TAUB CENTER
for Social Policy Studies in Israel

How Artificial Intelligence Changed the Composition of the Unemployed in Israel

Michael Debowy, Gil S. Epstein, and Avi Weiss

Policy Paper No. 05.2026

Jerusalem, March 2026

Taub Center for Social Policy Studies in Israel

The Taub Center for Social Policy Studies in Israel was established in 1982 under the leadership and vision of Herbert M. Singer, Henry Taub, and the American Jewish Joint Distribution Committee. The Center is funded by a permanent endowment created by the Henry and Marilyn Taub Foundation, the Herbert M. and Nell Singer Foundation, Jane and John Colman, the Kolker-Saxon-Hallock Family Foundation, the Milton A. and Roslyn Z. Wolf Family Foundation, and the American Jewish Joint Distribution Committee. In addition, generous support is also received each year from individual donors, foundations, and Jewish federations.

The Taub Center is an independent, nonpartisan, socioeconomic research institute based in Jerusalem that conducts high-quality, impartial research on socioeconomic conditions in Israel. The Center presents a broad social and macroeconomic perspective to leading policy makers and the wider public in the area of public policy. The Center's professional staff and its interdisciplinary policy program staff, which includes prominent researchers from academia and leading experts in the areas of policy, conduct research and develop evidence-based policy options in the socioeconomic areas on the country's public agenda. The Center presents long-term strategic analyses and policy options to policy makers and the public through direct communications, an active program of publications, conferences, and other activities in Israel and abroad.

Please cite this publication as:

Debowy, M., Epstein, G. S., & Weiss, A. (2026). How Artificial Intelligence Changed the Composition of the Unemployed in Israel. Taub Center for Social Policy Studies in Israel. https://doi.org/10.5281/zenodo.18266434

Center address: 15 Ha'ari Street, Jerusalem, Israel

Telephone: 02 5671818

Email: info@taubcenter.org.il   Website: www.taubcenter.org.il

How Artificial Intelligence Changed the Composition of the Unemployed in Israel

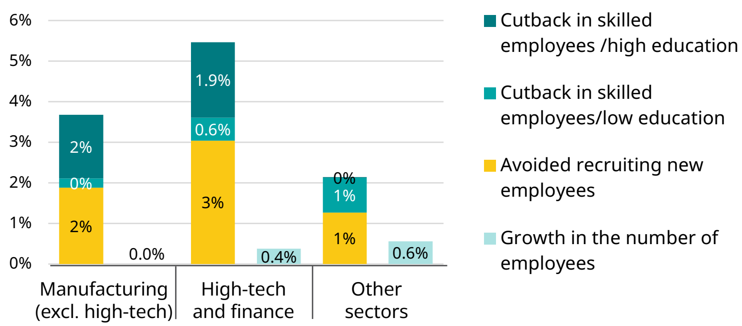
Michael Debowy, Gil S. Epstein, and Avi Weiss

Introduction

With the growing integration of GenAI (generative artificial intelligence) tools into the workplace and the broader economic arena, there are increasing signs that this technology is affecting demand for various skills and competencies in the Israeli labor market (Dor, 2024; Shulman, 2025). According to the Central Bureau of Statistics (CBS) Business Tendency Survey, as of June 2025, employers of approximately 3% of workers in Israel reported a decline in demand for employees due to the use of artificial intelligence (AI). About half of this decline reflects foregoing recruitment of new workers, and half a reduction in the existing workforce (Figure 1). The effect is particularly pronounced in the high-tech and financial sectors, where firms reporting a reduction in their workforce collectively employ about 5.5% of workers, and firms reporting layoffs of highly skilled or educated workers collectively employ about 2%.

* Michael Debowy, Researcher, Taub Center for Social Policy Studies in Israel; doctoral student, Department of Economics, Ben-Gurion University of the Negev. Prof. Gil S. Epstein, Principal Researcher and Chair, Taub Center Labor Policy Program; Department of Economics, Bar-Ilan University. Prof. Avi Weiss, President, Taub Center; Department of Economics, Bar-Ilan University.

Figure 1. Share of employees whose number of workers at their workplace changed following the use of AI, June 2025



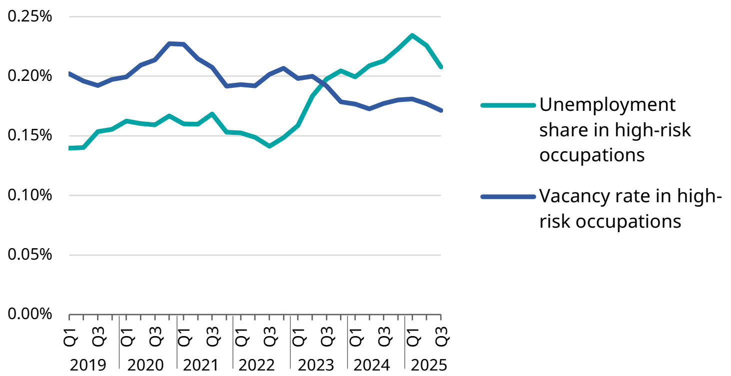
Source: Michael Debowy, Gil S. Epstein, and Avi Weiss, Taub Center | Data: Roash, Regev, & Ayash (2025); CBS

These data suggest that a small share of Israeli workers has been exposed to the threat of replacement by artificial intelligence, although it is not possible to determine the extent to which workers have actually been replaced. The occupational composition of the unemployed population in Israel has also changed over the past two years: the share of unemployed individuals in occupations at high risk of replacement by artificial intelligence, which stood at 14%–16% of all unemployed persons in 2019–2022, began to rise in the course of 2023, and, in 2025, ranged between one-fifth and one-quarter of the unemployed (Figure 2).[1] At the same time, a modest shift in the opposite direction was recorded in job vacancies: between 2019 and 2022, vacancies in roles that are now at high risk of replacement accounted on average for about one-fifth of all vacancies; in 2023, 19%; and in 2024–2025, less than 18%. While the overall change is small, even if the share of vacancies in high-risk roles had remained constant, as long as the share of relevant unemployed workers is rising, competition for each vacancy intensifies. Moreover, an increase in unemployment that is not matched by a decline in the number of vacancies suggests a deterioration in the match between unemployed workers and

1 Occupations at high risk of replacement are defined as those in the top quintile of the AI exposure index (E1), excluding occupations in the top quintile of the AI complementarity index, as these indices are defined in Debowy et al. (2025).

available jobs — perhaps due to a growing preference for highly experienced workers, as documented by Brynjolfsson et al. (2025) in the United States.

Figure 2. Share of unemployed individuals in occupations at high risk of displacement out of total unemployed, and share of job vacancies in occupations at high risk of displacement out of total vacancies, annual average by quarter, 2019–2025



Note: Occupations at high risk of displacement are defined as those in the top quintile of the AI exposure index (E1), excluding occupations in the top quintile of the AI complementarity index, as these indices are defined in Debowy et al. (2025).

Source: Michael Debowy, Gil S. Epstein, and Avi Weiss, Taub Center | Data: CBS

It is not clear to what extent artificial intelligence is driving this trend of a rise in the unemployment rate among workers with occupations at risk of displacement due to AI, which most likely began before the technology was integrated into workplaces and perhaps even before the technology was publicly launched. A steady rise in the prevalence of these occupations over the years explains nearly a quarter of the change in the composition of the unemployed. In addition, other factors may be at play, such as the slowdown in the high-tech sector and a longer-term correction following the shocks of the COVID-19 pandemic (which may have generated excess demand for the types of occupations that artificial intelligence is now expected to replace). In any case, a thorough analysis is needed to attempt to trace the impact of artificial intelligence on the occupational composition of the unemployed — an analysis this article seeks to provide.

We emphasize that our aim is not to assess the effect of artificial intelligence on the overall unemployment rate in the economy, which is unlikely to be significant at this stage, but rather on relative unemployment rates in occupations with higher AI displacement risk compared with those with lower risk.

The remainder of this article is structured as follows. First, we briefly review the existing literature on the topic and highlight key findings from Israel and abroad. We then present an empirical analysis examining the effect of exposure to artificial intelligence on structural unemployment and job vacancies, including a description of the data sources and methodology. We also interpret our findings through a brief decomposition of unemployment components in selected occupations and the contribution of artificial intelligence to each component. Finally, we summarize our findings and outline the implications and limitations of our analysis.

Literature survey

Recent years have seen a flood of scientific publications examining the impact GenAI technology on the labor market — potentially or in practice.[2] Marguerit (2025) examined the effect of artificial intelligence on employment and wages among workers with different skill levels over 2017–2022, focusing in particular on displacement on the one hand and worker complementarity on the other. He found that among low-skilled workers, artificial intelligence has a negative effect on both employment and wages, while among high-skilled workers its effect on employment is mixed (harmful displacement of some workers alongside beneficial complementarity for others) and its effect on wages is positive. Hampole et al. (2025) examined the effect of artificial intelligence on employment using a representative sample of U.S. firms over 2010–2023. They found that while demand for workers declines with their exposure to artificial intelligence, workers are shifted to tasks that are not exposed to artificial intelligence in a way that pushes up demand for them. These two mechanisms operate in opposite directions, so the net result is a negligible effect on aggregate employment. However, the study suggests that the impact on employment within particular occupations may be very large (for better or worse), and the authors note that exposure to artificial intelligence explains about 16% of the variation in employment change across occupations.

2 For a review of studies examining the influence of AI on the labor market and employment until 2024, see Debowy et al., 2024; 2025.

Other studies have found clear evidence of an effect of artificial intelligence on employment. Hui et al. (2023) found a decline in employment and income among freelancers on an intermediary platform after artificial intelligence tools capable of replacing them were introduced, a finding replicated by Demirci et al. (2024). Beyond this targeted effect, various studies have attempted to estimate the aggregate impact of generative artificial intelligence on employment today. Both Chandar (2025) and Johnston & Makridis (2025) examined this question using U.S. survey data, and found it difficult to conclude that there is a large effect, but also difficult to rule out an effect altogether. More recently, Brynjolfsson et al. (2025) drew on employment and wage data from the largest payroll company in the United States, covering about 25 million workers. The researchers showed a 13% decline in employment among younger workers (ages 22–25) in occupations at risk of replacement by artificial intelligence, with no meaningful effect on older workers, total employment, wages, or workers in occupations where artificial intelligence is expected to complement, rather than displace, human labor.

Overall, while focused micro-level studies have identified localized displacement of workers by artificial intelligence under certain conditions, the aggregate picture is mixed and there is no broad consensus regarding the true scale of artificial intelligence's impact on employment or wages (Santarelli et al., 2025). In Israel, Debowy et al. (2024) showed that exposure to artificial intelligence is particularly high in the high-tech and financial sectors, higher among Jewish workers than among Arab workers, and higher the more educated the worker is (although the most educated workers are not expected to be replaced by artificial intelligence). These findings were also validated by the Bank of Israel (2025). Debowy et al. (2025) later showed that in 2024, exposure to artificial intelligence was associated with unemployment (or discouragement from job search) in an overwhelming majority of occupations, even after controlling for confounders such as education, economic sector, and additional background factors. We now turn to the comprehensive empirical analysis we conducted to examine the causal effect of artificial intelligence on unemployment in Israel.

An empirical look

Our data are based on the CBS monthly Labor Force Surveys from January 2019 through September 2025, comprising about one million monthly observations. We aggregated observations by year–quarter and respondents' occupation, allowing us to estimate the unemployment rate for workers in a given occupation, on average, in each quarter over the period in question.[3] The final dataset includes unemployment-rate estimates for 46 occupations, and includes about 470 quarterly observations in the years 2022–2025, the key period we examine (and about 770 observations in total for 2019–2025).[4] In addition to the estimated unemployment rate, we attach to each observation the vacancy rate in the same occupation and period, and the 2024 AI exposure score (the E1 score from Debowy et al., 2025). The exposure score is held fixed for each occupation across all sample periods, in order to examine how its correlation with employment changed over time.

Unemployment is affected by many factors, including the vacancy rate (which roughly captures demand for additional workers) and, among other things, the match between the unemployed workers' skills and those required for the available vacancies. In principle, the unemployment rate and the vacancy rate affect one another simultaneously, and both are affected by the level of exposure to artificial intelligence. Identifying the effect of AI exposure on unemployment is therefore empirically challenging. An ideal analysis would estimate this web of relationships (between unemployment, vacancies, and artificial intelligence) in a way that allows one to compute, directly from the data, the total effect of artificial intelligence on unemployment (the "structural" effect unrelated to vacancies, alongside the effect operating through vacancies). Unfortunately,

---

3 For unemployed individuals, this refers to the occupation in which they are seeking work, or the last occupation in which they worked.

4 Due to the small number of observations, it is not possible to produce reliable estimates of the unemployment rate in some periods for some occupations (especially less common occupations). As a result, the resulting panel is unbalanced: some occupations do not appear fully or continuously (and some do not appear at all), and on average we observe 31 occupations in each period. Nevertheless, our observations represent about 85% of the Israeli labor force during the period in question (on average). As an additional robustness check, we broaden the occupation definition to the 2-digit classification, which allows us to replicate our findings in a balanced panel covering almost the entire labor force.

our data do not allow us to carry out such an estimation.[5] We therefore proceed as follows: First, we examine the direct effect of artificial intelligence on the vacancy rate on the one hand, and on the unemployment rate on the other (controlling in each case for other variables, including the unemployment rate and the vacancy rate, respectively). In the second stage, we aggregate these effects under different assumptions about how changes in vacancies translate into unemployment rates.

We begin with the first stage, in which we estimate the relationship between exposure to artificial intelligence and unemployment (or vacancies) within a model in the spirit of Şahin et al. (2014), although we do not focus on new jobs but rather on the overall employment rate (similar to Postings, 2022). In this model, we assume that the unemployment rate (or the vacancy rate) in a given occupation is determined by: short-run fluctuations in demand (or supply) for workers (captured by the vacancy rate or the unemployment rate), short-run economy-wide shocks, and structural features of that occupation's labor market (captured by average unemployment and vacancy rates in the period prior to the COVID-19 pandemic), alongside (possibly) exposure to AI.[6]

5 We were unable to obtain valid instrumental variables for estimating simultaneous equations for unemployment and vacancies across the different occupations.

6 This model is expressed in our estimation equation:

$$u_{it} = \alpha + \gamma \cdot v_{it} + \theta \cdot \bar{u}_{i\overline{2019}} + \delta_t + \sum_{t=2022Q1}^{2025Q3} \beta_t \cdot D_t \cdot AI_i + \varepsilon_{it}$$

Where u_{it} is the unemployment rate in occupation i in period (year-quarter) t, v_{it} is the share of job vacancies, $\bar{u}_{i\overline{2019}}$ is the average share for the occupation i over the year 2019 (as a substitute variable for long-term structural unemployment, δ_t is a series of dummy variables representing economy-wide shocks to labor supply and demand during the period t, D_t is the dummy variable with the value of 1 for the period t and 0 for the remaining time period and AI_i is the exposure to AI score of the occupation in 2024 (E1 score in Debowy et al., 2025). In our estimation, we test the hypothesis that the β_t coefficients increase between the pre-artificial intelligence period (in which it can be stated with certainty that the relationship does not reflect the effect of artificial intelligence) and the period in which artificial intelligence began to be adopted.

Exposure to AI and unemployment

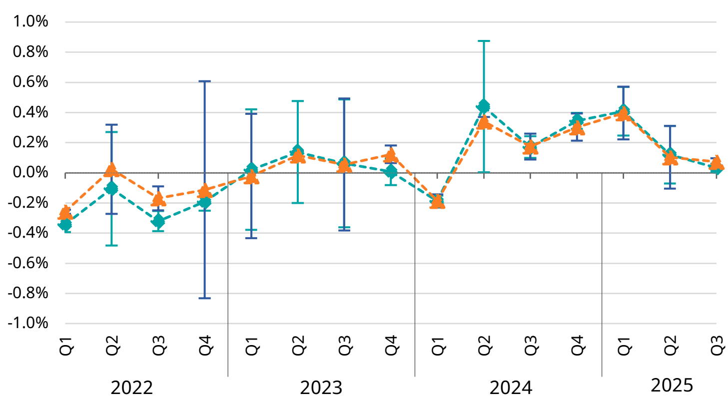
First, we examine the effect of artificial intelligence on unemployment net of the effect of the vacancy rate, in a way that reflects the "structural" unemployment attributed to artificial intelligence (commonly understood to stem primarily from a mismatch between workers' characteristics and employers' requirements). We estimate the relationship between exposure to artificial intelligence — as measured in 2024 — and the unemployment rate in each occupation relative to the economy-wide average in the same period, while controlling for the other factors mentioned above given their potential correlation with the exposure index. The hypothesis is that the estimated relationship between exposure to artificial intelligence and unemployment, once artificial intelligence is being adopted in the labor market (from 2024 onward), will be larger (more positive) than it was prior to the technology's emergence and adoption. We emphasize that we do not assume there was no relationship between unemployment across occupations and their future exposure to artificial intelligence; rather, we examine how that relationship changed (similar to a "difference-in-differences" approach).[7] We treat this change as an estimate of the causal effect of the diffusion of artificial intelligence on the unemployment rate in occupations exposed to replacement. Full estimation results are reported in Table A1 in the Appendix and shown in Figure 3.

The estimates indicate that from the second quarter of 2024, exposure to artificial intelligence began to predict a higher unemployment rate than in the two preceding years, although a gradual trend makes it difficult to determine with certainty whether the launch of the new technology played a decisive role. It is worth emphasizing that in earlier years (especially 2022), the exposure score actually predicted lower unemployment. This is consistent with the idea that AI tools were developed specifically to perform tasks for which demand is high ("to replace the most expensive workers"), so the occupations at the highest risk of replacement in 2024–2025 are those that enjoyed lower unemployment in 2022. While the change is statistically significant, its magnitude is very small: in the last quarter of 2025, a 10% increase in exposure to artificial intelligence was associated with unemployment higher by about one-tenth of a percentage point relative to the average, compared with unemployment similar to the

7 We clarify that this is not a valid "difference-in-differences" design, as the required assumptions of that method are not satisfied.

average in the corresponding quarter of 2023 and unemployment lower by one-fifth of a percentage point in the corresponding quarter of 2022. In other words, while the most exposed occupations had slightly lower-than-average unemployment in the past, over the past two years their unemployment rates converged with those of other occupations and even exceeded them by a negligible amount.

Figure 3. Change in the unemployment rate resulting from a 10% increase in exposure to artificial intelligence, controlling for the job vacancy rate, the 2019 unemployment rate, and the aggregate unemployment rate in each quarter, 2022–2024
Percentage points



Note: The figure presents the change in unemployment (in percentage points) predicted by a 10% change in exposure at the occupational level, based on the estimates reported in columns (1)–(2) of Table A1 in the Appendix. High-Tech occupations include Software and Applications Developers and Analysts (251), and Database and Network Professionals (252). Periods in which the confidence interval is particularly wide are typically those for which standard errors could not be clustered by year due to a limited number of observations.[8]

Source: Michael Debowy, Gil S. Epstein, and Avi Weiss, Taub Center | Data: CBS

8 Clustering standard errors by period is econometrically appropriate in this application (given the sampling design and the timing of AI diffusion). The fact that it reduces the width of the confidence interval reflects features of the data and the negative within-period correlation of unemployment residuals (suggesting that employment across occupations is substitutable from workers' perspective, as expected).

This finding withstands several robustness checks that validate it against certain weaknesses of the baseline analysis. First, because the generative AI revolution coincided with a structural slowdown in Israel's high-tech sector, there is a concern that the AI exposure index is correlated with the effects of that structural slowdown, biasing our estimate. Re-estimating the model while excluding high-tech occupations indicates that this is not the case: the resulting estimates are not significantly different in any period (Figure 3). In our view, this is reassuring with respect to bias in the overall results driven by the high-tech slowdown.[9]

A second issue concerns defining labor markets as narrow occupations, which does not necessarily capture second-order effects of artificial intelligence on employment — for example, increased competition in non-exposed occupations due to the influx of displaced workers from adjacent occupations. To address this, we group occupations into clusters based on the skills they require (as measured using the European Union's Skills, Competences, Qualifications and Occupations Dictionary).[10] Using this approach, we cluster occupations into 20 or 10 groups. As an additional robustness check, we replicate our original estimation using less detailed (2-digit) occupations and clustering them into 10 groups using the same method. Table 1 presents the effect of artificial intelligence on the change in unemployment between 2022 and 2024–2025 by quarter and across different clustering approaches. The results are similar across all methods to those in the baseline, although statistical significance is weaker in some periods (as expected given the smaller number of observations due to clustering). Overall, a 10% difference in exposure across occupations corresponds to a difference of between one-sixth and three-quarters of a percentage point in the increase in relative unemployment between 2022 and the corresponding periods in 2024 or 2025.

9 This refers to the direct effect of the slowdown in high-tech on workers in technological occupations. The high-tech slowdown may also affect other parts of the labor market and could therefore bias our results indirectly. For example, a decline in demand for support roles in high-tech may have increased the aggregate unemployment rate in non-technological occupations. We are unable to test this empirically.

10 The clustering was performed using the K-means clustering method, based on the listed skills appearing in European Skills, Competences, Qualifications and Occupations (ESCO) (Skills-Occupations Matrix Tables 2.3 version 1.2.0).

Table 1. Influence of AI on changes in unemployment between 2022 and the corresponding quarter in 2024 and 2025, by occupational cluster

	Occupation 3-digit	Skill-based cluster (occupation 3-digit)		Occupation 2-digit	Skill-based cluster (occupation 2-digit)
Number of clusters	**46**	**20**	**10**	**31**	**20**
2024/2022					
Q1	0.015***	0.030	-0.014	-0.009	-0.007
	(0.0044)	(0.0363)	(0.022)	(0.0085)	(0.044)
Q2	0.054	0.087**	0.040	0.017**	0.023
	(0.0406)	(0.0441)	(0.0249)	(0.0086)	(0.0427)
Q3	0.049***	0.034***	0.076***	0.049**	0.094**
	(0.0069)	(0.0089)	(0.0157)	(0.0242)	(0.0336)
Q4	0.054***	0.047	0.079**	0.035***	0.056*
	(0.0055)	(0.0628)	(0.0305)	(0.0111)	(0.0352)
2025/2022					
Q1	0.0749***	0.0902***	0.0296	0.0448***	0.0692**
	(0.0187)	(0.0260)	(0.0302)	(0.0092)	(0.0296)
Q2	0.0225	0.0374	0.0988	0.0128	0.0255
	(0.0378)	(0.0421)	(0.157)	(0.0121)	(0.0437)
Q3	0.0353***	0.0252*	0.1112**	0.0373**	0.1093***
	(0.0060)	(0.0104)	(0.0528)	(0.0169)	(0.0216)

Note: The table reports difference estimates for the average marginal effects (AMEs) of exposure to artificial intelligence on unemployment, comparing 2024 and 2025 with 2022 (each quarter relative to the corresponding quarter), based on columns (1) and (3)–(6) of Table A1 in the Appendix. They can be interpreted as the difference in the unemployment rate expected for an occupation with 100% exposure to artificial intelligence.

Source: Michael Debowy, Gil S. Epstein, and Avi Weiss, Taub Center | Data: CBS

Exposure to AI and job vacancies

As noted earlier, artificial intelligence is also expected to affect unemployment through its impact on the number of job vacancies (especially in particular occupations). We therefore estimate a parallel model examining the effect of AI on vacancies, including the various robustness checks previously reported for unemployment; full results are reported in Table A2 in the Appendix.[11] A summary of the differences in marginal effects between 2022 and 2024–2025 is presented in Table 2, in a format identical to that of Table 1. The results are less statistically significant for job vacancies than those reported above for unemployment, although they are generally consistent in magnitude and sign. On average, a 10% increase in exposure to artificial intelligence is associated with a decline of 0.4–1.4 percentage points in the vacancy rate between 2022 and 2024–2025, though there is substantial variation across periods and clustering approaches.

11 The estimation formula in the portion is:

$$v_{it} = \alpha + \rho \cdot u_{it} + \varphi \cdot \bar{v}_{i\overline{2019}} + \mu_t + \sum_{t=2022Q1}^{2025Q3} \beta_t \cdot D_t \cdot AI_i + \epsilon_{it}$$

Where v_{it} is the job vacancy rate in occupation i in the period (year-quarter) t, u_{it} is the unemployment rate, $\bar{v}_{i\overline{2019}}$ is the average vacancy rate for occupation i over the year 2019 (as a substitute variable for long-term structural demand), μ_t is a series of dummy variables economy-wide shocks to labor supply and demand during the period t, D_t is the dummy variable with the value of 1 for the period t and 0 for the remaining time period and AI_i is the exposure to AI score of the occupation in 2024 (EI score in Debowy et al., 2025).

Table 2. Influence of AI on the change in the share of job vacancies between 2022 and the corresponding quarter in 2024 and 2025, by occupational cluster

	Occupation 3-digit	Skill-based cluster (occupation 3-digit)		Occupation 2-digit	Skill-based cluster (occupation 2-digit)
Number of clusters	**46**	**20**	**10**	**31**	**20**
2024/2022					
Q1	-0.122**	-0.103	0.242**	-0.060**	-0.099**
	(0.0432)	(0.074)	(0.0963)	(0.0241)	(0.0403)
Q2	-0.062	-0.031	-0.045	-0.088**	-0.126*
	(0.0415)	(0.0228)	(0.0485)	(0.0334)	(0.0705)
Q3	-0.009	-0.020	-0.060*	-0.052*	-0.130*
	(0.0648)	(0.0324)	(0.037)	(0.0291)	(0.0732)
Q4	-0.085***	-0.065***	0.045	-0.060*	-0.078
	(0.0232)	(0.0121)	(0.0583)	(0.0351)	(0.0501)
2025/2022					
Q1	-0.1976***	-0.2258***	0.260*	-0.066**	-0.1966***
	(0.0489)	(0.0402)	(0.1112)	(0.0252)	(0.0171)
Q2	-0.1104***	-0.1016	-0.055	-0.0611***	-0.1513***
	(0.0395)	(0.0855)	(0.2229)	(0.0204)	(0.0409)
Q3	-0.0524	-0.0698	-0.6652*	-0.0282	-0.1739***
	(0.0645)	(0.0528)	(0.3678)	(0.0309)	(0.0441)

Note: The table reports difference estimates for the average marginal effects (AMEs) of exposure to artificial intelligence on unemployment, comparing 2024 and 2025 with 2022 (each quarter relative to the corresponding quarter), based on columns (1) and (3)–(6) of Table A1 in the Appendix. They can be interpreted as the difference in the unemployment rate expected for an occupation with 100% exposure to artificial intelligence.

Source: Michael Debowy, Gil S. Epstein, and Avi Weiss, Taub Center | Data: CBS

A comparison of Tables 1 and 2 indicates that, on average, the effect of artificial intelligence on the vacancy rate is less statistically significant than its effect on structural unemployment, although the average association tends to be negative and larger in absolute magnitude. It is plausible that the decline in vacancy rates in exposed occupations reflects factors unrelated to artificial intelligence, and that at this stage the effect is very small. Nevertheless, even if the statistical significance of artificial intelligence's effect on the number of job vacancies is uncertain, it is worth asking to what extent it could affect unemployment if the relationship is indeed present.

Full effect on unemployment: Number of vacancies and matching to vacancies

Our estimates alone do not allow us to answer this question or to determine the extent to which artificial intelligence's effect on the vacancy rate translates into unemployment, since we do not have an estimate of how vacancies translate into unemployment in general (the estimated relationship between vacancies and unemployment in our model is biased and is intended only to isolate the effect of artificial intelligence on structural unemployment). We therefore consider several alternative values for this parameter. First, while it is unlikely that the entire change in vacancies translates into an equivalent relative change in unemployment (i.e., an elasticity of -1) across different occupations (certainly not when the overall labor market is relatively tight), we can treat -0.8 as an upper bound (as estimated by Yashiv [2000] for the Israeli labor market as a whole in the 1970s and 1980s). This figure suggests that, for exposed occupations, the decline in vacancies increased unemployment by about 0.6 percentage points for every 10% increase in exposure (on average) over the quarters of 2024–2025 (compared with about 0.4 percentage points per 10% exposure attributable to artificial intelligence regardless of vacancies).[12] Alternatively, if we assume that, on average, a one-percentage-point decline in the vacancy rate leads to a 0.1 increase in the unemployment rate (as implied on average by the biased estimates reported in Table A1 in the Appendix), then artificial intelligence would raise unemployment (through the vacancy channel) by less than one-tenth of a percentage point for every 10% exposure.

To interpret these magnitudes, we focus on two highly exposed occupations in which unemployment rose between 2022 and 2024 (contrary to the average). For each such occupation, we document the increase in unemployment and

12 The effect of the decline in the number of job vacancies on unemployment was calculated as the average decline in the vacancy rate (the mean of the rightmost column in Table 2) multiplied by the assumed elasticity, -0.8. The effect of artificial intelligence on unemployment beyond its effect through job vacancies was calculated as the mean of the rightmost column in Table 1.

calculate how much is attributable to the components of the number of vacancies, matching, and artificial intelligence's effect on each component (as estimated in the general model). Such a calculation for software programmers and telephone sales representatives is presented in Table A3 in the Appendix.[13] The calculation indicates that for programmers, 12%–20% of the increase in unemployment between 2022 and 2024–2025 (which averaged 1.5 percentage points overall) can be attributed to artificial intelligence (averaged across quarters), with 9% of this due to artificial intelligence's effect on matching between vacancies and the unemployed (such as a shift in demand from junior programmers to more experienced ones), and the remainder (3%–11%, depending on assumptions about how vacancies translate into unemployment) due to artificial intelligence's effect on the overall number of vacancies. For telephone sales representatives, about 10%–26% of the average increase in unemployment between 2022 and 2024–2025 (1.6 percentage points) is explained by artificial intelligence, with about 6% due to its effect on matching and the remainder due to its effect on the number of vacancies.

Bottom line: artificial intelligence can be credited with about 0.2–0.4 percentage points of the increase in unemployment between 2022 and 2024–2025 in these high-exposure occupations — which translates to a negligible number of workers considering the economy-wide labor force.[14] Even relative to the total number of unemployed individuals, this is a small change, though its order of magnitude is far more meaningful. Recall that the share of occupations at the highest risk of displacement among the unemployed rose by about 6 percentage points on average between 2022 and 2024 (Figure 1). If we assume that the artificial-intelligence effect computed for software programmers and telephone sales representatives also applies to the other high-risk occupations, then artificial intelligence explains about 2%–6% of the change in the occupational composition of the unemployed in Israel during the period in question, as measured by the AI exposure index.

---

13 This refers to Software and Applications Developers and Analysts (251) and Other Sales Workers (524), with Contact Centre Salespersons ("telephone sales representatives") accounting for more than 60% of the second group.

14 For scale, the two occupations examined together account for about 6% of the Israeli labor force, or roughly a quarter of a million workers. An effect of 0.4 percentage points therefore corresponds to about 1,000 unemployed workers.

Conclusion

In this article, we examined the initial evidence on the impact of the generative artificial intelligence revolution on employment in Israel, and in particular on unemployment among occupations exposed to AI relative to those that are not. We referred to findings from the CBS Business Tendency Survey, according to which about 3% of employees in Israel work in establishments that reported some decline in labor demand due to the use of artificial intelligence. We showed that since the launch of the technology, the share of high-risk occupations among the unemployed has increased, while their share among job vacancies has declined. We then presented an empirical analysis indicating that artificial intelligence explains a non-negligible portion of the changes in the distribution of structural unemployment across occupations between 2022 and 2025, especially from the second half of 2024 onward. The empirical analysis also suggests that AI has a larger (though less statistically significant and less consistent) effect on the distribution of job vacancies.

Our calculations regarding the impact of AI on programmers and telemarketing sales representatives suggest that the technology accounts for at most one-sixth of the increase in unemployment among workers in these occupations. Up to half of this effect stems from a decline in job vacancies, and at least half from a greater mismatch between characteristics of the unemployed workers and those of the available positions. This latter finding aligns well with Brynjolfsson et al. (2025), who document that the impact has been concentrated among younger and less experienced workers, whose demand declined in favor of more experienced workers in the same occupation, without a substantial decline in overall demand for that occupation. In any case, the total effect we estimate is negligible in absolute terms and accounts for only a very small share of the change in the composition of the unemployed.

The analysis we present has several limitations worth noting. First, the quality of the data on which we rely is limited. In particular, there is difficulty in grouping occupations in a way that yields both accurate exposure measures and accurate unemployment estimates, making it likely that our data contain measurement error, which we assume to be random. Second, our estimates may still be biased by unobserved pre-existing trends, such as the slowdown in the high-tech sector and the long-term correction from the shocks of the COVID-19 pandemic. However, it is unclear why these factors would manifest specifically in the second half of 2024, the period in which we identify the most statistically significant effect. Finally, we reiterate that our method does not allow us to estimate the overall impact of AI on unemployment, but only its impact on unemployment in a given occupation relative to the economy-wide average at a given time. In this context, it is worth recalling that overall unemployment has not increased during the AI era. Thus, even if AI has a negative aggregate effect on employment (an unlikely assumption in and of itself), other forces currently outweigh it.

In conclusion, although changes in the occupational composition of the unemployed over the past two years are well documented (Lior, 2025), only a small portion of this change can be attributed to artificial intelligence. At the same time, it is unclear how developments will unfold as the technology advances and becomes more widely adopted. It is therefore reasonable to take into account the risk of worker displacement by AI when placing newly unemployed individuals and providing them with assistance. Continued monitoring of unemployment rates will allow for progressively deeper understanding of the effects of this technology on the labor market as it continues to develop and diffuse throughout the economy and our daily lives.

References

English

Bank of Israel (2025, March 26). Press release: *Box from the Bank of Israel Annual Report for 2024: The expected effect of generative artificial intelligence on employees: Implications for labor market policy*. Bank of Israel. (English summary)

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 Working Paper.

Chandar, B. (2025). *Tracking employment changes in AI-exposed jobs*. SSRN.

Debowy, M., Epstein, G. S., Bental, B., Weiss, A., & Weinreb, A. (2024). *Artificial intelligence and the Israeli labor market*. Taub Center for Social Policy Studies in Israel.

Debowy, M., Winter, J., Epstein, G. S., Weiss, A., & Behar-Netanel, E. (2025). *Employment trends and artificial intelligence in the Israeli labor market*. Taub Center for Social Policy Studies in Israel.

Demirci, O., Hannane, J., & Zhu, X. (2024). *Who is AI replacing? The impact of generative AI on online freelancing platforms*. CESifo Working Paper No. 11276.

Hampole, M., Papanikolaou, D., Schmidt, L. D., & Seegmiller, B. (2025). *Artificial intelligence and the labor market*. Working Paper 33509. National Bureau of Economic Research.

Hui, X., Reshef, O., & Zhou, L. (2023). The short-term effects of generative artificial intelligence on employment: Evidence from an online labor market. *Organization Science, 35*(6), 1977–1989.

Johnston, A., & Makridis, C. (2025). *The labor market effects of generative AI: A difference-in-differences analysis of AI exposure*. SSRN.

Marguerit, D. (2025). *Augmenting or automating labor? The effect of AI development on new work, employment, and wages*. SSRN.

Postings, V. (2022). Transforming naturally occurring text data into economic statistics. *Big Data for Twenty-First-Century Economic Statistics, 79*, 173.

Roash, D., Regev, Y., & Ayash, S. (2025, July 24). *Adoption of artificial intelligence in businesses by district: Findings from the Business Tendency Survey — June 2025*. CBS. Media Release. (English summary)

Şahin, A., Song, J., Topa, G., & Violante, G. L. (2014). Mismatch unemployment. *American Economic Review, 104*(11), 3529–3564.

Santarelli, E., Carbonara, E., & Tripathi, I. (2025). Assessing the impact of AI on labor market outcomes: A meta-analysis. SSRN.

Yashiv, E. (2000). The determinants of equilibrium unemployment. *American Economic Review, 90*(5), 1297–1322.

Hebrew

Dor, O. (2024, November 21). Some companies have already let employees go and replaced them with AI. Millions of jobs are at high risk — including lawyers and developers. *TheMarker*.

Lior, G. (2025, July 13). Employment service: About 14,000 workers from the high-tech sector are looking for work. *Ynet*.

Shulman, S. (2025, July 13). Slow down in high-tech employment does not necessarily indicate a crisis in the sector. *Calcalist*.

Appendix

Table A1. Regression results: The effect of a 100% increase in exposure to AI on the unemployment rate

	Dependent variable	Unemployment rate				
Occupation	Occupation 3-digit	Occupation 3-digit (excl. high-tech)	Skill-based cluster (occupation 3-digit)		Occupation 2-digit	Skill-based cluster (occupation 2-digit)
Number of clusters	46	44	20	10	31	10
Quarter/Column	(1)	(2)	(3)	(4)	(5)	(6)
2022						
Q1	-0.0341***	-0.0258***	-0.0526	-0.0085	-0.0065***	-0.0073
	(0.0026)	(0.0007)	(0.0207)ø	(0.0109)	(0.0024)	(0.0257)ø
Q2	-0.0105	0.0024	-0.0321	-0.0258***	0.0189***	0.0128
	(0.0188)ø	(0.0148)ø	(0.0227)ø	(0.0020)	(0.0018)	(0.0211)ø
Q3	-0.0320***	-0.0169***	-0.0263***	-0.0587***	-0.0184	-0.0668
	(0.0033)	(0.0040)	(0.0048)	(0.0093)	(0.0117)	(0.0151)ø
Q4	-0.0192***	-0.0112	-0.0087	-0.0710***	0.0033	-0.0278
	(0.0029)	(0.0360)ø	(0.0426)ø	(0.0075)	(0.0033)	(0.0199)
2023						
Q1	0.0021	-0.0021	0.0073	-0.0362***	-0.0310***	-0.0548
	(0.0200)ø	(0.0206)ø	(0.0226)ø	(0.0056)	(0.0069)	(0.0122)ø
Q2	0.0138	0.0116***	0.0016	-0.0182***	-0.0054	-0.0149
	(0.0169)ø	(0.0014)	(0.0216)ø	(0.0061)	(0.0077)	(0.0118)
Q3	0.0063	0.0055	0.0025	-0.0111***	-0.0122**	-0.0175
	(0.0212)ø	(0.0219)ø	(0.0243)ø	(0.0037)	(0.0052)	(0.0240)ø
Q4	0.0007	0.0123***	-0.0130	0.0117	0.0028	-0.0010
	(0.0044)	(0.0029)	(0.0229)ø	(0.0118)	(0.0056)	(0.0179)
2024						
Q1	-0.0188***	-0.0186***	-0.0228	-0.0222**	-0.0150**	-0.0145
	(0.0018)	(0.0022)	(0.0156)ø	(0.0111)	(0.0061)	(0.0183)
Q2	0.0439	0.0340***	0.0546	0.0139	0.0361***	0.0353
	(0.0218)ø	(0.0015) ø	(0.0214)ø	(0.0229)ø	(0.0068)	(0.0216)
Q3	0.0172***	0.0175***	0.0072*	0.0175***	0.0302**	0.0274
	(0.0036)	(0.0043)	(0.0041)	(0.0064)	(0.0125)	(0.0185)
Q4	0.0345***	0.0303***	0.0379	0.0084	0.0382***	0.0284*
	(0.0026)	(0.0045)	(0.0202)ø	(0.0230)ø	(0.0078)	(0.0153)

(table continues)

Table A1 (continued). Regression results: The effect of a 100% increase in exposure to AI on the unemployment rate

Dependent variable		Unemployment rate				
Occupation	Occupation 3-digit	Occupation 3-digit (excl. high-tech)	Skill-based cluster (occupation 3-digit)		Occupation 2-digit	Skill-based cluster (occupation 2-digit)
Number of clusters	**46**	**44**	**20**	**10**	**31**	**10**
Quarter/Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
2025						
Q1	0.0408**	0.0396**	0.0376***	0.0211	0.0383***	0.0619***
	(0.0161)	(0.0175)	(0.0053)	(0.0193)ø	(0.0068)	(0.0039)
Q2	0.0120	0.0104	0.0053	0.0730	0.0317***	0.0383*
	(0.0190)	(0.0208)	(0.0194)ø	(0.155)ø	(0.0103)	(0.0226)ø
Q3	0.0033	0.0073***	-0.0011	0.0525	0.0189***	0.0425***
	(0.0027)	(0.0023)ø	(0.0056)	(0.0435)	(0.0052)	(0.0065)
Vacancy rate	-0.0596**	***0.0717-	-0.0742	-0.0907***	-0.1405***	-0.1763**
	(0.0297)	(0.0292)	(0.0558)	(0.0311)	(0.0477)	(0.0765)
Additional variables	Average unemployment rate in 2019 in occupation/cluster, year-quarter fixed effects, intercept					
Number of observations	471	442	245	121	401	138
R^2	0.40	0.41	0.43	0.67	0.55	0.57
F-statistic	11.3	6.9	20.7	18.2	18.6	22.6
(p value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: The table presents regression results estimating the effect of the AI exposure index (E1) on the unemployment rate across different occupations (or occupation clusters) and time periods. Each cell reports the coefficient estimate, with the standard error shown in parentheses below. Standard errors are two-way clustered by year-quarter and occupation, except for those marked with ø, which are clustered by occupation only.

Significance levels: *p < 0.1; **p < 0.05; ***p < 0.01.

Source: Michael Debowy, Gil S. Epstein, and Avi Weiss, Taub Center | Data: CBS

Table A2. Regression results: The effect of a 100% increase in exposure to artificial intelligence on the job vacancy rate

	Dependent variable	Job vacancy rate			
Occupation	Occupation 3-digit	Skill-based cluster (occupation 3-digit)		Occupation 2-digit	Skill-based cluster (occupation 2-digit)
Number of clusters	**46**	**44**	**20**	**10**	**31**
Quarter/column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
2022					
Q1	0.0324	0.0301	-0.2276***	0.0070	-0.0024
	(0.0318)ø	(0.0329)ø	(0.0661)	(0.0146)	(0.0079)
Q2	-0.0264	-0.0280	0.0179	-0.0303	-0.0490*
	(0.0277)ø	(0.0213)ø	(0.0179)	(0.0188)	(0.0280)
Q3	-0.0221	-0.0176***	-0.0063	-0.0405***	-0.0221
	(0.0523)ø	(0.0021)	(0.0133)	(0.0125)	(0.0338)
Q4	0.0072	-0.0261***	0.0002	-0.0224*	-0.0393
	(0.0086)	(0.0060)	(0.0278)	(0.0131)	(0.0253)ø
2023					
Q1	-0.0289**	-0.0555***	0.0627***	0.0155*	0.0141
	(0.0136)	(0.0046)	(0.0189)	(0.0093)	(0.0178)
Q2	-0.0186	-0.0509***	0.0876***	0.0063	-0.0105
	(0.0122)	(0.0075)	(0.0225)	(0.0111)	(0.0137)
Q3	-0.0297**	-0.0541***	-0.0534***	0.0090	-0.0229***
	(0.0134)	(0.0061)	(0.0155)	(0.0088)	(0.0084)
Q4	-0.0407***	-0.0369***	-0.1275***	-0.0147	-0.0506
	(0.0115)	(0.0048)	(0.0081)	(0.0153)	(0.0318)
2024					
Q1	-0.0897***	-0.0729	0.0145	-0.0531***	-0.1013***
	(0.0114)	(0.0411)ø	(0.0302)	(0.0095)	(0.0324)
Q2	-0.0888***	-0.0585***	-0.0273	-0.1180***	-0.1754***
	(0.0138)	(0.0015)	(0.0306)	(0.0146)	(0.0425)
Q3	-0.0306**	-0.0379	-0.0658***	-0.0923***	-0.1522***
	(0.0125)	(0.0303)ø	(0.0237)	(0.0166)	(0.0394)
Q4	-0.0778***	-0.0906***	0.0456	-0.0823***	-0.1168***
	(0.0146)	(0.0061)	(0.0305)	(0.0220)	(0.0248)

(table continues)

Table A2 (continued). Regression results: The effect of a 100% increase in exposure to artificial intelligence on the job vacancy rate

	Dependent variable	Job vacancy rate			
Occupation	Occupation 3-digit	Skill-based cluster (occupation 3-digit)		Occupation 2-digit	Skill-based cluster (occupation 2-digit)
Number of clusters	**46**	**44**	**20**	**10**	**31**
Quarter/column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
2025					
Q1	-0.1652***	-0.1957***	0.0299	-0.0590***	-0.1990***
	(0.0171)	(0.0073)	(0.0451)	(0.0106)	(0.0092)
Q2	-0.1368***	-0.1296**	-0.0371	-0.0914***	-0.2003***
	(0.0118)	(0.0642)ø	(0.205)	(0.0016)	(0.0129)
Q3	-0.0745***	-0.0874*	-0.6715*	-0.0687***	-0.1960***
	(0.0122)	(0.0507)ø	(0.3545)ø	(0.0184)	(0.0103)
Unemployment rate	-0.2003***	0.0324	0.0301	-0.2276***	0.0070
	(0.0513)	(0.0318)ø	(0.0329)ø	(0.0661)	(0.0146)
Additional variables	Average vacancy rate 2019 in the occupation/cluster, year-quarter fixed effects, intercept				
Number of observations	471	245	121	401	138
R^2	0.70	0.40	0.20	0.87	0.82
F-statistic	63.1	15.1	11.7	162.3	37.5
(p value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: The table presents regression results estimating the effect of the AI exposure index (E1) on the job vacancy rate across different occupations (or occupation clusters) and time periods. Each cell reports the coefficient estimate, with the standard error shown in parentheses below. Standard errors are two-way clustered by year-quarter and occupation, except for those marked with ø, which are clustered by occupation only.

Significance levels: *p < 0.1; **p < 0.05; ***p < 0.01.

Source: Michael Debowy, Gil S. Epstein, and Avi Weiss, Taub Center | Data: CBS

Table A3. Change in unemployment (percentage points) between 2022 and the corresponding quarter in 2024 or 2025 among selected occupations, decomposed using estimates of the effect of artificial intelligence[15]

			2024				2025		
Software Developers and Applications Analysts (251) **γ = -0.1**			**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**
Change in unemployment — total			1.3	3.3	1.1	1.3	1.2	1.8	0.3
Of this:	Due to a decline in the match — total		0.4	2.7	0.9	1.2	0.2	1.3	0.1
	Of this:	Due to AI	0.04	0.2	0.1	0.1	0.1	0.2	0.02
	Due to a decline in jobs — total		0.9	0.6	0.2	0.2	0.9	0.6	0.2
	Of this:	Due to AI	0.0	0.0	0.0	0.0	0.1	0.1	0.0
Percent change in unemployment due to AI — total			5%	5%	13%	12%	15%	17%	15%
Of this:	Due to a decline in match		3%	5%	13%	11%	10%	12%	7%
	Due to a decline in jobs		2%	0%	0%	1%	5%	5%	8%

(table continues)

15 The decomposition is calculated for occupation i in quarter q, using the estimates reported in column (1) of Table A1 and column (1) of Table A2 in the Appendix. The components shown are calculated as follows:

Change in unemployment — total			$u_{iq}^{2024} - u_{iq}^{2022}$
Of this:	Due to a decline in match — total		$u_{iq}^{2024} - u_{iq}^{2022} - \gamma \cdot (v_{iq}^{2024} - v_{iq}^{2022})$
	Of this:	Due to AI	$\left(\beta^{u}{}_{q}^{2024} - \beta^{u}{}_{q}^{2022}\right) \cdot AI_i$
	Due to a decline in jobs — total		$\gamma \cdot (v_{iq}^{2024} - v_{iq}^{2022})$
	Of this:	Due to AI	$\gamma \cdot \left(v_{iq}^{2024}\beta^{v}{}_{q}^{2024} - v_{iq}^{2022}\beta^{v}{}_{q}^{2022}\right) \cdot AI_i$

Where $u_{iq}^{2024} - u_{iq}^{2022}$ is the change in unemployment between 2022 and 2024 (or 2025) in quarter q, $(v_{iq}^{2024} - v_{iq}^{2022})$ is the change in the share of job vacancies at the same time, Υ is derived from the job vacancy coefficient estimated in column (1) of Table 1 (and calibrated according to the value shown next to the title of each subtable in Table 3), and AI_i is the AI exposure score of occupation.

The differences between the estimates $\left(\beta^{u}{}_{q}^{2024} - \beta^{u}{}_{q}^{2022}\right)$ and $\beta^{v}{}_{q}^{2024} - \beta^{v}{}_{q}^{2022}$ are calculated based on column (1) of Table A1 and column (1) of Table A2, respectively. Their values in each quarter (with standard errors in parentheses) are reported below.

	Q1	Q2	Q3	Q4
$\left(\beta^{u}{}_{q}^{2024} - \beta^{u}{}_{q}^{2022}\right)$	0.015 (0.004)	0.054 (0.041)	0.049 (0.007)	0.054 (0.006)
$\beta^{v}{}_{q}^{2024} - \beta^{v}{}_{q}^{2022}$	-0.122 (0.043)	-0.062 (0.042)	-0.009 (0.065)	-0.085 (0.023)

Table A3 (continued). Change in unemployment (percentage points) between 2022 and the corresponding quarter in 2024 or 2025 among selected occupations, decomposed using estimates of the effect of artificial intelligence

			2024				2025		
Other sales workers (524) $\gamma = -0.1$			**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**
Change in unemployment — total			4.9	2.4	1.6	0.7	-0.6	0.5	1.9
Of this:	Due to a decline in the match — total		4.4	1.9	1.2	0.3	-0.6	0.5	0.6
	Of this:	Due to AI	0.03	0.1	0.1	0.1	0.3	0.1	0.1
	Due to a decline in jobs — total		0.5	0.5	0.4	0.4	0.0	0.0	1.3
	Of this:	Due to AI	0.07	0.02	0.00	0.00	0.0	0.0	0.5
Percent change in unemployment due to AI — total			2%	5%	6%	15%	0%	10%	31%
Of this:	Due to a decline in match		1%	4%	6%	15%	0%	10%	5%
	Due to a decline in jobs		1%	1%	0%	0%	0%	0%	26%

			2024				2025		
Software Developers and Applications Analysts (251) $\gamma = -1$			**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**
Change in unemployment — total			1.3	3.3	1.1	1.3	1.2	1.8	0.3
Of this:	Due to a decline in the match — total		-7.9	-2.6	-1.2	-0.6	-8.1	-3.7	-2.1
	Of this:	Due to AI	0.04	0.2	0.1	0.1	0.1	0.2	0.02
	Due to a decline in jobs — total		9.2	5.9	2.3	1.9	9.3	5.6	2.5
	Of this:	Due to AI	0.2	0.03	0.0	0.1	0.2	0.3	0.1
Percent change in unemployment due to AI — total			22%	6%	13%	21%	26%	27%	25%
Of this:	Due to a decline in match		3%	5%	13%	11%	10%	12%	7%
	Due to a decline in jobs		19%	1%	0%	10%	16%	15%	18%

(table continues)

Table A3 (continued). Change in unemployment (percentage points) between 2022 and the corresponding quarter in 2024 or 2025 among selected occupations, decomposed using estimates of the effect of artificial intelligence

			2024				2025		
Other sales workers (524) **γ = -1**			**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**
Change in unemployment — total			4.9	2.4	1.6	0.7	-0.6	0.5	1.9
Of this:	Due to a decline in the match — total		0.2	-2.8	-2.8	-3.8	-0.1	-1.2	1.4
	Of this:	Due to AI	0.0	0.1	0.1	0.1	0.0	0.1	0.1
	Due to a decline in jobs — total		5.4	4.2	18.0	7.7	0.5-	-3.0	13.3
	Of this:	Due to AI	0.5	0.2	0.0	0.3	0.0	0.0	0.5
Percent change in unemployment due to AI — total			11%	13%	6%	51%	50%	20%	32%
Of this:	Due to a decline in match		1%	4%	6%	15%	0%	10%	5%
	Due to a decline in jobs		10%	9%	0%	37%	0%	0%	26%

Note: Telephone sales representatives (5244) account for more than 60% of this group on average over the sample period.

Source: Michael Debowy, Gil S. Epstein, and Avi Weiss, Taub Center | Data: CBS