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Avi Weiss, and Efrat Behar-Netanel

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Policy Paper No. 02.2025

Jerusalem, April 2025

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Please cite this publication as:

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. <https://doi.org/10.5281/zenodo.15322163>

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# Employment Trends and Artificial Intelligence in the Israeli Labor Market

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## Introduction

Generative Artificial Intelligence (AI) is emerging as one of the most significant technological revolutions of our time, with growing influence across many domains — including the economy and the labor market. The rapid pace of technological development and its swift adoption for work-related purposes underscore both the necessity — and the challenge — of conducting empirical research on its impact on human employment, as well as the need to formulate effective public policy to address the risks and opportunities this technology presents for Israeli workers. The speed at which generative AI is advancing gives rise to a classic “moving target” problem: it is difficult to study a technology that is evolving faster than conventional tools of measurement and analysis can keep up with. In this paper, we respond to that challenge by cross-referencing the capabilities of generative AI models from two successive generations — before and after the release of GPT-4<sup>1</sup> — with Israeli employment data from 2023–2024, alongside an analysis of trends in both technology and employment. Our findings indicate that for the average Israeli worker in 2024,

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1 The innovation of GPT-4, compared to earlier models, lies in its enhanced ability to understand complex contexts, generate accurate and nuanced texts, and successfully handle a wider range of tasks.

a large language model such as Claude, Gemini, or ChatGPT can perform at least 17% of typical work tasks without any auxiliary tools. When additional tools are available — such as image or voice generation, internet access, or specialized datasets — this figure rises to 51%. In our estimation, these rates were at least 5.3% lower in 2023. We also find that the capabilities of generative AI help explain, to some extent, the occupational profile of the unemployed and those who have stopped looking for work. Individuals with skills that AI is able to substitute for are more likely to be out of work than those with skills that AI complements — suggesting a differential impact on employment.

We begin by reviewing key research findings from Israel and abroad over the past two years. We then explain the methodology we use and present the “big picture” of the Israeli labor market. Next, we offer a current snapshot broken down by industry, education level, residential district, sector, and gender, and examine the varying trends in exposure to generative AI. Finally, we explore whether AI exposure helps explain non-employment in Israel and conclude by summarizing our findings.

## Literature review

Measuring the presence and impact of generative artificial intelligence (AI) tools in the labor market — whether in terms of potential or actual influence — has been a focus of growing scholarly attention in recent years. Most studies find that AI is expected to have a particularly significant impact in high-paying occupations, among educated workers, and among women more than among men.<sup>2</sup> Various surveys have examined the actual adoption of the technology. Bick et al. (2024) analyzed recent and historical survey data to estimate the adoption of generative AI technology among the general population in the United States, and compared it to past adoption of revolutionary information technologies. The researchers documented widespread use of generative AI. For example, in December 2024, around 41% of the US population had used AI (34% in the past week), and about 27% had used it for work purposes (24% in the past week). Among those who used AI for work, about 32% used it for an hour or more on a typical day (52% among daily users), and over 40% reported that AI saved them at least 3 hours of work per week (51% among daily users).

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2 For a review of studies examining the impact of generative artificial intelligence on the labor market and employment up to 2023, see Debowy et al. (2024).

These findings point to extensive adoption of AI for work purposes (compared to earlier technologies),<sup>3</sup> and to the efficiency gains it enables in carrying out various tasks.<sup>4</sup> Jiang et al. (2025) examined the impact of AI on the working hours of American employees in recent years, challenging the classical view in the economics literature. They found a pattern opposite to that identified by Aguiar et al. (2007), who argued that technological improvements in the long run reduce working hours and increase leisure time. By combining patent-based AI exposure indices with data from the American Time Use Survey, the researchers found that AI exposure actually significantly increases working hours — especially when it acts as a complementary input to labor. Their findings point to a phenomenon akin to the Jevons paradox: just as improvements in energy efficiency lead to greater total consumption, so, too, does the increase in labor productivity enabled by AI lead to greater demand for working hours — particularly when it enhances monitoring and oversight of workers.

In addition to survey-based studies, Hui et al. (2024) provide direct empirical evidence of AI's short-term impact on employment, especially in online labor markets. Contrary to claims by Jiang et al. (2025) that AI complements workers and increases their working hours, Hui et al. (2024) found the opposite trend among freelancers on the Upwork platform. Following the release of models like ChatGPT and DALL-E 2, workers in fields exposed to these technologies experienced a 2% drop in the number of jobs and a 5.2% decline in monthly earnings. Their study shows that skilled and experienced workers were not immune — and in some cases were even more adversely affected than their peers. These findings do not necessarily contradict those of Jiang et al. (2025), but rather underscore the complexity of AI's impact on the labor market: while in some sectors AI may complement workers and extend their working hours, in others it may replace workers entirely and reduce demand for human labor.

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3 Bick et al. (2024) also found that the adoption of generative AI technology in 2024 was faster than the adoption of personal computers in the 1980s and 1990s or of the internet in the 1990s and 2000s — although adoption for work purposes so far resembles that of personal computers in the 1980s.

4 Another point worth emphasizing is that Bick et al. (2024) also found a notable correlation between reported use of generative AI for work purposes and the AI exposure index of Eloundou et al. (2024) — the primary index we use in this study (see below) — providing some validation of the index's predictive power regarding the integration of AI into workers' tasks.

Controlled experimental studies have also made important contributions to understanding the impact of AI on work and employment. Noy & Zhang (2023) conducted an experiment involving 453 workers with academic degrees who were asked to perform a writing task tailored to their profession; half of the participants were randomly assigned access to ChatGPT. The researchers found that the time needed to complete the task was, on average, 40% shorter for those with access, and the quality of the output was 18% higher. A notable finding was that AI primarily acted as a substitute for human effort rather than a complement to worker skills — about 68% of participants with access submitted ChatGPT's initial output without any editing, and there was no correlation between editing time and the quality of the final result.

Beyond writing tasks — where generative AI technologies are known to have a relative advantage — Dell'Acqua et al. (2023) examined the technology's contribution to completing a variety of tasks required in consulting professions. In a business-academic collaboration, the researchers conducted a field experiment at the management consulting firm Boston Consulting Group, involving 758 consultants (about 7% of the firm's global workforce). The consultants were given tasks and randomly assigned to one of three groups: no AI access; access to ChatGPT-4, and access to ChatGPT-4 with prompt engineering coaching.<sup>5</sup> The experiment revealed that AI's effects vary depending on the type of task and its proximity to the technological frontier — the limits of AI's current capabilities. For tasks at the frontier (e.g., data analysis and structured writing), AI significantly increased the number of tasks completed, their speed, and the quality of output. The improvement was observed across all consultants, but was especially pronounced among those with lower skill levels. For tasks beyond the technological frontier (e.g., complex strategic thinking), AI actually degraded performance — users tended to accept incorrect but plausible-sounding answers, leading to mistakes.

Beyond studies that examined the effects of AI on specific tasks or occupations, another strand of the research literature adopts a comprehensive approach, assessing the technology's impact across the entire labor market. A common method in this literature is the development of consistent indices to quantify the capabilities of AI in performing various tasks, and cross-referencing

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5 Prompt engineering in this context refers to training in how to formulate queries to improve AI performance, along with iterative refinement of prompts through testing and adjustment.

those tasks with different occupations. This method — with various versions developed by, among others, Felten et al. (2019), Webb (2019), and Eloundou et al. (2024) — enables mapping of AI exposure across different labor market dimensions (education, gender, etc.) based on occupations or worker skills. Such a mapping of the Israeli labor market was conducted a year ago and is presented in Debowy et al. (2024), with its findings recently replicated and expanded by the Bank of Israel (2025).

Overall, the scientific literature suggests that AI has broad effects on many occupations — and the potential for even greater impact. Given the rapid advancement of the technology, and findings pointing to its swift adoption by workers, there is a need to update the mapping of AI exposure in the Israeli labor market. This will allow an assessment of the extent to which the advancement of the technological frontier — alongside other factors — has affected the Israeli labor market one year after the data analyzed in Debowy et al. (2024) and the Bank of Israel (2025). We now turn to a description of the AI exposure indices used in this study, followed by our findings for the Israeli labor market in 2024.

## AI exposure indices and measures of complementarity

To construct a comprehensive picture of the capabilities of generative artificial intelligence, we use the AI exposure index developed by Eloundou et al. (2024), which approximates the ability of fourth-generation generative AI models, such as ChatGPT-4, to perform typical tasks and activities associated with different occupations. The index is based on the O\*NET database,<sup>6</sup> which links more than 21,000 tasks and activities to hundreds of occupations. Each task and activity was classified according to its degree of exposure to AI into one of three categories:<sup>7</sup>

1. *Non-exposed task*. A task for which the use of an existing LLM tool, such as ChatGPT, does not significantly reduce the time required to complete it, or alternatively, degrades the quality of the output.
2. *Exposure E1*. A task for which basic use of an existing LLM tool, such as ChatGPT, can reduce the time required to complete the task by at least 50% without compromising the quality of the output.
3. *Exposure E2*. A task that either qualifies as an E1-level task, or one for which the LLM tool alone (e.g., ChatGPT) cannot reduce the required time by 50%, but paired with supplementary software or additional capabilities (e.g., image generation), such a reduction becomes possible.<sup>8</sup>

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6 The O\*NET (Occupational Information Network) database was established under the auspices of the US Department of Labor, with the goal of describing occupations and job roles in a detailed, accurate, and comparable manner. The classification includes a breakdown of the tasks and activities that comprise each occupation (including the relative weight of each task), as well as additional characteristics that allow for comparisons between occupations (such as "to what extent the job involves exposure to the elements," "how much responsibility is taken for the health of others," "how much public speaking is involved," and so on).

7 As a validation method, the researchers also asked GPT-4 to classify the tasks in a similar manner and found that it tended to agree with human judgment in the majority of cases.

8 According to the definitions in the original article, E2 exposure does not necessarily include E1 exposure. In other words, the definition of E2 in this paper is equivalent to "E2 + E1" in the original article by Eloundou et al. (2024).

After classifying the tasks, they were aggregated to occupations in a weighted manner, so that each occupation in the O\*NET database received E1 and E2 scores ranging from 0 to 1, reflecting the extent of that occupation's overall exposure according to the above criteria.<sup>9</sup> The resulting scores refer to occupations as classified by the American SOC system. To align these scores with the occupational classification used in the Israeli Labor Force Survey by the Central Bureau of Statistics (CBS) (based on the ISCO classification), we used the conversion table provided by the US Bureau of Labor Statistics.<sup>10</sup>

The exposure of different tasks to generative AI is not, by itself, a sufficient metric to describe its potential impact on employment in different occupations. It is reasonable to assume that the effect will differ considerably depending on the nature of the occupation — even among occupations with similar levels of exposure. In some cases, the ability to perform tasks with AI may render human employment redundant; in others, generative AI may assist human workers and enhance their performance. In the long run, some occupations may disappear from the labor market entirely, others may shrink while the remaining workers enjoy higher productivity, and others may even grow in employment volume (it is also possible that entirely new occupations will emerge).

Given this complex dynamic, the complementarity index developed by Pizzinelli et al. (2023) offers a crucial perspective. The index assigns each occupation a complementarity score (in parallel with the exposure indices), which assesses the necessity of human labor in the work processes of the given occupation. This score essentially distinguishes between professions in which AI is expected to act as a complement to human labor and those in which it may substitute for workers. Thus, even when two occupations are equally exposed to AI, the actual impact may differ substantially. In occupations with low complementarity (high substitutability) — such as telemarketing representatives or accountants — AI is

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9 In their original article, Eloundou et al. (2024) examine several options for *weighting* tasks and activities within occupations and show that their aggregate results do not vary significantly depending on the method used. We use the average of the *relevance* and *importance* weights for each task and activity — a weighting method not examined in their original article but used by Felten et al. (2023), which we adopt to facilitate comparison between indices.

10 The mapping is not one-to-one, and several groups of occupations in the SOC classification are matched to a single occupation in the ISCO classification (at the 4-digit level). In such cases, the occupation was assigned the unweighted average values of the exposure indices.

likely to replace human labor. In contrast, in occupations with high complementarity (low substitutability) — such as teachers or physicians — AI is more likely to serve as a complement to human workers.<sup>11</sup>

## AI exposure and complementarity in Israel, 2024: The big picture

In this study, the AI exposure and complementarity indices were cross-referenced with employment data from the Central Bureau of Statistics' Labor Force Surveys. Each observation in the sample (individual-month) is assigned exposure and complementarity scores based on the occupation recorded for that individual.<sup>12</sup> The final sample includes approximately 170,000 monthly observations, covering about 42,000 Israeli men and women aged 25–64, from January 2023 through December 2024. Exposure and complementarity scores are determined based on the occupation in which the individual was employed during the survey month.<sup>13</sup> An aggregate analysis of the data shows that the exposure rate for the average occupation in Israel in 2024 ranged between 0.17 (E1) and 0.51 (E2). A certain share of workers can also be identified as having a high exposure level (above 0.5): 2.4% of workers according to the E1 index,

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11 For occupations with low complementarity (high substitutability), generative AI is expected to have a clear negative impact on human employment. However, for occupations with high complementarity (low substitutability), increased employment is not necessarily expected. Even under the assumption that worker productivity rises, the effect on labor demand depends on the production process of the good or service, particularly on the elasticity of final output with respect to various human tasks and other production inputs. For a theoretical discussion, see Acemoglu (2025).

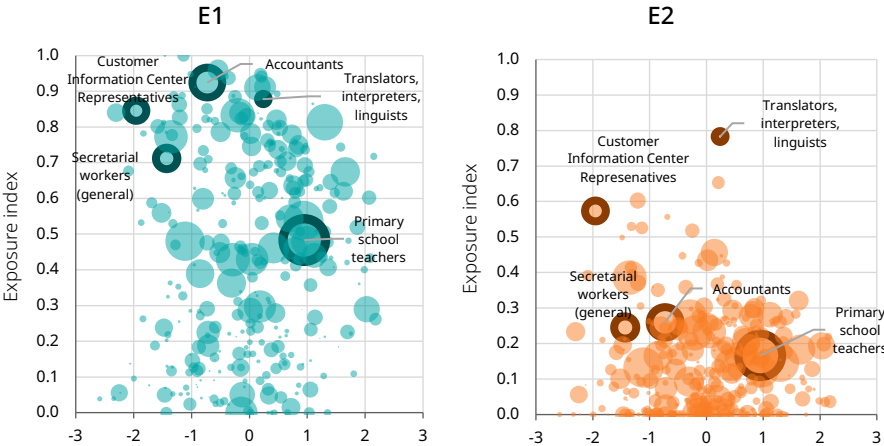
12 An occupation at the 4-digit level, as required, was recorded for approximately 89% of employed individuals, 65% of unemployed individuals, and 8% of non-participants within the age range examined (25–64). For these individuals, we impute the average exposure and complementarity scores of individuals whose occupation is known at the 4-digit level and who share the same 3-digit occupation code. Using this method, exposure and complementarity scores are available for approximately 96% of employed individuals, 94% of unemployed individuals, and 83% of non-employed individuals (with the average scores remaining unchanged). After repeating this process for 2-digit occupations and main occupation categories, scores are available for about 97% of the employed, 95% of the unemployed, and 83% of the non-employed. These individuals comprise the sample used in this study. For full details on occupation coding and average scores, see Appendix Table 1.

13 For unemployed individuals and non-participants, the occupation refers to the job they are seeking or the last job they held.

and 48.3% according to the E2 index — for reference, 2.4% of the workforce represents more than 80,000 individuals. A more nuanced picture emerges when exposure indices are considered alongside the complementarity index.

Figure 1 presents the distribution of occupations in Israel by AI exposure indices (E1 and E2) and the complementarity index, averaged over the course of 2024. The size of each bubble reflects its share of total employment, the vertical position reflects the exposure level of tasks within the occupation, and the horizontal position reflects the extent to which AI is expected to complement (right) or substitute (left) for human labor. As noted, in occupations with low complementarity, AI is expected to replace human workers. In occupations with high complementarity, AI may not replace any workers and may simply assist existing ones (and perhaps even increase demand for workers in those occupations). However, it is also possible that AI could partially replace some workers while enhancing the productivity of those who remain.

**Figure 1. AI exposure (E1 and E2) and complementarity in Israel, ages 25–64, 2024**

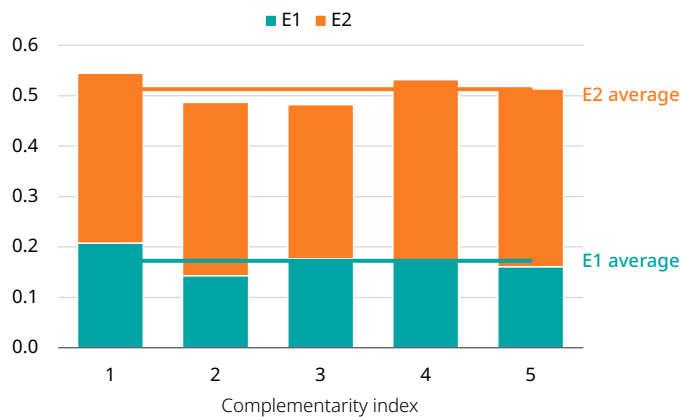


Note: Bubble size represents the relative weight of the occupation in the sample, on average in 2024.

Source: Debowy et al., Taub Center and Mosaic Institute | Data: CBS

The figure enables a comparison across occupations and provides insight into how the exposure and complementarity indices apply to them. Focusing on the basic exposure index (E1), we observe that primary school teachers and accountants have similar exposure levels, but differ in their complementarity scores: while teachers exhibit high complementarity, accountants score lower. This aligns with the expectation that teachers — despite being able to use AI for various tasks such as lesson planning, grading, and administrative work — are essential for other aspects of the educational process, such as maintaining discipline and supporting students’ social development. In contrast, human presence is less essential in the work of accountants.

**Figure 2. AI exposure (E1 and E2), by complementarity quintiles, ages 25–64, 2024**



Note: The horizontal lines represent the market-wide average. The complementarity quintiles range from 1 (low complementarity/high substitutability) to 5 (high complementarity).

Source: Debowy et al., Taub Center and Mosaic Institute | Data: CBS

A more concise picture of the relationship between complementarity and exposure can be drawn by simplifying the complementarity index into an ordinal classification that divides all occupations in the labor market into five equally sized groups according to their level of complementarity. Figure 2 presents the average exposure scores for each of these groups. We observe that

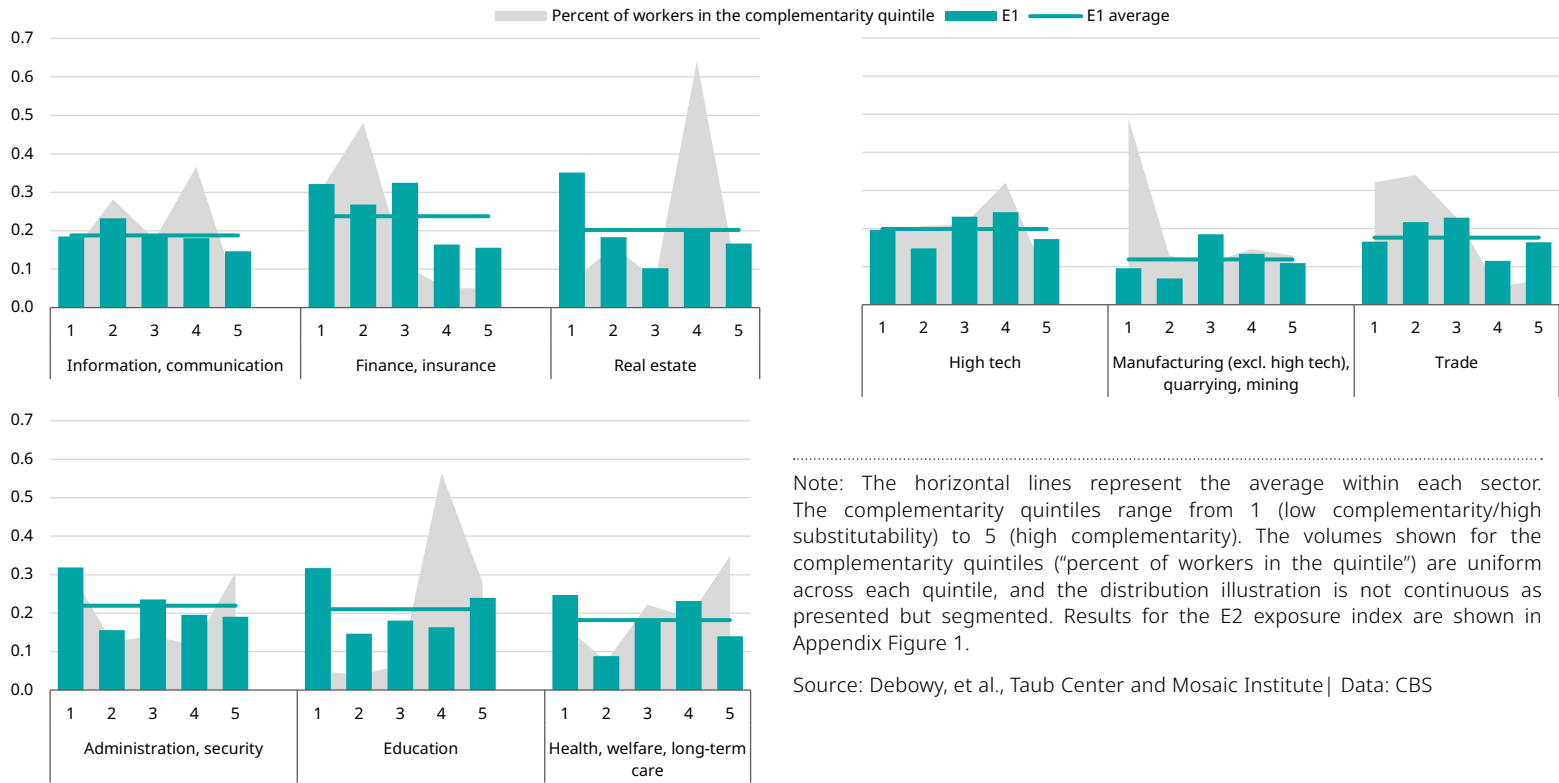
exposure levels are, on average, similar across the complementarity groups, although slightly higher among occupations with the lowest complementarity (and highest substitution risk) — a group that includes occupations such as bookkeepers and secretarial staff (alongside low-exposure occupations such as butchers or pastry chefs). However, this aggregate summary of the labor market tells only a partial story. We now turn to a more detailed snapshot segmented by different parts of the working population, in order to better understand the potential impact of artificial intelligence on the labor market.

## **Exposure and complementarity by industry sector, education, residential district, gender, and sector**

It is worth recalling that when the index was developed (about a year prior to the publication of this paper), the E2 criterion referred to auxiliary tools — some of which existed at the time, while others have since been developed (and some remain theoretical at this stage). Therefore, it is reasonable to assume that the practical applicability of these tools varies across occupations, and that the *current* score of each occupation lies somewhere between the E1 and E2 levels. As a conservative step, we now focus on exposure scores according to the E1 index (which refers to tasks that language models can perform independently), which we interpret as a lower bound for actual exposure. Results for the E2 index are presented in the Appendix.

We begin with an examination of economic sectors. Figure 3 presents exposure rates across selected sectors, similar to Figure 2 — the gray shading behind each bar represents the share of workers in the sector whose occupation falls into the relevant complementarity quintile (the quintile division is based on the entire labor market and remains consistent across sectors). Notable differences can be observed between sectors. For example, while the real estate and finance sectors exhibit similar average exposure rates (approximately 0.2–0.3 for E1 and about 0.7 for E2), the distribution of jobs across complementarity levels differs significantly. In real estate, jobs are concentrated in occupations with high complementarity, whereas in finance, jobs are concentrated in occupations with low complementarity (high substitutability). This suggests that despite similar exposure rates, the risk of human workers being replaced is substantially higher in the finance sector than in real estate.

Figure 3. AI exposure (E1), by economic branch and complementarity quintile, ages 25–64, 2024

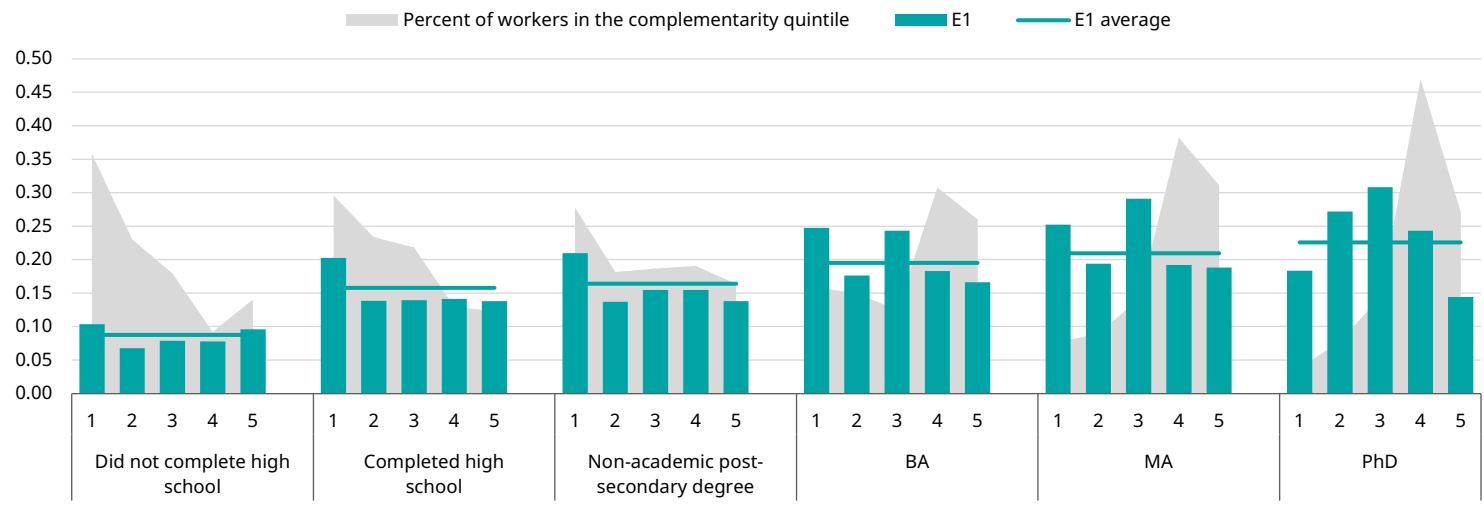


Note: The horizontal lines represent the average within each sector. The complementarity quintiles range from 1 (low complementarity/high substitutability) to 5 (high complementarity). The volumes shown for the complementarity quintiles ("percent of workers in the quintile") are uniform across each quintile, and the distribution illustration is not continuous as presented but segmented. Results for the E2 exposure index are shown in Appendix Figure 1.

Source: Debowy, et al., Taub Center and Mosaic Institute | Data: CBS

Similar to the analysis by economic sector, we can examine exposure rates by the education level of workers (Figure 4). While exposure scores consistently increase with higher education, the distribution of workers across complementarity quintiles varies significantly across education levels. Workers with academic degrees tend to be concentrated in occupations with high complementarity, whereas other workers are concentrated in occupations with low complementarity (high substitutability). For example, among employed individuals with a bachelor's degree, 16% are in the highest substitution risk category, compared to 30% among those with only a high school education — even though exposure levels are higher in the former group. This finding underscores the complexity of analyzing AI capabilities and highlights the importance of the complementarity index: the claim that artificial intelligence primarily threatens the most educated workers is inaccurate — in some respects, the risk of replacement may actually be higher among less-educated workers, even if their exposure to AI is lower.

Figure 4. AI exposure (E1), by highest educational attainment and complementarity quintile, ages 25–64, 2024



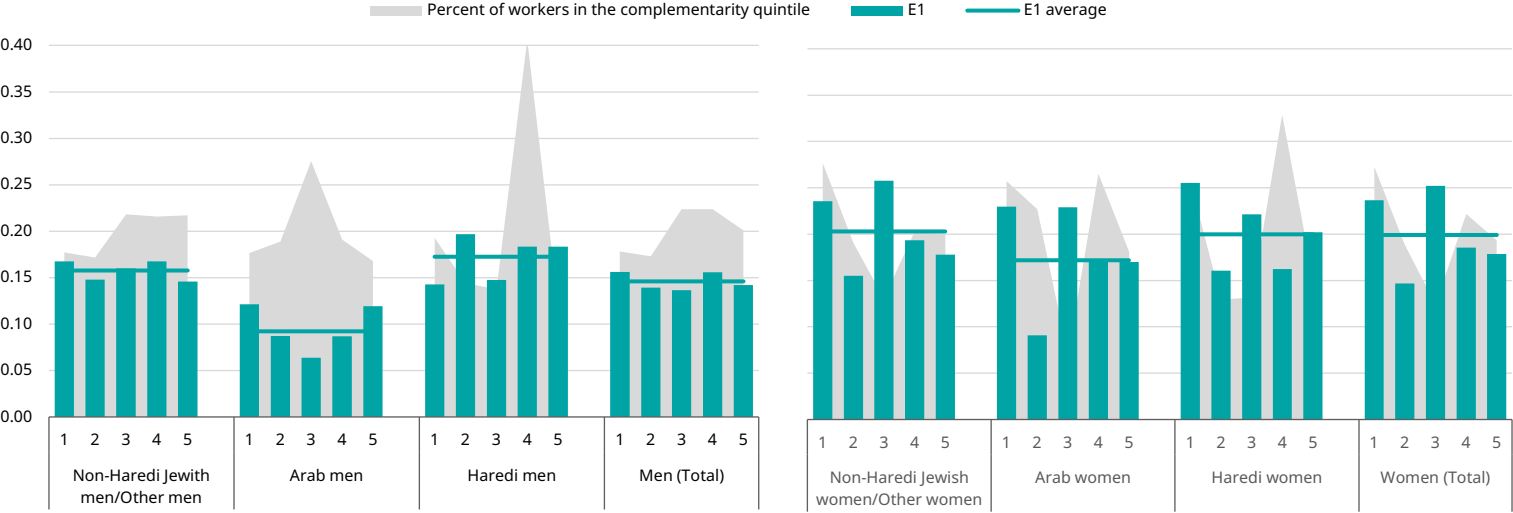
Note: The horizontal lines represent the average within each sector. The complementarity quintiles range from 1 (low complementarity/high substitutability) to 5 (high complementarity). The volumes shown for the complementarity quintiles (“percent of workers in the quintile”) are uniform across each quintile, and the distribution illustration is not continuous as presented but segmented. Results for the E2 exposure index are shown in Appendix Figure 2.

Source: Debowy, et al., Taub Center and Mosaic Institute | Data: CBS

Some variation is also observed by residential district (Appendix Figure 3), with exposure rates among residents of the Tel Aviv and Central districts slightly higher than those in other districts, though the difference is not substantial.

Further insights emerge when looking at gender and population group (Figure 5). On average, the exposure rate for women is higher than for men (0.20 vs. 0.15 in the E1 index, and 0.56 vs. 0.47 in the E2 index). It is evident that women are “polarized” along the complementarity index, with a relatively high share concentrated at both ends of the distribution. The main source of the average gap stems from those employed in occupations with the highest substitution risk: more than a quarter of women are in the lowest complementarity quintile (compared to less than a fifth of men), and their exposure rates are considerably higher than those of their male counterparts. This is due, in part, to the concentration of women in occupations such as secretarial work and customer service or telemarketing roles. This pattern holds within each population group, and the largest gender gap is found in the Arab sector, where the exposure rate for women is twice that of men on average — although the exposure rates for both Arab women and men are significantly lower than those of Jewish women and men across the entire complementarity distribution. This suggests that, despite the pronounced gender dimension of AI exposure — which is expected to affect women more than men — the sectoral characteristics of the Israeli labor market are substantial enough to generate differences between population groups.

Figure 5. AI exposure (E1), by gender, sector, and complementarity quintile, ages 25–64, 2024



Note: The horizontal lines represent the average within each sector. The complementarity quintiles range from 1 (low complementarity/high substitutability) to 5 (high complementarity). The volumes shown for the complementarity quintiles (“percent of workers in the quintile”) are uniform across each quintile, and the distribution illustration is not continuous as presented but segmented. Results for the E2 exposure index are shown in Appendix Figure 4.

Source: Debowy et al., Taub Center and Mosaic Institute | Data: CBS

To summarize the broader picture, four key findings stand out. First, the risk of worker replacement is particularly pronounced in the finance sector; in other high-exposure sectors — such as high-tech, education, and healthcare — the situation regarding AI complementarity is more mixed. Second, exposure to AI increases with education, but its potential effects are not uniform: among the most highly educated workers, the share at high risk of replacement is lower than among those with only a high school or non-academic post-secondary education. Third, AI exposure is higher among women than men, both in terms of substitution risk and the likelihood of relying more heavily on AI tools. Fourth, exposure to AI is higher among Jews and Others than among Arabs, and the exposure levels of Haredim are similar to those of non-Haredi Jews and Others; however, the complementarity scores for Haredim tend to be higher — mainly due to the overrepresentation of teaching professions among Haredi women, and especially among Haredi men.

These findings align with the snapshot presented in Debowy et al. (2024) and the Bank of Israel (2025), although the new exposure indices allow for a more precise quantification of AI capabilities than was possible in previous years. Nonetheless, technological developments and labor market changes have indeed led to shifts over the past two years. These shifts are crystallizing into emerging trends that may indicate longer-term transformations in the broader picture. We now turn to an analysis of short-term trends in AI exposure and employment.

## **Employment trends and exposure to AI in Israel, 2023–2024**

To track trends in the capabilities of the technology and to estimate the extent of AI exposure in 2023, we rely on an additional index — the one developed by Felten et al. (2023). This is the primary index used in past work on the subject, such as Debowy et al. (2024) and the Bank of Israel (2025). Unlike the E1 and E2 indices, which allow for direct interpretation, this index is purely relative: it captures differences between occupations but does not provide absolute scores. We convert this *older* index so that its values approximate the E1 score of each occupation relative to artificial intelligence as of 2022. This conversion is based on several unverifiable assumptions. However, we rely as much as possible on the underlying data and aim to be conservative — so that the 2023

score represents an upper bound on the technology's performance at that time, and the trend from 2023 to 2024 reflects a lower bound on the true pace of increased exposure. It is important to note that while the absolute trend presented in this paper depends on these assumptions, the relative trends across occupations depend only on the assumption that the different indices measure the same underlying phenomenon. For this reason, we focus primarily on the relative trends in our analysis. For further details, see *Harmonizing AI Exposure Indices* in the Appendix.

According to our conservative estimate, the average exposure rate in 2023 was 0.12, compared to 0.17 in 2024 (E1). This change in exposure is driven almost entirely by technological developments, given the near-zero change in the distribution of occupations over such a short time span. For example, if we had matched the 2024 exposure scores to the occupational structure of 2023, the average score (E1) would have been lower by only 0.001 compared to the 2024 average. Conversely, had we matched the 2023 exposure scores to the 2024 occupational structure, the average score would have been lower by only 0.0005. Thus, over the short time period examined, the aggregate trend is entirely determined by the technology's capabilities and not by shifts in the composition of the labor force.

As noted, this aggregate trend represents a conservative estimate of the overall increase in AI exposure between 2023 and 2024. Differences in trends across different groups of workers reveal a more complex picture — one that is also less dependent on the specific methodology used to estimate the trend. Table 1 presents the change in AI exposure relative to the average change in the labor market, broken down by complementarity quintile, gender, and sector (population group), as in Figure 5. The figure shown in each cell represents the ratio between the average increase in AI exposure across the entire labor market and the average increase in that specific group. For example, if we accept our estimate that the average increase across the labor market was approximately 0.053, then among workers in the lowest complementarity quintile, the average increase was 1.55 times greater — about 0.08. Looking at the labor market as a whole, we find that the growth rates in the bottom and middle quintiles were twice as high (or more) as those in other occupations. Additionally, by gender, we see not only that the average exposure rate for women is higher than for men, but also that it is increasing much more rapidly among women.

**Table 1. Changes in AI exposure (2024/2023) relative to the average in the labor market, by gender, sector, and complementarity quintile, ages 25–64**

| Gender and sector                   | Complementarity quintile |      |      |      |      | Total |
|-------------------------------------|--------------------------|------|------|------|------|-------|
|                                     | 1                        | 2    | 3    | 4    | 5    |       |
| Total labor market                  | 1.55                     | 0.67 | 1.43 | 0.63 | 0.71 | 1.00  |
| Non-Haredi Jewish men/Other men     | 1.22                     | 0.71 | 1.24 | 0.75 | 0.52 | 0.89  |
| Arab men                            | 0.67                     | 0.30 | 0.28 | 0.05 | 0.36 | 0.33  |
| Haredim                             | 0.74                     | 1.49 | 1.03 | 0.53 | 0.93 | 0.83  |
| All men                             | 1.07                     | 0.68 | 0.99 | 0.61 | 0.50 | 0.77  |
| Non-Haredi Jewish women/Other women | 1.80                     | 0.70 | 2.24 | 0.79 | 0.86 | 1.25  |
| Arab women                          | 1.93                     | 0.53 | 2.47 | 0.34 | 0.89 | 1.05  |
| Haredi women                        | 1.96                     | 0.70 | 2.24 | 0.24 | 1.45 | 1.17  |
| All women                           | 1.83                     | 0.67 | 2.24 | 0.64 | 0.91 | 1.22  |

Note: The complementarity quintiles range from 1 (low complementarity/high substitutability) to 5 (high complementarity). The figure shown represents the ratio between the average change in the exposure index for the given group and the average change across the entire labor market (a value of 1.00 corresponds to a 5.3 percentage point increase, according to our conservative estimate).

Source: Debowy et al., Taub Center and Mosaic Institute | Data: CBS

When looking by economic sector (Appendix Table 2), greater variability is observed, including groups of workers for whom AI exposure actually declined over 2023–2024 — primarily due to changes in the occupational composition within the group. While such shifts carry little weight in the labor market as a whole, they can be significant within specific groups. More generally, the exposure rate in the finance sector increased at more than twice the rate of the overall labor market. Less expectedly, sharp above-average increases in exposure were also observed in public administration and security, as well as in commerce; in these sectors, the increase was concentrated mainly among workers in occupations with low complementarity. Even in some sectors where overall exposure increased more slowly than the average, workers in the lowest complementarity quintile experienced faster-than-average increases in exposure.

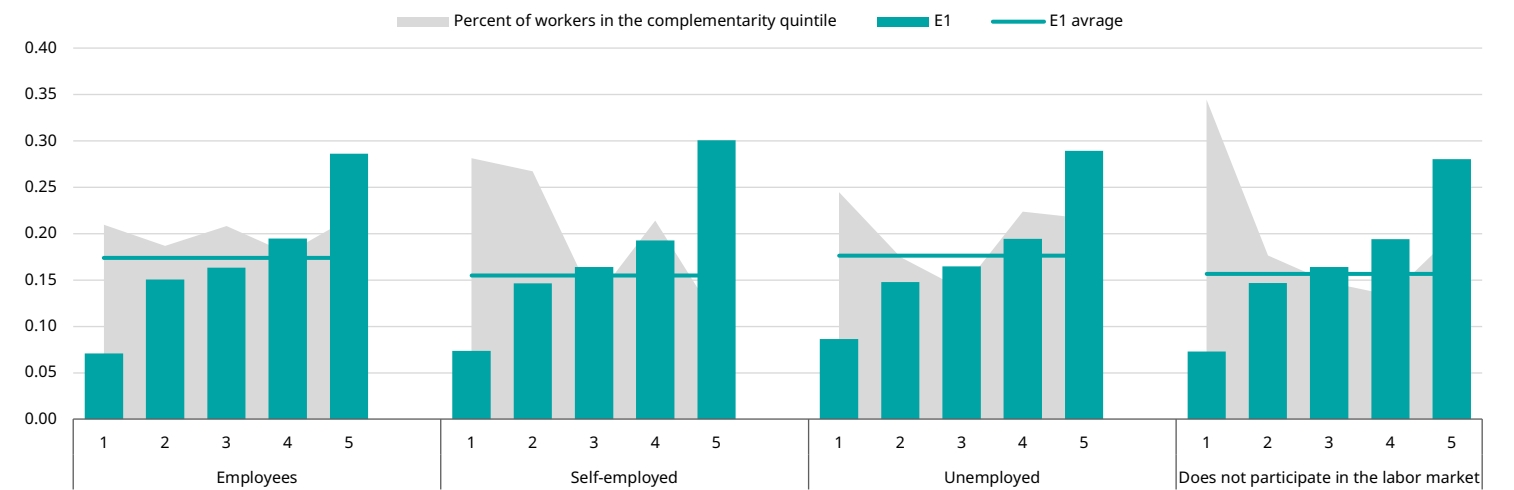
These findings indicate that the general trend in the labor market is a particularly sharp increase in exposure precisely in those occupations where AI poses a risk of replacing workers — a pattern seen across most sectors, as well as across most gender and population groups. In other words, while by the end of 2024 the picture was not clear-cut — with exposure rates similar between occupations with high and low complementarity — current trends suggest a sharper rise in exposure among the latter group. If these trends continue, the data suggest that the impact of AI on the labor market may manifest more in worker replacement than in complementing their work. The accelerated increase in AI exposure in low-complementarity occupations — where technology tends to substitute for human labor rather than enhance it — indicates that AI capabilities are advancing most rapidly in precisely those areas where the likelihood of replacing workers is greatest. To examine this issue more closely, we conducted an analysis of the relationship between AI exposure, unemployment, and employment. We now present the main findings of that analysis.

## **Does AI explain unemployment in Israel 2023–2024?**

Workers can change occupations, and even more so, unemployed individuals may end up working in a profession different from their last occupation or from the one they were seeking at the time of the survey. Focusing on the exact occupation of an unemployed person therefore yields only a partial picture of their exposure to artificial intelligence, as it omits information about the exposure levels of other employment opportunities available to them — or the exposure levels of other workers competing with them for jobs. (This is, of course, also true for employed individuals.) For this reason, we adjust the AI exposure indices in a way that reflects the fuller picture. To do this, we focus on the skills required in each occupation and define the similarity between any two occupations based on the overlap in required skills, using data from the European Union's labor organization. Each occupation then receives a new exposure score, derived from the raw exposure scores of individuals working in that occupation and in similar occupations — with greater weight given to scores from more similar occupations. This skill-adjusted exposure index reflects, for each individual, the average level of AI exposure among others with similar required skills. We use this skill-based exposure index throughout the rest of the analysis. For further details, see *From Occupations to Skills* in the Appendix.

Since the complementarity index is strongly correlated with the skills required of workers to begin with, adjusting exposure scores based on skills creates a strong correlation between exposure and complementarity. Figure 6 demonstrates this, with data shown separately for employees, self-employed individuals, unemployed persons, and those not participating in the labor force. In all groups, AI exposure rises sharply with complementarity, in line with the skills required in those occupations. This means that among workers with low complementarity (Quintile 1), most individuals are employed in (or seeking work in) occupations whose required skills are not highly exposed to AI — even if their specific occupation is. (For example, consider call center representatives, whose required skills may substantially overlap with those of in-person sales representatives.) Conversely, among workers with high complementarity (Quintile 5), individuals' skill sets tend to be highly exposed to AI, even if their specific occupation is not. (For instance, one might think of architects, whose skills substantially overlap with those of engineers or designers — professions with higher AI exposure than architecture itself.)

Figure 6. AI exposure (E1), by employment status and complementarity quintile, skills-adjusted indices, ages 25–64, 2024



Note: The indices presented have been adjusted to reflect workers' required skills, as explained in "From Occupations to Skills" in the Appendix. The horizontal lines represent the average within each group. The complementarity quintiles range from 1 (low complementarity/high substitutability) to 5 (high complementarity). The volumes shown for the complementarity quintiles ("percent of workers in the quintile") are uniform across each quintile, and the distribution illustration is not continuous as presented, but segmented.

Source: Debowy et al., Taub Center and Mosaic Institute | Data: CBS

Controlling for complementarity quintile, exposure tends to be similar between employed and non-employed individuals, although in the lowest quintile, exposure is slightly higher among the non-employed. The distribution of individuals across complementarity quintiles differs between employees, the self-employed, and non-employed individuals. In particular, non-salaried workers tend to be concentrated at the extremes of the distribution (far from Quintile 3), especially in the lowest quintile. As a result, average exposure rates differ across groups, with slightly lower exposure among the self-employed and those not participating in the labor force, compared to employees and the unemployed.

Moreover, when controlling for additional factors, we find that the AI exposure index is a key predictor of non-employment: an individual's probability of being unemployed or discouraged from job searching increases significantly with higher exposure to AI, especially in low-complementarity occupations. We estimated a logit regression to examine the relationship between various factors and the likelihood of being employed, using a sample that included only employed individuals, unemployed individuals, and non-participants who had given up looking for work. The regression controlled for a range of factors that may be correlated with employment status and skill profile, including education, age, gender and population group, economic sector, district of residence, and military reserve service. The full results are presented in Appendix Table 3.

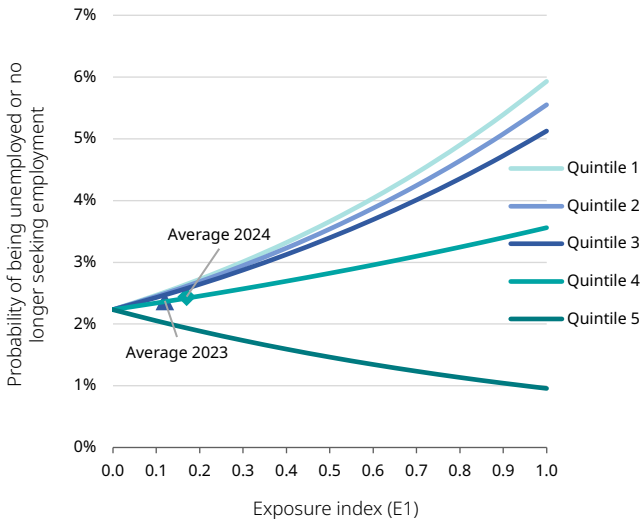
The estimates indicate that the probability of an individual being unemployed or discouraged (as opposed to employed) increases significantly and substantially with the exposure index (E1), both in 2023 and in 2024.<sup>14</sup> On average, a 0.1 increase in the exposure index corresponds to a 0.02 percentage point decrease in the likelihood of employment in 2024. This aggregate effect is driven primarily by individuals in the lower complementarity quintiles, with significant effects found only in Quintiles 1–3. Figure 7 highlights the differences across quintiles and shows the predicted probability of an “average” individual in the sample being unemployed or discouraged, given different levels of

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14 The estimation indicates that the average effect in 2023 was greater than in 2024, although the difference is not statistically significant, and we cannot rule out the possibility that the effects are identical. This finding likely reflects the difficulty of controlling for the impact of the war, particularly its effect on low-exposure occupations in sectors such as tourism, construction, and infrastructure. Isolating the effects of the war from those of technological change in an unbiased manner is beyond the scope of this study and would require dedicated research.

exposure. The probability of being unemployed or discouraged increases with exposure to AI for the bottom 80% of the complementarity distribution, but decreases with exposure for the top 20%. In the lowest quintile, a 0.1 increase in the exposure index corresponds to a 0.04 percentage point decrease in employment, whereas in the highest quintile, the same increase predicts a 0.01 percentage point increase in employment.

**Figure 7. Probability of being unemployed or discouraged from job search, by exposure index (E1) and complementarity quintile**  
Skill-adjusted indices; ages 25–64, 2024



Note: Controlling for age, education, gender and population group, economic sector, district of residence, evacuee status, military reserve service, and survey year. The figure shows the predicted probability of employment for different levels of exposure and complementarity, assuming all other variables are held constant across the predictions. Estimates are based on the regression results shown in Column (3) of Appendix Table 3. Complementarity quintiles range from 1 (low complementarity/high substitutability) to 5 (high complementarity). The markers indicating the average values for 2023 and 2024 represent the predicted employment probability for a hypothetical worker whose exposure level equals the average across the labor market, calculated using the 2024 regression coefficients.

Source: Debowy et al., Taub Center and Mosaic Institute | Data: CBS

The figure also includes the predicted non-employment probabilities for workers with average exposure levels in 2024 and 2023. The gap between the averages suggests that for the “average” worker, the change in AI exposure between 2023 and 2024 corresponds to a 0.07 percentage point decrease in the probability of being employed, holding all other observed employment-related factors constant. However, since the two years lie within one another’s sampling margin of error, this estimate cannot be validated statistically. Still, given larger aggregate changes, the model predicts a statistically significant effect on individual employment: a change twice the size of that observed between 2023 and 2024 (which, as noted, is a lower bound on the true change) would predict a 0.14 percentage point decrease in the likelihood of employment. In other words, it is possible that generative artificial intelligence has already affected individual employment and aggregate employment rates. Indeed, the multivariate analysis indicates that we can reject the hypothesis that AI technology had no effect on employment in 2024.

This analysis suggests that AI exposure indices have predictive power regarding employment outcomes in Israel today, even if their aggregate effect appears minor over the span of a single year. Moreover, the analysis offers partial confirmation of the value in using exposure and complementarity indices jointly to understand the relationship between AI and employment. Further in-depth research is required to establish causality and determine to what extent generative AI is already affecting employment and unemployment in Israel.

## Conclusion

The unprecedented pace at which generative artificial intelligence (AI) technologies are developing and being adopted — alongside the breadth of their impact across a wide range of occupations — has sparked extensive public and academic debate regarding their implications for the labor market. Our study contributes to this discourse through an empirical analysis of Israeli labor market data, allowing us to identify initial, concrete signs of the technology’s impact, as opposed to merely theoretical forecasts. For this analysis, we adopted the AI exposure indices developed by Eloundou et al. (2024) and applied them to employment data from Israel’s Labor Force Surveys for the years 2023–2024. These indices allow us to quantify the potential impact of generative AI on different occupations, distinguishing between tasks that

large language models (LLMs) can perform independently (E1) and those that require integration with additional tools (E2). Our analysis combines exposure indices with complementarity indices — a framework that enables us to assess not only which occupations are exposed to the technology but also the degree to which AI could replace the workers in them.

Our findings indicate that, in 2024, approximately 17% of the tasks performed by the average worker in Israel were exposed to being carried out by LLMs alone (E1) — that is, LLMs could perform these tasks in at least half the time required by a human worker, while maintaining or improving output quality. When auxiliary capabilities are added to LLMs — such as image generation, internet access, or specialized datasets (E2) — this share rises to about 51%.

A comparison between 2023 and 2024 reveals several key trends. First, we estimate that average worker exposure to AI in Israel increased by at least 5% between 2023 and 2024, a rise driven almost entirely by technological advancement rather than shifts in the occupational composition of the workforce. Second, the sharpest increase in exposure was observed among workers in low-complementarity occupations — that is, occupations in which AI is more likely to replace human labor. This finding suggests that AI capabilities are advancing most rapidly in areas where the risk of worker replacement is highest. Third, we observe disparities across population groups within Israeli society. For example, women are more exposed to AI than men, and this gender gap grew slightly from 2023 to 2024. The gap is especially pronounced in occupations with low complementarity, where women are more concentrated than men. Finally, our multivariate analysis reveals a significant association between high AI exposure and a greater likelihood of being unemployed or discouraged from seeking work — especially in occupations with low complementarity. This suggests that AI's imprint on the Israeli labor market is no longer purely theoretical, but is already reflected — albeit in early stages — in real indicators of non-employment.

It is important to note that our study is subject to several methodological limitations. First, our analysis focuses on mapping AI exposure according to the recorded occupations of survey respondents, providing only a partial picture of AI's effects on the labor market. We cannot track actual implementation of the technology or its precise impact on work processes, even though it may already be reshaping task compositions within occupations and even creating entirely new ones — developments not captured in the data at our disposal. Second,

the study focuses specifically on generative AI (particularly LLMs), excluding other AI technologies that are likely to affect the labor market. For example, drivers and operators of heavy machinery — together accounting for over 5% of total employment — may face replacement by autonomous systems not included in this study. Third, a clear limitation arises from the rapid pace of technological progress and the resulting obsolescence of research in the field. The most up-to-date exposure index available to us is based on technological capabilities that are already considered nearly outdated by the time of this publication.

Nevertheless, our analysis of changes between 2023 and 2024 — both technological and employment-related—provides insight into the direction and pace of AI's influence on the labor market. Even if the course of future developments diverges from the trend we identified, we can at least use the recent past to deepen our understanding of implementation, substitution, and complementarity processes — and to prepare accordingly in terms of public policy. In addition to all these limitations, it is important to stress that the complementarity index itself may shift rapidly in response to technological developments and societal adaptation. Occupations that today exhibit high complementarity — where AI mainly serves to enhance human labor — could quickly become low-complementarity occupations as new technologies emerge. This dynamic makes long-term forecasting difficult and underscores the need for ongoing monitoring of technological change and its implications for the nature of work in Israel.

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## Appendix

**Appendix Table 1. Sample coverage**

|                                                  | 2023     |            |                     | 2024     |            |                     |
|--------------------------------------------------|----------|------------|---------------------|----------|------------|---------------------|
|                                                  | Employed | Unemployed | Not in labor market | Employed | Unemployed | Not in labor market |
| Share of observations, occupation 4-digit level  | 89%      | 62%        | 8%                  | 89%      | 68%        | 8%                  |
| E1 status for these observations only            | 0.17     | 0.19       | 0.17                | 0.17     | 0.18       | 0.16                |
| Share of observations, occupation 3+digit level  | 96%      | 94%        | 83%                 | 96%      | 94%        | 83%                 |
| E1 status for these observations only            | 0.17     | 0.19       | 0.17                | 0.17     | 0.18       | 0.16                |
| Share of observations, occupation 2+ digit level | 97%      | 95%        | 83%                 | 97%      | 95%        | 83%                 |
| E1 status for these observations only            | 0.17     | 0.19       | 0.17                | 0.17     | 0.18       | 0.16                |
| Share of observations, occupation 1+ digit level | 97%      | 95%        | 83%                 | 97%      | 95%        | 83%                 |
| Final E1 status                                  | 0.17     | 0.19       | 0.17                | 0.17     | 0.18       | 0.16                |

Notes: The table presents the share of observations in the Labor Force Survey (LFS) data from 2023–2024 for which an occupation (ISCO classification) is known, by level of classification detail, as well as the resulting average exposure score (E1) based on those observations. An exposure score is assigned directly only to observations with a 4-digit occupation code; when the 4-digit code is unknown, the observation is assigned a score based on the average for the corresponding 3-digit occupation (among those with a known 4-digit code), and so on for 2-digit and 1-digit codes.

Source: Debowy et al., Taub Center and Mosaic Institute | Data: CBS

**Appendix Table 2. Change in AI exposure (2024/2023), relative to the market average, by industry sector and complementarity quintile, ages 25–64**

| Industry sector                                                    | Complementarity quintile |       |       |       |       | Total |
|--------------------------------------------------------------------|--------------------------|-------|-------|-------|-------|-------|
|                                                                    | 1                        | 2     | 3     | 4     | 5     |       |
| Overall labor market                                               | 1.55                     | 0.67  | 1.43  | 0.63  | 0.71  | 1.00  |
| Finance, insurance                                                 | 2.89                     | 2.07  | 2.93  | 0.04  | -0.24 | 2.19  |
| Administration, security                                           | 2.99                     | 0.64  | 1.98  | 0.90  | 1.30  | 1.78  |
| Trade                                                              | 0.94                     | 1.89  | 2.35  | 0.20  | 0.93  | 1.55  |
| Arts, entertainment, leisure                                       | 0.46                     | 2.84  | 0.94  | 0.24  | 2.73  | 1.32  |
| High tech                                                          | 1.30                     | 0.16  | 1.80  | 1.82  | 0.71  | 1.30  |
| Health, welfare, long-term care                                    | 1.68                     | 0.11  | 1.46  | 1.57  | 0.40  | 1.05  |
| Communication (excl. high tech)                                    | 0.92                     | 1.66  | 0.96  | 0.67  | 0.34  | 1.04  |
| Hospitality, foot services                                         | 1.04                     | 0.75  | 1.37  | 0.15  | 1.20  | 0.99  |
| Management, support services                                       | 3.44                     | 0.30  | -0.07 | -0.28 | -0.42 | 0.91  |
| Education                                                          | 2.99                     | 0.62  | 1.33  | 0.10  | 2.03  | 0.89  |
| Professional services, science, technicians (excl. high tech)      | 1.78                     | 0.10  | 2.38  | 0.91  | -0.40 | 0.83  |
| Real estate                                                        | 3.62                     | 0.69  | 0.30  | 0.70  | 0.23  | 0.82  |
| Transportation services, storage, mail, courier                    | 1.41                     | 1.36  | 0.50  | 0.27  | 0.08  | 0.68  |
| Electricity, gas, steam & water; infrastructure & waste management | 1.41                     | 2.16  | 1.07  | -0.02 | -0.48 | 0.66  |
| Manufacturing (excl. high tech), mining, quarrying                 | 0.32                     | -0.25 | 1.63  | 0.71  | -0.12 | 0.38  |
| Construction                                                       | 2.12                     | -0.11 | 0.16  | -0.02 | 0.14  | 0.28  |
| Agriculture                                                        | 0.51                     | 0.06  | -0.27 | 1.29  | 0.28  | 0.15  |
| Other services                                                     | 1.34                     | -0.92 | 2.03  | 1.27  | 1.11  | 0.13  |
| Sector unknown                                                     | 0.90                     | 0.12  | 2.06  | 0.61  | 0.26  | 0.96  |

Notes: The complementarity quintiles range from 1 (low complementarity/high substitutability) to 5 (high complementarity). The figure shown represents the ratio between the average change in the exposure index for the given group and the average change across the entire labor market (1.00 corresponds to a 5.3 percentage point change according to our conservative estimate).

Source: Debowy et al., Taub Center and Mosaic Institute | Data: CBS

**Appendix Table 3. Logit estimation results for the probability of being employed, controlling for age, industry sector, gender, sector, residential district, evacuee status, reserve duty, and survey year, ages 25–64, 2023–2024**

|                                  |                                           | Dependent variable = Likelihood of being employed |                       |                             |                       |
|----------------------------------|-------------------------------------------|---------------------------------------------------|-----------------------|-----------------------------|-----------------------|
|                                  |                                           | Total                                             |                       | By complementarity quintile |                       |
|                                  |                                           | (1)                                               | (2)                   | (3)                         | (4)                   |
| Year (interaction with exposure) | Exposure index / complementarity quintile | E1 (skills-adjusted)                              | E2 (skills-adjusted)  | E1 (skills-adjusted)        | E2 (skills-adjusted)  |
| 2023                             | Total                                     | -1.512***<br>(0.2744)                             | -1.475***<br>(0.2747) |                             |                       |
| 2024                             |                                           | -0.973***<br>(0.2505)                             | -0.590**<br>(0.1916)  |                             |                       |
|                                  | Quintile 1                                |                                                   |                       | -1.373***<br>(0.2740)       | -1.380***<br>(0.2736) |
|                                  | Quintile 2                                |                                                   |                       | -1.727***<br>(0.4185)       | -1.736***<br>(0.4180) |
|                                  | Quintile 3                                |                                                   |                       | -1.559***<br>(0.3991)       | -1.566***<br>(0.3980) |
|                                  | Quintile 4                                |                                                   |                       | -0.960<br>(0.5049)          | -0.985*<br>(0.5009)   |
|                                  | Quintile 5                                |                                                   |                       | -0.198<br>(0.6867)          | -0.224<br>(0.6841)    |
|                                  | Quintile 1                                |                                                   |                       | -1.027***<br>(0.2879)       | -1.052***<br>(0.2748) |
|                                  | Quintile 2                                |                                                   |                       | -0.956*<br>(0.4123)         | -0.988*<br>(0.3955)   |
|                                  | Quintile 3                                |                                                   |                       | -0.870**<br>(0.3095)        | -0.873**<br>(0.2960)  |
|                                  | Quintile 4                                |                                                   |                       | -0.484<br>(0.5036)          | -0.600<br>(0.3289)    |
|                                  | Quintile 5                                |                                                   |                       | 0.865<br>(0.6631)           | 0.730*<br>(0.3724)    |

**Appendix Table 3 (continued). Logit estimation results for the probability of being employed, controlling for age, industry sector, gender, sector, residential district, evacuee status, reserve duty, and survey year, ages 25–64, 2023–2024**

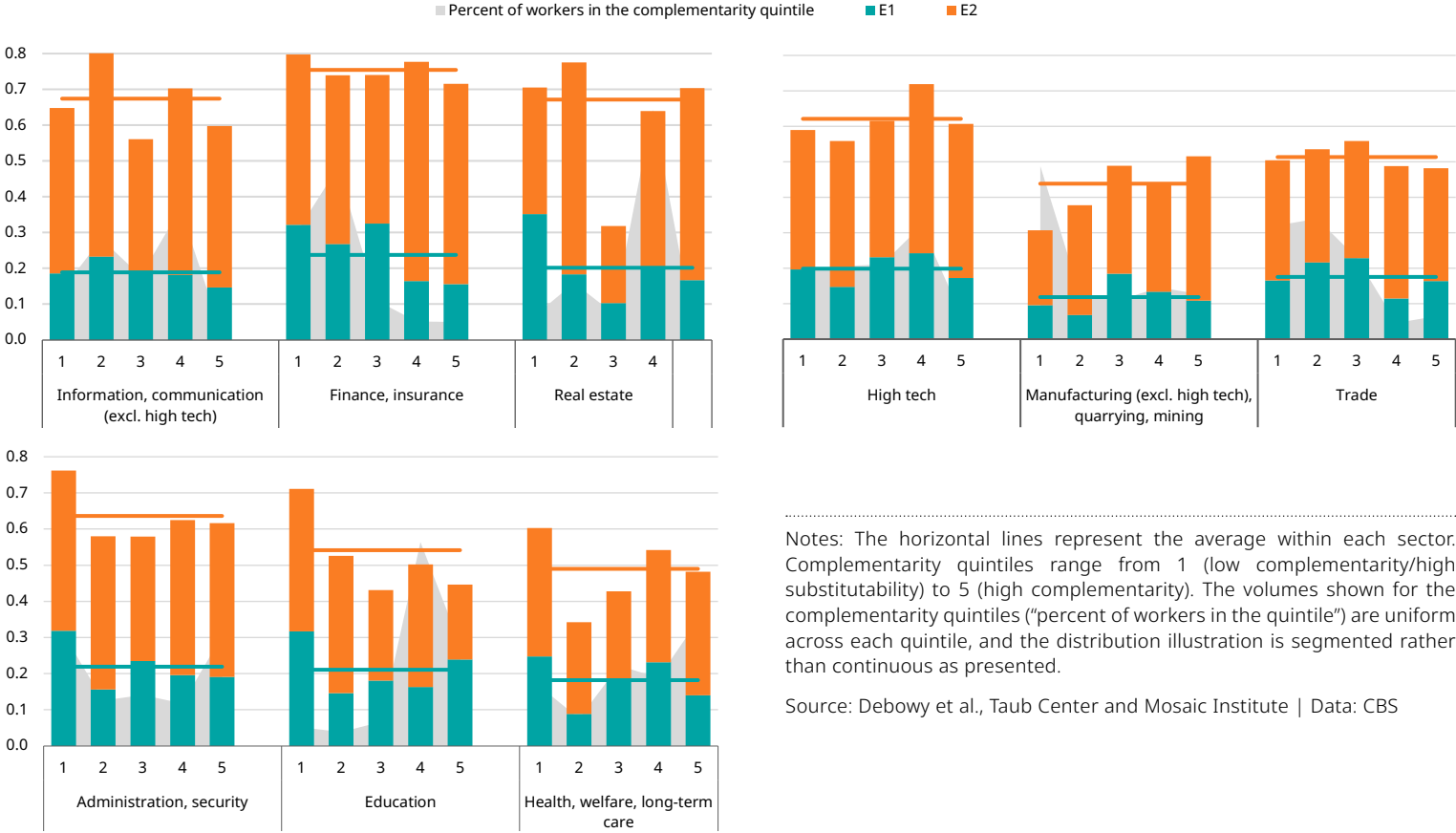
|                                                                                                                                                                                                 |                                           | Dependent variable = Likelihood of being employed |                      |                             |                      |
|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------|---------------------------------------------------|----------------------|-----------------------------|----------------------|
|                                                                                                                                                                                                 |                                           | Total                                             |                      | By complementarity quintile |                      |
|                                                                                                                                                                                                 |                                           | (1)                                               | (2)                  | (3)                         | (4)                  |
| Year (interaction with exposure)                                                                                                                                                                | Exposure index / complementarity quintile | E1 (skills-adjusted)                              | E2 (skills-adjusted) | E1 (skills-adjusted)        | E2 (skills-adjusted) |
| Additional variables: age, age squared, residential district (broken down by evacuated areas during the war), evacuated, industry sector, highest educational certificate, gender, sector, year |                                           | √                                                 | √                    | √                           | √                    |
| Number of observations                                                                                                                                                                          |                                           | 158,761                                           | 158,761              | 158,761                     | 158,761              |
| Pseudo R <sup>2</sup>                                                                                                                                                                           |                                           | 0.04                                              | 0.04                 | 0.04                        | 0.04                 |
| Statistical χ <sup>2</sup>                                                                                                                                                                      |                                           | 937.7                                             | 925.8                | 931.2                       | 930.6                |
| p value statistical                                                                                                                                                                             |                                           | 0.000                                             | 0.000                | 0.000                       | 0.000                |

Notes: Each cell presents the coefficient estimate, with the standard error in parentheses below. In the regressions reported in columns (1) and (2), the exposure coefficient is estimated uniformly for the entire population, while in columns (3) and (4) it is estimated separately for each complementarity quintile. Complementarity quintiles range from 1 (low complementarity / high substitutability) to 5 (high complementarity). Exposure indices are adjusted for worker skills, as described in *From Occupations to Skills* later in this appendix. For 2023, our estimate of E1 is used even when E2 is used for 2024. Standard errors are clustered at the individual level. The reserve duty variable is calculated as the share of survey waves (up to and including the current one) in which the respondent was partially or fully absent from work — or unable to search for work — due to military reserve service. The regression sample includes only individuals who were employed, unemployed, or discouraged from job search in the survey month.

Significance levels: \*p < 0.10; \*\*p < 0.05; \*\*\*p < 0.01.

Source: Debowy et al., Taub Center and Mosaic Institute | Data: CBS

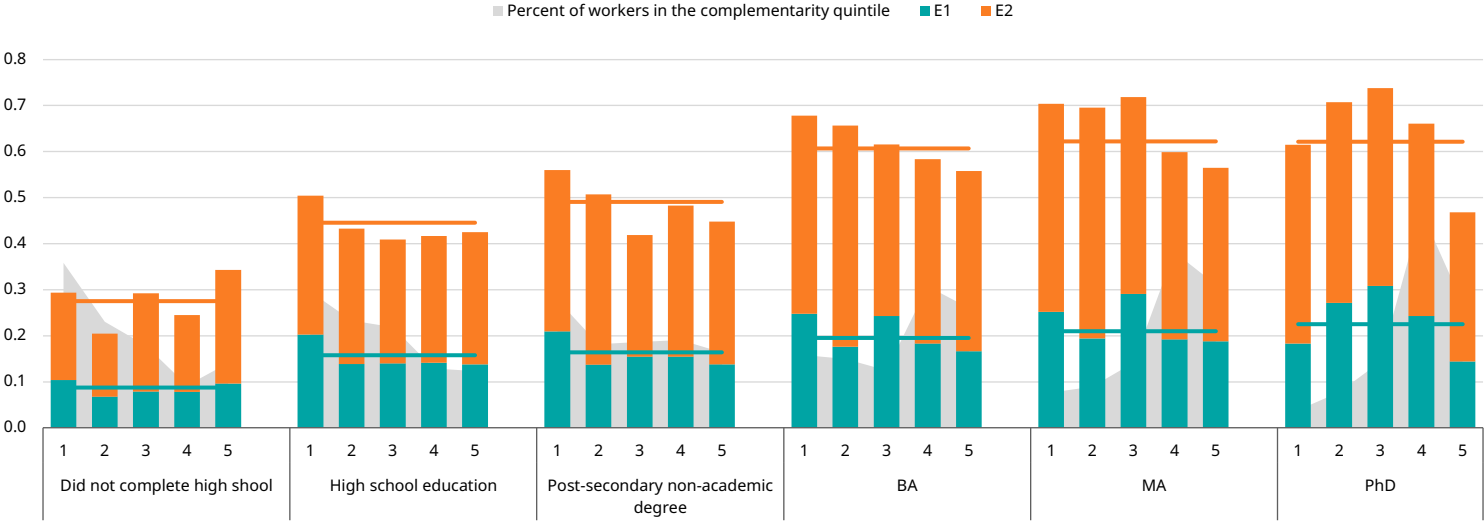
Appendix Figure 1. AI exposure (E1 and E2), by industry sector and complementarity quintile, ages 25–64, 2024



Notes: The horizontal lines represent the average within each sector. Complementarity quintiles range from 1 (low complementarity/high substitutability) to 5 (high complementarity). The volumes shown for the complementarity quintiles (“percent of workers in the quintile”) are uniform across each quintile, and the distribution illustration is segmented rather than continuous as presented.

Source: Debowy et al., Taub Center and Mosaic Institute | Data: CBS

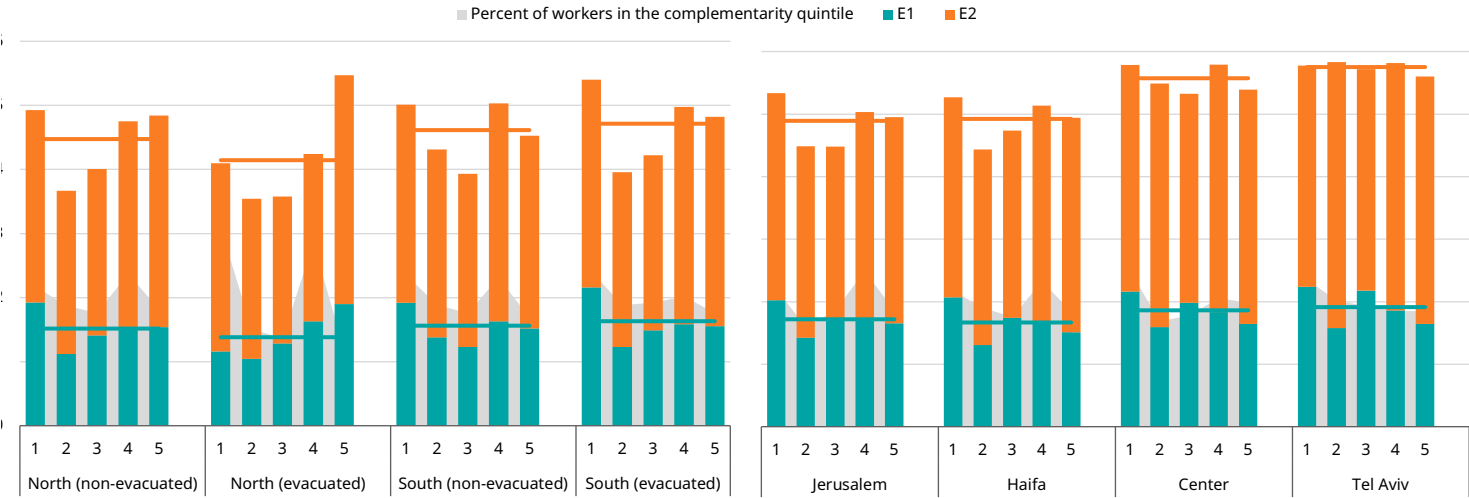
**Appendix Figure 2. AI exposure (E1 and E1), by highest educational certificate and complementarity quintile, ages 25–64, 2024**



Notes: The horizontal lines represent the average within each sector. Complementarity quintiles range from 1 (low complementarity/high substitutability) to 5 (high complementarity). The volumes shown for the complementarity quintiles (“percent of workers in the quintile”) are uniform across each quintile, and the distribution illustration is segmented rather than continuous as presented.

Source: Debowy et al., Taub Center and Mosaic Institute | Data: CBS

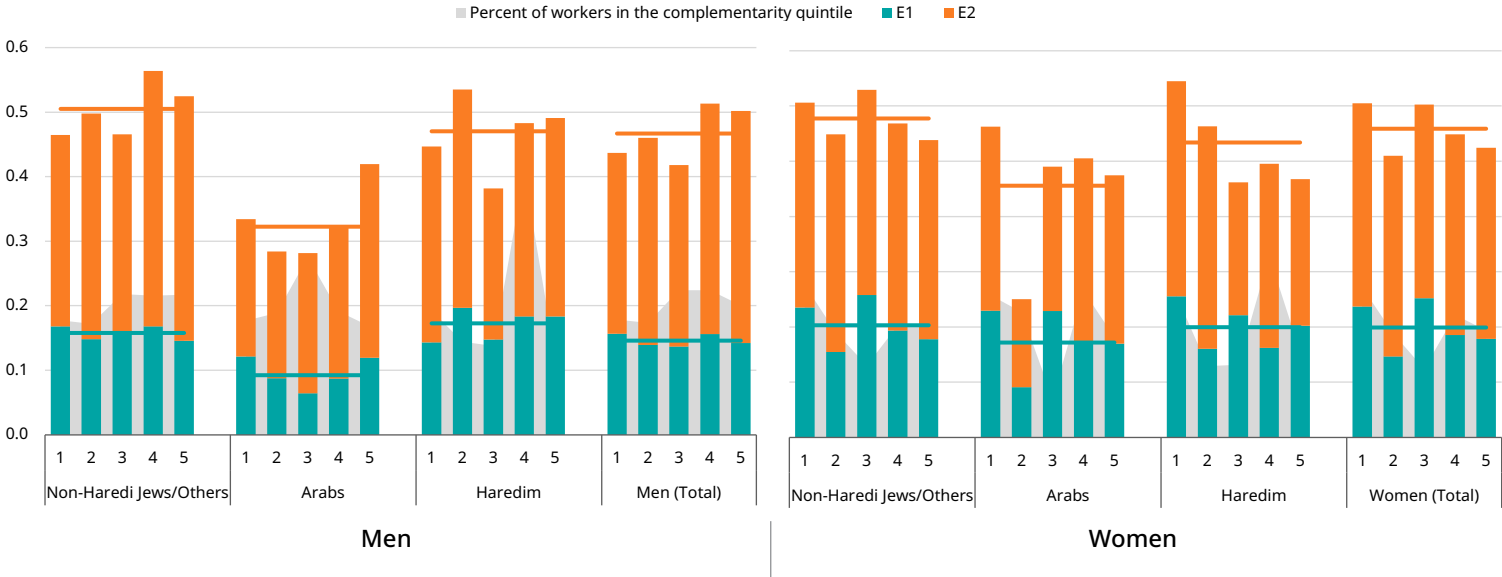
Appendix Figure 3. AI exposure (E1 and E2), by residential district and complementarity quintile, ages 25–64, 2024



Notes: Residents of the Northern and Southern districts are divided into those living in localities that were evacuated during the war and those in localities that were not evacuated. The horizontal lines represent the average within each sector. Complementarity quintiles range from 1 (low complementarity/high substitutability) to 5 (high complementarity). The volumes shown for the complementarity quintiles (“percent of workers in the quintile”) are uniform across each quintile, and the distribution illustration is segmented rather than continuous as presented.

Source: Debowy et al., Taub Center and Mosaic Institute | Data: CBS

Appendix Figure 4. AI exposure (E1 and E2), by gender, sector, and complementarity quintile, ages 25–64, 2024



Notes: The horizontal lines represent the average within each sector. Complementarity quintiles range from 1 (low complementarity/high substitutability) to 5 (high complementarity). The volumes shown for the complementarity quintiles ("percent of workers in the quintile") are uniform across each quintile, and the distribution illustration is segmented rather than continuous as presented.

Source: Debowy et al., Taub Center and Mosaic Institute | Data: CBS

## Harmonizing AI Exposure Indices

### Background

The goal of the harmonization process is to combine different AI exposure indices, estimated for different time periods, into a unified index that varies over time. The underlying assumption of this process is that the various indices are capturing the distribution of the same latent variable, which indeed evolves over time, and that the resulting unified index reflects changes in that latent variable over time to a large extent, and differences in measurement methods to a lesser extent.

To strengthen this assumption and minimize differences arising from measurement methods, we selected two indices that are relatively similar in how they assess AI exposure across occupations. The index developed by Eloundou et al. (2024) is based on assigning exposure scores to specific tasks, which are then aggregated into occupations using the O\*NET database; the original scores are derived from the authors' assessments and human survey data. The index by Felten et al. (2023), on the other hand, assigns exposure scores to different capabilities, which are then similarly aggregated into occupations using the same database. The original scores in this case are based on expert opinions regarding AI capabilities across several domains, each of which is weighted into multiple capabilities according to human survey data. The aggregation of tasks into occupations in Eloundou et al. (2024)'s index uses the same weighting method as the aggregation of capabilities into occupations in Felten et al.'s (2023) index.

Beyond the differences in timing and methodology, the two indices also differ in their mathematical nature. The index by Eloundou et al. (2024) ranges from 0 to 1 and represents an interpretable value: the percentage of weighted tasks in an occupation that AI can perform at least 50% faster than a human without compromising output quality. In contrast, the index by Felten et al. (2023) is entirely relative and does not have a clear interpretation. Therefore, we choose to base the unified index on that of Eloundou et al. (2024), and to convert Felten et al.'s (2023) index onto a comparable scale.

## Harmonizing the indices

To preserve the original variation in the index of Felten et al. (2023), the harmonization method relies on an affine transformation of that index, involving only linear scaling and shifting.

Formally, let  $\mathbb{x}_i$  denote the exposure score (E1) of occupation  $i$  according to Eloundou et al. (2024), and let  $x_i$  denote the exposure score of the same occupation according to Felten et al. (2023).

The unified index  $y_{i,t}$  representing the harmonized exposure score of occupation  $i$  in year  $t$ , is constructed as follows:

$$y_{i,t} = \begin{cases} \mathbb{x}_i & \text{if } t = 2024 \\ \alpha \cdot (x_i + \beta) & \text{if } t < 2024 \end{cases}$$

Regarding the shift, we assume in advance that the minimum score in each index is the same, since 0 is the lower bound of the index in 2024 — and as long as there are occupations with this score in that year, there certainly were such occupations in the previous year as well.

$$\beta = -\min(x)$$

As for the linear scaling, we examine various options for aligning a specific percentile of the 2024 distribution with that of 2023. These options reflect different plausible assumptions about the share of occupations for which there was little to no change in AI exposure between the two periods.

Formally, let  $p_{(w,k)}$  denote the  $k$ th percentile of the variable  $w$ .

$$\alpha = \frac{p(\mathbb{x}, k)}{p(x - \min(x), k)}$$

For example, when  $k = 0.5$ , the transformation ensures that the median score in 2024 is equal to that of 2023; combined with the previously established shift, this means that the lower half of the distribution remains within the same range across the two periods.

Finally, we examine several versions of the unified index  $y_{i,t}$ , which differ only in the choice of the anchoring percentile  $k$ , and are calculated as follows:

$$y_{i,t} = \begin{cases} x_i & \text{if } t = 2024 \\ \frac{p(x, k)}{p(x, k)} \cdot (x_i - \min(x)) & \text{if } t < 2024 \end{cases}$$

Each choice of  $k$  produces different results and offers a different depiction of the change between 2023 and 2024.

Appendix Table 4 presents the average and median changes according to the parameter  $k$ . It can be seen that after converting the indices to the ISCO classification (Panel B), the mean or median score in the distribution decreases between the years for values of  $k < 0.5$ . Under the assumption that technological exposure has not decreased, we are therefore constrained to define  $k \leq 0.5$ .

**Appendix Table 4. Relative change in the average and median exposure score in the unified index, by harmonization parameter k**

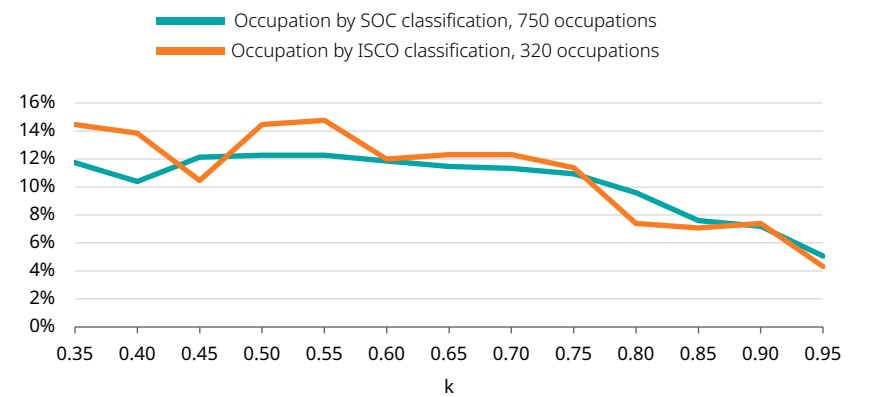
| Panel A: Occupation by SOC classification (750 occupations)  |      |      |      |      |      |      |      |      |      |      |      |      |      |
|--------------------------------------------------------------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| k                                                            | 0.35 | 0.40 | 0.45 | 0.50 | 0.55 | 0.60 | 0.65 | 0.70 | 0.75 | 0.80 | 0.85 | 0.90 | 0.95 |
| Difference between means                                     | 56%  | 43%  | 36%  | 21%  | 16%  | 10%  | 2%   | 1%   | -12% | -17% | -28% | -45% | -71% |
| Difference between medians                                   | 40%  | 24%  | 14%  | -6%  | -10% | -16% | -24% | -25% | -38% | -43% | -53% | -68% | -92% |
| Change in mean                                               | 53%  | 41%  | 34%  | 20%  | 16%  | 10%  | 2%   | 1%   | -11% | -17% | -27% | -43% | -67% |
| Change in median                                             | 29%  | 17%  | 11%  | -4%  | -7%  | -12% | -18% | -18% | -28% | -31% | -39% | -50% | -68% |
| Panel B: Occupation by ISCO classification (325 occupations) |      |      |      |      |      |      |      |      |      |      |      |      |      |
| k                                                            | 0.35 | 0.40 | 0.45 | 0.50 | 0.55 | 0.60 | 0.65 | 0.70 | 0.75 | 0.80 | 0.85 | 0.90 | 0.95 |
| Difference between means                                     | 141% | 88%  | 50%  | 35%  | 14%  | 2%   | 3%   | -3%  | -6%  | -13% | -17% | -25% | -40% |
| Difference between medians                                   | 78%  | 39%  | 11%  | 0%   | -16% | -24% | -24% | -28% | -31% | -36% | -38% | -44% | -55% |
| Change in mean                                               | 56%  | 45%  | 32%  | 25%  | 12%  | 2%   | 3%   | -3%  | -6%  | -14% | -19% | -31% | -63% |
| Change in median                                             | 29%  | 19%  | 10%  | 3%   | -9%  | -17% | -17% | -21% | -24% | -28% | -32% | -41% | -64% |

Notes: The data are presented for the list of occupations without any employment weighting. “Difference between averages/medians” refers to the percentage gap between the average and median occupation in each year; “Average/median change” refers to the average and median occupation in the distribution of annual differences.

Source: Debowy et al., Taub Center and Mosaic Institute | Data: Elandou et al., (2024); Felten et al., (2023)

We choose to adopt the most conservative possible assumption for  $k$  (within the constraint defined above) and use the magnitude of changes in the index to quantify this conservatism. Appendix Figure 5a shows the share of occupations for which the average score changes by less than one standard deviation (in 2024 terms) between the two years, as a function of the parameter  $k$ . It can be observed that the region around  $k \approx 0.5$  constitutes a local maximum, meaning that for this value of  $k$ , the share of occupations that experienced only negligible changes in technological exposure is at its lowest.

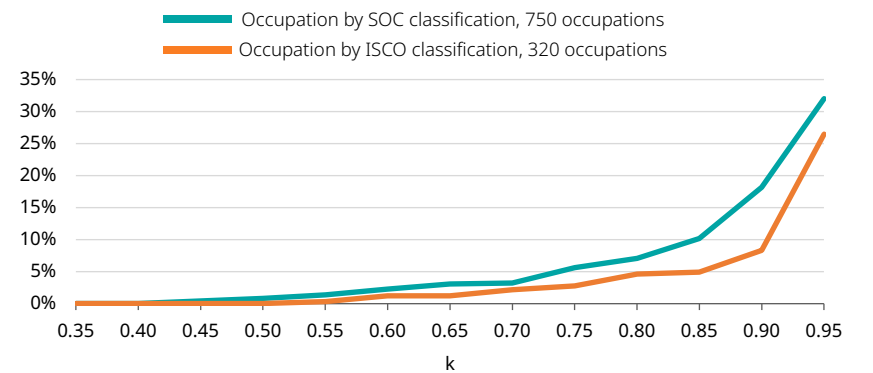
**Appendix Figure 5a. Share of occupations with  $\Delta y \approx 0$ , by harmonization parameter  $k$**



Note: The figure shown represents the percentage of occupations (in soc classification) for which the change between 2023 and 2024 was one-tenth of a standard deviation (in 2024 terms) or less.

Source: Debowy et al., Taub Center and Mosaic Institute | Data: Elandou et al., (2024); Felten et al., (2023)

**Appendix Figure 5b. Share of occupations with a significant decrease in score between 2023 and 2024, by harmonization parameter k**



Note: The lines represent the share of occupations in which the exposure score “decreased” from 2023 to 2024 by one standard deviation or more.

Source: Debowy et al., Taub Center and Mosaic Institute | Data: Elandou et al., (2024); Felten et al., (2023)

Moreover, the share of occupations for which the exposure score increases substantially between the years — contrary to the underlying assumptions — is negligible for  $k \approx 0.5$  (Figure A5b). Therefore, we adopt  $k = 0.5$  as our baseline assumption, which we view as a reasoned yet conservative estimate of the extent of technological change in the AI exposure index.

## From occupations to skills

The impact of AI exposure on an individual's employment is not limited to its effect on the typical tasks associated with their own occupation. Even if AI leads to full automation within a given occupation, the individual may switch occupations and remain employed. Conversely, even if AI does not directly affect a person's current occupation, it may displace other workers from their jobs, forcing them to compete with the individual in ways that could affect their employment.

These examples, of course, depend on individuals' ability to move between occupations. Many factors influence this ability, but in this study we focus on the skills required for each occupation. We quantify the "distance" or "proximity" between different occupations in terms of skill requirements using the [Skills-Occupations Matrix Tables](#) from the European Commission's labor organization (Matrix 2.4 of version 1.2.0), which rates the importance of 74 distinct skills across all occupations classified at the ISCO 4-digit level. Each skill receives a score between 0 (not important) and 1 (critically important) for each occupation.<sup>15</sup>

Using this matrix, we calculated the Euclidean distance between every pair of occupations across the 74 skills, and re-calculated the exposure and complementarity indices for each occupation based on the original indices of other occupations and their distance from it. This was done using an inverse sigmoid weighting function (following Acemoglu & Restrepo, 2022). Formally, let  $S_i$  be the skill vector for occupation  $i$ . The relative proximity of occupation  $j$  to occupation  $i$  is defined as  $d_{ij}$ <sup>16</sup>

$$d_{ij} = \frac{\ln(\|S_i - S_j\|)}{\sum_{j=1}^N \ln(\|S_i - S_j\|)}$$

And the skill-based index for occupation  $i$  is defined as follows (where  $w_j$  is the labor market weight of occupation  $j$ ):

$$y_i^{skills} = \sum_{j=1}^N (d_{ij} w_j y_j)$$

15 The score of 1 is purely theoretical; in practice, the highest score in the matrix is 0.66, and 99% of the scores are below 0.17.

16 In practice, for the purpose of computing the logarithm, we defined  $\|S_i - S_i\| = 1 \times 10^{-50}$