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Artificial Intelligence and the Israeli Labor Market

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Artificial Intelligence and the Israeli Labor Market

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Introduction

The penetration of artificial intelligence into the economy began in the previous decade and has already had a significant economic impact in various applications, including content writing and advertising, online retail, customer service and trading in the capital market.[1] During the last two years, there has been increasing discussion of the technological potential of artificial intelligence, particularly following the launch of tools based on large language models such as ChatGPT and Gemini. These tools have demonstrated their potential to perform complex and multifaceted tasks — tasks that require significant time, effort and skills when performed by humans, but are executed quickly and efficiently by AI tools. These tools are already widely used in tasks such as translation and proofreading, design and graphics, and communication via messaging or email — and are also applied to a lesser extent in areas such as driving, pharmaceutical development and radiology (Agrawal et al., 2019). The impact of this technological progress on the labor market has been a subject of public discourse in Israel, with forecasts ranging from cautious optimism (Manela, 2023; Sivilia, 2023) to a more reserved approach (Raphael, 2023) — alongside much more gloomy forecasts regarding the impact of the technology beyond the labor market (Harari, 2023; Shwartz Altshuler et al., 2022).

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1 For further details on the economic impact of artificial intelligence tools during the past decade, see Agrawal et al., 2018; Bresnahan, 2019; Parteka & Kordalska, 2023.

The development of artificial intelligence and its impact on the economy are being studied by important national and international bodies.[2] In 2022, the White House published a paper summarizing some of the scientific literature dealing with artificial intelligence and the labor market and presented policy recommendations that included investment in vocational training and assistance in professional retraining for workers who will be replaced by AI; investment in AI that will assist human workers at the expense of AI that has the potential to replace them; and increasing regulation of AI to improve safety and consumer protection (the White House, 2022). The European Central Bank has also recently addressed the issue, and its researchers have adopted a cautious stance (based on the existing literature), which states that it is too early to predict the impact of artificial intelligence on the labor market with any certainty, although it appears that employment in particularly exposed occupations has in fact increased in Europe in recent years, while wages in those professions have not (Albanesi et al., 2023).[3]

The International Labor Organization has also addressed the potential impact of artificial intelligence on the labor market. In a study of large language models initiated by the ILO, Gmyrek et al. (2023) examined how GPT-4 ranks artificial intelligence capabilities in the performance of tasks in various occupations. Based on a repeated sampling of the “opinion” of artificial intelligence on its capabilities (and those of other AIs) in performing various tasks, the researchers formulated a score for “exposure to artificial intelligence” for each occupation (similar to the exposure indices described below). The score is calculated according to the relative proportion of tasks that the artificial intelligence claims to be able to perform from among the tasks that make up the occupation. The researchers estimate that the clerical occupations are the only ones with the potential for complete automation and that for most other occupations, there is a small or negligible proportion of tasks that

2 The impact of artificial intelligence on the economy will be felt not only in employment and the education and health systems but will also by way of geostrategic changes resulting from the new Cold War developing around technology (The Economist, 2024), since the two military superpowers — the United States and China — are recruiting allies to their sides, and, in the shadow of the Israel-Gaza and Ukraine-Russia wars, they are discussing rules for managing artificial intelligence mechanisms during war (Sanger, 2024).

3 The World Economic Forum dealt with the impact of artificial intelligence on the labor market as a central issue in its January 2024 deliberations. The Knesset Subcommittee on Artificial Intelligence and Advanced Technologies has also initiated discussions on the subject at its May 15, 2024 meeting.

artificial intelligence can perform with at least human quality and efficiency. By correlating these exposure estimates with global employment data, the researchers argue that the proportion of workers at risk of replacement is only 0.4% in the labor markets of developing countries and 5.5% in those of developed countries. At the same time, the proportion of workers expected to benefit from artificial intelligence stands at 10.4% and 13.4%, respectively.

The OECD is one of the organizations studying the impact of artificial intelligence on the labor market, and in 2023 a significant portion of its annual labor market reviews focused on the impact of artificial intelligence. Researchers from the organization noted that while there are signs of increasing adoption of artificial intelligence tools in various industries, no substantial impact has been observed on employment or wages (Green, 2023). Furthermore, in January-February 2022, the organization conducted a survey among about 5,000 workers and 2,000 businesses that have adopted artificial intelligence technologies in the manufacturing and finance sectors in several European and North American countries. Among the workers, it was found that the use of artificial intelligence tools was primarily in repetitive and tedious tasks, thus giving the human worker more autonomy and discretion in task management, and most workers reported that the adoption of artificial intelligence increased their job satisfaction (Green et al., 2023). These findings are consistent with other surveys conducted worldwide among workers in businesses that have adopted artificial intelligence, such as Ipsos (2018) and Yamamoto (2019). However, the OECD survey found that the effects of technological change on physical and mental health varied: while a vast majority of male workers and workers with degrees reported improvements in physical safety and mental state (both in manufacturing and finance), among women and workers without degrees fewer reported improvements (and in the finance sector, a minority of female workers and workers without degrees reported an improvement). Moreover, over 75% of the workers in each sector reported that the use of artificial intelligence increases the pace of work, an effect that certainly boosts productivity but could also lead to increased burnout and fatigue.

Researchers have attempted to indirectly estimate the potential impact of artificial intelligence on the labor market by developing various indices to measure its impact on specific jobs or functions. To get an overall picture of the risk or opportunity facing workers, they sought to aggregate these indices according to the distribution of jobs and functions in a specific industry or population group within a country. Felten et al. (2019) based their findings on the AI Occupational Impact (AIOI) index they formulated, and found that the main impact of technology in recent years has been among high-income workers, contributing to a modest (though statistically significant) increase in wages but without a significant impact on employment. In a follow-up paper in the spring of 2023, the researchers updated the index and showed that developments in large language models have significantly increased the exposure to artificial intelligence in various occupations, including educators, salespeople and workers in the finance sector.

Webb (2020) developed a parallel index, based on registered patents in the field of artificial intelligence. His findings were similar to those of Felten et al. (2019), with the main exposure to artificial intelligence concentrated in knowledge-intensive professions, especially technological professions. It also showed that based on historical patterns of automation, the rise of artificial intelligence is expected to erode wages among the upper deciles of workers, although the top percentile of workers is not expected to be affected.

Acemoglu et al. (2022) used these two indices to track employment trends in the US between 2010 and 2018. They relied on the Burning Glass database (based on the collection and processing of job advertisements from the internet), which enables the identification of employers seeking to recruit workers by industry, geographical location and employment status. It was found that during this period there was an across-the-board increase in demand for workers with artificial intelligence skills, even among businesses that reduced their demand for other skilled workers. At the same time, a change was observed in the type of characteristics and skills required of workers in businesses more exposed to artificial intelligence. However, the researchers found no evidence that artificial intelligence has a substantial aggregate impact on entire professions or industries.

Pizzinelli et al. (2023) expanded on the approach of using indices by adding the *complementarity* index to the exposure indices. This index estimates the extent to which artificial intelligence might act as a complementary factor of production to human labor, making it more likely to benefit workers than replace them. The researchers combined their complementarity index with exposure indices, in a way that made it possible to characterize occupations by both their exposure to artificial intelligence and the risk or opportunity this exposure represents for employment. By linking their indices to employment data from the US, Britain, Brazil, Colombia, South Africa, and India, the researchers found that even among occupation groups with similar levels of exposure, there is a large degree of variability in the potential for complementarity. For example, those employed in “female-dominant” occupations (such as teachers, nurses and social workers) tend to have a higher potential to benefit from artificial intelligence than “male-dominant” occupations (such as tradesmen and machine operators). Additionally, when the researchers focused on occupations that are both highly exposed to artificial intelligence and also suffer from a high risk of replacement (low complementarity), they discovered that their share is higher in developed countries than in developing ones, although the share of occupations with high exposure and high complementarity is also higher in these countries. The researchers thus concluded that developed countries are more *polarized* in the potential impact of artificial intelligence on their labor markets, with a larger proportion of workers threatened by replacement, along with a larger proportion of workers whose productivity is likely to be enhanced by AI (and a smaller proportion of workers who will not be affected at all relative to developing countries).

The literature is still in its early stages, but the exposure indices formulated by Webb (2020) and Felten et al. (2023), as well as the complementarity index formulated by Pizzinelli et al. (2023), provide tools — albeit preliminary ones — for examining and mapping the potential of artificial intelligence in the labor market. In what follows, we present a somewhat deeper analysis of these indices and their use in studying the Israeli labor market, based on data from the CBS Labor Force Survey. We will first discuss the exposure indices and then integrate the complementarity index within the discussion.

Exposure to AI indices: Background

The intelligence of artificial intelligence is usually measured by its ability to complete a specific task or group of tasks. Contemporary AI systems can perform various tasks with a degree of success equivalent to that of a skilled human, often at a significantly greater speed. The term “exposure to artificial intelligence” relates to the extent of AI capabilities that correspond to a set of tasks that characterize a particular occupation, and accordingly the potential for AI to streamline and improve the performance of a human worker — or to replace him. The indices presented below are indifferent to the distinction between potential for improvement (complementarity) and the potential for replacement. Later in the paper, we will combine them with another index that takes this distinction into account.

As noted, we use two AI exposure indices that were developed by researchers in recent years and that were used in the aforementioned articles, among others. The first index was developed by Webb (2020) and estimates the degree of exposure by scanning AI patent titles and cross-referencing them with the typical tasks of various occupations, based on common word pairs (verb–noun), such as “clean-surface” or “drive-vehicle.” The index assigns exposure scores to occupations according to the number of patents associated with each of their typical tasks (while taking into consideration the “weight” of each task in the occupation). The second index was developed by Felten et al. (2023) and estimates the degree of exposure by connecting AI capabilities (derived from data from the AI Progress Measurement program of the Electronic Frontier Foundation) to tasks associated with different occupations (this latter part is identical to what was used in the construction of the first index).[4] The differences in the construction of the indices — registered patents that are related to very specific tasks in Webb (2020) versus an assessment of general capabilities in Felten et al. (2023) — necessarily imply they do not measure the same thing. Webb (2020)’s index, which has not yet been updated to include contemporary large language models, primarily measures narrowly focused tools and is particularly relevant for occupations that have been affected by AI for some time (such as content writing and advertising, online retail and customer service), as well as dedicated autonomous systems for operating various physical tools and facilities. In contrast, Felten et al. (2023)’s index is based on the aggregate capabilities of AI as a category, and thus also measures the potential of multi-purpose tools, such as large language models and systems for visual data analysis. Due to these differences, the indices do not necessarily give similar scores to similar occupations (Table 1), and, as we will see below, they even contradict each other in significant ways in certain contexts.

4 The combining of capabilities and tasks is multidimensional, and therefore the different capabilities are associated with the different tasks using varying weights. In the latest versions of the index, these weights were estimated based on a large-scale survey that reflects to some extent the “wisdom of the crowd” regarding AI performance.

The indices assign AI exposure scores to occupations based on the O*NET classification.[5] To combine these indices with the occupational classification of the CBS Labor Force Survey (ISCO classification), we used the Bureau of Labor Statistics' conversion table.[6] Occupations at the required level of detail were reported for about 85% of employees (working at least 10 hours per week) among the respondents to the Labor Force Survey between January 2018 and December 2023. These form the sample that we use to characterize the Israeli labor market. The indices of raw exposure (to AI) do not have a clear quantitative meaning. However, they can provide insight into the relative exposure of each occupation to AI technology. For this purpose, the exposure indices of occupations were normalized by subtracting the average exposure index of all occupations in the sample from that of each occupation, and dividing the difference by the standard deviation of the exposure indices in the sample. As a result, the average of the normalized exposure indices is zero and their standard deviation is one (for more details, see Adapting the exposure indices to Labor Force Survey data and normalizing them to the sample in the appendix). Accordingly, any occupation with a positive normalized index is more exposed to AI technology than average, and any occupation with a negative normalized index is somewhat exposed to this technology, but less than the average.

5 The O*NET classification (Occupational Information Network) is based on a database established under the auspices of the US Department of Labor. Its purpose is to describe various occupations and functions in a detailed, accurate and comparable manner. The classification includes a breakdown of different tasks that make up each occupation (including their relative weights) and other characteristics that can be used to compare occupations (such as "the extent to which the job involves exposure to the elements," "the degree of responsibility for the health of others," "the extent of public speaking involved," etc.).

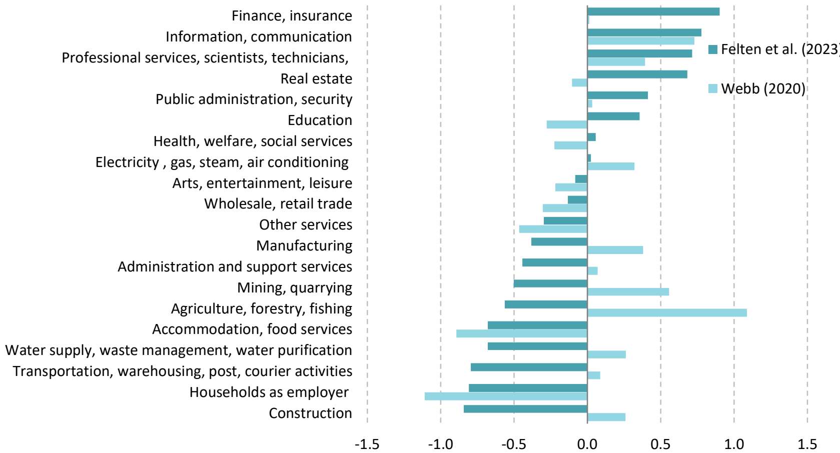
6 The conversion is not "one-to-one," and there are several clusters of occupations in the O*NET classification that are combined into a single occupation in the ISCO classification (4-digit level). In these cases, the occupation was assigned the average values (not weighted) of the exposure indices.

AI exposure indices: Findings for the Labor Force Survey in Israel, 2018–2023

As mentioned, the relative AI exposure scores were assigned to each employee in the sample according to their occupation. The distribution of occupations is not identical across the various population groups. For instance, it is likely that educated workers are more inclined to be in occupations with relatively high exposure to AI technology compared to their less-educated counterparts. Therefore, in our attempt to examine the relative exposure of population groups to artificial intelligence, we base the analysis on the alignment between the distribution of occupations and the characteristics that define the different population groups (industry, education, age, gender, population group, etc.).

A straightforward starting point for such characteristics is industry. Figure 1 presents the exposure indices by industry (average across the entire sample). It can be seen that, relative to the average, the prominent high-tech industries (information and communication and professional, scientific and technical services) are significantly exposed to artificial intelligence according to both indices, while the Israeli finance industry is highly exposed according to Felten et al. (2023)'s index. In contrast, entertainment, trade, and accommodation and food services is primarily composed of occupations that are less exposed according to both indices. There are also a number of sectors for which each exposure index shows different results. For example, manufacturing and mining and quarrying are particularly exposed according to Webb (2020) but less so according to Felten et al. (2023). This difference stems from the fact that these industries invest substantial resources in developing dedicated automation tools, while there is not much use of general tools such as large language models in those industries. The opposite is observed in education: while few dedicated artificial intelligence tools had been developed for education as of the end of the previous decade, the capabilities of contemporary general tools can certainly have a major impact on this sector.

Figure 1. Exposure to artificial intelligence by industry, 2018–2023

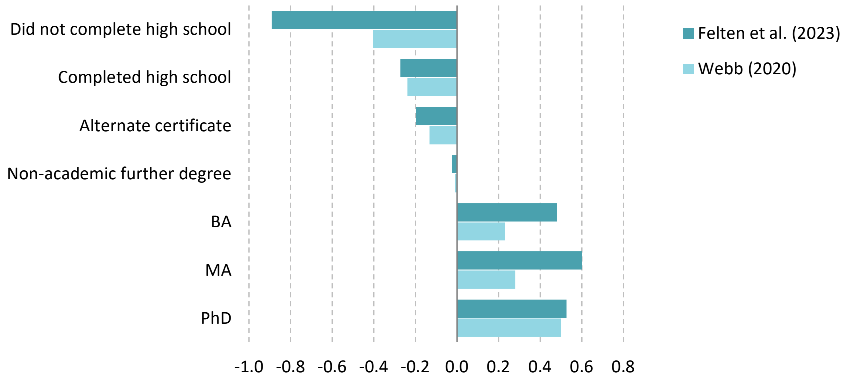


Source: Debowy et al., Taub Center | Data: CBS

Another interesting characteristic worth mentioning is education level. Figure 2 presents the exposure indices according to this characteristic. Unsurprisingly, all indices rise sharply with level of education. According to Felten et al. (2023), the exposure of employees who completed high school is more than half a standard deviation higher than those who did not, and the exposure of employees with an academic degree is 0.7–0.9 standard deviations higher than that of employees who only completed high school. Furthermore, according to both indices, the exposure of employees who usually work from home (about 5% of the workforce) is 0.5–0.7 standard deviations higher than that of other employees (Figure 3).[7] This finding aligns with previous findings regarding education level and industry and supports the notion that artificial intelligence is expected to primarily impact knowledge-based occupations, including those that allow working from home or require an academic education.

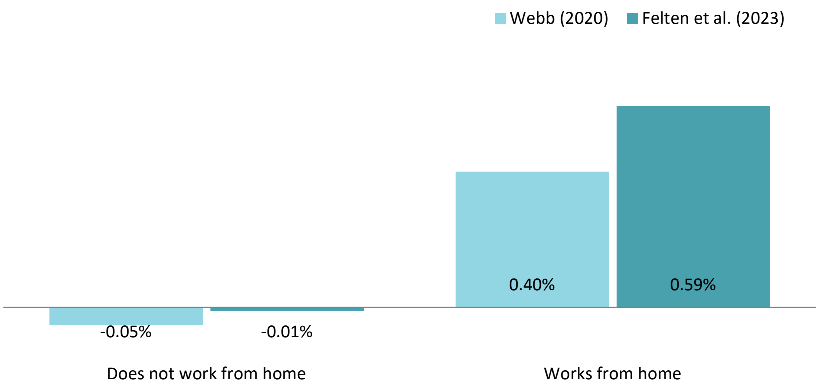
7 Those who work from home according to the responses in the Labor Force Survey to the question: “Do you in general work from home most of the days of the week rather than at your main workplace?”.

Figure 2. Exposure to arificial intelligence by official level of schooling completed, 2018–2023



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

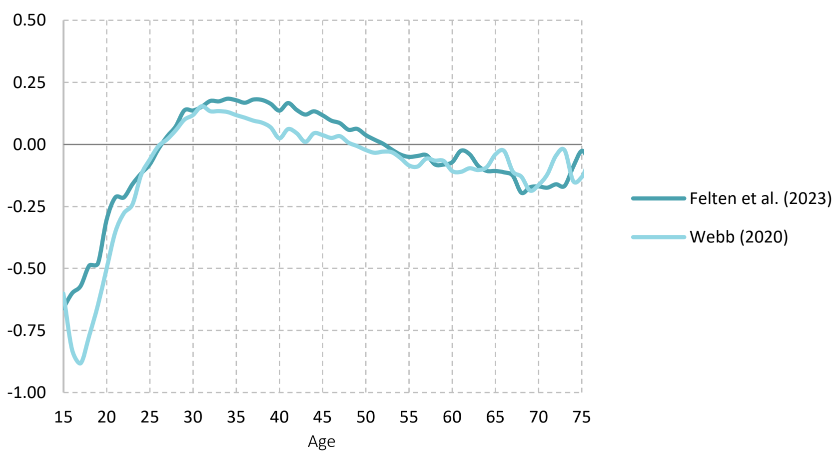
Figure 3. Exposure to artificial intelligence by whether people usually work from home, 2018–2023



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

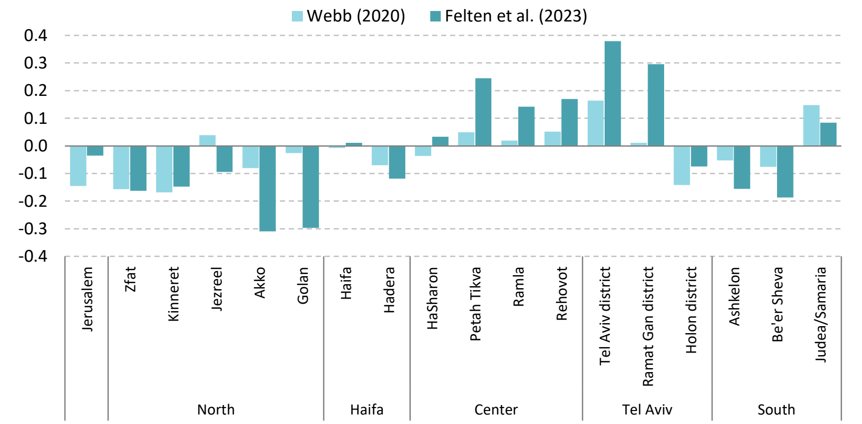
Figure 4 shows that the two indices provide similar results also in the case of AI exposure according to age. Thus, both rise with age up to 34 and then decline. Employees aged 27–51 (about 55% of the workforce) are more exposed than average, while younger or older employees are less exposed. The geographic distribution also shows similar results for both exposure indices, and in a not surprising direction (Figure 5). Residents of the Central and Tel Aviv districts, except for the Holon area and the Sharon district, have an average exposure that is higher than the national average; residents of the Haifa, Sharon and Jezreel districts are exposed at about the national average level; and the rest of the residents of the Haifa and northern districts, as well as residents of the Southern and Jerusalem districts, are less exposed than average according to both indices.

Figure 4. Exposure to artificial intelligence by age, 2018–2023



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

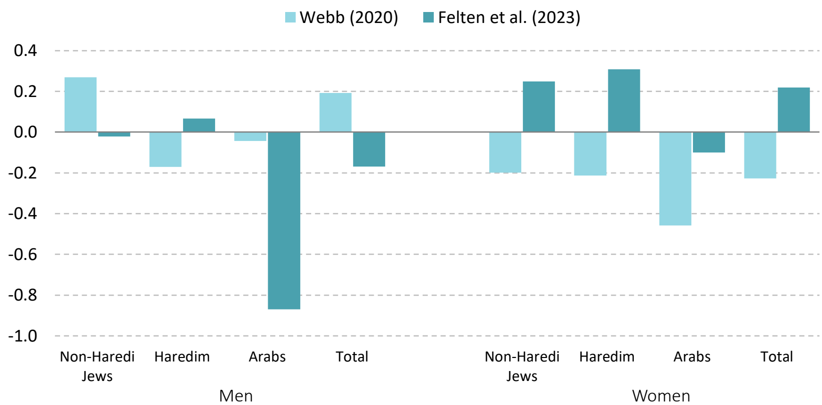
Figure 5. Exposure to artificial intelligence by residential district, 2018–2023



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

However, there are distributions where the two indices present entirely different results. In this context, it is particularly interesting to note how the exposure of occupations to artificial intelligence is distributed by gender and industry. Figure 6 divides employees into non-Haredi (ultra-Orthodox) Jews, Arabs and Haredim (ultra-Orthodox Jews). In general, Webb (2020)'s index is above average among men and below average among women — a finding identical to that published for employees in the US based on the same methodology (Muro et al., 2019) — while Felten et al. (2023)'s index shows the opposite. Felten's index suggests that Israeli women work in occupations exposed to the impact of general tools such as large language models (e.g., knowledge-intensive occupations or occupations based on interpersonal interaction), whereas Israeli men work in occupations exposed to the impact of specific tools (i.e., occupations focused on a specific skill or specific set of skills).

Figure 6. Exposure to artificial intelligence by sector and gender, 2018–2023



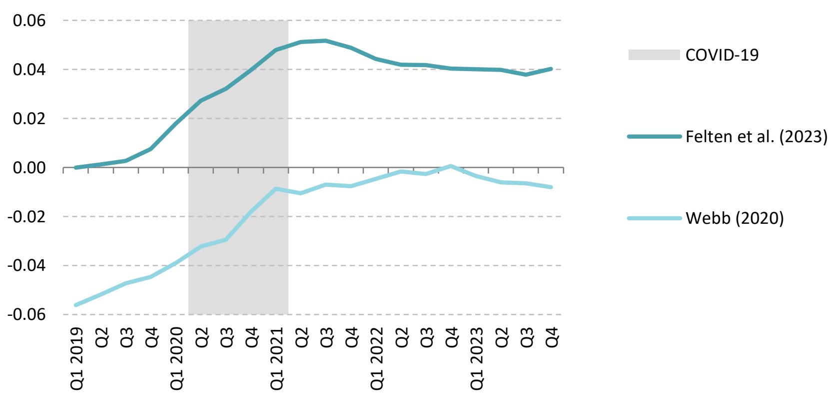
Source: Debowy et al., Taub Center | Data: CBS

There is much greater variation with respect to population group. The average exposure scores for employees from the Arab sector are significantly lower than those for their Jewish counterparts. Among Jewish women, there is no substantial difference between Haredi and non-Haredi women, whereas among Jewish men, Haredi workers have exposure scores that are opposite to those of non-Haredi workers. This difference stems from the tendency of these two populations to work in entirely different occupations.

It should be emphasized that while the absolute magnitude of the sectoral and gender differences is due to other characteristics of the employees (such as industry, education and age), the relative gaps between them remain the same even after controlling for these factors. Appendix Figure 1 presents the exposure indices by gender and sector for 2023 only, after controlling for industry, education, age, working from home and survey month. (The results of the multivariate estimation on which the graph is based are presented in Appendix Table 2.) Similarly, industry, age, district of residence and working from home maintain their predictive power regarding an employee's exposure score when other factors are controlled for. The absolute differences in the indices are small, but they maintain a similar ratios that were seen in the descriptive statistics (i.e., without control for other influences).

In addition to these cross-sections, it is also worth examining the trend in AI exposure indices in recent years. Figure 7 presents the average indices for the 12 months ending in each quarter (a kind of moving average) from the beginning of 2019 to the end of 2023.[8] First and foremost, it should be noted that the change over time is very small in magnitude, amounting to about 0.05 standard deviations for both indices. Nonetheless, both indices have increased over the sample period, especially during the COVID-19 pandemic. Moreover, the increase in Felten et al. (2023)'s index between quarters during the pandemic (from the first quarter of 2020 to the third quarter of 2021) was about 29% on average, compared to a negligible increase prior to that and a negligible decrease (of less than 2%) since the pandemic. This finding suggests that the pandemic pushed the Israeli labor market towards occupations that are more exposed to artificial intelligence.

Figure 7. Exposure to artificial intelligence by quarter, 2018–2023



Notes: The value presented for each quarter is the annual (weighted) average at the end of the quarter. The COVID-19 pandemic refers to the period between the first quarter of 2020 and the third quarter of 2021, the period during which the pandemic's effects on employment were most pronounced.

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

8 The value calculated for each quarter is the weighted average of the quarter and the three preceding quarters. For example, the value for the first quarter of 2019 is the average of all observations from the second quarter of 2018 until the first quarter of 2019 (inclusive).

All of the above findings refer to AI exposure and do not allow us to hypothesize how it will impact employment in each occupation. We will now incorporate the complementarity index formulated by Pizzinelli et al. (2023), which is designed to measure the potential of artificial intelligence to improve employee performance (or alternatively, to replace employees), and discuss the findings.

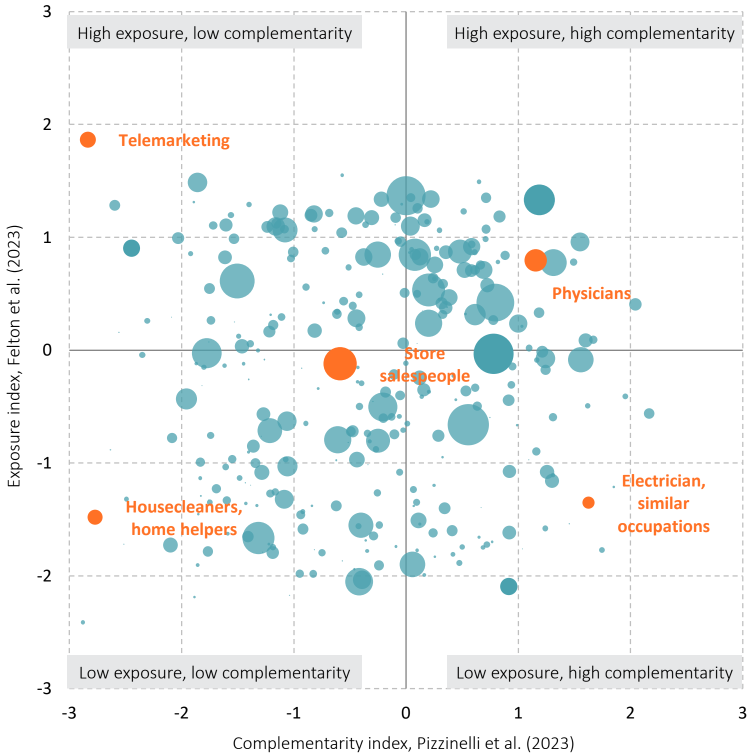
Complementarity and exposure to artificial intelligence

As mentioned, the impact of AI tools varies across occupations. On the one hand, they can assist workers and enhance their performance, while on the other hand, they can also replace them. It is likely that both processes will occur to some extent in the labor market. Thus, certain occupations will disappear, others will be strengthened and grow, and there will be those that contract although the productivity of the remaining workers will increase significantly. The complementarity index of Pizzinelli et al. (2023) allows us to make cautious predictions on this issue by assigning a score to each occupation (similar to what was done with the exposure indices) that reflects how likely AI is to provide a complementary product to human workers in that occupation. A high score on the index means a high potential for augmenting human capabilities, suggesting that AI has the potential to increase productivity in that occupation. A low score implies a low potential, whereby it is more likely that AI will replace human workers or will have no impact in occupations where AI has fewer applications.

Combining the complementarity index with the exposure indices makes it possible to estimate the extent to which workers in different occupations are likely to "gain", "lose" or not be affected by AI tools. Figure 8 is based on our sample data and integrates the exposure index of Felten et al. (2023), which will now be the main exposure index we use (similar results according to the other exposure index are provided in the appendix).[9] Each bubble in the figure represents one occupation, where the height of the bubble represents the exposure of the occupation, its horizontal position represents its complementarity and its size represents its relative weight on average within the sample. There is considerable variation across occupations with respect to both exposure and complementarity.

9 The graphs are based on a similar graph in Pizzinelli et al. (2023) after re-sorting of occupations according to the ISCO system and adjusting the points to the Israeli data.

Figure 8. Distribution of occupations by exposure complementarity levels



Note: The size of the bubble represents the relative weight of the occupation in the sample on average between 2018 and 2023. The average and standard deviation of the sample as a whole for each of the indices is 0 and 1, respectively. The list of the occupations and their scores on the various indices appear in Appendix Table 1a.

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

We divide the occupations into four categories corresponding to the quadrants in the graph. We are really only interested in two of them — those with high exposure. Industries in the "high exposure and high complementarity" (upper-right) quadrant which includes workers such as family physicians who are expected to benefit from AI in a way that enhances their performance without a threat of being replaced. The second category of interest is "high exposure and low complementarity" (upper-left quadrant) which includes workers such as telemarketers who are particularly at risk of being replaced by AI.[10]

For convenience of presentation and interpretation, we ignore each occupation's actual scores, and simply assign it to one of the four categories corresponding to the quadrants in Figure 8. We then use these categories to map out the Israeli labor market in terms of exposure and complementarity. The drawback of this approach is the loss of information about the variation within each category. For example, in the lower-left quadrant of Figure 8, there are both house cleaners and sales assistants in stores. While both of these occupations have below-average exposure and complementarity scores, they differ significantly with respect to both indices, with sales assistants in stores able to utilize AI tools more than house cleaners. Simplifying the indices into four categories necessarily treats workers in these professions identically, and this limits the effectiveness of the approach, but it yields a measure that is simple and easy to interpret. We will focus on the two categories corresponding to the upper quadrants in Figure 8, in which occupations are likely to be affected — either positively or negatively — by AI more than average ("high exposure and high complementarity" and "high exposure and low complementarity").

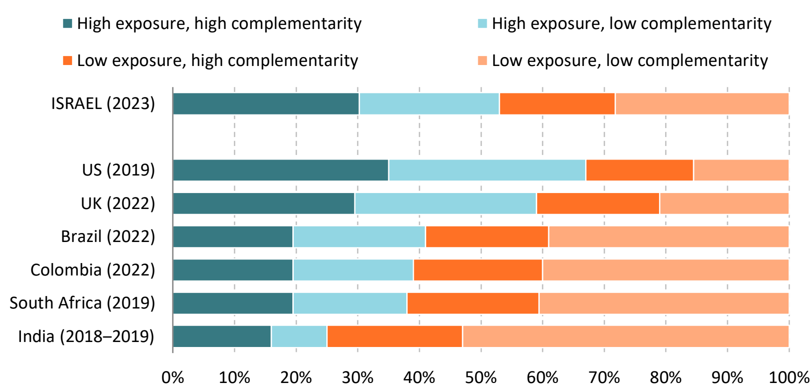
Figure 9 presents the proportion of workers with high exposure (alongside the complementarity breakdown of these workers) in aggregate within the Israeli labor market (average for 2023) and compares it to the distribution among other countries as estimated in Pizzinelli et al. (2023).[11] In 2023, about 30% of the workers in the labor market (approximately 1.3 million workers) were engaged in occupations categorized as "high exposure and high complementarity" and about 23% (approximately 995,000 additional workers) were engaged in occupations categorized as "high exposure and low complementarity."

10 The other two categories, "low exposure and high complementarity" and "low exposure and low complementarity" — represented in the two lower quadrants of Figure 8 — include occupations with below-average exposure to artificial intelligence. In these occupations, the degree of complementarity is not particularly important, since they represent occupations that are not expected to be directly affected by AI. Examples include construction electricians (low exposure and high complementarity) and house cleaners (low exposure and low complementarity).

11 The distribution according to these categories in Israel remained almost identical throughout the entire sample period (as expected given the negligible change in exposure indices, as shown in Figure 7).

This finding can be interpreted to suggest that if the composition of occupations remains similar, the number of workers expected to "gain" from artificial intelligence is slightly larger than the number of workers expected to "lose." The fact that these groups are similar in size, with "high exposure" categories making up at least 50% of the labor market, aligns with the findings of Pizzinelli et al. (2023) for other developed countries. However, comparisons between Israel and other countries should be treated with caution, since the distribution presented for foreign countries was estimated by Pizzinelli et al. (2023) and is based on different sample years and slightly different standardizations across countries (including different occupational coding).

Figure 9. Exposure and complementarity, Israel and selected countries

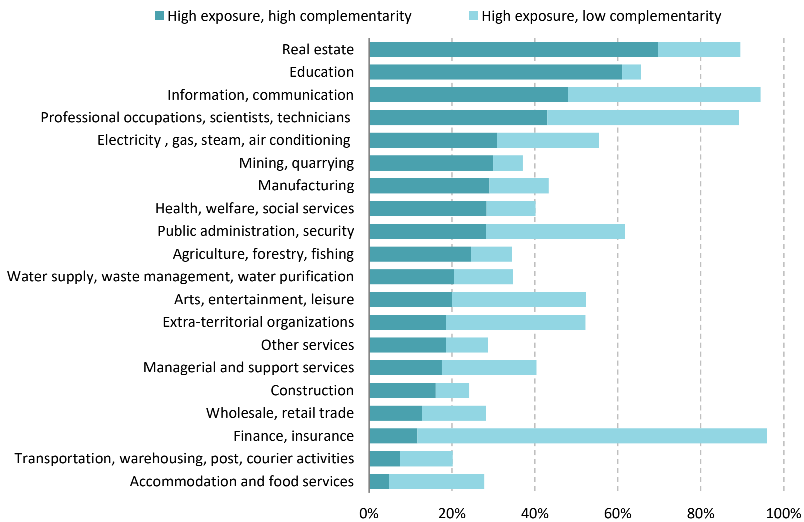


Notes: The categories are based on the exposure index of Felten et al. (2023) and the complementarity index of Pizzinelli et al. (2023). The distribution presented for other countries was estimated by Pizzinelli et al. (2023) and is based on different sample years and slightly different definitions across countries (including different occupational coding). The distribution presented for Israel was estimated as part of the current study, and the index values presented were normalized for the Israeli labor market. Therefore, comparisons between Israel and other countries should be treated with caution.

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

It is also interesting to look at the distribution of exposure-complementarity within the Israeli labor market, as in the exposure mappings presented earlier. Figure 10 shows this distribution by industry (average across the entire sample). It is evident that the complementarity distribution varies to a great extent even between industries with similar exposure rates. For example, in the leading high-tech sectors (information and communication and professional, scientific and technical services), the exposure rate exceeds 90%, i.e., over 90% of the employees in the industry have an above average level of exposure, with a fairly equal division between highly complementary professions (where AI is expected to benefit workers, such as software developers) and highly substitutable professions (where AI may replace workers, such as advertising and marketing consultants). In contrast, in the finance and insurance industry (which also has an exposure rate exceeding 90%), an overwhelming majority of exposed workers are expected to be negatively impacted by AI, while a negligible proportion is expected to benefit. It is easy to imagine that the development and adoption of AI tools will shrink the workforce in this industry to a minimal managerial core as AI tools largely replace brokers, analysts and even some accounting and legal professionals. A contrasting picture emerges in education (in which over 60% of the workers have an above average level of exposure), where most of the exposed workers are expected to benefit from AI, and only a negligible proportion is expected to be negatively impacted. It is easy to imagine that teachers, for example, will use AI to develop lesson plans, grade assignments and maintain communication with students and parents, while the teaching and pedagogy itself will remain in human hands, thus requiring the same number of teachers.

Figure 10. Exposure and complementarity by industry, 2018–2023



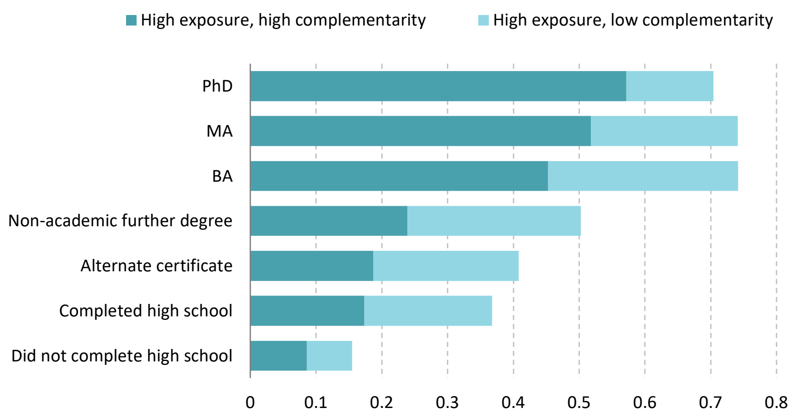
Note: The exposure groups are based on the index of Felten et al. (2023). Appendix Figure 2 presents a parallel distribution according to Webb (2020)'s exposure index.

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

Another interesting characteristic is the education level of the workers. Figure 11 presents the exposure-complementarity distribution according to this characteristic. As shown in Figure 2, exposure tends to increase with education (although grouping occupations into a limited number of categories blurs the differences between the various degree types). This increase is consistent with the weight of the "high exposure and high complementarity" group, but in the "high exposure and low complementarity" group, the picture is more complex, such that the proportion of this group increases with education up to a bachelor's degree and then decreases. In other words, workers with a bachelor's degree or a non-academic post-secondary education are employed at the highest rates in occupations that AI might replace, while those with more or less education tend to have a lower representation in these occupations.

Nonetheless, the ratio between the "high exposure and high complementarity" group and the "high exposure and low complementarity" group — a ratio that predicts the net aggregate impact of AI — increases fairly consistently with education level. For example, for every worker with a PhD expected to be negatively impacted by AI, there are four workers expected to benefit (a ratio of 1:4). In the case of a master's degree, this ratio is 1:2, and for a bachelor's degree, it is 2:3. For workers with a high school education or less, this ratio reverses, such that less than one worker is expected to benefit from AI for every worker negatively impacted. Therefore, while better-educated workers are more exposed to the effects of AI, they are also expected to benefit from it at much higher rates, whereas less educated workers are more likely to be negatively impacted (or, in the case of workers without a high school education, to benefit less).

Figure 11. Exposure and complementarity by official level of schooling completed, 2018–2023

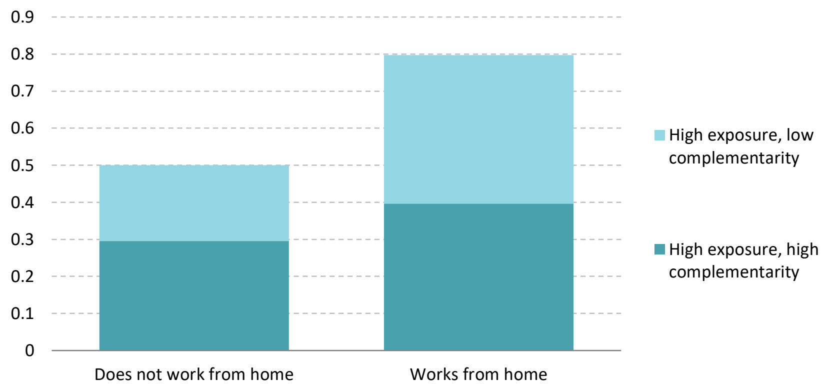


Note: The exposure groups are based on the index of Felten et al. (2023). Appendix Figure 3 presents the parallel distribution according to Webb (2020)'s exposure index.

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

A parallel and interesting phenomenon is seen in the distribution for those who "usually works from home" (Figure 12). Employees who usually work from home are much more exposed to artificial intelligence, but they are equally divided between occupations that are expected to gain and those that are expected to lose. In contrast, among workers in high-exposure occupations who do not usually work from home, a higher proportion is expected to gain than to lose. A similar view can be taken of the exposure-complementarity distribution by age (Figure 13). Among employees aged 27 or older, the proportion of workers expected to gain from AI is slightly larger than that of workers expected to lose, and this ratio increases up until around age 50.

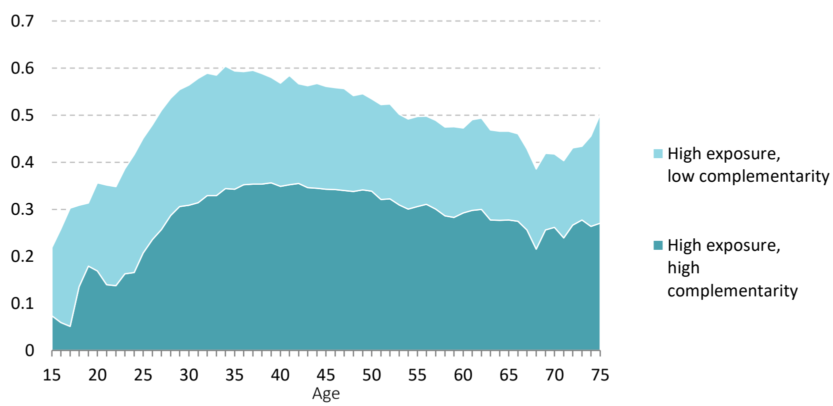
Figure 12. Exposure and complementarity by whether people usually work from home, 2018–2023



Note: The exposure groups are based on the index of Felten et al. (2023). Appendix Figure 4 presents the parallel distribution according to Webb (2020)'s exposure index.

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

Figure 13. Exposure and complementarity by age, 2018–2023

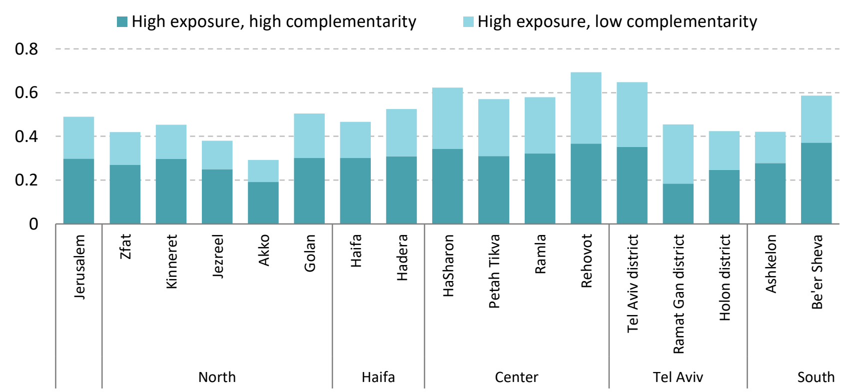


Note: The exposure groups are based on the index of Felten et al. (2023). Appendix Figure 5 presents the parallel distribution according to Webb (2020)'s exposure index.

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

In the case of geographic distribution (Figure 14), it appears that the ratio between the proportion of workers in occupations expected to gain and those expected to lose is fairly consistent, although there are modest differences in the relative weight of the groups across regions. For example, in the northern districts and Be’er Sheva, there are nearly two workers expected to gain for every worker expected to lose. In contrast, in the Tel Aviv district, the ratio is closer to 1:1 or even less (the Holon area — including Holon, Bat Yam and Azor — is the only geographic district where the proportion of those expected to lose is greater than the proportion of those expected to gain).

Figure 14. Exposure and complementarity by residential district, 2018–2023



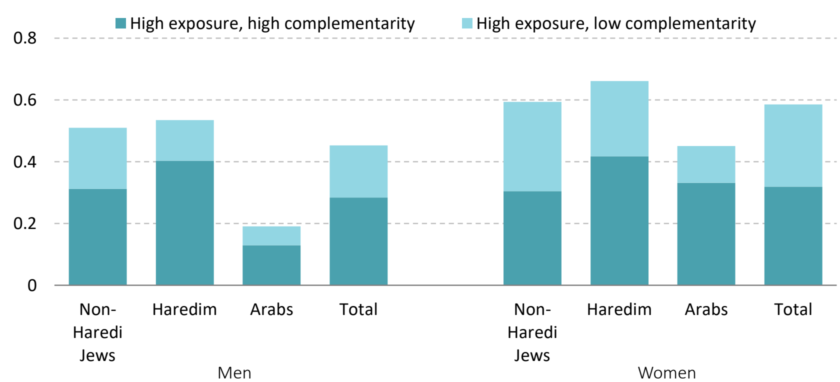
Note: The exposure groups are based on the index of Felten et al. (2023). Appendix Figure 6 presents the parallel distribution according to Webb (2020)’s exposure index.

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

The distribution by gender (Figure 15) reveals that overall the exposure of female workers is slightly higher than that of male workers (similar to the results of Felten et al. (2023)’s index in Figure 6). However, this difference is mostly due to the proportion of workers in occupations expected to be negatively impacted by artificial intelligence (27% of female workers as compared to 17% of male workers), while the proportion of workers in occupations expected to gain is similar (32% of female workers compared to 28% of male workers).

This gender difference in the proportion of workers expected to gain versus those expected to lose is also present within the Jewish sectors. For example, the “high exposure and high complementarity” group includes about 40% of Haredi women and a similar percentage of Haredi men while the “high exposure and low complementarity” group includes 24% of Haredi women and only 13% of Haredi men. Furthermore, about 30% of the remaining Jewish women and Others and the remaining Jewish men and Others are included in the “high exposure and high complementarity” group, while 29% of the remaining Jewish women and Others are included in the “high exposure and low complementarity” group and only 20% of the remaining Jewish men and Others are included. In contrast to these groups, women in the Arab sector tend to be in high-exposure and high-complementarity occupations at a much higher rate than men (33% vs 13%), alongside a greater presence in high-exposure and low-complementarity occupations (12% vs 6%).

Figure 15. Exposure and complementarity by gender and sector, 2018–2023



Note: The exposure groups are based on the index of Felten et al. (2023). Appendix Figure 7 in the appendix presents the parallel distribution according to Webb (2020)’s exposure index.

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

It is important to emphasize — especially regarding these last findings but also the previous ones — that the estimates reflect the current distribution of occupations. Even if the exposure and complementarity indices accurately predict which occupations are likely to be replaced by artificial intelligence and which are likely to benefit from it, it is not possible to determine how workers will respond and how the distribution of occupations will change as a result. Workers replaced by AI might find better jobs (perhaps in occupations that benefit from AI) or they may find themselves in a much worse situation. In any case, the process will likely be accompanied by the movement of workers between occupations, thus altering the distribution of occupations by gender, sector, place of residence or any other characteristic, and with it the exposure-complementarity distribution.

Conclusion

Since the agrarian revolutions of the Neolithic period, which gave rise to the first "complex society," technological transitions have continuously altered employment patterns and, in turn, the balance of power within and between societies. Since the 18th century, this process has created fear, widespread unrest and a rich body of political and academic literature dealing with the tension between increased labor productivity and profitability on the one hand and the loss of human labor and its replacement by machines on the other. However, and despite the concerns that arose with the introduction of new technologies, it appears that the process of their adoption was accompanied by the relatively rapid adaptation of the labor market to the changing circumstances (see, for example, Autor, 2015).

Despite the increasing presence of artificial intelligence in human society in general and in economic activities in particular, research literature in the field is still in its infancy, and it is too early to tell how the continued development and integration of AI tools will affect the labor market in Israel and globally. Nevertheless, AI exposure indices — combined with the complementarity index — make it possible to estimate which occupations are likely to be more or less affected and to predict — albeit with caution — whether this impact will benefit those in the occupation or replace them. Labor Force Survey data make it possible to map the population currently employed in these occupations in Israel.

These indices reveal a significant difference between the AI revolution, which is permeating the world's economies, and most — if not all — of the technological transitions that preceded it. Until recently, attention was primarily focused on the impact of automation on the employment of unskilled workers, including skilled tradesmen (similar to the concerns of the Luddite movement for the welfare of similar workers in early 19th-century England). Our estimates show that the sectors most exposed to AI in the Israeli economy are high-tech and finance, which are characterized by workers from the middle class or higher. In particular, most workers in the finance sector are in occupations facing a high risk of replacement, while in the high-tech sector, the proportion of workers in occupations at risk of replacement is similar to the proportion in occupations expected to benefit from AI adoption. At the same time, various indices indicate high exposure in education and manufacturing (Webb's index is high in manufacturing while Felten et al.'s index is high in the education sector); the proportion of workers in those sectors who are expected to benefit from AI is much greater than the proportion that is expected to be negatively impacted.

Moreover, it is evident that AI exposure rises sharply with a worker's education level. However, the effect of this exposure varies: the proportion of workers at risk of replacement by AI is highest among those with a bachelor's degree or a non-academic post-secondary certificate, higher educated workers are primarily expected to benefit from AI, and less educated workers are expected to be less affected. It was also found that AI exposure is particularly high for those who usually work from home and for residents of Tel Aviv and the Central region where the proportion of workers at risk of replacement is also relatively high.

Moreover, it appears that the exposure of workers from the Arab sector is lower than that of the rest of the population, even after controlling for background variables. It was found that Haredi workers and Arab female workers have the highest ratio between the proportion of workers in occupations expected to gain from AI and the proportion in occupations expected to lose (even among Arab male workers and Haredi female workers, this ratio is higher than among the non-Haredi Jewish population).

In conclusion, the analysis suggests that the impact of AI on the Israeli labor market will be concentrated mainly among the educated Jewish population, particularly in central Israel and in the high-tech and finance sectors. However, the impact is not uniform, and certain occupations are expected to contract while others are expected to expand (it is also likely that new occupations will emerge). In addition to these direct impacts on the work itself, AI tools are expected to affect other aspects of the economy and the labor market, perhaps even dramatically. It appears that AI is changing the field of higher education, hiring, human resource management and of course non-financial business activities (customer relations, the implementation of various transactions, research and development, etc.). These changes, and their implications for Israeli workers, will provide fertile ground for future research.

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Appendix

Appendix Table 1. List of occupations, the exposure indices of Felten et al. (2023) and Webb (2020) and the complementarity index of Pizzinelli et al. (2023)

ISCO	Occupation	Pizinnelli et al. (2023)'s complementarity index	Felton et al. (2023)'s exposure indices	Webb (2020)'s exposure indices
1112	Senior government officials	1.31	0.78	0.05
1114	Senior officials of special-interest organizations	0.71	0.98	0.17
1211	Finance managers	0.17	1.15	0.30
1212	Human resource managers	0.10	1.26	0.43
1219	Business services and administration managers not elsewhere classified	0.24	0.64	0.13
1221	Sales and marketing managers	0.04	1.10	1.79
1222	Advertising and public relations managers	0.30	1.06	-0.71
1223	Research and development managers	0.66	0.75	-0.13
1311	Agricultural and forestry production managers	1.62	-0.49	2.43
1321	Manufacturing managers	1.60	0.09	0.02
1323	Construction managers	2.04	0.41	2.21
1324	Supply, distribution and related managers	0.69	0.71	1.48
1330	Information and communications technology service managers	0.26	0.76	-0.24
1341	Child care services managers	1.49	0.78	1.23
1342	Health services managers	-0.09	1.17	0.96
1344	Social welfare managers	0.71	1.07	-0.65
1345	Education managers	1.55	0.96	0.26
1411	Hotel managers	1.03	0.21	-0.11
1412	Restaurant managers	0.12	-0.24	-0.45
1431	Sports, recreation and cultural centre managers	0.10	0.50	-0.90
2111	Physicists and astronomers	0.05	0.89	2.84
2112	Meteorologists	-0.10	1.11	2.24
2113	Chemists	0.33	0.32	1.03
2114	Geologists and geophysicists	0.53	0.32	0.90
2120	Mathematicians, actuaries and statisticians	-0.81	1.07	0.79

Appendix Table 1 (continued). List of occupations, the exposure indices of Felten et al. (2023) and Webb (2020) and the complementarity index of Pizzinelli et al. (2023)

ISCO	Occupation	Pizinnelli et al. (2023)'s complementarity index	Felton et al. (2023)'s exposure indices	Webb (2020)'s exposure indices
2131	Biologists, botanists, zoologists and related professionals	0.72	0.58	0.77
2132	Farming, forestry and fisheries advisers	1.10	0.02	1.83
2141	Industrial and production engineers	0.52	0.71	0.67
2143	Environmental engineers	0.61	0.87	-0.23
2144	Mechanical engineers	0.38	0.47	1.11
2145	Chemical engineers	0.61	0.71	4.45
2146	Mining engineers, metallurgists and related professionals	0.36	0.38	1.65
2149	Engineering professionals not elsewhere classified	0.33	0.59	1.38
2151	Electrical engineers	0.58	0.71	-0.24
2153	Telecommunications engineers	-0.42	0.20	0.88
2161	Building architects	0.35	0.38	0.76
2162	Landscape architects	0.25	0.63	1.50
2163	Product and garment designers	-0.62	0.32	1.63
2164	Town and traffic planners	0.27	0.90	0.86
2165	Cartographers and surveyors	0.00	-0.12	0.74
2166	Graphic and multimedia designers	-0.44	0.28	2.87
2211	Generalist medical practitioners	1.19	0.77	-0.50
2212	Specialist medical practitioners	1.24	-0.07	0.29
2221	Nursing professionals	1.56	-0.08	0.13
2240	Paramedical practitioners	-0.27	-0.88	-0.78
2250	Veterinarians	1.95	-0.41	1.11
2261	Dentists	2.17	-0.56	0.01
2262	Pharmacists	1.18	0.33	-0.96
2263	Environmental and occupational health and hygiene professionals	0.82	0.78	-0.66
2264	Physiotherapists	1.24	-0.17	0.92
2265	Dieticians and nutritionists	0.51	1.23	0.03
2266	Audiologists and speech therapists	0.88	0.84	0.11

Appendix Table 1 (continued). List of occupations, the exposure indices of Felten et al. (2023) and Webb (2020) and the complementarity index of Pizzinelli et al. (2023)

ISCO	Occupation	Pizinnelli et al. (2023)'s complementarity index	Felton et al. (2023)'s exposure indices	Webb (2020)'s exposure indices
2267	Optometrists and ophthalmic opticians	1.16	-0.09	2.97
2269	Health professionals not elsewhere classified	1.21	-0.01	3.29
2330	Secondary education teachers	0.78	-0.03	-0.08
2341	Primary school teachers	0.80	0.42	-0.18
2342	Early childhood educators	0.20	0.24	-0.19
2351	Education methods specialists	0.83	1.18	-0.69
2352	Special needs teachers	1.16	0.80	-0.04
2353	Other language teachers	-0.07	0.97	-0.06
2359	Teaching professionals not elsewhere classified	0.00	1.37	0.45
2411	Accountants	-1.08	1.07	-0.02
2412	Financial and investment advisers	-0.85	1.20	0.94
2413	Financial analysts	-1.08	1.07	0.91
2421	Management and organization analysts	-0.31	1.17	0.03
2422	Policy administration professionals	-0.51	0.73	1.73
2423	Personnel and careers professionals	-0.22	1.34	0.09
2431	Advertising and marketing professionals	-1.12	1.22	3.12
2433	Technical and medical sales professionals (excluding ICT)	0.58	0.94	-0.28
2434	Information and communications technology sales professionals	0.08	0.85	-0.08
2511	Systems analysts	-0.38	0.83	-0.27
2512	Software developers	0.08	0.85	1.42
2514	Applications programmers	-0.25	0.85	1.95
2519	Software and applications developers and analysts not elsewhere classified	0.35	0.87	0.19
2521	Database designers and administrators	-1.03	0.81	0.23
2522	Systems administrators	-1.18	0.22	0.47
2529	Database and network professionals not elsewhere classified	-1.01	0.87	-1.23
2611	Lawyers	1.19	1.33	-0.39
2612	Judges	0.65	1.49	1.86

Appendix Table 1 (continued). List of occupations, the exposure indices of Felten et al. (2023) and Webb (2020) and the complementarity index of Pizzinelli et al. (2023)

ISCO	Occupation	Pizinnelli et al. (2023)'s complementarity index	Felton et al. (2023)'s exposure indices	Webb (2020)'s exposure indices
2619	Legal professionals not elsewhere classified	-0.57	1.55	0.97
2621	Archivists and curators	0.30	0.45	-0.71
2622	Librarians and related information professionals	-0.47	0.39	-0.79
2631	Economists	-0.45	1.19	-0.27
2632	Sociologists, anthropologists and related professionals	0.19	1.14	1.84
2633	Philosophers, historians and political scientists	-0.04	1.29	0.94
2634	Psychologists	0.22	1.34	0.20
2635	Social work and counselling professionals	0.48	0.87	-0.07
2636	Religious professionals	0.71	1.35	-1.35
2641	Authors and related writers	-1.24	1.09	0.33
2642	Journalists	0.04	1.35	-1.21
2643	Translators, interpreters and other linguists	-0.68	1.22	-1.60
2651	Visual artists	-1.69	-1.23	-0.22
2652	Musicians, singers and composers	-0.56	0.43	-1.02
2653	Dancers and choreographers	0.26	-1.83	-1.05
2654	Film, stage and related directors and producers	-0.01	0.51	0.31
2655	Actors	-0.61	0.34	-1.17
2656	Announcers on radio, television and other media	0.03	0.87	-1.24
3111	Chemical and physical science technicians	-0.40	-0.29	-0.33
3112	Civil engineering technicians	0.53	-0.36	1.72
3113	Electrical engineering technicians	-0.13	-0.59	0.97
3115	Mechanical engineering technicians	-0.18	-0.37	1.97
3118	Draughtspersons	-1.11	0.29	0.49
3119	Physical and engineering science technicians not elsewhere classified	0.62	-0.33	1.31
3123	Construction supervisors	1.67	0.09	0.67
3131	Power production plant operators	0.42	-0.23	2.18
3132	Incinerator and water treatment plant operators	0.25	-1.20	2.29

Appendix Table 1 (continued). List of occupations, the exposure indices of Felten et al. (2023) and Webb (2020) and the complementarity index of Pizzinelli et al. (2023)

ISCO	Occupation	Pizinnelli et al. (2023)'s complementarity index	Felton et al. (2023)'s exposure indices	Webb (2020)'s exposure indices
3133	Chemical processing plant controllers	0.32	-0.95	-0.48
3134	Petroleum and natural gas refining plant operators	0.44	-0.44	0.37
3135	Metal production process controllers	-1.28	-1.79	-0.56
3139	Process control technicians not elsewhere classified	-1.76	0.07	0.79
3141	Life science technicians (excluding medical)	-0.43	-0.15	0.33
3142	Agricultural technicians	0.20	-0.37	0.25
3143	Forestry technicians	-1.43	-1.18	-0.41
3151	Ships' engineers	0.75	-0.60	-0.63
3152	Ships' deck officers and pilots	1.85	-1.21	-0.54
3153	Aircraft pilots and related associate professionals	1.31	-1.11	0.56
3154	Air traffic controllers	-0.74	0.42	0.12
3211	Medical imaging and therapeutic equipment technicians	-0.20	-0.60	-0.34
3212	Medical and pathology laboratory technicians	-0.41	-0.50	3.01
3213	Pharmaceutical technicians and assistants	-0.78	-0.34	-1.31
3221	Nursing associate professionals	0.01	-0.65	-0.75
3222	Midwifery associate professionals	0.71	0.00	0.69
3240	Veterinary technicians and assistants	-0.32	-0.81	0.68
3251	Dental assistants and therapists	-0.03	-0.71	-0.28
3254	Dispensing opticians	-0.43	-0.28	-0.40
3255	Physiotherapy technicians and assistants	1.31	-0.59	-0.15
3256	Medical assistants	-0.65	-0.13	-0.52
3257	Environmental and occupational health inspectors and associates	0.94	-0.31	1.60
3259	Health associate professionals not elsewhere classified	-0.30	-0.45	-0.58
3311	Securities and finance dealers and brokers	-0.36	1.11	0.46
3313	Accounting associate professionals	-1.50	0.61	-1.02
3314	Statistical, mathematical and related associate professionals	-0.21	0.67	1.01

Appendix Table 1 (continued). List of occupations, the exposure indices of Felten et al. (2023) and Webb (2020) and the complementarity index of Pizzinelli et al. (2023)

ISCO	Occupation	Pizinnelli et al. (2023)'s complementarity index	Felton et al. (2023)'s exposure indices	Webb (2020)'s exposure indices
3315	Valuers and loss assessors	-0.89	0.56	1.66
3321	Insurance representatives	-0.82	1.21	0.24
3323	Buyers	0.12	0.83	1.64
3332	Conference and event planners	0.78	0.27	1.01
3334	Real estate agents and property managers	0.58	0.92	-0.30
3339	Business services agents not elsewhere classified	-0.57	1.04	0.00
3342	Legal secretaries	-1.53	0.99	-0.96
3343	Administrative and executive secretaries	-1.61	0.82	-1.31
3344	Medical secretaries	-1.16	1.10	-0.94
3351	Customs and border inspectors	0.14	-0.41	-0.06
3352	Government tax and excise officials	-1.72	1.10	-0.62
3353	Government social benefits officials	-1.40	1.29	-0.82
3354	Government licensing officials	-1.56	1.20	-1.42
3355	Police inspectors and detectives	0.95	-0.14	-0.23
3411	Legal and related associate professionals	-0.72	0.88	-0.40
3412	Social work associate professionals	0.61	0.32	-1.39
3421	Athletes and sports players	0.10	-1.77	0.39
3422	Sports coaches, instructors and officials	-0.11	-0.22	-0.25
3423	Fitness and recreation instructors and program leaders	1.26	-1.08	-0.90
3431	Photographers	-0.11	-0.75	1.81
3432	Interior designers and decorators	-0.03	0.06	-0.18
3434	Chefs	0.63	-0.50	0.03
3435	Other artistic and cultural associate professionals	-0.89	-0.65	1.01
3511	Information and communications technology operations technicians	0.15	0.35	0.34
3521	Broadcasting and audio-visual technicians	-0.34	-0.74	0.13
4110	General office clerks	-1.86	1.49	-0.37
4120	Secretaries (general)	-1.78	-0.03	-1.25

Appendix Table 1 (continued). List of occupations, the exposure indices of Felten et al. (2023) and Webb (2020) and the complementarity index of Pizzinelli et al. (2023)

ISCO	Occupation	Pizinnelli et al. (2023)'s complementarity index	Felton et al. (2023)'s exposure indices	Webb (2020)'s exposure indices
4131	Typists and word processing operators	-2.31	0.26	-1.19
4132	Data entry clerks	-1.87	-0.12	1.98
4211	Bank tellers and related clerks	-0.81	0.17	-0.68
4212	Bookmakers, croupiers and related gaming workers	-1.49	0.12	-0.74
4214	Debt-collectors and related workers	-1.16	1.12	-1.15
4221	Travel consultants and clerks	-1.22	0.16	-0.03
4222	Contact centre information clerks	-2.45	0.90	0.95
4223	Telephone switchboard operators	-2.60	1.28	-0.18
4224	Hotel receptionists	-0.42	0.49	-1.47
4225	Enquiry clerks	-1.92	0.86	0.14
4312	Statistical, finance and insurance clerks	-1.61	1.11	-1.15
4313	Payroll clerks	-2.03	0.99	-1.41
4321	Stock clerks	-1.21	-0.71	0.23
4323	Transport clerks	-0.05	0.96	0.97
4411	Library clerks	-1.32	0.00	-1.00
4412	Mail carriers and sorting clerks	-1.55	-0.97	-0.77
4413	Coding, proof-reading and related clerks	-1.89	1.31	1.67
4415	Filing and copying clerks	-2.35	-0.04	-1.29
4419	Clerical support workers not elsewhere classified	-1.75	0.55	-1.34
5111	Travel attendants and travel stewards	-0.06	-0.59	-1.26
5113	Travel guides	0.31	0.42	-0.93
5120	Cooks	-1.06	-1.03	-1.01
5132	Bartenders	-2.08	-0.78	-1.28
5141	Hairdressers	-0.44	-0.97	-1.25
5142	Beauticians and related workers	-1.06	-0.63	-0.34
5153	Building caretakers	-0.40	-1.55	-0.46
5163	Undertakers and embalmers	0.99	-0.66	-1.32

Appendix Table 1 (continued). List of occupations, the exposure indices of Felten et al. (2023) and Webb (2020) and the complementarity index of Pizzinelli et al. (2023)

ISCO	Occupation	Pizinnelli et al. (2023)'s complementarity index	Felton et al. (2023)'s exposure indices	Webb (2020)'s exposure indices
5169	Personal services workers not elsewhere classified	0.10	0.06	-0.97
5211	Stall and market salespersons	-1.74	0.26	-1.09
5212	Street food salespersons	-0.52	-0.82	-0.67
5222	Shop supervisors	-0.53	-0.09	0.29
5223	Shop sales assistants	-0.59	-0.12	-1.12
5230	Cashiers and ticket clerks	-1.96	-0.43	-0.64
5241	Fashion and other models	-2.63	-0.88	-1.43
5244	Contact centre salespersons	-2.83	1.87	-1.60
5246	Food service counter attendants	-1.46	0.03	-1.28
5249	Sales workers not elsewhere classified	-1.80	-0.15	-1.42
5311	Child care workers	-0.21	-0.50	0.26
5312	Teachers' aides	0.20	0.53	-1.21
5322	Home-based personal care workers	0.55	-0.66	-1.27
5329	Personal care workers in health services not elsewhere classified	-0.47	-0.72	-0.66
5411	Fire-fighters	1.75	-1.77	-0.72
5412	Police officers	1.30	-1.16	0.14
5413	Prison guards	1.16	-0.90	0.08
5414	Security guards	-0.61	-0.79	1.30
5419	Protective services workers not elsewhere classified	-0.05	-0.40	0.61
6111	Field crop and vegetable growers	-1.60	-1.33	2.62
6113	Gardeners, horticultural and nursery growers	1.00	0.24	-0.28
6121	Livestock and dairy producers	-0.62	-1.38	1.98
6210	Forestry and related workers	-0.36	-1.69	0.05
6222	Inland and coastal waters fishery workers	1.00	-2.02	-0.70
7112	Bricklayers and related workers	-0.24	-1.91	-0.44
7113	Stonemasons, stone cutters, splitters and carvers	0.16	-1.99	-0.79

Appendix Table 1 (continued). List of occupations, the exposure indices of Felten et al. (2023) and Webb (2020) and the complementarity index of Pizzinelli et al. (2023)

ISCO	Occupation	Pizinnelli et al. (2023)'s complementarity index	Felton et al. (2023)'s exposure indices	Webb (2020)'s exposure indices
7114	Concrete placers, concrete finishers and related workers	-0.46	-1.94	-0.93
7115	Carpenters and joiners	0.72	-1.72	0.92
7119	Building frame and related trades workers not elsewhere classified	0.24	-1.62	-0.26
7122	Floor layers and tile setters	-0.75	-1.79	-0.02
7123	Plasterers	-0.95	-1.98	-0.44
7124	Insulation workers	-0.35	-1.78	0.10
7125	Glaziers	0.69	-1.75	0.98
7126	Plumbers and pipe fitters	0.92	-1.62	-0.51
7127	Air conditioning and refrigeration mechanics	0.91	-0.44	1.97
7131	Painters and related workers	-0.83	-1.98	-0.30
7132	Spray painters and varnishers	-2.09	0.29	-1.26
7211	Metal moulders and coremakers	-1.04	-2.17	-0.04
7212	Welders and flamecutters	-1.77	-1.78	0.35
7213	Sheet-metal workers	-0.42	-1.56	-0.42
7214	Structural-metal preparers and erectors	-0.39	-2.03	-0.35
7215	Riggers and cable splicers	1.04	-1.76	3.07
7222	Toolmakers and related workers	-0.26	-1.26	-0.65
7223	Metal working machine tool setters and operators	-1.39	0.06	0.81
7224	Metal polishers, wheel grinders and tool sharpeners	-1.59	-1.63	0.40
7231	Motor vehicle mechanics and repairers	0.11	-1.51	-0.40
7232	Aircraft engine mechanics and repairers	0.06	-1.24	-0.27
7233	Agricultural and industrial machinery mechanics and repairers	0.41	-1.60	0.28
7311	Precision-instrument makers and repairers	-1.07	-0.97	-0.64
7312	Musical instrument makers and tuners	-0.62	-0.97	0.33
7313	Jewellery and precious-metal workers	-1.61	-1.03	-0.40
7314	Potters and related workers	-1.22	-1.72	-1.13
7315	Glass makers, cutters, grinders and finishers	-3.68	-1.38	-0.45

Appendix Table 1 (continued). List of occupations, the exposure indices of Felten et al. (2023) and Webb (2020) and the complementarity index of Pizzinelli et al. (2023)

ISCO	Occupation	Pizinnelli et al. (2023)'s complementarity index	Felton et al. (2023)'s exposure indices	Webb (2020)'s exposure indices
7316	Sign writers, decorative painters, engravers and etchers	-1.83	-1.29	0.01
7318	Handicraft workers in textile, leather and related materials	-1.85	-1.45	-1.12
7321	Pre-press technicians	-1.82	-0.32	2.17
7322	Printers	-1.21	-1.27	1.82
7323	Print finishing and binding workers	-1.75	-1.35	0.70
7411	Building and related electricians	1.62	-1.35	-0.13
7412	Electrical mechanics and fitters	0.29	-0.76	0.46
7413	Electrical line installers and repairers	1.24	-1.58	-0.16
7421	Electronics mechanics and servicers	-0.49	-0.72	-0.34
7422	Information and communications technology installers and servicers	0.16	-0.35	-0.03
7511	Butchers, fishmongers and related food preparers	-1.41	-1.65	-0.43
7512	Bakers, pastry-cooks and confectionery makers	-1.36	-0.85	-1.06
7513	Dairy-products makers	-1.40	-0.26	0.22
7514	Fruit, vegetable and related preservers	-0.34	-1.01	1.32
7515	Food and beverage tasters and graders	-1.40	-0.90	1.23
7521	Wood treaters	-0.82	-1.77	0.82
7522	Cabinet-makers and related workers	-0.92	-1.58	0.23
7523	Woodworking-machine tool setters and operators	-1.26	-0.08	1.33
7531	Tailors, dressmakers, furriers and hatters	-1.34	-1.00	1.37
7532	Garment and related pattern-makers and cutters	-1.83	-1.13	1.30
7533	Sewing, embroidery and related workers	-2.51	-1.72	-1.20
7534	Upholsterers and related workers	-1.86	-1.90	0.64
7541	Underwater divers	1.46	-1.54	-0.80
7542	Shotfirers and blasters	0.67	-1.39	-0.77
8111	Miners and quarriers	-0.57	-1.87	0.17
8112	Mineral and stone processing plant operators	-0.93	-0.16	0.54

Appendix Table 1 (continued). List of occupations, the exposure indices of Felten et al. (2023) and Webb (2020) and the complementarity index of Pizzinelli et al. (2023)

ISCO	Occupation	Pizinnelli et al. (2023)'s complementarity index	Felton et al. (2023)'s exposure indices	Webb (2020)'s exposure indices
8113	Well drillers and borers and related workers	0.65	-1.66	0.38
8114	Cement, stone and other mineral products machine operators	-0.84	-1.38	-1.31
8121	Metal processing plant operators	-1.45	-0.12	-0.30
8122	Metal finishing, plating and coating machine operators	-1.21	0.31	0.87
8131	Chemical products plant and machine operators	-0.06	-1.08	0.94
8132	Photographic products machine operators	-1.53	0.25	1.17
8141	Rubber products machine operators	-1.48	-1.13	0.69
8142	Plastic products machine operators	-1.76	-1.33	-2.12
8151	Fibre preparing, spinning and winding machine operators	-2.56	0.16	1.43
8152	Weaving and knitting machine operators	-1.62	-0.14	2.57
8154	Bleaching, dyeing and fabric cleaning machine operators	-1.43	-1.36	2.83
8156	Shoemaking and related machine operators	-2.75	-1.50	-1.41
8157	Laundry machine operators	-2.49	-1.32	0.22
8160	Food and related products machine operators	-1.27	-0.57	-0.46
8171	Pulp and papermaking plant operators	-1.29	-0.76	1.21
8172	Wood processing plant operators	-1.19	-1.75	-0.20
8182	Steam engine and boiler operators	1.09	-0.97	0.42
8183	Packing, bottling and labelling machine operators	-0.94	-1.46	-0.62
8189	Stationary plant and machine operators not elsewhere classified	-1.39	-1.20	0.96
8211	Mechanical machinery assemblers	-0.92	-1.43	0.40
8212	Electrical and electronic equipment assemblers	-1.28	-1.08	-0.09
8219	Assemblers not elsewhere classified	-1.16	-1.26	2.31
8311	Locomotive engine drivers	0.12	-1.54	2.55
8312	Railway brake, signal and switch operators	0.07	-1.38	-0.03
8322	Car, taxi and van drivers	-0.25	-0.80	-0.55
8331	Bus and tram drivers	-1.09	-1.32	-0.14

Appendix Table 1 (continued). List of occupations, the exposure indices of Felten et al. (2023) and Webb (2020) and the complementarity index of Pizzinelli et al. (2023)

ISCO	Occupation	Pizinnelli et al. (2023)'s complementarity index	Felton et al. (2023)'s exposure indices	Webb (2020)'s exposure indices
8332	Heavy truck and lorry drivers	0.06	-1.90	0.46
8342	Earthmoving and related plant operators	0.34	-1.40	1.01
8343	Crane, hoist and related plant operators	-0.24	-1.55	1.62
8350	Ships' deck crews and related workers	0.77	-1.70	-0.84
9111	Domestic cleaners and helpers	-2.77	-1.48	-1.30
9112	Cleaners and helpers in offices, hotels and other establishments	-0.42	-2.05	-0.93
9121	Hand launderers and pressers	-2.88	-2.41	-0.87
9129	Other cleaning workers	-0.09	-1.74	-0.10
9214	Garden and horticultural labourers	-1.88	-2.19	-1.12
9311	Mining and quarrying labourers	0.92	-2.09	1.15
9312	Civil engineering labourers	0.47	-1.89	-0.43
9313	Building construction labourers	-0.29	-1.65	-0.88
9321	Hand packers	-1.32	-1.66	1.46
9329	Manufacturing labourers not elsewhere classified	-1.19	-1.79	-0.06
9333	Freight handlers	0.92	-1.07	-0.21
9411	Fast food preparers	-1.74	-0.76	-1.29
9412	Kitchen helpers	-2.10	-1.73	-1.49
9611	Garbage and recycling collectors	0.50	-1.74	-0.01
9621	Messengers, package deliverers and luggage porters	0.09	-1.35	-0.78
9622	Odd job persons	0.42	-1.81	-0.29
9623	Meter readers and vending-machine collectors	-1.33	-1.38	-0.46
9629	Elementary workers not elsewhere classified	-1.83	-0.99	0.36

Note: The presented index scores were calculated so that the average of the entire sample is 0 for each index and the standard deviation is 1.

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

Appendix Table 2. The results of a multivariate estimation of the association between various characteristics and the AI exposure indices

Period / Explanatory variable / Dependent variable	January 2018–December 2023		January 2023–December 2023	
	Felten et al. (2023)	Webb (2020)	Felten et al. (2023)	Webb (2020)
Industry (base group: Agriculture)				
Mining and quarrying	0.00 (0.034)	-0.67*** (0.041)	0.08 (0.084)	-0.73*** (0.103)
Manufacturing	0.08*** (0.012)	-0.79*** (0.014)	0.07* (0.030)	-0.87*** (0.037)
Supply of electricity, gas, steam and air conditioning	0.38*** (0.018)	-0.95*** (0.021)	0.46*** (0.045)	-1.03*** (0.056)
Supply of water, sewage services and waste disposal	-0.10*** (0.018)	-0.88*** (0.021)	-0.16*** (0.046)	-0.89*** (0.056)
Construction	-0.10*** (0.012)	-0.84*** (0.015)	-0.07* (0.031)	-0.89*** (0.038)
Wholesale and retail commerce; vehicle and motorcycle repair	0.39*** (0.012)	-1.34*** (0.014)	0.34*** (0.030)	-1.43*** (0.037)
Transportation, storage and postal and courier services	-0.11*** (0.012)	-0.99*** (0.015)	-0.14*** (0.031)	-1.07*** (0.038)
Hospitality and food services	-0.08*** (0.012)	-1.91*** (0.015)	-0.07* (0.031)	-2.03*** (0.038)
Information and communication	0.95*** (0.012)	-0.64*** (0.015)	0.91*** (0.031)	-0.73*** (0.037)
Financial services and insurance services	1.11*** (0.013)	-1.19*** (0.015)	1.10*** (0.032)	-1.30*** (0.039)
Real estate	1.02*** (0.015)	-1.31*** (0.018)	0.96*** (0.039)	-1.42*** (0.048)
Professional, scientific and technical services	0.88*** (0.012)	-0.90*** (0.015)	0.84*** (0.030)	-0.96*** (0.037)
Management and support	0.11*** (0.012)	-0.98*** (0.015)	0.07* (0.031)	-1.08*** (0.038)
Local administration, public administration and defense	0.71*** (0.012)	-1.17*** (0.015)	0.69*** (0.031)	-1.26*** (0.038)
Education	0.54*** (0.012)	-1.40*** (0.014)	0.54*** (0.030)	-1.49*** (0.037)
Health, welfare and nursing care	0.30*** (0.012)	-1.31*** (0.014)	0.28*** (0.030)	-1.42*** (0.037)
Art, entertainment and leisure	0.27*** (0.013)	-1.38*** (0.016)	0.23*** (0.033)	-1.49*** (0.041)

Appendix Table 2 (continued). The results of a multivariate estimation of the association between various characteristics and the AI exposure indices

Period	January 2018–December 2023		January 2023–December 2023	
	Felten et al. (2023)	Webb (2020)	Felten et al. (2023)	Webb (2020)
Other services	0.09***	-1.50***	-0.02	-1.60***
	(0.013)	(0.015)	(0.032)	(0.039)
Households as employers	-0.22***	-1.97***	-0.24***	-2.11***
	(0.013)	(0.016)	(0.034)	(0.041)
Non-state organizations and bodies	0.56***	-0.95***	0.27**	-0.72***
	(0.038)	(0.045)	(0.098)	(0.121)
Unknown	0.52***	-0.85***	0.45***	-0.94***
	(0.015)	(0.018)	(0.038)	(0.046)
Education (base group: did not graduate high school)				
Graduated high school	0.33***	0.08***	0.33***	0.09***
	(0.003)	(0.004)	(0.009)	(0.011)
Non-academic post-secondary certificate	0.45***	0.26***	0.46***	0.27***
	(0.004)	(0.005)	(0.011)	(0.013)
Bachelor’s degree	0.81***	0.47***	0.79***	0.46***
	(0.004)	(0.005)	(0.009)	(0.012)
Master’s degree	0.94***	0.56***	0.92***	0.57***
	(0.004)	(0.005)	(0.010)	(0.013)
PhD	0.91***	0.76***	0.87***	0.68***
	(0.009)	(0.010)	(0.021)	(0.026)
Other certificate	0.34***	0.18***	0.27***	0.09*
	(0.012)	(0.015)	(0.030)	(0.036)
Age	0.00***	0.01***	0.00***	0.01***
	(0.000)	(0.000)	(0.001)	(0.001)
Age squared	-0.00***	-0.00***	-0.00***	-0.00***
	(0.000)	(0.000)	(0.000)	(0.000)
Usually works from home	0.16***	0.19***	0.17***	0.20***
	(0.004)	(0.005)	(0.008)	(0.009)
Gender and sector (base group: Arab man)				
Haredi man	0.63***	-0.02*	0.62***	-0.08***
	(0.007)	(0.008)	(0.016)	(0.019)
Non-Haredi Jewish man or other	0.44***	0.17***	0.44***	0.12***
	(0.004)	(0.004)	(0.009)	(0.011)
Arab woman	0.40***	-0.32***	0.42***	-0.38***
	(0.005)	(0.006)	(0.012)	(0.015)
Haredi woman	0.68***	-0.13***	0.67***	-0.18***
	(0.005)	(0.007)	(0.013)	(0.016)
Non-Haredi Jewish woman or other	0.64***	-0.17***	0.65***	-0.22***
	(0.004)	(0.004)	(0.009)	(0.011)

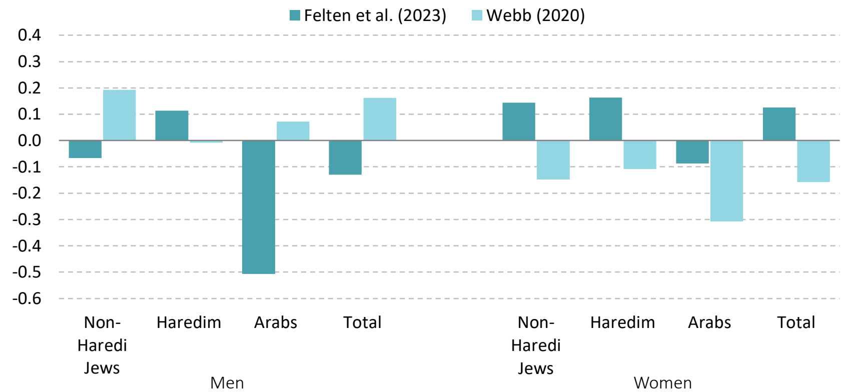
Appendix Table 2 (continued). The results of a multivariate estimation of the association between various characteristics and the AI exposure indices

Period	January 2018–December 2023		January 2023–December 2023	
	Felten et al. (2023)	Webb (2020)	Felten et al. (2023)	Webb (2020)
Monthly trend	-0.00***	0.00***	-0.00	0.00
	(0.000)	(0.000)	(0.001)	(0.001)
Constant	-1.21***	0.43***	-0.98*	0.51
	(0.035)	(0.042)	(0.495)	(0.608)
N	679,532	679,532	106,787	106,787
R2	0.41	0.23	0.42	0.24
F	13,315	5,679	2,171	962
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)

Note: the table presents the OLS estimation results with standard errors grouped at the level of the individuals.

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

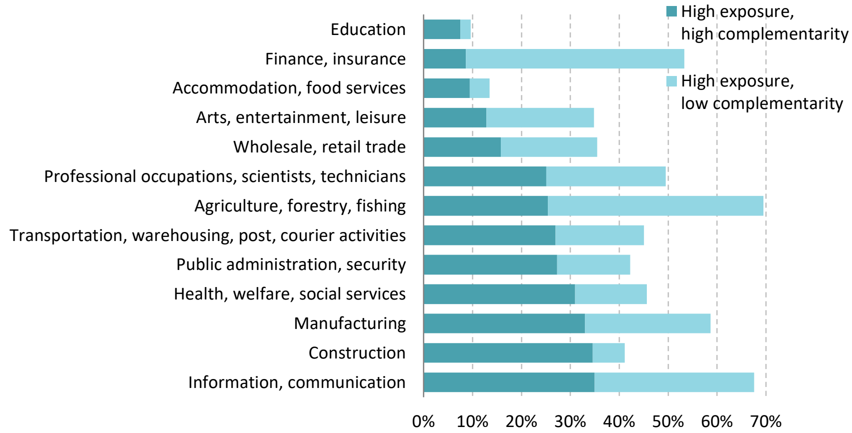
Appendix Figures 1. Exposure to artificial intelligence by gender and sector, adjusted for industry sector, education, age, work from home and survey period, 2018–2023



Note: The graph is based on estimates from the first two (right hand) columns in Appendix Table 2.

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

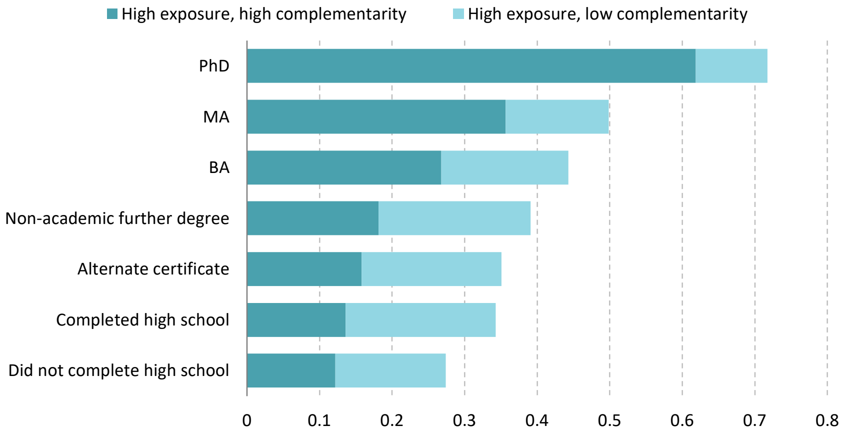
Appendix Figure 2. Exposure and complementarity by industry, 2018–2023



Note: Exposure groups are based on Webb's index (2020). Figure 10 in the body of the paper presents the same distribution using the exposure index of Felten et al. (2023).

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

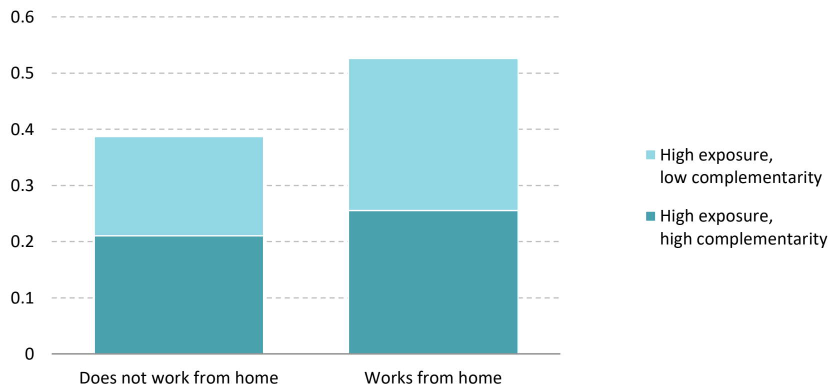
Appendix Figure 3. Exposure and complementarity by official level of schooling completed, 2018–2023



Note: Exposure group is based on Webb's index (2020). Figure 11 in the body of the paper presents the same distribution using the exposure index of Felten et al. (2023).

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

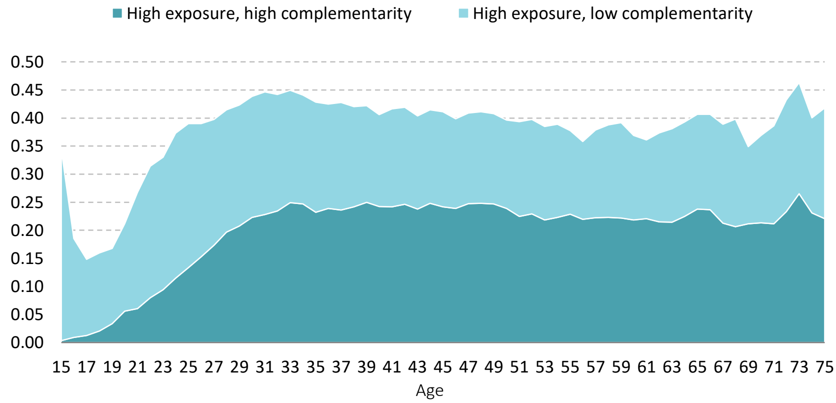
Appendix Figure 4. Exposure and complementarity by whether people usually work from home, 2018–2023



Note: Exposure groups are based on Webb's index (2020). Figure 12 in the body of the paper presents the same distribution using the exposure index of Felten et al. (2023).

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

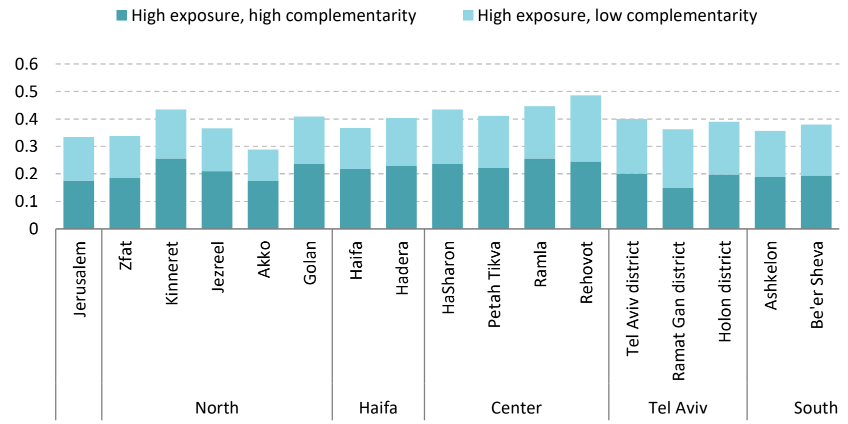
Appendix Figure 5. Exposure and complementarity by age, 2018–2023



Note: Exposure groups are based on Webb's index (2020). Figure 13 in the body of the paper presents the same distribution using the exposure index of Felten et al. (2023).

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

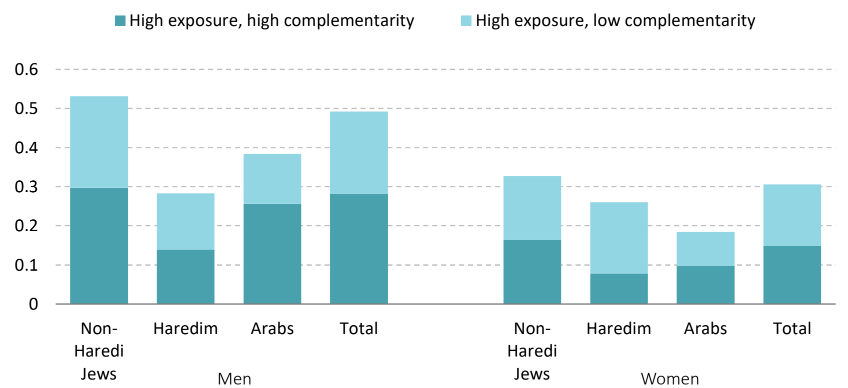
Appendix Figure 6. Exposure and complementarity by residential district, 2018–2023



Note: Exposure groups are based on Webb's index (2020). Figure 14 in the body of the paper presents the same distribution using the exposure index of Felten et al. (2023).

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

Appendix Figure 7. Exposure and complementarity by gender and sector, 2018–2023



Note: Exposure groups are based on Webb's index (2020). Figure 14 in the body of the paper presents the same distribution using the exposure index of Felten et al. (2023).

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

Adapting the exposure indices to Labor Force Survey data and normalizing them to the sample

The exposure scores according to the indices of Webb (2020) and Felten et al. (2023) and the complementarity score according to the index of Pizzinelli et al. (2023) are assigned to occupations according to the O*NET classification. However, the Labor Force Survey data from the Central Bureau of Statistics classify respondents' occupations according to the ISCO (4-digit) classification. Therefore, the first step in adapting the indices was to convert them from O*NET to ISCO (a step for which we used the conversion table of the Bureau of Labor Statistics). The conversion is not unambiguous, and therefore some occupations under O*NET were grouped into a single occupation under ISCO. The exposure score of this occupation (in ISCO) is a simple average of the exposure scores of the various occupations (in O*NET) that were matched to it.

The Labor Force Survey data to which we attached the exposure scores were taken from the monthly surveys of the Central Bureau of Statistics from January 2018 to December 2023. We focus on individuals who typically work at least 10 hours per week. The data include occupation at the required level of detail (4 digits) for about 85% of the workers who constitute the final sample in this research, comprising about 680,000 monthly observations for about 85,000 Israeli workers. After matching the exposure indices to the sample, the three indices (Webb's and Felten et al.'s exposure indices and the complementarity index of Pizzinelli et al.) were normalized to the sample so that their mean value is 0 and their standard deviation is 1.[12] Normalizing the indices to the

12 Formally, the final score ($score_i$) is obtained by shifting the raw score (raw_score_i) (which is assigned to individual *i* in the survey according to that individual's occupation) by the weighted mean (μ) across all occupations and dividing by the weighted standard deviation of the raw scores (σ):

$$score_i = \frac{raw\_score_i - \mu_{raw\_score}}{\sigma_{raw\_score}}$$

where the weighted average and the weighted standard deviation are derived from the raw scores (raw_score_i) and from the survey weights w_i ($\sum_{i=1}^{n} w_i = 1$):

$$\mu_{raw\_score} = \sum_{i=1}^{n} [w_i \times raw\_score_i]$$

$$\sigma_{raw\_score} = \sqrt{\sum_{i=1}^{n} \left[w_i \times \left(raw\_score_i - \mu_{raw\_score}\right)^2\right]}$$

sample is intended to facilitate comparison between them and between subgroups in the sample, since the distributions of the raw indices are very different, and their scores do not have quantitative significance.