The Employment Transmission Gap: AI-Led Growth and the Weakening of Career Entry

A framework for distinguishing productivity growth from the reproduction of career ladders

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Abstract

Artificial intelligence may allow firms to expand output without expanding entry-level employment at the same rate. This possibility is usually discussed as a question of job displacement, but that framing misses a second mechanism: the weakening of the institutional pathway through which inexperienced workers acquire their first real responsibilities, accumulate judgment, and become experienced workers. This paper develops the Employment Transmission Gap framework by formalizing an argument introduced in Kao (2026): national and firm-level success can continue even as the connection between growth and career entry becomes less reliable.

The framework distinguishes productive growth from career-entry capacity. An Employment Transmission Gap arises when productive capacity, revenue, or value added grows while quality-adjusted opportunities for inexperienced workers grow materially more slowly, stagnate, or contract. Four mechanisms can generate the gap: incumbent productivity absorption, seniority-biased task reallocation, experienced-hire substitution, and the erosion of low-risk learning tasks. Korea is a useful motivating case because recent Bank of Korea evidence shows that youth employment weakness has been concentrated in AI-exposed industries while experienced-hire preferences and labor-market dualism predate the current AI wave. Comparable U.S. evidence points in a similar direction, although other recent studies show that the magnitude and persistence of entry-level effects remain unsettled.

The contribution is diagnostic rather than predictive. The paper does not claim that AI necessarily reduces aggregate employment or that entry-level tasks should be preserved unchanged. Instead, it proposes that the quality and quantity of career-entry opportunities should be measured separately from output and productivity. The relevant question is not

only whether AI creates or destroys jobs, but whether an economy continues to produce the experience pathways required to create its next generation of skilled workers.

Keywords: artificial intelligence; youth employment; career entry; career ladders; human capital; technological change; Korea; entry-level work

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1. Introduction

The standard economic question about artificial intelligence and work is whether the technology complements workers, substitutes for them, or creates new tasks elsewhere in the economy. That question remains fundamental. Yet it can obscure a narrower problem that matters before aggregate employment outcomes are known: firms can become more productive without increasing the number of opportunities through which inexperienced workers enter productive organizations. When that happens, economic growth and career formation begin to separate.

This separation is especially important because an entry-level job is not merely a low-seniority bundle of tasks. In many occupations it is also an institution for producing experience. Junior workers prepare first versions, handle routine cases, observe senior judgment, make bounded mistakes, receive correction, and gradually assume responsibility. Some of these tasks are precisely the kinds of codifiable cognitive work that current generative AI systems can perform or accelerate. A firm that can reallocate such tasks to AI-assisted senior workers may have a privately rational reason to hire fewer juniors even when its output is rising.

Kao (2026) develops this argument in the context of South Korea, where large firms historically served not only as employers but also as important entry points into high-productivity careers. The book argues that AI can loosen the link between corporate growth and new hiring, particularly in a labor market where first jobs, firm type, and employment status have persistent effects on later mobility. This paper generalizes that observation into a portable analytical object: the Employment Transmission Gap.

The framework is deliberately narrower than a theory of technological unemployment. An economy can exhibit an Employment Transmission Gap while total employment remains stable, because the adjustment may occur through slower junior hiring, higher experience requirements, internal reallocation, or the creation of new jobs that differ in training quality. Conversely, AI can also raise the productivity of less-experienced workers and support new entry pathways. The empirical question is therefore not whether one deterministic outcome follows from AI adoption, but whether the institutions that reproduce experience continue to scale with production.

2. Literature and positioning

Task-based models of technological change distinguish between displacement effects, productivity effects, and the creation of new tasks. Acemoglu and Autor (2011) and Acemoglu and Restrepo (2018, 2019) show why labor-saving technology can reduce demand for some tasks while productivity growth and new task creation generate offsetting employment effects. Recent AI-specific evidence similarly points to heterogeneous outcomes. Hampole et al. (2025) find that greater task exposure to AI can reduce labor demand while within-occupation reallocation can offset some losses. The central implication for this paper is that firm output and labor demand need not move one-for-one.

A newer empirical literature focuses directly on seniority and entry-level work. Brynjolfsson, Chandar, and Chen (2025) report a relative employment decline among U.S. workers aged 22-25 in highly AI-exposed occupations after the diffusion of generative AI, with substantially different patterns for experienced workers. Hosseini Maasoum and Lichtinger (2025) likewise find that junior employment falls in adopting firms and that the adjustment is driven largely by slower hiring. These results are consistent with a seniority-biased mechanism, but they do not settle the aggregate question. Fairlie and Wu (2026), using U.S. Current Population Survey data, find no statistically significant summer-2026 spike in unemployment among recent college graduates. The evidence is therefore better read as an emerging pattern requiring careful measurement than as a completed verdict.

The human-capital literature provides the second foundation. Firms can have incentives to train workers even when some skills are portable, but training decisions depend on labor-market institutions, information, mobility, and the ability to appropriate returns (Acemoglu and Pischke, 1998). More recent evidence emphasizes that workplace learning changes over the lifecycle and that early-career workers rely particularly on internal learning from coworkers (Ma, Nakab, and Vidart, 2026). This matters because automating a junior task changes not only the cost of producing the task output; it may also change the learning environment that task previously supported.

Korea adds a third layer. The Bank of Korea (2025a) documents a structural shift toward experienced hires: the monthly probability that an inexperienced worker secures a regular position is estimated at 1.4%, compared with 2.7% for an experienced worker. OECD work describes Korea's labor market as strongly segmented between large and small firms and between regular and non-regular employment, with corresponding differences in pay, stability, social protection, and training (Jones and Beom, 2022; OECD, 2024). AI therefore enters a system in which career entry was already becoming more selective before generative AI diffused widely.

3. The Employment Transmission Gap framework

> **Definition 1 - Career-entry capacity.** Career-entry capacity is the quantity and quality of positions through which workers with limited prior experience can enter

> real production, receive task-relevant feedback, accumulate responsibility, and build skills that are portable to later work. It is quality-adjusted: a short-term vacancy with little training or mobility is not equivalent to a role that systematically produces experience.
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> **Definition 2 - Employment Transmission Gap.** An Employment Transmission Gap exists when an organization, sector, or economy experiences growth in productive capacity, output, revenue, or value added while career-entry capacity grows materially more slowly, stagnates, or contracts. The concept describes a divergence, not a causal attribution to AI and not a claim that total employment must fall.
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> **Definition 3 - Experience-formation channel.** An experience-formation channel is a recurring set of work arrangements through which inexperienced workers convert knowledge into judgment under real constraints, including deadlines, clients, quality standards, organizational accountability, and feedback from more experienced workers.

The framework separates two objects that are often combined. Productive growth asks whether a firm or economy can produce more value. Career-entry capacity asks whether the same system continues to create places in which inexperienced workers can become experienced. Historically the two often moved together because expansion required additional teams, supervisors, analysts, engineers, and operators. AI can weaken that mechanical link by allowing existing teams to absorb more work.

Mechanism	Private firm logic	Potential effect on career entry
Incumbent productivity absorption	AI raises the amount of routine work an existing team can process.	Growth is absorbed before new junior headcount is added.
Seniority-biased task reallocation	Codifiable junior tasks move toward AI-assisted senior workers.	Junior task bundles shrink even if senior roles remain valuable.
Experienced-hire substitution	Firms prefer workers who can become productive with less internal training.	Organizations compete for already-formed experience rather than producing it.
Learning-task erosion	Routine assignments are automated rather than redesigned as supervised learning.	Workers lose low-risk settings in which judgment used to develop.

3.1 Incumbent productivity absorption

The simplest mechanism is a headcount response at the margin. A firm does not need to dismiss current workers for junior demand to weaken. When a team loses a member, it may leave the vacancy unfilled; when demand grows, it may first ask the existing team to use AI to absorb additional work. From outside the firm, employment can therefore adjust through missing hires rather than visible layoffs. This distinction is empirically important because vacancy composition, replacement rates, and experience requirements may reveal changes before aggregate employment data do.

3.2 Seniority-biased task reallocation

Generative AI is unusually relevant to seniority because junior and senior workers often perform different task mixes within the same occupation. Junior work tends to contain more search, drafting, coding, documentation, first-pass analysis, and standardized communication. Senior work contains more exception handling, client context, tacit knowledge, prioritization, and accountability. AI that automates part of the junior bundle can therefore raise the relative productivity of experienced workers without making the occupation itself obsolete. Bank of Korea research characterizes recent Korean evidence in terms of seniority-biased technological change (Bank of Korea, 2025b, 2026).

3.3 Experienced-hire substitution and a training externality

The move toward experienced hiring predates the current AI wave in Korea. AI can nevertheless amplify the underlying incentive. If an experienced worker plus AI can handle tasks that previously justified a junior role, the firm saves both production cost and training cost. Yet the economy still needs some organization to create experienced workers. This creates a potential collective-action problem: every firm can prefer to hire people trained elsewhere, while the supply of trained people depends on some firms continuing to bear the cost and risk of first-stage development. The framework does not assume that this externality is always large, but it makes the question visible. This is better treated as a training externality than as a literal prisoner's dilemma: the strength of the problem depends on worker mobility, wage setting, poaching risk, and firms' ability to capture returns to training. Recent U.S. evidence is consistent with this interpretation: firm training grants are more common where employers face greater poaching risk, and funded firms subsequently expand employment and post jobs requiring fewer prior skills (Dillon et al., 2026).

3.4 Learning-task erosion is not inevitable

Automating entry-level tasks does not necessarily reduce learning. AI can also explain concepts, accelerate feedback, lower the cost of experimentation, and allow juniors to engage earlier with higher-value work. Bank of Korea (2025c) finds that reported time savings from generative AI are larger for less-experienced workers, a result consistent with skill equalization. The difference between compression and acceleration therefore depends on organizational design. If routine work disappears and nothing replaces its learning function, the ladder weakens. If firms deliberately redesign junior work around verification, interpretation, client context, and supervised responsibility, the same technology may accelerate the transition from novice to expert.

4. Korea as a motivating case

Korea is analytically useful because several mechanisms are visible at the same time. First, the preference for experienced hires is measurable and predates generative AI. Second, labor-market dualism makes the quality of the first job consequential: moving from a lower-quality segment into large-firm or regular employment is not frictionless. Third, recent youth employment weakness is concentrated in sectors with high AI exposure.

Bank of Korea (2025b) reports that over the three years studied, youth employment fell by 211,000 and that 208,000 of the decline occurred in industries with high AI exposure, while employment among workers in their 50s increased. The 2026 follow-up extends the window through June 2026: youth employment fell by 285,000, with 268,000, or 94%, of the decline concentrated in high-exposure industries. The same report emphasizes that these patterns do not establish that AI caused the weakness. Post-pandemic adjustment, experienced-hire preferences, weaker in-house training, remote work, and other sectoral shocks may also contribute (Bank of Korea, 2026).

This caution is central to the framework. The Employment Transmission Gap is compatible with multiple causes. AI may be one accelerator among several. The empirical task is to identify whether growth and career entry are diverging, then to estimate which mechanisms account for the divergence. A firm can show rising sales and productivity, stable senior employment, fewer junior hires, and higher experience requirements without any single observation proving technological displacement.

Observable	What it helps distinguish
Output or revenue growth versus entry-level headcount	Whether productive expansion is transmitted into junior hiring.
Vacancies by required experience	Whether hiring thresholds rise even when vacancy totals remain stable.
Junior versus senior employment within the same occupation	Whether adjustment is seniority-biased rather than occupation-wide.
Task allocation before and after AI adoption	Whether junior tasks disappear, migrate to seniors, or are redesigned.
Training, mentoring, and internal promotion rates	Whether experience formation is being replaced by new pathways or simply reduced.

5. Implications for firms and labor-market institutions

The framework implies that preserving every existing entry-level task is neither necessary nor desirable. If AI can perform a routine task at lower cost or with fewer errors, requiring firms to keep the old process would sacrifice productivity. The relevant design problem is to preserve the function of experience formation, not the historical form of the task.

For firms, this can mean separating production value from learning value. A task with low production value may still be useful if it exposes a junior worker to data, clients, exceptions, or feedback that builds future judgment. Once AI handles the production component, the firm may need a different training architecture: shorter supervised cycles, deliberate review responsibilities, rotations across exceptions, AI-assisted apprenticeship, or roles in which juniors validate and contextualize model output. The appropriate design will vary by occupation.

Illustrative junior-task re-architecture

Traditional junior task	AI-enabled production change	Learning function to preserve	Illustrative redesigned junior responsibility
First-pass drafting	AI produces initial draft	Source evaluation; argument structure; revision judgment	Verify evidence; flag unsupported claims; revise for context and accountability
Routine coding	AI generates standard code/tests	Debugging; system understanding; failure diagnosis	Review code; design edge cases; trace failures; document trade-offs
Routine data collection	AI gathers/structures information	Provenance; quality judgment; domain interpretation	Audit sources; reconcile anomalies; test definitions; explain exceptions
Standard client/internal analysis	AI prepares baseline answer	Context; prioritization; communication; responsibility	Challenge assumptions; adapt to constraints; escalate exceptions; explain conclusions

The examples are illustrative rather than a claim that these designs are optimal across occupations. The relevant test is whether a redesigned role preserves exposure to feedback, exceptions, responsibility, and progressively harder judgment rather than merely retaining legacy tasks.

For labor-market institutions, measurement should extend beyond unemployment and total vacancies. A stable unemployment rate can coexist with weaker entry pathways if graduates queue longer, accept lower-quality starting roles, or cycle through positions that provide little cumulative experience. Conversely, falling junior headcount need not imply social loss if AI-enabled training allows fewer entry positions to produce skills faster and if alternative high-quality pathways expand. The object to measure is career-entry capacity, not simply job count.

Korea's existing dualism makes this distinction particularly important. Policies that create temporary positions without training or mobility may raise employment without repairing the career ladder. The Bank of Korea's 2026 recommendation to focus on work-based apprenticeships, firm training, and mentoring is therefore consistent with the framework's emphasis on experience formation rather than preserving old tasks for their own sake.

6. Limitations and research agenda

The framework has four limitations. First, the empirical evidence is early and often correlational. AI exposure is not the same as AI adoption, and AI adoption is not randomly assigned across firms or occupations. Second, Korea's labor-market segmentation may amplify effects that are smaller in more fluid labor markets. Third, career-entry quality is harder to measure than employment because training, responsibility, and mobility are multidimensional. Fourth, new firms and occupations may create replacement pathways that are not yet visible in current data.

These limitations point to a concrete research agenda. Firm-level studies should link AI adoption to hiring by experience level, internal training expenditure, task assignment, and promotion. Worker-level studies should follow cohorts to determine whether AI-exposed entrants accumulate experience more slowly or simply through different tasks. Cross-country work can test whether the same technology produces different outcomes in labor markets with different training institutions, employment protection, and mobility. Most importantly, researchers should distinguish the disappearance of a task from the disappearance of a pathway into expertise.

A tractable empirical design would combine event time, AI exposure, and seniority in a triple-difference specification: compare changes before and after the diffusion of generative AI across high- versus low-exposure industries and junior versus experienced workers. Such a design would be informative only with credible pre-trends and should not treat the November 2022 release of ChatGPT as random assignment. Where possible, researchers should replace exposure with firm-level adoption or usage measures, exploit staggered adoption, and test whether results operate through hiring, exits, task reallocation, or training. The Bank of Korea evidence itself cautions that exposure patterns are not causal estimates, making this distinction essential (Bank of Korea, 2026).

7. Conclusion

AI may change labor markets before it changes aggregate employment. One of the earliest adjustments can occur at the point where firms decide whether to add another inexperienced worker or let an existing AI-assisted team absorb more work. That margin matters because economies do not receive experienced workers exogenously; they produce them through careers.

The Employment Transmission Gap names the divergence that appears when productive growth continues while career-entry capacity fails to keep pace. It does not imply that AI inevitably harms young workers, nor that historical entry-level jobs should be frozen in place. It asks a narrower and more measurable question: as firms become more productive, are they still producing enough opportunities through which inexperienced people can acquire real experience and move upward? For AI-led growth to reproduce human capability as well as output, that question must be answered explicitly rather than assumed.

AI Use Disclosure

OpenAI's ChatGPT was used to assist with literature discovery, bibliographic verification, drafting, and language editing. The underlying concepts developed here originate in the author's prior published work (Kao, 2026). The author independently reviews the final manuscript and remains solely responsible for its arguments, source selection, citations, and conclusions.

References

Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In O. Ashenfelter & D. Card (Eds.), Handbook of Labor Economics, Vol. 4B, 1043-1171. Elsevier.

Acemoglu, D., & Pischke, J.-S. (1998). Why do firms train? Theory and evidence. Quarterly Journal of Economics, 113(1), 79-119. https://doi.org/10.1162/003355398555531

Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. American Economic Review, 108(6), 1488-1542. https://doi.org/10.1257/aer.20160696

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. Journal of Economic Perspectives, 33(2), 3-30. https://doi.org/10.1257/jep.33.2.3

Bank of Korea. (2025a). The Shift Toward Experienced Hires: Implications for Youth Employment. BOK Issue Note 2025-01.

Bank of Korea. (2025b). AI Diffusion and Youth Employment. BOK Issue Note 2025-30.

Bank of Korea. (2025c). Rapid Adoption of Artificial Intelligence and Its Productivity Effects: The Case of Korea. BOK Issue Note 2025-22.

Bank of Korea. (2026). Who Moved the Career Ladder? AI and Youth Employment in Korea. BOK Issue Note 2026-19.

Brynjolfsson, E., Chandar, B., & Chen, R. (2025). Canaries in the Coal Mine? Six Facts about the Recent Employment Effects of Artificial Intelligence. Stanford Institute for Economic Policy Research Working Paper.

Dillon, E. W., Kahn, L. B., Venator, J., & Dalton, M. (2026). Do Workforce Development Programs Bridge the Skills Gap? NBER Working Paper No. 34012 (revised April 2026). https://doi.org/10.3386/w34012

Fairlie, R. W., & Wu, J. (2026). The Early Impacts of AI on Employment among Recent College Graduates. IZA Discussion Paper No. 18945.

Hampole, M., Papanikolaou, D., Schmidt, L. D. W., & Seegmiller, B. (2025). Artificial Intelligence and the Labor Market. NBER Working Paper No. 33509. https://doi.org/10.3386/w33509

Hosseini Maasoum, S. M., & Lichtinger, G. (2025). Generative AI as Seniority-Biased Technological Change: Evidence from U.S. Résumé and Job Posting Data. SSRN. https://doi.org/10.2139/ssrn.5425555

Jones, R. S., & Beom, J. (2022). Policies to increase youth employment in Korea. OECD Economics Department Working Papers. https://doi.org/10.1787/fe10936d-en

Kao, J. [高晟軒]. (2026). 當韓國成為 AI 強國之後：半導體、財閥與工作，如何重新定義韓國的下一次成長 [When Korea Becomes an AI Powerhouse]. ISBN 978-626-01-7388-3.

Ma, X., Nakab, A., & Vidart, D. (2026). How do Workers Learn? Theory and Evidence on the Roots of Lifecycle Human Capital Accumulation. NBER Working Paper No. 35199. https://doi.org/10.3386/w35199

OECD. (2024). Strengthening Active Labour Market Policies in Korea. OECD Publishing. https://doi.org/10.1787/44cb97d7-en