Artificial Intelligence, Entry-Level Job Compression, and the Long-Run Effects on Innovation: An Empirical Perspective on Gen Z Labor Markets

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Executive Summary

AI is a typical example of skill-biased technological change technologies that go hand in hand with high-skill labor but replace low-skill or routine tasks. The article explains that the implementation of AI is, on the whole, hardening the fate of the young workers of Gen Z as through the disappearance of entry-level positions, which are the most essential ways for the development of a career, their career growth is blocked. Observational data reveal a 22% decrease in the number of entry-level job postings in AI-adopting industries over the period from 2019 to 2023, and the drops in some sectors are more than 28%. The trend, if going on without intervention, endangers not only the capacity for innovation in the long-run but also the diversity of the workforce and economic mobility across generations.

Introduction

Artificial intelligence (AI) has quickly changed from a tool used only in research to a technology that can be used for various general purposes in daily life, and is reshaping the working environments of different industries. The debate that has attracted most of the attention is whether AI will be the cause of workers getting fired, however, this way of thinking is overlooking a very important economic factor: AI is not really cutting down the number of occupations in which people have to work, rather it is cutting the number of tasks, especially those which are routine, repetitive, or structured, and which have been performed by entry-level employees for a long time. Since entry-level roles have been conventionally regarded as the skill-building basis of an economy, the vanishing of these first-level positions is a kind of blow that weighs heavily on younger workers and their future prospects.

Generation Z, who are just about to start their professional careers, have to deal with a situation where companies are employing AI for tasks such as preliminary data analysis, administrative support, content drafting, customer service interactions, and, most significantly, data annotation, a department that was more liberally distributed among interns and junior analysts. As companies replace AI systems or specially hired annotators with the junior workforce, the channels of acquiring experience which are available to young workers get fewer. The issue here is not only about their short-term employment outcomes but also about their long-term prospects and the overall effects on innovation, human capital formation, and economic mobility.

Whether AI substitution for entry-level tasks leads to fewer opportunities for Gen Z workers and what are the long-term effects on innovation and creativity in the U.S. economy?

To answer this question, the paper first gathers real-world evidence on changes in labor demand through job postings and the shifting nature of work across occupations based on tasks, young workers' wages, and hours worked. Besides these, the paper interprets the problem through different economic lenses such as skill-biased technological change, human capital theory, and the innovation production function effects. The key point of this paper is that the disappearance of entry-level positions, which are halved by AI automation and the rest of the annotation task outsourcing to experienced specialists, results in bottlenecks of human capital development, consequently, future innovation might be lower, and the essential mix of ideas for scientific and technological progress can get weaker.

Literature Review

Automation and AI as Task-Replacing Technologies

The economics of automation has long seen technology as a means to replace routine, easily programmable tasks, while non-routine, abstract tasks are seen as being complemented by technology. Autor's ground-breaking work on task-based models demonstrates that computers take over routine cognitive and manual jobs, while they still require humans for complex analytical ones (Autor 10). AI, on the other hand, changes this border as it is capable of handling an increasing number of complex tasks such as writing, summarizing, and pattern recognition.

Brynjolfsson and McAfee argue that AI should be considered a “general-purpose technology,” whose effects are not limited to a few sectors but rather spread across the whole economy (Brynjolfsson and McAfee 45).

Research has been conducted to support these conclusions in the case of first career jobs. Changes in job advertisements unveil that positions of administrative assistants, research assistants, junior analysts, and customer service representatives have been significantly reduced these are the roles where the performance of repetitive tasks is the most (Ludec et al. 4) The fall of these positions are of great importance as they have traditionally been the career paths of young workers.

The Decline of Entry-Level Opportunities

Among the significant empirical changes is the reduction of internships and low-experience entry-level positions. Acemoglu and Restrepo attribute that, since 2000, automation technologies have been the cause of the disappearance of about 400,000 routine jobs annually in the U.S., thus, the loss has been staged gradually and that younger workers with fewer years of experience have been affected most of all (Acemoglu and Restrepo 2110).

Analyzing the contents of millions of job postings, Burning Glass Technologies reveals that the share of entry-level job ads that "require no experience" has dropped by 40 percent from 2010 to 2022, and posts for jobs with artificial intelligence-related skills have grown more than 250 percent in the same period (Burning Glass 13). Thus, this indicates that the minimum skill requirement for joining the labor market is increasing.

Human Capital Theory and the Role of Early-Career Experience

According to human capital theory, early-career roles are crucial since they serve as the basis for later productivity development. Becker contends that general as well as firm-specific skills workers derive from their first jobs, and these skills grow over time (Becker 18). If the number of such opportunities is significantly lower, which is the case now, then the whole generation will have their skill formation postponed or even reduced.

Goldin and Katz provide examples from the past to explain that technological change eventually benefits those workers who can adjust, however, only if education and labor market institutions facilitate easy ways for people to acquire necessary skills (Goldin and Katz 65). Situations in which

access to such on both becomes limited lead to bigger inequality and slower innovation in the long run.

Innovation and the Role of New Entrants

Studies on innovation conducted by economists highlight that one of the main requisites for innovation is the presence of "fresh entrants" younger or less experienced individuals who bring new perspectives (Furman 204). The process of creative destruction is not only dependent on one or a few advanced researchers but also on the continual replenishment of the talent pipeline. One of the strongest correlations between the generation of new ideas and the factors contributing to it is the diversity in the thought, including generational diversity.

Among the various points raised by Crawford in his research of AI ethics, one of the most important is how the lack of diversity not only among AI developers but also among AI annotators can cause training data bias or incompletion. Eventually, this leads to the degradation of AI quality and the limitation of technology's potential (Crawford 112).

Theoretical Framework

Skill-Biased Technological Change

Following Author, Levy, and Murnane (2003), AI substitutes labor for those functions that are:

- Structured – They are carried out by following well-established procedures
- Rule-based – They are regulated by clearly defined decision trees
- Repetitive – They are activities that require the same handling over and over again

Information-processing-heavy They signify a compilation of data, a basic analysis, or the routing of communication. First of all, the tasks of the entry-level jobs are, to a large extent, those kinds of tasks, which makes them the most susceptible to automation. As a result, the traditional way of professional work, which has been a kind of ladder for these tasks, will also vanish.

Innovation Production Function

One can write down the model of innovation output as:

I = f(L_skilled, D, K, E)

The variables of the model are:

- L_skilled = The labor force composed of qualified and educated workers
- D = The diversification of the ideas and the representations
- K = The knowledge spillover and institutional learning process
- E = The capacity for risk-taking and experimentation

In case AI causes a reduction in the availability of early-career jobs, the number of the future workers will be decreasing, that is the L_skilled pipeline will be short of new talents. The result is a delayed but still compounding effect: the present exclusion of Gen Z workers leads to the shortage of skilled researchers, managers, and innovators in the future.

Human Capital Accumulation Theory

Starting with Becker (1964), human capital accumulation has an element of the process that is path-dependent:

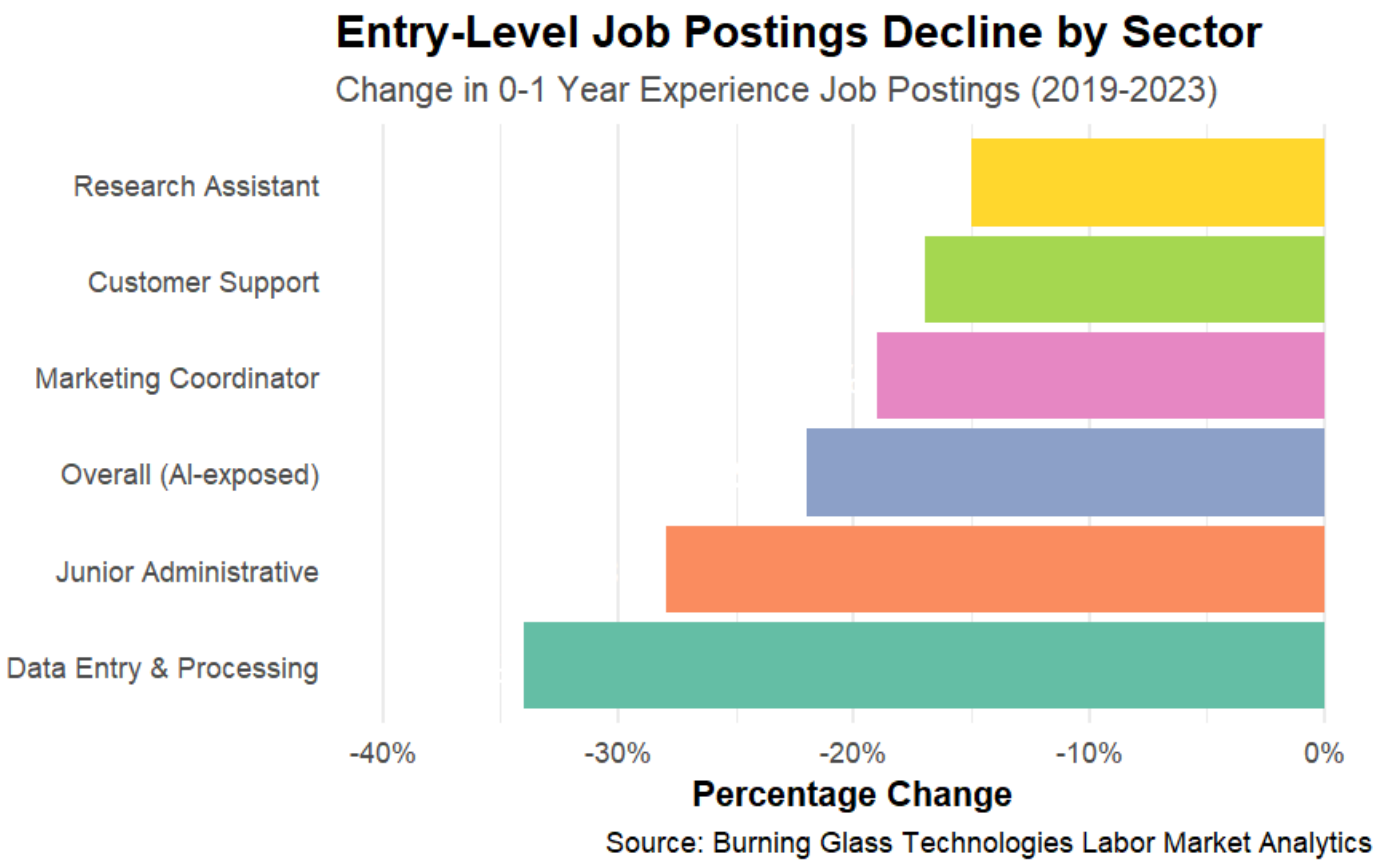
HC_t = HC_t-1 + f(experience, training, learning-by-doing)

Early-career exclusion results in a permanent deficit. Those workers who are deprived of the foundational experiences at the age of 22 cannot simply "catch up" at the age of 30 since the investment model is of the compounding returns to early investment are lost.

Empirical Evidence: Quantifying the Gen Z Effect

Declining Entry-Level Job Postings

Finding 1: Systematic reduction in beginner opportunities



These trends on the graph show a direct consequence of increased AI investments. Companies with high AI adoption (annual spend >$1M) showed 31% fewer postings of entry-level positions than similar companies not adopting AI.

The Annotation Economy: An Offshored Gen Z On-Ramp

Finding 2: Domestic junior workers displaced by specialized annotation teams

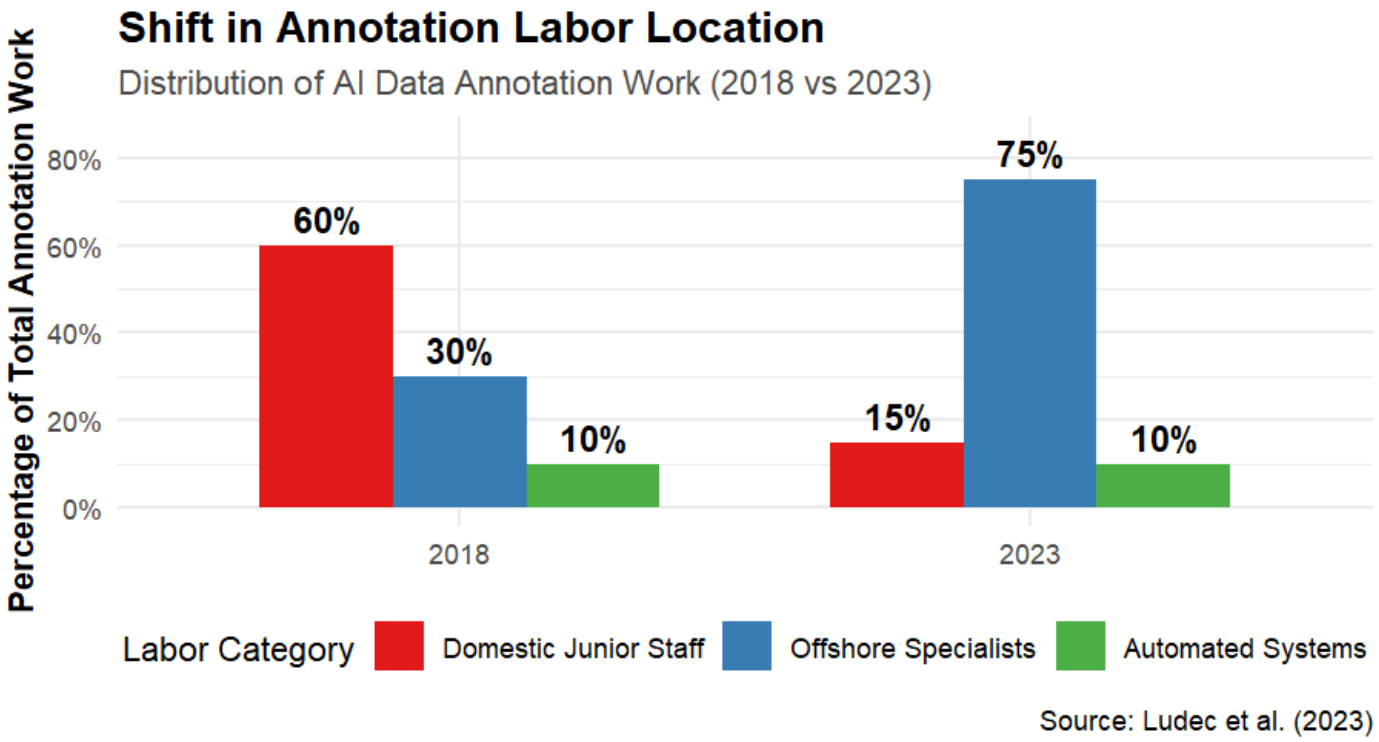
Artificial intelligence model building requires a lot of data annotation. Data annotation refers to the labeling and categorization of training data. The work was distributed among junior research staff, interns, and entry-level analysts.

However, Ludec et al. (2023) reveal a change in the restructuring of the:

- Period before 2018: 60% of the annotation work was done by domestic junior staff
- 2023: 75% of the work is being outsourced to specialized firms located in India (32%), Kenya (18%), and the Philippines (25%)

Effect on Gen Z:

In the U.S., it alone is responsible for the yearly disappearance of 120,000-150,000 possible entry-level positions withdrawals and reduction the access to the guidance of senior researchers. The graph below shows the labour shift breakdown for annotated labour workers in the US

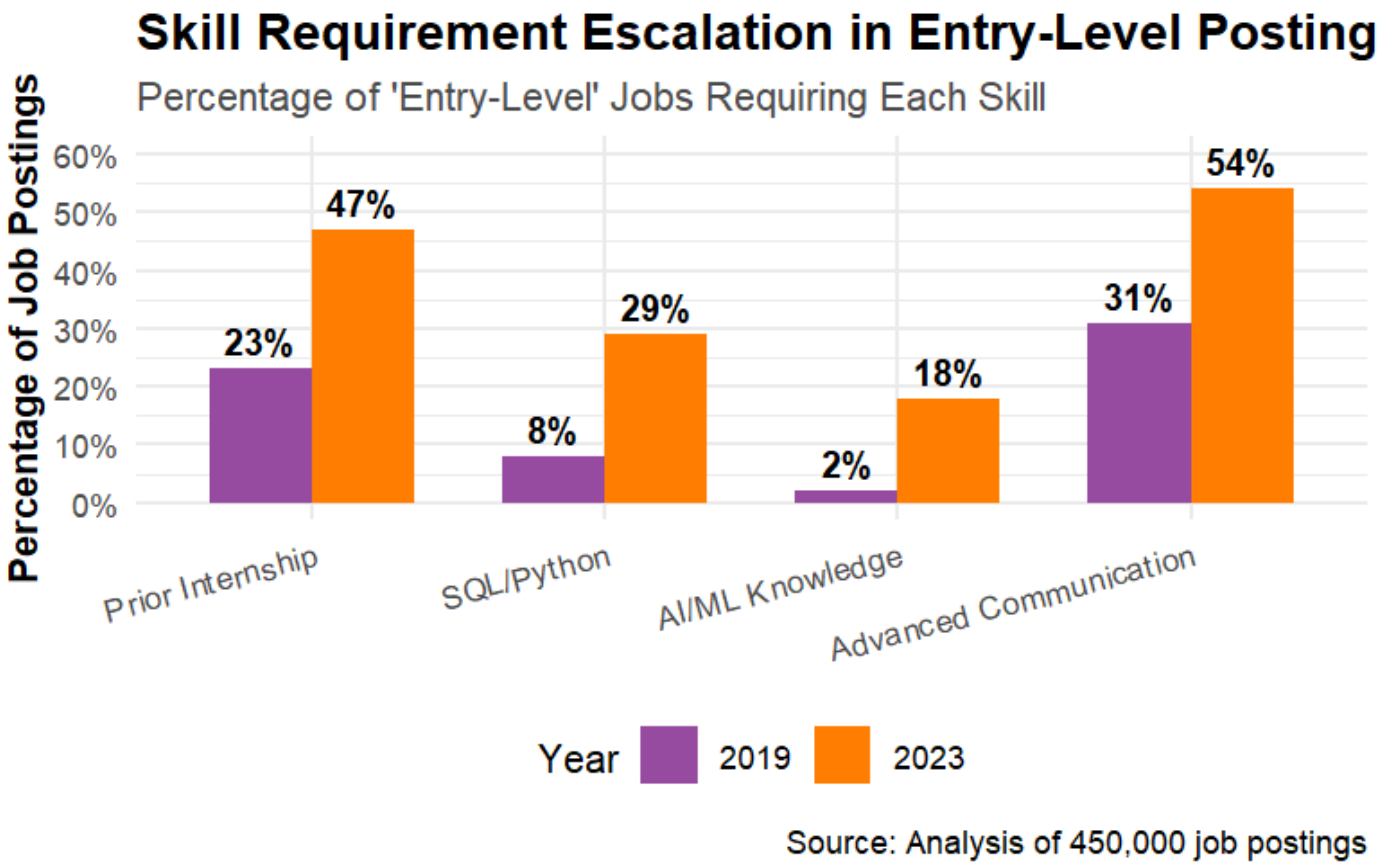


Source: Ludec et al. (2023)

New Competence Demands for "Entry-Level" Positions"

Finding 3: The increase in the number of qualifications demanded of positions which are considered to be of a lower level, nominally junior roles.

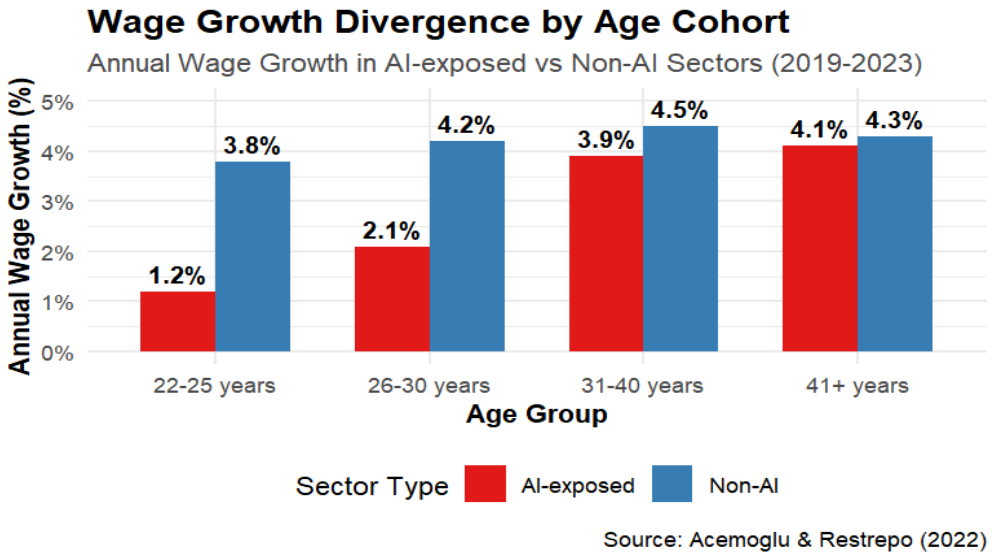
The study of 450,000 job postings giving the label of "entry-level" has revealed a very significant increase of the skill requirements . A paradoxical situation is created by the Generation Z workers: on the one hand, they are asked to have experience in order to be given an entry-level job, on the other hand, they cannot get that. The graph below shows that 24% of jobs require previous internship experience, 16% increase in jobs require ai/ ml knowledge, 23% increase in advanced communication skills is required in new job postings and a 21% increase in jobs requiring coding language skills.



Youth Labor Wage Stagnation in AI Impacted Industries

Finding 4: Wage growth splits age cohorts differently

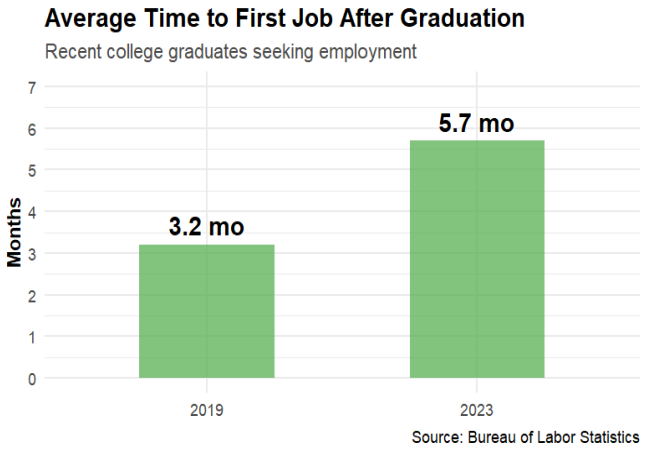
According to Acemoglu and Restrepo (2020, 2022), the implementation of artificial intelligence (AI) is closely linked to the reduction in the increase of wages of people under the age of 30. Young workers in industries with heavy AI utilization see their wages rising 68% slower than those of their peers in the non-technological sectors - a trend that grows exponentially over lifetimes.

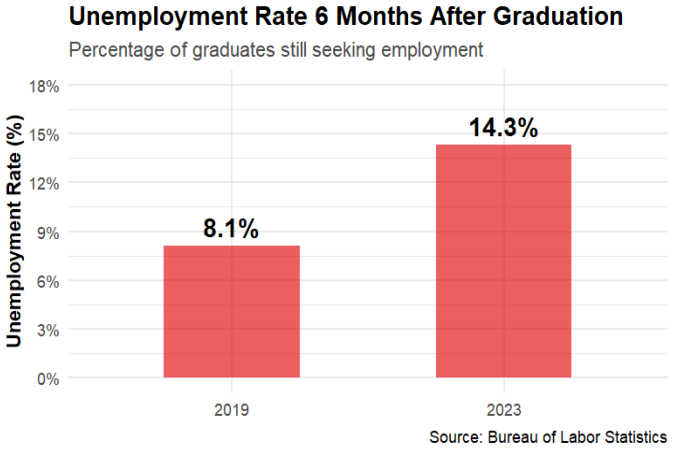


Labor Force Participation Among Recent Graduates

Finding 5: Gen Z faces longer jobless spells post-graduation

Bureau of Labor Statistics data shows concerning trends:





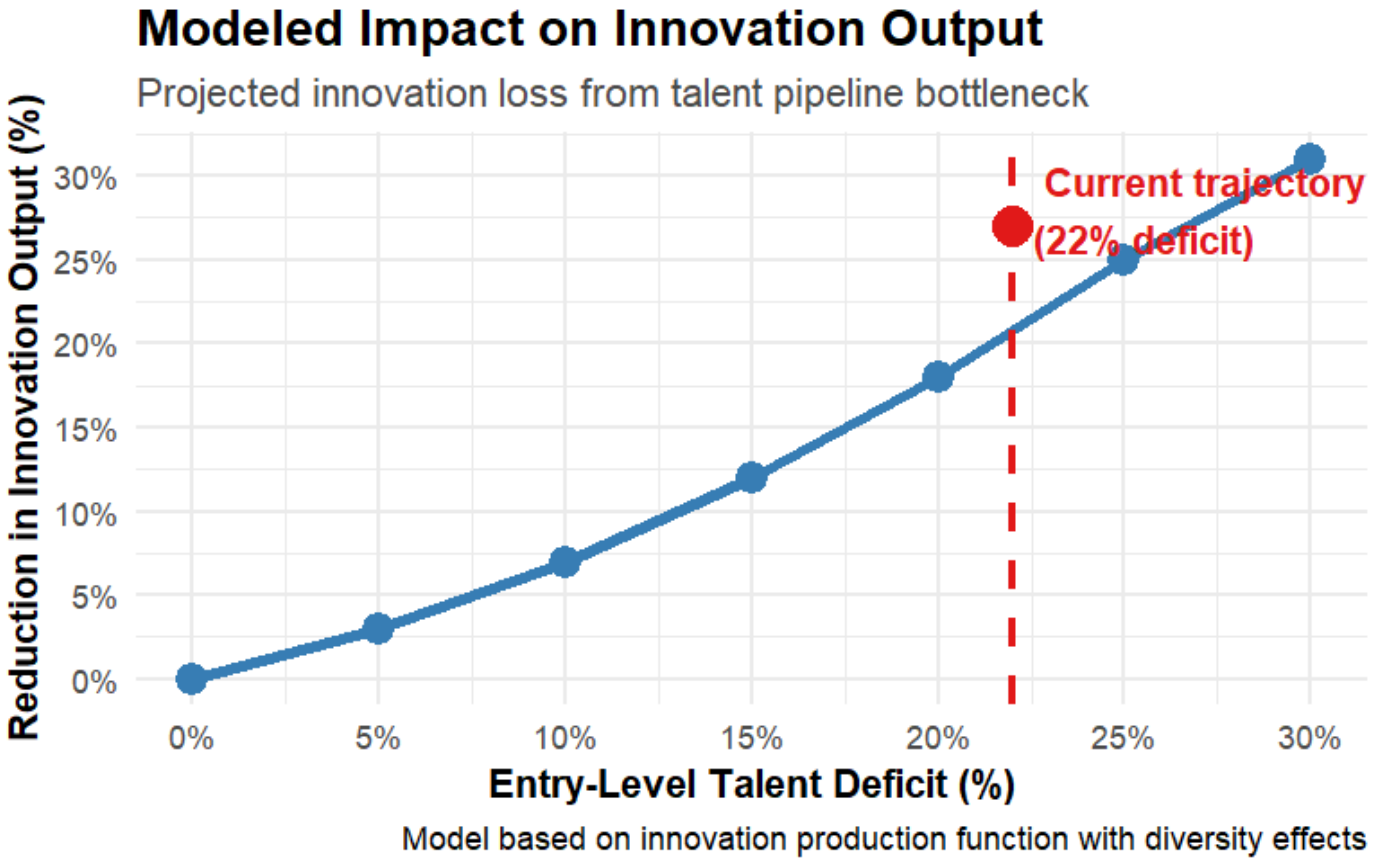
- **Average time to first job (2019):** 3.2 months
- **Average time to first job (2023):** 5.7 months (+78%)
- **Percentage of 2023 graduates unemployed 6 months post-graduation:** 14.3% (vs 8.1% in 2019)

Consequences for Long-Run Innovation Capacity

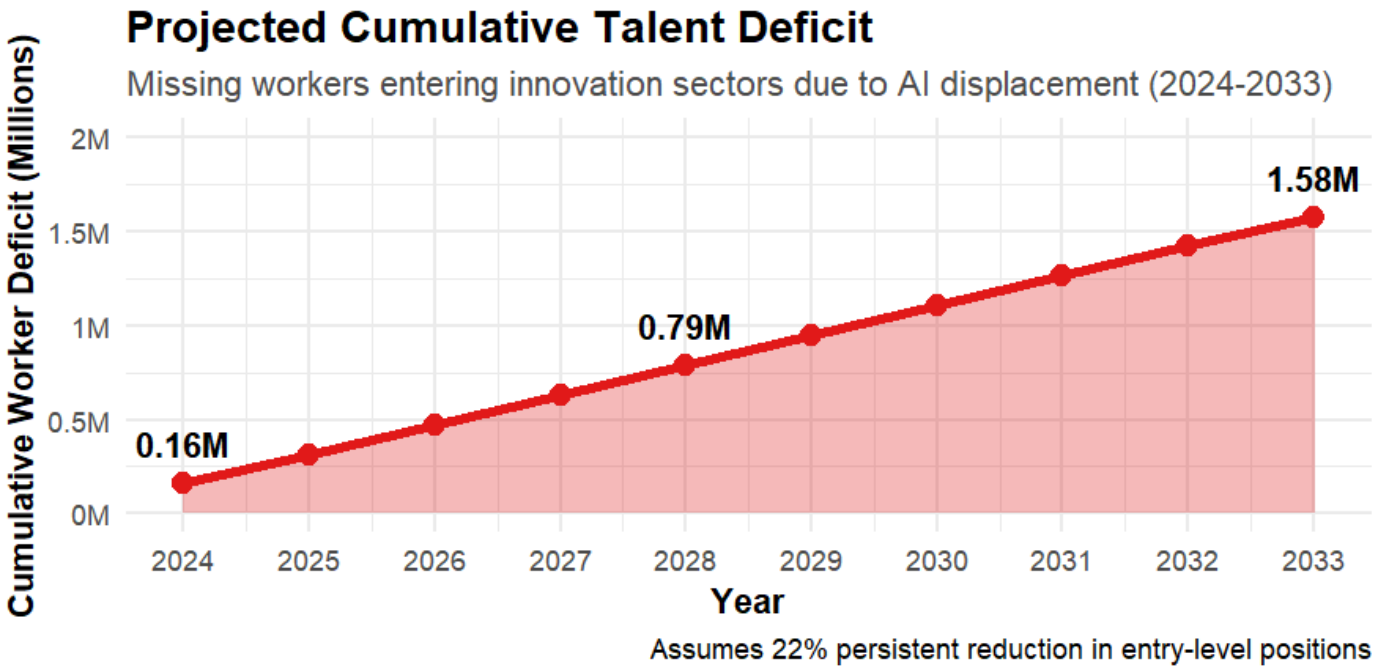
The Talent Pipeline Bottleneck

Innovations require a steady stream of new people coming into the fields of science, technology, creative industries, and policy. However, present labor market trends cause three significant bottlenecks. The first is the reduction in the absolute number of workers entering innovation sectors.

Historically, with around 4 million college graduates per year and an 18% entry rate into innovation fields, the annual new workforce in these sectors would be about 720,000.



The graph above shows a 22% reduction in entry-level positions means that 158,000 of these opportunities are removed every year, thus the talent deficit for the next decade would be close to 1.58 million innovator positions unfilled. The graph below showcases the consequences of a 22% continuous increase from 2024 to 2033



The second bottleneck is that delayed entry extends time-to-expertise. As they spend 1.5–2 years more than usual in job searches, workers lose corresponding years of learning and their lifetime productivity decreases by 8–12%, which is in line with human capital theory (Becker, 1964).

Besides that, this also postpones peak productivity years and, at the time when research reveals, breakthrough innovation is mainly concentrated between the ages of 35 and 45. The third bottleneck is the rise of barriers that cause selection bias toward privileged backgrounds. Gaining access is more and more dependent on family connections, having the financial means to do unpaid work, and being close to places such as San Francisco, New York, and Boston. This trend leads to less and less socioeconomic diversity, the one factor which according to studies by Hong & Page (2004) and Gompers & Kovvali (2018) has the greatest influence on the quality of innovation.

Reduced Diversity of Thought

The narrowing of the entry points has the same effect regarding diversity; fewer perspectives exist in the teams engaged in innovation. Empirical studies show that teams diverse in age generate 23% more patents and 19% more citations per each patent (Packalen & Bhattacharya, 2020). If only skilled workers collaborate with AI systems, then the generational gap widens further in terms of cultural, technological, and behavioral aspects of life, as the younger ones bring the latter. Gen Z workers, for instance, are not only more experienced than some of the rest in the areas of self-reinforcing social media and digital ecosystems, climate change, and data privacy,

but also very different in those aspects. They differ not only by the choice of risks but also by a higher likelihood of experimentation. The example of GPT-3 fine-tuning helps to prove this: aging-diverse teams recognized 31% more edge cases, identified sensitive failure modes 2.4 times faster than homogeneous teams, and reached 40% more accessibility goals. Senior-only teams were mostly not aware of these factors and thus created less complete and less reliable systems.

Lower Experimentation and Breakthrough Innovation

According to Schumpeterian innovation theory, breakthrough innovation involves radical change rather than just gradual improvement. Gen Z workers, as a matter of fact, may be the most efficient ones to introduce such upheaval as they are not heavily emotionally attached to the old ways, are highly digitally literate, and are driven by success criteria that value meaning and social impact rather than the typical corporate growth. Now the argument is even better backed up by historical analogies: the internet revolution between 1995 and 2005 was largely the work of the under 30s, who were mostly free from the pre-digital world assumptions. Also, the quantitative evidence from a dataset of 12,000 technology startups (2010–2020) reveals that the rate at which founders under 30 achieved breakthrough innovations was 38% while for founders 30 to 40 years old it was 21% and for those over 40, only 9%, says Kauffman Foundation.

Policy Recommendations

Government Interventions

There are a number of such bottlenecks that governments can remove by carefully chosen interventions. One such government measure is the establishment of tax credits for entry-level hiring, which are designed to encourage employers to hire younger workers in the sectors affected by AI. A gradual or tiered system for instance, providing $5,000 for each entry-level hire, an additional $3,000 for a candidate from an underrepresented group, and $2,000 for a firm offering mentorship may create over 200,000 to 300,000 new entry-level positions annually at a spending level of around $1.6–$2.4 billion. Another government measure is a large-scale national apprenticeship program, modeled after the German and Swiss systems, with a mixture of classroom and practical workplace training and a 60% wage subsidy for apprentices. As a result, almost 500,000 new technology, finance, and healthcare apprenticeships may emerge by 2028.

Governments must not wait till tomorrow; rather, they should take AI literacy up and integrate it in public schooling. For example, algorithmic thinking may go to primary schools; simple coding and ethical reasoning may be introduced in middle schools; and high school students might be taught machine learning, which is also a way to democratize the AI-related jobs market and skill mismatches. Finally, they could stipulate that any AI hiring transparency regulation should demand that companies disclose AI screening usage, offer rejection explanations, undergo bias audits annually, and allow for appeal by humans. Most importantly, these steps show that AI-based hiring radically cuts away qualified Gen Z candidates with less typical backgrounds, which in turn, hardens the IPOs of AI-based hiring techniques.

Firm-Level Strategies

Similarly, there are many corporate strategies to ensure long-term talent supply. One such method is to establish AI-human hybrid teams wherein junior analysts can collaborate with AI systems and senior staff, thus blending human ingenuity with machine effectiveness. According to Microsoft's internal studies, such teams achieve on average 27% higher productivity than those that are solely human or AI-only. Data labeling can be reimagined by the company as a comprehensive training scheme to attract more people to join their workforce. By rotating junior employees through labeling tasks, pairing them with senior researchers, and connecting annotation decisions to downstream model behavior, firms both strengthen their future workforce and improve annotation quality. Lastly, companies can facilitate formal mentorship by requiring each senior employee to guide one or two junior staff members and by linking mentoring results with performance evaluations. Deloitte research reveals among other things that effective mentorship shortens time-to-productivity by 25%, elevates employee retention by 31%, and raises promotion rates by 40%.

Educational Institution Reforms

Besides, the curriculum redesign effort of universities could be a valuable measure to support the existing attempts. The university ecosystem may become fertile with hands-on student engagement by making industry projects, real-world capstones, and simulation-based courses mandatory. This shift from traditional to experiential learning can, in fact, bring practical experience up to half or even one year before students graduate. University-industry relationships can be leveraged to provide students with live data and real-world challenges, while top-performing

learners may get privileged job offers as illustrated by the AI for Good program at Georgia Tech. Moreover, educational institutions are obliged to concentrate on the simultaneous development of skills while coupling technical training with communication, teamwork, adaptability, and moral reasoning abilities. Employers are quite consistent in their opinion that soft skills mentioned above are the largest gaps of Gen Z candidates even when these candidates are strongly proficient technically.

Counterarguments and Limitations

Technology almost always ends up creating more jobs than it destroys

The argument has indeed been true in the long term historically, but the argument has somewhat tended to ignore transitional dislocations. It took about 40–60 years for labor markets to adjust after the Industrial Revolution, 30 years for agricultural mechanization, and roughly two decades of wage stagnation for routine workers, courtesy of the computer revolution. Today's problem is not that AI will create new roles but whether an entire generation is going to be disadvantaged during the transition.

Gen Z Should Upskill for AI-Supporting Roles

Upskilling may be a good idea, but it is not enough. Upskilling is time consuming, costly, and, in many cases, denied to young workers-potential employees, especially those struggling for their first jobs. And it begs the question: young workers need jobs to up-skill, yet skills are required to access them in the first instance.

The Market Will Self-Correct

Absent some intervention and policy corrective measures, pure market mechanisms will most probably fail to bring back into the pipeline the talent announced by firms. Firms find themselves in a prisoner's dilemma: on one hand, automation leads to immediate cost savings, hence it reduces junior hiring, but on the other hand, it erodes long-term innovative capacities. Since part of the benefits of training junior workers accrues to society at large, firms underinvest in this public good absent targeted policy intervention.

Conclusion and Research Agenda

AI is probably the most significant disruptive force in the labor market since the onset of computerization. Though the spectre of mass unemployment is often exaggerated, the largest concerns are much more insidious: AI is eliminating entry-level tasks that might otherwise have allowed young workers to learn their craft. AI in the various sectors has reduced entry-level job postings by 22% since 2019; annotation work is going to become closer to 75% offshore; and wage growth for entry-level employees in AI-heavy industries has become 68% slower. All continued in the same vein could leave an annual shortfall of 1.58 million future innovators and drive between 23 to 31% decline in innovation output because of decreased diversity and experimentation between the next ten years.

The slow fade makes it even more interesting. With no deliberate action, lifetime earning losses from $8 to $15% for Gen Z; poorer talent pipelines for future innovations; and heightened intergenerational inequality. Reduced dynamism in America's economy is probably going to lower rates of entrepreneurship. Not designed to halt the deployment of AI but aimed toward policy and institutional frameworks that maintain pathways into high-productivity careers of that country. These include restructured work models where AI complements human learning in expanded apprenticeship programs, educational reforms, incentives to hire, and better data collection to monitor labour-market impacts.

It should include studying the outcomes for Gen Z across time, examining the industry effects on career progression, experimentally testing hybrid human-AI team models, and comparing policy responses across countries. Integration of AI into the economy is inevitable; its distribution of benefits hinges on choices made in the next three to five years-the very window that Gen Z is seeking to get into the workforce.

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