the production process will neither deepen understanding of the work nor internalize tacit knowledge. As a result, the essential value of membership-based employment, i.e., that understanding deepens with accumulated experience, will be undermined. To judge whether an output is correct, one needs to know the correct answer. In other words, experienced workers can identify issues in GenAI output and correct them, but those who do not understand the task are incapable of approving the output.

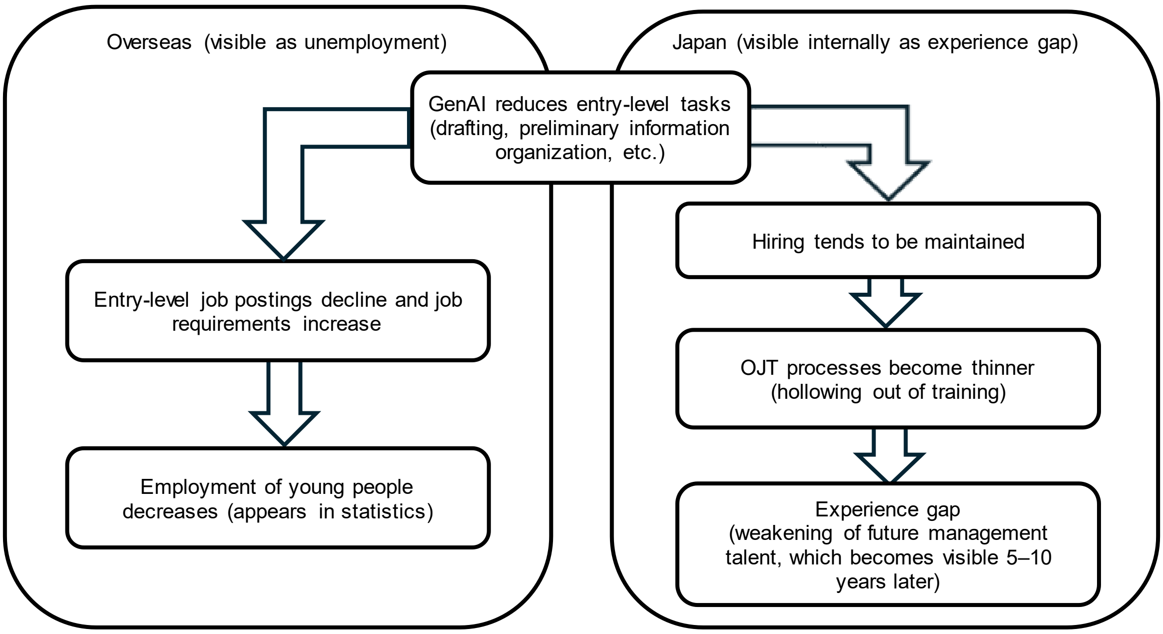
Second, there will be a break in the transmission of tacit knowledge (Cianciolo, et al. [2005]). Experience in exception handling and troubleshooting consists of tacit knowledge that is difficult to codify, and acquiring it requires encountering situations where one must "use one's own hands."

Third, there will be a qualitative deterioration in managers in the future. Managers who have moved up the career ladder without knowledge of frontline operations may perform adequately in normal times but reveal fatal weaknesses when making judgments in abnormal situations or trying to turn organizations around.

These effects are difficult to visualize in the short term. Immediately after GenAI adoption, various "good numbers," such as reduced labor hours and higher output quality, appear. However, the strengths of membership-based employment are lost from within. The problem surfaces five or ten years later, when the cohort that joined companies during the GenAI deployment period become managers (Sato [2015]). A structurally similar situation to the hollowing out of mid-career employees that occurred as a result of the reduced hiring during Japan's Employment Ice Age (period from the mid-1990s to the early 2000s when young graduates faced significant challenges in securing stable employment due to economic recession) may reappear, this time in the form of a "generation that was able to get jobs, but was unable to acquire skills" (Ebisuno, Oguma, and Murasugi [2014]).

Given the above, the risk that may materialize in Japan is not the "decline in youth employment" seen overseas. Rather, it will take a less visible form in which employment is maintained but the "quality of experience" deteriorates (Figure 11).

Figure 11. Different pathways through which AI affects employment overseas and in Japan



Source: Prepared by JRI based on various materials
Note: The main reasons for differences between countries include membership-based employment, simultaneous new-graduate hiring, and flexibility in job rotation. In Japan, the experience gap will likely surface when the cohort that joined companies during the GenAI deployment period reach managerial positions (5–10 years later). As with the Employment Ice Age, early policy intervention is essential.

(5) Gaps in training investment across firms and sectors

To overcome the experience gap problem, intentional human resource development design to compensate for the hollowing out of entry-level tasks will be essential. Specifically, it will be necessary to redesign OJT so that the experience of performing entry-level tasks now handled by GenAI can be reproduced in other forms, and to ensure that young people have opportunities to grasp the overall nature of work and receive feedback from their seniors.

However, expanding training investment entails structural challenges that cannot be resolved solely by the goodwill and efforts of individual companies. According to the Ministry of Health, Labour and Welfare [2025b], only 61.1% of businesses provide organized OJT for regular employees, meaning that about 40% do not. Furthermore, 48.6% of companies, around half, did not spend anything on off-the-job training in the past three years, and 39.0% do not plan to do so over the next three years, about the same percentage as those that intend to increase such spending (37.0%). Even though limiting investment in training may be a rational choice for individual firms, assuming that it would be good for all companies to behave in this way would be a "fallacy of composition," as society as a whole would fail to provide the necessary training. Three structural problems underlie this.

The first is the problem of externalities in human resource development. Companies cannot necessarily monopolize the benefits of OJT. If young people who have been trained change jobs, the company that bore the cost loses out. Japan's membership-based employment has mitigated this problem, but as the market value of workers with AI-related skills rises, incentives to change jobs will strengthen, weakening this mitigating effect. If each firm believes that "even if we train them, they will be poached," overall training investment across industry may stagnate.

The second is the problem of invisibility. Immediately after GenAI adoption, effects such as reduced labor hours and higher output quality appear, but deterioration in the quality of experience is unlikely to emerge for five to ten years. By the time management recognizes the problem, the young people of that period will already be approaching managerial positions. This "invisible deterioration" will be difficult to detect and correct through the attention and efforts of individual firms, creating a need for objective external indicators and disclosure requirements.

The third is the problem of cost competition. If competing companies reduce their OJT investment and thus improve their cost competitiveness, the firms that maintain their training investment will be placed at a short-term disadvantage. Under such conditions, without pressure from capital markets to invest in human capital or public subsidies to help cover training costs, even companies that wish to maintain training may find it difficult to do so. The risk that differences in firm-level responses become entrenched as differences in human resource competitiveness arises from these structural factors, and cannot necessarily be left to individual companies to mitigate.

6. Policy directions

The analysis in Chapter 5 highlighted two implications for GenAI and employment in Japan. First, GenAI must be actively utilized as a response to labor shortages accompanying the declining birthrate and aging population. As the working-age population shrinks rapidly, appropriate advancement of labor-saving through GenAI can ease labor shortages while maintaining the vitality of the overall economy. Second, if the introduction of GenAI hollows out entry-level tasks, there is a danger that young people will lose the route through which they accumulate experience and acquire skills via OJT. This experience gap will develop quietly as a deterioration in the quality, not the quantity, of employment, with the problem becoming visible five to ten years later, when the cohort that joined companies during the GenAI deployment period become managers.

Chapter 6 organizes the policy directions the government should take regarding this experience-gap problem into three categories: (1) support for expanding in-company education, (2) information disclosure to provide discipline to corporate behavior, and (3) building of data foundations for gauging actual experience-gap status.

(1) Support for expanding in-company education

The first pillar is for the national government and local governments to support, both financially and institutionally, companies that maintain/expand investment in developing young people in parallel with GenAI adoption.

On the financial side, the main tool should be expanding the "Human Resource Development Support Subsidy" program administered by the Ministry of Health, Labour and Welfare. This program partially subsidizes costs for companies that provide education and training for employees, but by adding requirements that provide preferential subsidy rates for firms that adopt GenAI while also implementing training programs for employees in their first to third years, it will be possible to financially support both labor-saving and training. The average length of service of Japanese employees is long at 12.4 years (Ministry of Health, Labour and Welfare [2025a]), so because employees tend to remain with their employers for many years, it is easier for companies to recoup training investment. It is important to design the system such that it leverages this characteristic.

On the institutional side, the Ministry of Economy, Trade and Industry and the Ministry of Health, Labour and Welfare should jointly formulate guidelines that present approaches to developing young people in workplaces where GenAI has been deployed, and disseminate them across industries. The core concept that the guidelines should present is the idea of consciously distinguishing between "work assigned to AI" and "work that young people should perform to gain experience." The "Digital Skill Standards ver.1.2" established by the Information-technology Promotion Agency and the Ministry of Economy, Trade and Industry lists skills such as "asking questions" and "formulating and verifying a hypothesis" as required competencies for GenAI use, emphasizing the importance of humans being able to explain the basis for decisions even when they are using AI. Work that young people should perform themselves can be organized into three categories: "confirmation and verification," which involves finding evidence to back up the GenAI output, checking the figures in the output, and so on; "exception handling," which involves discerning irregular cases that cannot be handled by following the manual; and "explanation and documentation," which involves writing down why a particular judgment was made. Even when GenAI is assigned document drafting or data organization, these three processes should remain in the workflow as tasks performed directly by young people, and the guidelines will need to clearly state this.

Basic education before entering the workforce is also essential. The Ministry of Education, Culture, Sports, Science and Technology and the Ministry of Economy, Trade and Industry should work with universities and colleges of technology to establish systems through which students can learn general tasks such as drafting and proofreading documents, preparing simple research reports, organizing data, and handling routine email correspondence as part of industry-linked educational programs. If young people acquire these basic abilities before entering companies, the OJT burden for firms can be reduced, and the learning foundation for young people can be augmented. The government is also advancing policies to strengthen the human resource development functions of technical colleges, in line with the "Grand Design and Action Plan for a New Form of Capitalism 2025 Revised Version." Colleges of technology already have strengths in practical technical education and are well positioned to serve as early models for such initiatives. It would be desirable to design subsidies for industry-academia collaboration programs such that local governments can also utilize them.

There is also room for policy involvement in evaluation design. Companies that use only labor-hour reduction rates or processing volumes as performance indicators for GenAI adoption may perceive postponing investment in human resource development as advantageous in the short term. By mandating the use of medium- to long-term training indicators such as understanding of work, ability to respond to problems, and time spent receiving guidance from senior employees as conditions for the initial and ongoing award for subsidies, it will be possible to put a stop to such short-sighted management decisions.

(2) Information disclosure

The second pillar is for the government to correct short-sighted decisions among firms, namely the belief that "if AI deployment reduces labor hours, then it is acceptable to reduce training costs as well," through information-disclosure systems and industrial policy. For listed companies, disclosure of information on human capital investment is already required under both the Corporate Governance Code, which sets basic rules for corporate governance, and the disclosure rules for annual securities filings. The next step is to use this framework to require concrete disclosure of companies' approaches to developing young people during the GenAI adoption period. If firms are required to disclose, in connection with their management strategies, information such as which tasks are now being handled by GenAI, how they are designing the processes that young people will continue to perform, and how the time and money allocated to OJT has changed, investors will have the information they need to assess the quality of human capital development from the perspective of long-term enterprise value. This will allow market discipline to function as a deterrent to management that is overly fixated on short-term cost reduction.

Collecting and sharing leading practices is also a role the government should play. The Ministry of Economy, Trade and Industry has already shared practical examples in the "Ito Report for Human Capital Management 2.0," a policy document encouraging firms to link management strategy and human capital strategy. Building on this, it will be effective to share the practices of companies that design work processes in ways that consider the development of young people even as the firms adopt GenAI. In any industry, a "fallacy of composition" can manifest itself, as once individual firms cut training investment, competitors find it easier to follow suit. By horizontally disseminating exemplary designs for training processes, the government can help prevent such vicious cycles.

That said, it is unrealistic to expect companies exposed to global competition to uniformly maintain generous budgets for training investment for all young people. The purpose of this paper is to raise the overall baseline, and introducing perspectives that would widen disparities in training investment is not desirable. Even so, given resource constraints, establishing a dual-track system that focuses on intensive programs for future management candidates may become unavoidable for companies. In that case, several conditions will need to be met to minimize disparities. For example, policy measures will be necessary to ensure that firms clearly inform employees which track they are on, provide reasonable justification for differences in treatment between tracks, provide opportunities for employees to move between tracks, and offer supplementary training opportunities to those on tracks with less training as standard, which they can take advantage of if they so wish.

(3) Building of data foundations

The third pillar is for the government to build data foundations that enable continuous monitoring of how the introduction of GenAI is affecting the development of young people. At present, information on how entry-level tasks have changed as GenAI use spreads within workplaces, and how much opportunity to accumulate experience young people have actually lost, remains inside individual companies, and there is no statistical foundation for externally grasping nationwide trends. Without such data, it would be difficult both to verify whether the subsidies discussed in (1) are actually effective and to make the disclosure requirements discussed in (2) meaningful.

A first step is to add new questions to the "Basic Survey of Human Resources Development" conducted annually by the Ministry of Health, Labour and Welfare. This survey already captures, on a national scale, how companies conduct education and training for employees, including new graduates. Adding questions on the status of GenAI deployment and changes in the tasks performed by employees in their first to third years would make it possible to track changes in entry-level tasks and training opportunities as national statistics. One idea is to ask about the degree of GenAI involvement in tasks such as document preparation and data organization, for example, "not used," "used as assistance," "GenAI produces output that humans check and use," or "almost fully automated," as well as how the share of routine tasks has changed compared with the previous year.

To visualize qualitative aspects of training, improvements to corporate disclosure rules will also be necessary. The "Human Capital Visualization Guidelines" produced by the Cabinet Secretariat provide reference indicators that companies can use when disclosing information on investment in employees, but they currently focus only on quantitative indicators such as training hours and training costs. The 2026 draft revision mentions responding to changes in skill demand due to advances in GenAI, but does not include qualitative indicators such as "what kinds of work experience employees have accumulated." By adding indicators suited to the GenAI era, such as the types and breadth of tasks actually performed by young people within a certain period after joining the company, as examples of voluntary disclosure, firms will find it easier to demonstrate internally and externally the risks of training hollow-out.

The corporate panel survey conducted by the Japan Institute for Labour Policy and Training (JILPT), which is under the jurisdiction of the Ministry of Health, Labour and Welfare, follows the same companies over multiple years and is well suited for comparing conditions before and after GenAI adoption. Adding questions on the uses of GenAI and its impact on entry-level tasks would make it possible to causally estimate "how training was affected in firms that adopted GenAI," and thereby improve the accuracy of policy effectiveness assessments.

7. Conclusion

This paper has analyzed how the proliferation of GenAI affects employment and skill development for young people, comparing findings from U.S. research with the institutional characteristics of Japan's labor market. In the U.S., occupations highly exposed to GenAI are seeing a relative decline in the employment of young people, and a shift is occurring toward favoring experienced workers, which can be described as "seniority-biased technological change." In Japan, however, labor shortages accompanying the declining birthrate and aging population as well as systemic constraints such as membership-based employment practices and the simultaneous hiring of new graduates act as buffers, making it less likely that Japan will experience the same kind of youth unemployment shock seen overseas. The issue is that "unlikely to occur" does not mean "no problem exists."

Japan's distinctive risk is a deterioration not of the "quantity" of employment, but of its "quality." If entry-level tasks such as drafting documents, organizing data, and handling routine responses performed during the first one to three years after hiring are replaced by GenAI, the entry point for skill development through OJT will be eroded. Organizational tacit knowledge and understanding of work are internalized through accumulated experience, but if GenAI produces the output and young people become mere approvers, this mechanism will be disrupted. The impact will become visible five to ten years later, when the cohort that joined companies during the GenAI deployment period become managers. The reduced hiring during the Employment Ice Age has caused a hollowing out of mid-career employees, and a similar loss may emerge in the future in the form of a "generation that was employed but could not accumulate experience."

This paper has presented three pillars as policy recommendations: (1) expand public support for in-house training by companies and pre-employment training opportunities at universities and colleges of technology, (2) curtail short-termism through information disclosure so that companies do not neglect "investing in people," and (3) build data foundations, including national statistics, to ascertain the impact of GenAI on experience accumulation among young people. What is important is not to limit the evaluation of GenAI deployment to short-term labor-hour reductions, but to incorporate medium- to long-term training indicators such as depth of work understanding and ability to handle exceptions. Even while leveraging GenAI to improve productivity amid labor shortages, it will also be essential to intentionally preserve routes along which young people can accumulate experience, in order to maintain the strengths of membership-based employment.

Finally, it must be emphasized that the issues raised in this paper are not limited to training. As Murase and Nishioka [2026] illustrate, if GenAI utilization in Japan remains confined to efficiency gains, its contribution to economic growth will be limited. They contend that expanding the scope of human-GenAI collaboration and increasing complementarity will be vital for delivering growth. The human resources underpinning this growth will be those who have acquired, through real-world experience, competence in "domains that require the human touch," such as interpersonal interaction, explanation of judgments, and relationship building. Allowing a structure in which young people grow without experiencing entry-level tasks to persist would not only constitute a training problem, but would also trap Japan's GenAI utilization within an efficiency-only paradigm. Balancing short-term efficiency gains with medium- to long-term human capital development will be both the source of competitiveness for Japanese industry in the GenAI era and a condition for the nation's economic growth.

At the 2003 peak of the Employment Ice Age (1993-2004), reduced hiring of new graduates amid economic stagnation had led to the existence of 2.17 million "freeters" (people stuck in casual, low-paid jobs) (Ministry of Health, Labour and Welfare [2010]), and the economic and social disparities endured by that generation have become entrenched, continuing even to this day. The environment surrounding today's young people is very different, as labor shortages are supporting hiring. Therefore, a repeat of the same type of "ice age," i.e., no jobs being available, is unlikely. However, policymakers must pay close attention to the possibility that an invisible experience gap may develop, in the form of a "generation that was employed but could not accumulate experience." Ensuring the quality of employment for young people in the GenAI era cannot be left solely to companies or industries. From the perspective of maintaining social stability, too, it is essential that the government also works hard to address this issue.

References

(English)

- Atkinson, T., & Yamco, S.[2026]. “Young workers’ employment drops in occupations with high AI exposure.”, Federal Reserve Bank of Dallas. January 6.
（https://www.dallasfed.org/research/economics/2026/0106）
- Autor, D. H., Katz, L. F., & Krueger, A. B.[1998]. “Computing inequality: Have computers changed the labor market?”, The Quarterly Journal of Economics. November.
（https://doi.org/10.1162/003355398555874）
- Brüll, A., Mäurer, M., & Rostam-Afschar, D.[2025]. “Beliefs about Bots: How Employers Plan for AI in White-Collar Work.”, IZA Discussion Paper No. 18225.
（https://docs.iza.org/dp18225.pdf）
- Brynjolfsson, E., Chandar, B., & Chen, R.[2025]. “Canaries in the Coal Mine? Six Facts about the Recent Employment Effects of Artificial Intelligence.”, Stanford Digital Economy Lab. November 13.
（https://digitaleconomy.stanford.edu/app/uploads/2025/11/CanariesintheCoalMine_Nov25.pdf）
- Brynjolfsson, E., Li, D., & Raymond, L. R.[2023]. “Generative AI at work.”, NBER Working Paper No. 31161, National Bureau of Economic Research.
（https://www.nber.org/papers/w31161）
- Brynjolfsson, E., & Mitchell, T.[2017]. “What can machine learning do? Workforce implications.”, Science, 358(6370), 1530–1534. December 22.
（https://doi.org/10.1126/science.aap8062）
- Challenger, Gray & Christmas[2026a]. “Challenger Report December 2025: Job Cut Announcement Report.” January 8.
（https://www.challengergray.com/wp-content/uploads/2026/01/ChallengerReport-December-2025.pdf）
- Challenger, Gray & Christmas[2026b]. “Challenger Report January 2026: Job Cut Announcement Report.” February 5.
（https://www.challengergray.com/wp-content/uploads/2026/02/CR126007123.pdf）
- Chatterji, A., Cunningham, T., Deming, D., Hitzig, Z., Ong, C., Shan, C., & Wadman, K.[2025]. “How People Use ChatGPT.”, OpenAI. September 15.
（https://cdn.openai.com/pdf/a253471f-8260-40c6-a2ccaa93fe9f142e/economic-research-chatgpt-usage-paper.pdf）
- Cianciolo, A. T., Matthew, C. T., Sternberg, R. J., & Wagner, R. K.[2005]. “Tacit knowledge, practical intelligence, and expertise.”, In R. J. Sternberg & J. A. Horvath（Eds.）, Tacit Knowledge in Professional Practice.
- Eloundou, T., Manning, S., Mishkin, P., & Rock, D.[2023]. “GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models.”, arXiv:2303.10130. 2023, March 20.
（https://arxiv.org/abs/2303.10130）
- Federal Reserve Bank of New York. [n.d.]. “The Labor Market for Recent College Graduates: Underlying data.”
(https://www.newyorkfed.org/research/college-labor-market#--:explore:unemployment)

- Filippucci, F., Gal, P., Laengle, K., & Schief, M.［2025］.“Macroeconomic productivity gains from Artificial Intelligence in G7 economies.”, OECD Artificial Intelligence Papers, No. 41. OECD Publishing.
（https://www.oecd.org/content/dam/oecd/en/publications/reports/2025/06/macroeconomic-productivity gains-from-artificial-intelligence-in-g7-economies_dcf91c3e/a5319ab5-en.pdf）
- Freeman, J.［2025］.“HEPI/Kortext Student Generative AI Survey 2025.”, Higher Education Policy Institute. February.
（https://www.hepi.ac.uk/wp-content/uploads/2025/02/HEPI-Kortext-Student-Generative-AI-Survey-2025.pdf）
- Gmyrek, P., Berg, J., Kamiński, K., Konopczyński, F., Ładna, A., Nafradi, B., Rosłaniec, K., & Troszyński, M.［2025］.“Generative AI and jobs: A 2025 update.”, International Labour Organization. May 20.
（https://www.ilo.org/publications/generative-ai-and-jobs-2025-update）
- Handa, K., Tamkin, A., McCain, M., Huang, S., Durmus, E., Heck, S., Mueller, J., Hong, J., Ritchie, S., Belonax, T., Troy, K. K., Amodei, D., Kaplan, J., Clark, J., & Ganguli, D.［2025］.“Which Economic Tasks are Performed with AI? Evidence from Millions of Claude Conversations.”, arXiv:2503.04761. February 11.
（https://arxiv.org/abs/2503.04761）
- Hosseini, S. M., & Lichtinger, G.［2025］.“Generative AI as Seniority-Biased Technological Change: Evidence from U.S. Résumé and Job Posting Data.” October 6.
（https://ssrn.com/abstract=5425555）
- Infocomm Media Development Authority; Personal Data Protection Commission; & Lee Kuan Yew Centre for Innovative Cities, Singapore University of Technology and Design［2020］.“A guide to job redesign in the age of AI.”
（https://file.go.gov.sg/ai-guide-to-jobredesign.pdf）
- Kosmyna, N., Hauptmann, E., Yuan, Y. T., Situ, J., Liao, X.-H., Beresnitzky, A. V., Braunstein, I., & Maes, P.［2025］.“Your Brain on ChatGPT: Accumulation of Cognitive Debt when Using an AI Assistant for Essay Writing Task.”, arXiv:2506.08872. June 10.
（https://arxiv.org/abs/2506.08872）
- National Association of Colleges and Employers［2023］.“Job Outlook 2024: Grab and Go.”, November.
（https://www.naceweb.org/docs/default-source/default-document-library/2023/resources/nace-job outlook-2024-grab-and-go.pdf）
- Noy, S., & Zhang, W.［2023］. “Experimental evidence on the productivity effects of generative artificial intelligence.”, Science, 381（6654）, 187–192. July 14.
（https://doi.org/10.1126/science.adh2586）
- OECD［2018］. “Working Better with Age: Korea.”, OECD Publishing.
（https://doi. org/10.1787/9789264208261-en）
- OECD［2024］. “Job Creation and Local Economic Development 2024: The Geography of Generative AI.”, OECD Publishing. November 28.
（https://doi.org/10.1787/83325127-en）

- OECD［2025a］. “The effects of generative AI on productivity, innovation and entrepreneurship.”, OECD Publishing. June.
（https://doi.org/10.1787/b21df222-en）
- OECD［2025b］. “Generative AI and the SME workforce: How is generative AI impacting SMEs’ skill and labour needs?”, OECD Publishing. November 5.
（https://doi.org/10.1787/2d08b99d-en）
- OECD［2026］. “OECD unemployment rate remained stable at 5.0% in December 2025.” February 12.
（https://www.oecd.org/en/data/insights/statistical-releases/2026/02/unemployment-rates-updated february-2026.html）
- Restrepo, P.［2023］. “Automation: Theory, Evidence, and Outlook.”, NBER Working Paper No. 31910. National Bureau of Economic Research.
（https://www.nber.org/papers/w31910）
- Rogelberg, S.［2026］. “Sam Altman says the quiet part out loud, confirming some companies are ‘AI washing’ by blaming unrelated layoffs on the technology.”, Fortune. February 19.
（https://fortune. com/2026/02/19/sam-altman-confirms-ai-washing-job-displacement-layoffs/）
- Layoffs.fyi［n.d.］. “Tech and Startup Layoff Tracker.”
（https://layoffs.fyi/）
- Stanford Institute for Human-Centered Artificial Intelligence AI Index Steering Committee［2025］. “Artificial Intelligence Index Report 2025.” April.
（https://hai.stanford.edu/assets/files/hai_ai_index_ report_2025.pdf）
- TrueUp［n.d.］. “Tech Layoffs Tracker.”
（https://www.trueup.io/layoffs）
- Workplace Intelligence［2025］. “College Graduate Skills Study.” January 21.
（https:// workplaceintelligence.com/college-graduate-skills-study）

(Japanese)
- Ueda, K. [2025]. “Japan's Labor Market under Demographic Decline: Evolving Dynamics and Macroeconomic Implications” (speech). Bank of Japan, August 23.
(https://www.boj.or.jp/about/press/koen_2025/ko250824a.htm)
- Ebisuno, S., Oguma, S., and Murasugi, Y. [2014]. “The current situation and challenges of mid-career employees in the workplace: from the perspective of labor-management relations.” The Japanese Journal of Labour Studies, No. 653, pp. 45−58, December.
(https://www.jil.go.jp/institute/zassi/backnumber/2014/12/pdf/045-058.pdf)
- Osawa, N., Kamiyama, K., Nakamura, K., Noguchi, T., and Maeda, E. [2002]. “An Examination of Structural Changes in Employment and Wages in Japan.” Bank of Japan, August 2.
(https://www.boj.or.jp/research/brp/ron_2002/data/ron0208a.pdf)
- Otake, F. [2026]. “GenAI has not led to ‘younger researchers’: not democratization, but a harsh and fair era in which people are judged on whether they possess the essence from the start.” Toyo Keizai Online, January 16.

(https://toyokeizai.net/articles/-/928669)

- Ministry of Health, Labour and Welfare [2010]. "Trends in freeters and NEETs." May 12. (https://www.mhlw.go.jp/shingi/2010/05/dl/s0512-7h_0004.pdf)
- Ministry of Health, Labour and Welfare [2025a]. "Results of the 2024 Basic Survey on Wage Structure." March 17. (https://www.mhlw.go.jp/toukei/itiran/roudou/chingin/kouzou/z2024/dl/13.pdf)
- Ministry of Health, Labour and Welfare [2025b]. "Results of the 2024 Basic Survey of Human Resources Development." June 27. (https://www.mhlw.go.jp/content/11801000/001548719.pdf)
- Kosugi, R. [2018]. "Recent employment issues of young people in Japan: light and shadow of the new graduate recruitment system." Japan Institute for Labour Policy and Training. (https://www.jil.go.jp/foreign/report/2018/pdf/18-03_04.pdf)
- Sato, K. [2015]. "How does promotion to a managerial position affect mental health?". RIETI Discussion Paper Series 15 J 062, December. (https://www.rieti.go.jp/jp/publications/dp/15j062.pdf)
- Ministry of Internal Affairs and Communications [2025]. "Information and Communications in Japan 2025." July 8. (https://www.soumu.go.jp/johotsusintokei/whitepaper/r07.html)
- Bank of Japan Research and Statistics Department [2025]. "Tankan (Summary) − December 2025 − (207th Short-Term Economic Survey of Enterprises in Japan)." December 15. (https://www.boj.or.jp/statistics/tk/gaiyo/2021/tka2512.pdf)
- Keidanren [2022]. "Survey on expectations for recruitment and university reform." January 18. (https://www.keidanren.or.jp/policy/2022/004_kekka.pdf)
- Hamaguchi, K. [2013]. Youth and labor: Understanding the mechanisms of "entry into employment". Chuokoron-Shinsha.
- Hamaguchi, K. [2022]. "What is a job-based employment society?". Material 2 for the 10th General Meeting of the Government Tax Commission, Cabinet Office, May 17. (https://www.cao.go.jp/zei-cho/content/4zen10kai2.pdf)
- Murase, T., and Nishioka, S. [2026]. "If AI introduction ends with 'efficiency', growth will remain low: Demand-side policies for product innovation." Research Focus No. 2025 065, February 19. (https://www.jri.co.jp/report/researchfocus/detail/16468/)
- Morita, K. [2026]. "AI behind the U.S. 'jobless growth': employment declines already visible in white-collar sectors." Research Eye No. 2025 142, February 25. (https://www.jri.co.jp/report/research/detail/16475/)
- Japan Institute for Labour Policy and Training [2022]. "Research on difficulties and support for young people with atypical careers." JILPT Research Report No. 214, March 24. (https://www.jil.go.jp/institute/reports/2022/documents/0214.pdf)
- Japan Institute for Labour Policy and Training [2025a]. "Survey on the impact of AI introduction in workplaces on working styles (worker web survey)." JILPT Research Series No. 256, May.

(https://www.jil.go.jp/institute/research/2025/256.html)

- Japan Institute for Labour Policy and Training [2025b]. "Survey on the current situation and challenges of human resource development and skill formation (enterprise survey)." JILPT Research Series No. 257, November.
(https://www.jil.go.jp/institute/research/2025/documents/0257_01.pdf)