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DATA DISPATCH

AI AND THE FUTURE OF WORK:

ARE ENTRY-LEVEL JOBS DISAPPEARING?

No mass layoffs. Just a quieter shift — fewer young people getting in.



REAL PEOPLE.
REAL JOBS.
BIGGER QUESTIONS.

THE EVIDENCE

No unemployment shock, but a narrower door for youth.

THE BIGGER PICTURE

What this means for emerging economies like India.

WHAT'S NEXT

Implications for policy, talent and the future of work.

About this report

This Stat and State Data Dispatch reads the newest evidence on artificial intelligence and jobs for students, employers, policymakers and general readers. It rests on two primary studies, a new measure of AI use at work [1] and the first test of the graduating class of 2026 [2], set against global and Indian data from the ILO, IMF, WEF, NITI Aayog and IHD.

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numerals point to footnotes at the bottom of the page that explain technical terms.

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AI and the Future of Work: Are Entry-Level Jobs Disappearing?

DATA DISPATCH | STAT AND STATE LEAD TEAM |

30 SEPTEMBER 2026

New evidence on how AI is actually used at work finds no unemployment shock among the most exposed workers, and none yet among the class of 2026. It finds something quieter instead: fewer young people getting in. What that means for emerging economies like India, for policy, and for anyone whose sense of self is bound up with a job.

At a glance: the numbers that matter

Table 1 **The report in eight numbers**

Number	What it tells us	Source
+0.2 pp[1]	Change in the unemployment gap between the most and least AI exposed US workers since late 2022; statistically zero	[1]
14%	Fall in the rate at which 22 to 25 year olds start jobs in the most exposed occupations, against 2022	[1]
7.3%	Summer 2026 unemployment of US graduates aged 22 to 25, inside the 6.3% to 7.8% range seen since 2022	[2]
10.4%	The same rate counting graduates who want a job but have stopped searching; the highest of five summers, by 0.3 pp	[2]
33% of 94%	Share of computer and maths tasks where AI is actually used, against the share it could do	[1]
2.5% to 7.0%	Share of AI using US firms replacing a large number of employee tasks, early 2024 to early 2026	[3]
1 in 4	Workers worldwide in an occupation with some generative AI exposure	[4]
7.5 to 8 million to 6 million	Indian tech services workforce, 2023 to 2031, if nothing changes	[5]

PROLOGUE

The question beneath the payslip

If a machine could do the work that names you, what would be left of the name?

Ask a stranger who they are and, within two sentences, most will tell you what they do. We are, it seems, what we are paid for. The Austrian social psychologist Marie Jahoda understood this better than most. In the early 1930s she studied Marienthal, a village near Vienna whose textile mill had shut, and watched men with nowhere to be lose their grip on the hours. Decades later she named what a job quietly supplies beyond a wage: a shape to the day, company outside the family, a

[1]**pp (percentage points).** The plain difference between two percentages. A rise from 7.3% to 7.8% is 0.5 pp, not 0.5%.

share in some larger purpose, a place in the social order, and the plain discipline of regular activity [6]. Take the job away and all five go at once.

That is why the argument about artificial intelligence and work never stays economic for long. Sooner or later it arrives at a particular desk. A 23 year old in Pune, one of the fastest growing technology hubs in India, rewriting her CV for the fortieth analyst opening. A support executive in Gurugram who has noticed that the easy tickets no longer reach him. An accountant in Kolkata, twelve years into her career, wondering whether the skill she built is about to become cheap.

The public mood swings between alarm and dismissal. Bill Gates has written that he is "especially worried about young people, who will enter a workforce with fewer entry-level openings"; Jensen Huang of NVIDIA calls talk of AI reducing jobs "complete nonsense" [7], [8]. Where evidence is thin, anxiety rushes in. **So the more useful question is not whether AI will take our jobs, but something narrower and more honest: what, today, can we actually measure about who is being touched, and how?**

Two studies published in 2026 offer the most careful answers yet. In March the economists Maxim Massenkoff and Peter McCrory built a new measure of which jobs AI is actually being used in [1]. In September, Robert Fairlie and Jane Wu of UCLA tested whether the class of 2026, the first to graduate into widespread workplace AI, struggled to find work [2]. Their headlines are calmer than most headlines: no systematic rise in unemployment. Their fine print is sharper. The door into exposed jobs appears to be narrowing, and it is narrowing for the young.

SECTION 1

A century of false alarms, and a better instrument

In the autumn of 1930, with the world sliding into depression, John Maynard Keynes warned of a "new disease": ***technological unemployment***, which he described as *"our discovery of means of economising the use of labour outrunning the pace at which we can find new uses for labour"* [9]. The diagnosis has been repeated in every decade since. It has rarely been confirmed.

Forecasters have earned their humility. A widely cited study once judged roughly a quarter of US jobs to be offshorable; ten years on, most of those occupations were still adding workers [10], [11]. Official US occupational projections, though pointed in the right direction, have added little beyond extending past trends [12]. Even in hindsight, economists still argue over how many jobs industrial robots or Chinese import competition actually destroyed.

From "could" to "does"

Part of the trouble lies in what we measure. Most AI exposure scores ask what a model *could* do. Massenkoff and McCrory [1] ask what it *is being used to do* at work, and call the result **observed exposure**[2].

[2]Observed exposure. The share of the tasks in an occupation that AI is both able to do and actually used for at work, weighted by the time each task takes, with automated use counted in full and assisted use counted at half [1].

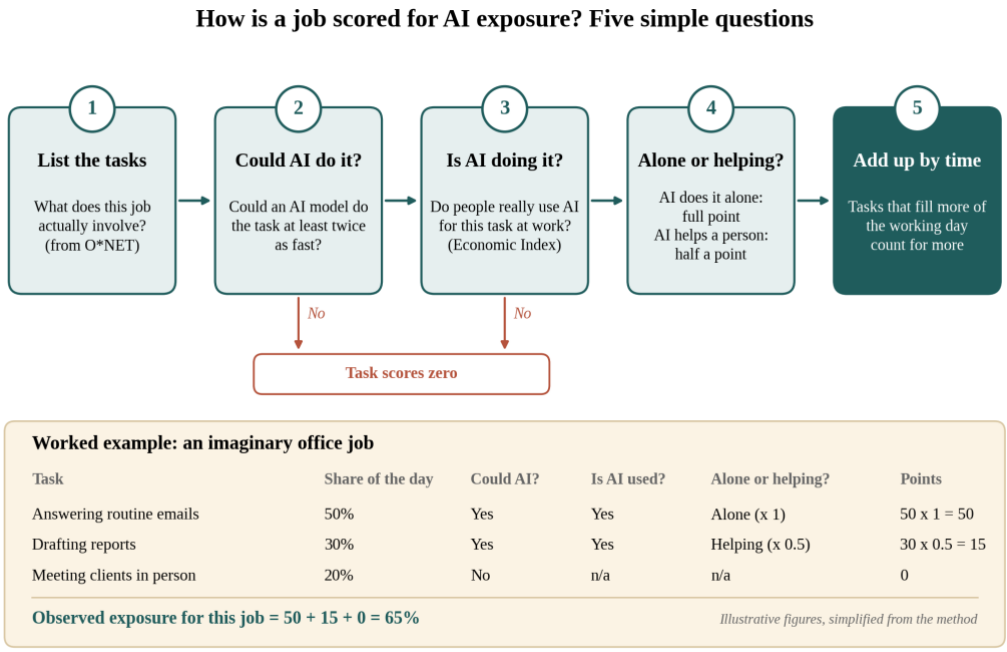


Figure 1 *How observed exposure is built, in five questions, with an illustrative worked example. Adapted from [1].*

A task counts only if a language model could at least double its speed [13] and if it actually turns up in work related conversations recorded in the Anthropic Economic Index. Fully automated use counts in full; augmentative use, with a person still in the loop, counts half. Task scores are then averaged into each occupation according to how much working time each task takes.

Possibility and practice turn out to be close cousins. Tasks rated fully feasible account for 68% of observed usage, partly feasible tasks for 29%, and infeasible ones for only 3% [1].

SECTION 2

The distance between can and does

The most revealing number in the study is a gap. On paper, language models could speed up 94% of tasks in computer and mathematical occupations and 90% in office and administrative ones. In practice, observed use covers just 33% of computer and mathematical tasks [1]. The remainder is capability in waiting, held back by regulation, missing software, verification rules and, not least, trust.

Where the exposure sits

Table 2 **Most exposed occupations (selected rows)**

Occupation	Observed exposure	Leading automated task
Computer programmers	74.5%	Writing and maintaining software
Customer service representatives	70.1%	Handling customer queries and orders
Data entry keyers	67.1%	Reading documents and entering data
Medical record specialists	66.7%	Compiling and coding patient data
Market research analysts	64.8%	Preparing and writing up findings
Financial and investment analysts	57.2%	Analysing financial information

Source: [1], Figure 3.

At the other end, almost 30% of US workers register no observed coverage at all. They are mainly cooks, motorcycle mechanics, lifeguards, bartenders and dishwashers: people whose work is done with hands, in rooms, in real time.

The gap is starting to close

Fairlie and Wu [2] argue that what matters now is not a new leap in capability but the narrowing of this very gap, and 2026 is when it began to narrow in earnest. A US Census Bureau survey of more than 117,000 firms, fielded from November 2025 to February 2026, found that among firms using AI in place of employee tasks, the share replacing a *large number* of tasks rose from 2.5% to 7.0% since early 2024 [3]. In the Ramp AI Index, a panel of about 70,000 US firms that leans towards venture backed companies, median monthly AI spending per employee more than doubled between December 2025 and July 2026, and metered API use, the kind built into production workflows, passed half of all business AI spending [14].

A faint but telling signal

The US Bureau of Labor Statistics projects employment for every occupation from 2024 to 2034 [15]. Occupations with higher observed exposure are expected to grow a little more slowly: each 10 percentage point rise in coverage goes with a projected growth rate 0.6 points lower. The link is weak, yet revealing, because the purely theoretical score shows no such relationship. Use, it seems, is a better early warning than possibility.

SECTION 3

The new face of exposure

Earlier waves of automation came for the factory floor and the typing pool, the routine jobs in the middle of the wage ladder. This one is climbing higher. Using US Current Population Survey[3] data for August to October 2022, the three months before ChatGPT launched, Massenkoff and McCrory [1] compare the most exposed quarter of workers with the 30% who have no exposure at all.

Table 3 **Differences between high and low exposure workers**

Indicator	No exposure	Top quartile	Gap
Women (% of workers)	38.8%	54.4%	+15.5 pp
Graduate degree	4.5%	17.4%	+12.8 pp
Bachelor degree	13.3%	37.1%	+23.8 pp
Average hourly wage (USD)	22.23	32.69	+10.45
Union members	11.7%	5.3%	−6.4 pp

Source: [1], Figure 5.

The contrast is stark. Exposed workers earn about 47% more an hour and are almost four times as likely to hold a graduate degree. They are also less than half as likely to belong to a union (5.3%

[3]Current Population Survey (CPS). The monthly household survey run by the US Census Bureau and the US Bureau of Labor Statistics, covering more than 130,000 people; the source of official US unemployment figures [2].

against 11.7%), which leaves fewer collective buffers should disruption arrive. The people most exposed to AI are, in short, the people who were told that education was their insurance.

> **THE TAKEAWAY** AI exposure now sits with the educated, the better paid and women, the groups least protected by unions.

SECTION 4

No layoff wave, but a narrowing door

Unemployment: the dog that has not barked

If AI were pushing exposed workers out of their jobs, their unemployment rate should be rising faster than everyone else. It is not. Since late 2022 the gap between the most exposed and the unexposed has moved by an estimated 0.2 percentage points, too small to tell apart from zero. Nor is this a case of looking and failing to see. The method would catch a differential rise of about 1 point, and a "Great Recession for white collar workers", in which exposed unemployment doubled from roughly 3% to 6%, would stand out plainly [1].

Other researchers see the same calm. The Budget Lab at Yale finds that the occupational makeup of the US economy has shifted unremarkably since ChatGPT arrived [16].

Hiring: the canaries

The disturbance, if there is one, is at the entrance rather than the exit. The Stanford economists Erik Brynjolfsson, Bharat Chandar and Ruyu Chen chose their title with care: *Canaries in the Coal Mine?* Using payroll data, they found that employment among 22 to 25 year olds in exposed occupations fell by 6 to 16%, driven by fewer hires rather than more firings [17].

Massenkoff and McCrory hear an echo in survey data. Among young workers, the monthly rate of starting a job in a low exposure occupation holds steady at about 2%. Entry into the most exposed occupations has slipped by about half a percentage point, a 14% fall against 2022 levels. The estimate only just clears the bar of statistical significance[4], and workers over 25 show no such decline.

The caveats deserve their due. Young people not hired into exposed roles may be staying put, taking other work or going back to study. Still, the direction is hard to ignore. AI seems to be sawing at the lowest rung of the ladder before it troubles anyone already standing on it.

> **THE TAKEAWAY** no layoff wave among exposed workers, but young people are being hired into those jobs about 14% less often than in 2022.

SECTION 5

The class of 2026: the first real test

If AI is closing the entry door, summer 2026 is when it should show. Graduates enter the job market in a narrow window between June and August, and this was the first cohort to graduate after firms began using AI intensively. Robert Fairlie and Jane Wu followed US graduates aged 22 to 25 who

[4]Statistically significant. A change too large to be put down to chance in the sample, usually judged at the 5% level. "Not significant" does not prove there is no effect; it means the data cannot yet rule out zero.

hold a bachelor degree and are no longer studying, using Current Population Survey microdata from January 2022 to August 2026 [2].

Two choices make their test sharper than most. First, summer matters: graduate unemployment in June to August typically runs nearly 2 points above its level of about 5% in the rest of the year, so 2026 has to be compared with earlier summers. Second, they count the **sidelined**[5]: graduates who say they want a job but have not searched in the past four weeks, and so fall outside official unemployment.

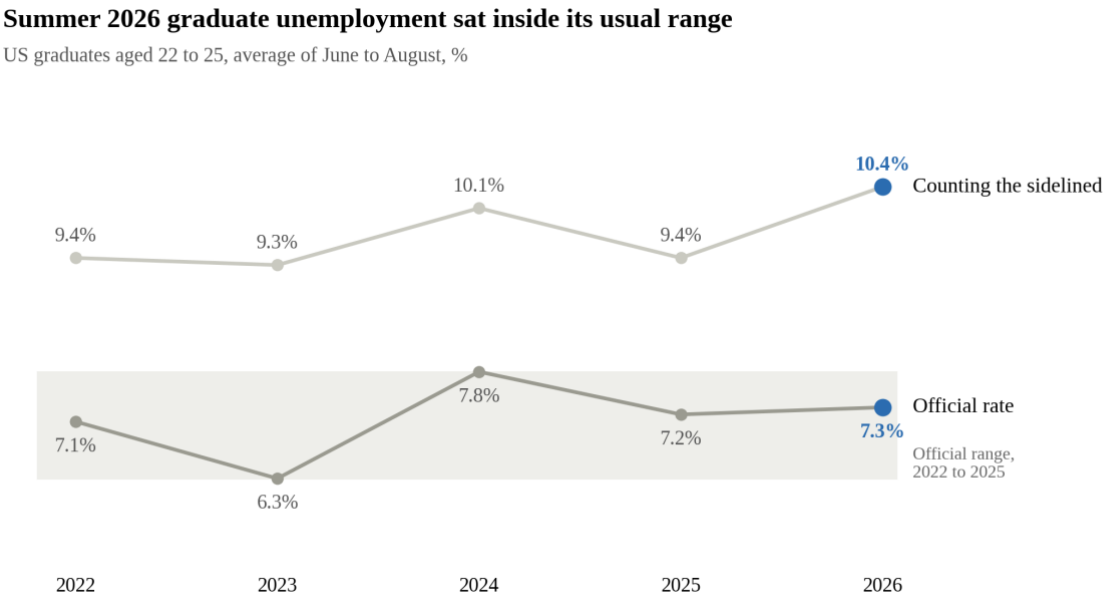


Figure 2 *Summer unemployment of young US graduates, official and counting the sidelined, 2022 to 2026. Source: [2], Figures 2a and 2b.*

The result is steadiness. Official summer unemployment was 7.3% in 2026, against 7.1% in 2022, 6.3% in 2023, 7.8% in 2024 and 7.2% in 2025. Adding the sidelined lifts 2026 to 10.4%, the highest of the five summers, but only 0.3 points above 2024. Regression estimates for summer 2026 are small and statistically insignificant in every specification, and fewer than 17% of unemployed recent graduates had lost a job through layoffs; most simply had not yet found one.

The hints beneath the calm

Table 4 **How young US graduates fared against comparison groups, June to August**

Summer comparison	2025	2026	What moved
Young graduates vs graduates aged 30 to 49, official gap	4.5 pp	4.5 pp	No change
Same comparison, counting the sidelined	5.3 pp	6.2 pp	Widened by 0.9 pp
Young graduates vs young non graduates, official	−0.3 pp	+0.5 pp	Graduates now slightly worse off
Graduate advantage over non graduates, counting the sidelined	2.2 pp	0.3 pp	Smallest of five summers

[5]Sidelined. Graduates outside the labour force who say they want a job but have not actively searched in the past four weeks, and so are left out of official unemployment [2].

Source: [2].

None of these shifts is statistically significant, and part of the narrowing came from non-graduates doing better rather than graduates doing worse. Other margins lean the same way. The share of young graduates either unemployed or working in jobs that need no formal qualification rose to 17.1% in summer 2026, from 15.6% in 2022.

AI, or the empty office?

When Fairlie and Wu split graduates by occupation, the link with AI exposure was positive but not significant, on both the observed and the theoretical measure. The clearer link was with remote work: graduates from occupations that can be done from home[6] fared measurably worse. The two overlap heavily, with correlations of 0.58 and 0.66 between remote work and the two AI measures, and earlier research finds remote work thins out the informal mentoring that junior staff need [18]. For now, AI and the empty office are hard to tell apart.

The class of 2026 did not hit a wall. But the measures that look past the official rate point the same way as the canaries: the entrance is a little narrower, and more of the young who cannot get in are waiting on the sidelines rather than being counted as unemployed.

> **THE TAKEAWAY** the class of 2026 found work at the usual rate, but more of those who did not are now out of the official count.

SECTION 6

Beyond America: the global and Indian picture

Wherever researchers look, the pattern rhymes: exposure is wide, displacement so far is thin, and the pressure gathers around clerical and early career work.

Table 5 Global estimates of AI exposure and job change

Source	Headline estimate
ILO and NASK [4]	1 in 4 workers globally in an occupation with some generative AI exposure; 3.3% in the highest exposure band (4.7% of women, 2.4% of men)
ILO and NASK [4]	Exposure reaches 34% of employment in high income countries versus 11% in low income ones
IMF [20]	Almost 40% of global employment exposed to AI, rising to about 60% in advanced economies
WEF Future of Jobs [21]	170 million roles created and 92 million displaced by 2030, a net gain of 78 million; 39% of core skills expected to change

Sources: [4], [20], [21].

The International Labour Organization is careful on this point. Because almost every occupation still contains tasks that need a human, the likeliest outcome is that most jobs will be *transformed* rather than erased [4].

[6]Teleworkable occupations. Occupations whose tasks can plausibly be done from home, as classified by Dingel and Neiman [19].

What this means for India

India stands at an awkward crossroads. Its services export model rests on precisely the tasks at the top of the exposure table: writing code, testing it, answering customers and processing data. NITI Aayog, working with NASSCOM and BCG, estimates that under business as usual the tech services workforce of 7.5 to 8 million in 2023 could shrink to about 6 million by 2031. With timely investment in skills, it sees room instead for up to 4 million new AI linked roles [5].

Demography raises the stakes. In 2022 young people made up 82.9% of the unemployed, and those with secondary or higher education accounted for 65.7% of the jobless young [22]. If AI trims entry level hiring in India as the US data hints, it will fall on the very cohort already queuing for a first job. The American evidence carries a second warning: much of the early strain shows up among graduates who have stopped searching, a group that headline unemployment rates, in India as in the US, do not count.

> **THE TAKEAWAY** India exports the very tasks AI does best, and its jobless are already young and educated.

SECTION 7

The AI survival scenario: what needs updating

Because Massenkoff and McCrory [1] set out thresholds, we can say in advance what each possible future would look like in the data, and check it against the numbers as they arrive.

Table 6 Scenarios and their signatures in the data

Scenario	What the data would show
Slow diffusion	Observed exposure creeps towards theoretical capability; unemployment gap stays near zero
Entry squeeze (today)	Unemployment flat, graduate unemployment within its usual range, but young hiring into exposed jobs keeps falling and more graduates wait on the sidelines
White collar recession	Exposed unemployment doubles, roughly 3% to 6%
Severe displacement	If the top 10% by coverage lost their jobs, exposed unemployment would jump from 3% to 43%, and US unemployment from 4% to 13%

Source: derived from [1] and [2].

Survival, in this sense, is not a single act of reskilling. It is an adjustment at three levels at once.

For the individual: climb towards judgement

The MIT economist David Autor argues that wages follow scarce expertise. Borrowing a line from a cartoon villain, he notes that "if everyone is an expert, no one is an expert" [23]. As AI makes routine competence plentiful, value migrates to what it cannot finish alone: judgement, verification, negotiation and accountability. Learn the tools, by all means, but invest most in the part of the work where a human has to sign.

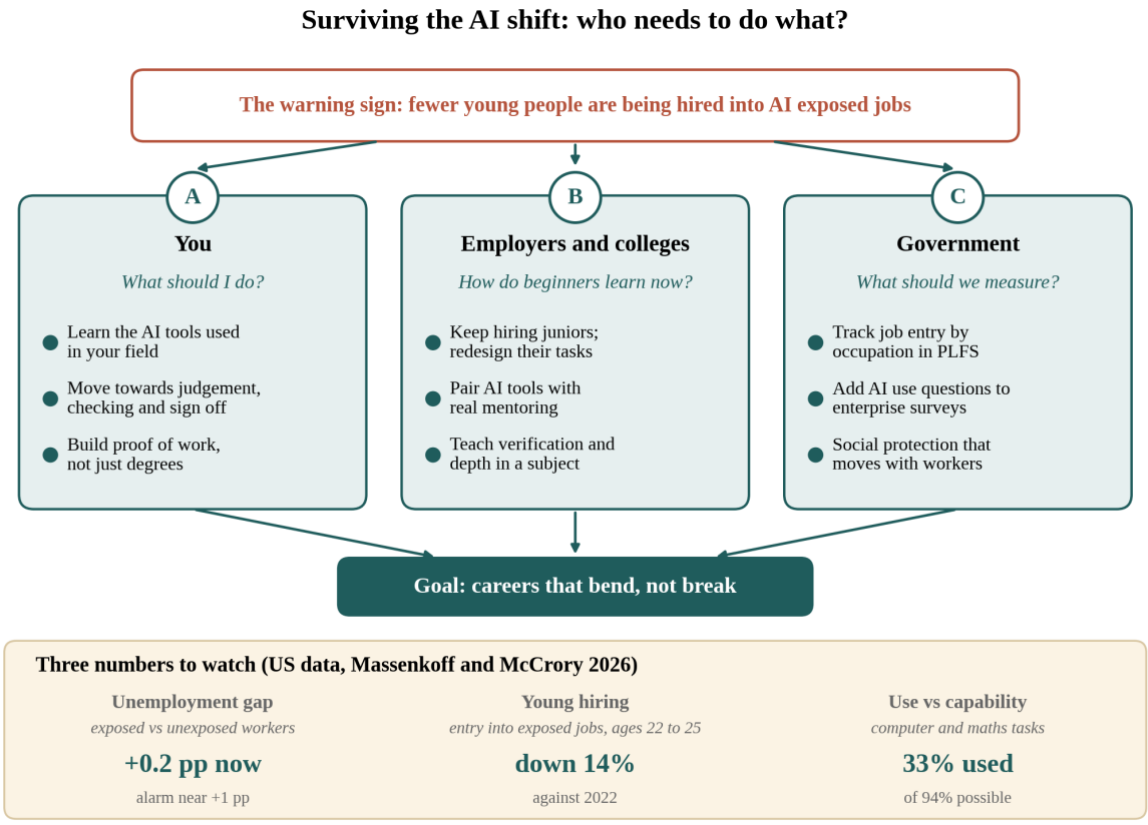


Figure 3 *A three level response framework, with the numbers to watch. Stat and State, using data from [1].*

For employers and universities: rebuild the first rung

First drafts, basic code and data cleaning were never glamorous, but they were how beginners became experts. Fairlie and Wu [2] put it plainly: entry level tasks produce output, but they also train people, through learning by doing and time beside experienced colleagues. If AI absorbs those tasks, and remote work thins the mentoring around them, apprenticeship will have to be designed on purpose rather than inherited by accident. Erik Brynjolfsson has warned of the "Turing Trap", the temptation to build machines that imitate and replace people instead of extending what they can do [24]. Which path a firm takes is a managerial choice as much as a technical one.

For policy and statistics: measure hiring, not just jobs lost

Unemployment is a late and blunt signal, and the class of 2026 shows why. Its strain surfaced not in the headline rate but among the sidelined, the mismatched and the seasonal peaks. India would be better served by occupation level tracking of job entry in the Periodic Labour Force Survey, regular counts of graduates who want work but have stopped searching, an AI usage module in enterprise surveys, and social protection that travels with early career workers from job to job. The time to build the instruments is before the weather turns.

EPILOGUE

The door, not the floor

Keynes, writing in 1930, blamed the pain of rapid technical change on the "growing-pains of over-rapid changes". Nearly a century later, two careful studies agree that AI has not pulled the floor

from under working people, not even from under the class of 2026. What it may be doing, more quietly, is narrowing the door through which the next generation walks in.

Which brings us back to Marienthal. If work gives us a shape to the day, company, purpose and a sense of who we are, then the deepest risk is not only lost income. It is a generation that never quite gets to begin. The numbers are early and the effects small. That is exactly why this is the moment to watch them.

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Data: observed exposure at task and job level is available from the Anthropic Economic Index, https://huggingface.co/datasets/Anthropic/EconomicIndex. Current Population Survey microdata are published by the US Census Bureau and the US Bureau of Labor Statistics.

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Declaration on the use of AI

Stat and State used an AI writing assistant (Claude, developed by Anthropic) to improve the structure, language and readability of the text, to draft tables and figures, and to check figures and citations for consistency. Anthropic also published source [1]; that source was used on its merits and cited like every other. Every data point was checked against its original source, and the Stat and State Lead Team reviewed, edited and approved the final text. Responsibility for the content, analysis and any errors rests with Stat and State.