AI Unboxed and Jobs: A Novel Measure and Firm-Level Evidence from Three Countries*

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Abstract

We unbox developments in artificial intelligence (AI) to estimate how exposure to these developments affect firm-level labour demand, using detailed register data from Denmark, Portugal and Sweden over two decades. Based on data on AI capabilities and occupational work content, we develop and validate a time-variant measure for occupational exposure to AI across subdomains of AI, such as language modelling. According to the model, white collar occupations are most exposed to AI, and especially white collar work that entails relatively little social interaction. We illustrate its usefulness by applying it to near-universal data on firms and individuals from Sweden, Denmark, and Portugal, and estimating firm labour demand regressions. We find a positive (negative) association between AI exposure and labour demand for high-skilled white (blue) collar work. Overall, there is an up-skilling effect, with the share of white-collar to blue collar workers increasing with AI exposure. Exposure to AI within the subdomains of image and language are positively (negatively) linked to demand for high-skilled white collar (blue collar) work, whereas other AI-areas are heterogeneously linked to groups of workers.

Keywords: Artificial intelligence; Labour demand; Multi-country firm-level evidence

JEL Codes: E24, J23, J24, N34, O33.

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1. Introduction

This paper investigates the impact of artificial intelligence (AI) technologies across nine AI sub-areas on labour demand of the near-universe of firms in three countries and across almost two decades. Previous research has investigated the average impact of AI and typically using aggregate or limited sample data sets for the USA (e.g., Felten *et al.*, 2019, Fossen and Sorgner, 2022, Lane and Saint-Martin, 2021), while a few studies have used, e.g., online job ads, also in the USA (e.g., Acemoglu *et al.*, 2022, Babina *et al*, 2022a). However, identifying the detailed, heterogeneous effects of AI is critical (Seamans and Raj, 2018, Frank *et al.*, 2019, Zolas *et al.*, 2021). Workers, businesses and countries are likely to be differently impacted depending on their characteristics. In addition, the tremendous recent progress in AI technologies has been heterogeneous across subdomains and time. For example, there was substantial progress in image recognition and speech recognition in the early 2010s, important advances in machine translation occurring in the mid-2010s (Zhang *et al.*, 2021), while language modelling saw a breakthrough around 2020. With this paper, we aim to shed light on these nuanced interactions between AI technology and the economy.

AI technologies are computer-based algorithms with abilities for addressing problems that would traditionally require human intelligence. They use large amounts of data, operate with varying degrees of supervision and can assist decision-makers or even themselves make decisions (OECD, 2019). With recent breakthroughs fuelled by the combination of more powerful processors, large data sets, and the invention of new algorithms, AI technologies are expected to profoundly impact labour markets, including for white collar workers.

Conceptually, AI can replace, assist or complement workers. Much of the literature presumes that AI is yet another automation technology that replaces workers in performing specific tasks. However, more recently, studies suggest that advanced technologies like AI may instead complement workers and contribute to firm innovation and the launch of new products, stimulating labour demand (e.g., Babina *et al*, 2022b, Bessen *et al*, 2022, Hirvonen *et al.*, 2022).

We contribute to the literature on AI and jobs in two ways. First, we develop an occupational exposure measure that unboxes developments in AI, building on the seminal work of Felten *et al.* (2018, 2021).[1] Our measure is a set of dynamic AI occupational exposure (DAIOE) indices on how exposed a particular occupation is to AI, over time; an overall AI index, and sub-indices for each of nine AI *applications*, such as language modelling or image classification. The exposure indices reflect the year-by-year across different areas of AI during the recent "AI summer". To estimate AI progress, we collect data on benchmarks that have been used in AI research to measure AI capabilities, for the period 2010-2023. In contrast, most of the measures in the previous literature have included aggregate AI exposure only (Webb, 2020, Felten *et al.*, 2021), and to the extent that data on AI capabilities was collected, it was not on a year-by-year basis (Felten *et al.*, 2018, Webb, 2020). Our approach also puts an emphasis on the importance of social interaction in jobs, which we assume to be associated with lower exposure to AI; an important dimension of work which was not incorporated in, e.g., Felten *et al.* (2021). The DAIOE measure can be used for backward-looking analysis, studying the evolution of AI and its impact on occupational exposure in recent years. By looking at the data for the latest year, 2023, we can get an indication of where we are today. And the model can be repurposed for testing future scenarios. In our interpretation, *exposure* according to the index indicates that AI technology is potentially useful for an occupation, but it is beyond the scope of the model to predict whether or how exposure will lead to a change in the demand for human labour. The most AI-exposed occupations are more cognitive, less physical, and less social. In other words, these are white collar occupations, and especially white collar jobs that entail relatively little social interaction.

Second, we illustrate the usefulness of the DAIOE measure by bringing it to highly detailed administrative data on firms and workers. Studying firms' and workers' detailed exposure

[1] AI occupational exposure measures have been found to be strongly linked to changes in hiring patterns of establishments, indicating their usefulness in capturing impacts of AI development on economic activity Acemoglu *et al.* (2022).

and response is instrumental for identifying heterogeneous effects and key underlying features that determine the impact on labour demand. These data enable us to estimate firm-level labour demand regressions, where the measure of AI exposure is linked to the granular workforce composition of firms at the start of the study period.

We apply the analysis to data from three countries of the European Union (EU), namely Denmark, Portugal, and Sweden. The three countries are quite different in many regards, such as labour market rigidity, industrial structure, productivity, digital intensity, and AI adoption. This heterogeneity provides us with a laboratory for exploring how different economies are heterogeneously affected by AI advances.

We find that pre-period exposure to the advances of AI is associated with an up-skilling of the workforce. More exposed firms reduce their employment of blue collar workers, and increase their employment of high-skilled white collar workers. Importantly, further results indicate that the impacts across subdomains of AI substantially differ across blue and high-skilled white collar workers, with image and language advances benefiting labour demand for high-skilled white collar but negatively impacting blue collar workers.

The rest of the paper is organised as follows. In Section 2., we provide a primer on the three economies that we study. In Section 3., we present our conceptual framework. In Section 4., we introduce our dynamic AI occupational exposure measure, the register data, and our estimation and identification strategy. In Section 5., we present our econometric results on the relationship between AI exposure and firm labour demand. In Section 6., we conclude. Additional results and technical details are provided in the Online Appendix.

2. A primer on the three economies

The three countries that we study are all three relatively open economies, but they differ widely in many other respects, see Figure 1, such as, labour market characteristics, digitalisation, productivity and industrial structure.[2] These differences opens up the possibility both to arrive at general patterns in terms of how AI technologies impact the labour market, but also in understanding how differences, e.g, in labour market characteristics, may lead to differential labour market impacts from technological developments.

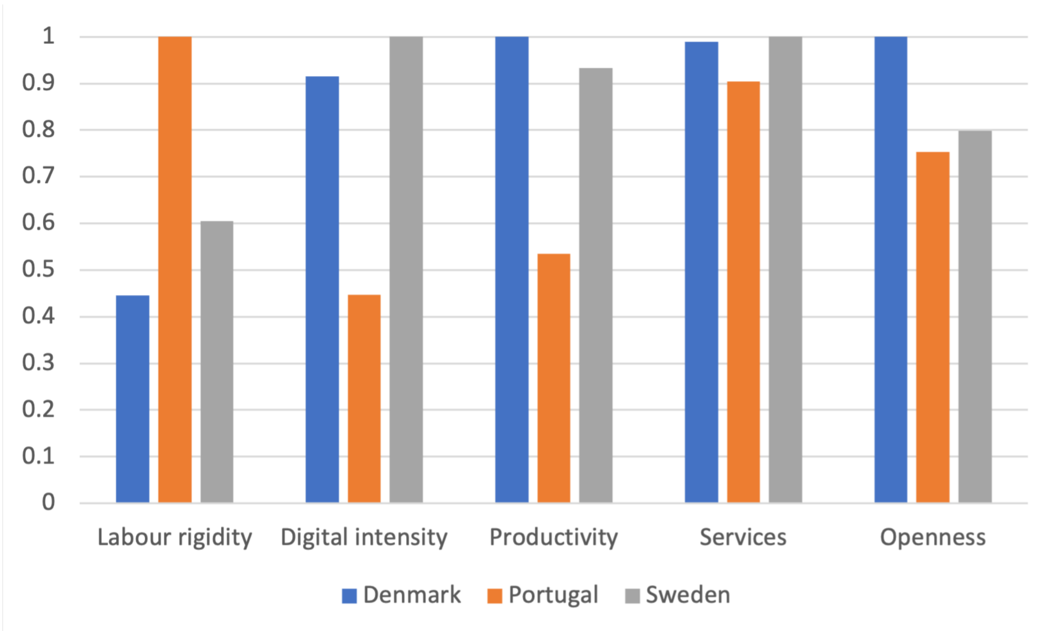

Figure 1: A snapshot of country characteristics.

Notes: The figure displays indicators for the three countries in terms of labour market rigidity (regulatory framework for unfair individual dismissals of regular workers, 2019), firm digital intensity (Share of firms with high to very high digital intensity, 2021), productivity (GDP per hour worked, 2019), services employment share (services employment over total employment in services and manufacturing, Q4 2019), and trade openness (export share of GDP, 2016) (Sources: own calculations, with "1" being the most and "0" the least rigid, digitally intense, productive, services-oriented or open economy, OECD 2021a,b and Eurostat 2022).

Denmark and Sweden stand out among the three countries in terms of having relatively flexible labour markets that also provide employment security (so-called "flexicurity"). Denmark and Sweden also have in common having had an integrated labour market for almost 70 years and sharing many features of the Nordic welfare model. Portugal is at the other end of the spectrum, with the least flexible labour market. Portugal also has the lowest

[2]The countries also differ in economic size and geographic size and location. Sweden, Denmark and Portugal jointly account for 7% and 5% of the EU GDP and population. Geographically, Sweden is the third largest EU country, while Portugal and Denmark are ranked 12 and 21 in size. Together, the three countries cover three of the four European climate zones, from Nordic to Mediterranean climate, representing vastly different conditions, e.g., for the primary sector.

employment, labour market participation and post-secondary education rates (See Figure A1 of the Online Appendix).

Turning to the other characteristics of Figure 1, we note that Denmark and Sweden have the highest share of digitally intensive enterprises. They are also highly services-oriented. In contrast, Portugal is the major manufacturing economy of the three. Portugal is also the least digitally intense, least productive and least open of the three economies.

It may be added that according to survey data for the use of AI among enterprises in the EU in 2021 with at least 10 employees, Portuguese and Danish firms stand out (Eurostat, 2022). Approximately 17 and 24 percent of the firms in Portugal and Denmark use AI, respectively, while only 10 percent in Sweden.

3. Conceptual framework

In this section, we outline a conceptual framework that opens for studying how sub-areas of AI impact labour demand both overall and heterogeneously across firms and workers. We have a particular interest in effects on white collar work, where AI can have an impact by not being limited to codifiable work. The framework draws on Acemoglu and Restrepo (2018), Aghion *et al* (2019), Bessen *et al* (2022) and Zeira (1998).

Firms produce output Y according to a constant returns to scale production function combining a unit measure of intermediate inputs or tasks, denoted X_i:

$$Y = \left(\int_{N-1}^{N} X_i^{\frac{\sigma-1}{\sigma}} \, di \right)^{\frac{\sigma}{\sigma-1}} \tag{1}$$

where σ marks the elasticity of substitution between tasks. The tasks are ranked according to complexity. Simple tasks can be automated and produced by capital (K) alone, for instance in the form of AI-enabled software or algorithms, while the most complex tasks can only be produced by workers (L). At any point in time there is a complexity level I beyond which

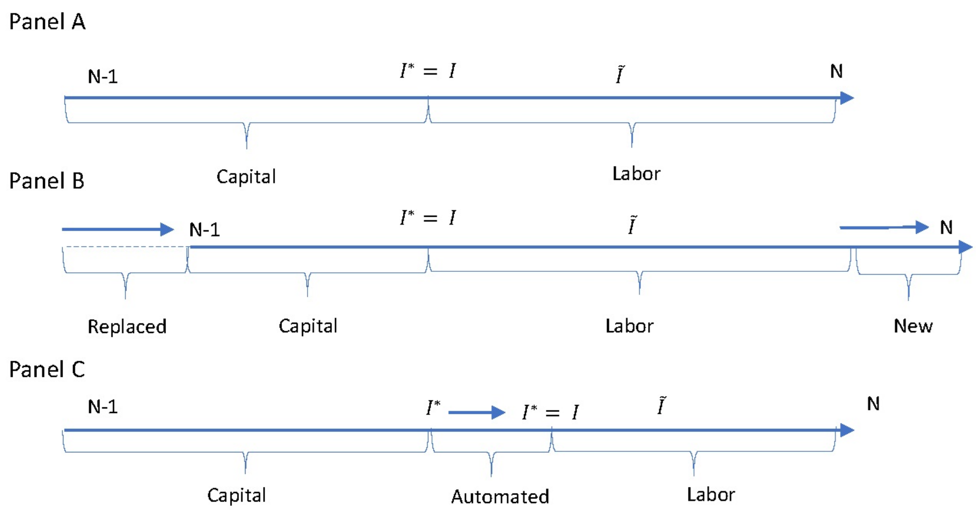

Figure 2: Task creation, automation and replacement.
Source: Acemoglu and Restrepo (2018)

tasks cannot be automated with existing technology. Hence, each task is either performed by capital or labour as follows:

$$X_i = \alpha(i)K_i + \gamma(i)L_i \tag{2}$$

where $\gamma(i) = e^{A_i}$ and $\alpha(i) = 0$ if $i > I$, $\alpha(i) = 1$ if $i \leq I$. Technical and economic feasibility of automation may differ, and there is a unique level of complexity $\tilde{I}$ where the unit cost of production is the same when produced by capital or labour. The realised threshold is determined by firms minimising unit cost, given technical constraints, if any. The unique equilibrium threshold task is thus given by $I^* = min\{I, \tilde{I}\}$. All tasks for which $i < I^*$ are automated. If $I^* = \tilde{I} < I$, there are tasks that can technically be automated, but automation does not pay off.[3] This setup ensures that humans have a comparative advantage in performing complex tasks.

The possible directions of innovation are illustrated in Figure 2. Panel A shows the ranking

[3]Conceptually $I^* = I < \tilde{I}$ is also a possibility, implying that some automatable tasks for which the unit cost is lower with automation would not be automated because of technological constraints.

along the unit measure of tasks and the critical level of complexity.[4] The further to the left in the graph, the more automatable - or AI exposed - is the the task. Innovation may take two different directions, automating existing tasks or creating new tasks. If capital is abundant relative to labour, innovation will focus on automation, and the capital share of output will increase. If the capital endowment is not too large relative to workers, there will be both automation and creation of new tasks.[5].

Panel B depicts the case where innovation generates new tasks. At the same time, the least complex tasks that are already automated, exit the market, moving the unit measure of tasks to the right. Clearly, as the critical level of complexity remains constant, the share of tasks performed by labour increases. Furthermore, as new tasks are always more complex than existing tasks, the sector or occupation becomes more skills-intensive. The simultaneous digitization and servicification of industries is a case in point. For example, the digital and AI transformation of media has replaced automated printing of newspapers by digital platforms where journalists, photographers, software developers and others perform new AI-enabled tasks such as video interviews simultaneously translated to many languages; video reporting, real time analytics of financial data; real time interaction with readers; and many more.

Innovations that automate the existing most AI exposed tasks are depicted in Panel C. Our DAIOE measure represents the dynamics of how the threshold moves over time as illustrated by the arrows. This type of innovation obviously reduces the share of tasks performed by workers.

AI may generate algorithms that replace tasks as in panel C or create new tasks as in panel B. A third possibility is that AI assists workers. To see how, we follow Bessen *et al* (2022) and add quality of task performance to the framework while simplifying the production function of final output to the Cobb-Douglas special case.

[4] We can interpret the unit measure as applying to a sector, an occupation or even an individual worker.

[5] Acemoglu and Restrepo (2018) develop the conditions for balanced growth where automation and task creation advance at the same pace.

$$Y = \Pi_{i=1}^{N} q_i A(i) K^{\alpha} L^{1-\alpha} \tag{3}$$

The quality parameter, $0 \leq q_i \leq 1$, is equal to 1 if the task is automated, i.e. if $i < I^*$. With this O-ring style task-specific quality parameter, automating one task for which quality is less than one would raise the productivity of all tasks. This shift may take place *within* an occupation or across occupations within a sector. In the former case, the occupation becomes more skills intensive and the workers performing it more productive. An example could be legal services where AI enables the automation of sifting through case law allowing lawyers to focus on the specifics of the case being considered. One could also envisage that sifting through case law was done by assistants and paralegals in the first place. Their jobs would be rendered obsolete with AI-enabled identification and summary of case law.

The conceptual framework provides a basis for the empirical analysis of the employment effects of AI exposure. It captures a range of possible outcomes depending on factor prices and the elasticity of substitution between factors. Factor prices are the main determinants of the direction of innovation - i.e. automation or the creation of new tasks.

Innovation will always raise productivity and total output, while automation will by definition render workers obsolete in the automated task. The framework offers two additional sources of labour demand. First, the jobs created by the introduction of new tasks (panel B in Figure 2). Second, the jobs created when automation raises quality and demand for complementary non-automated tasks (the remainder effect (Bessen *et al*, 2022)). The remainder effect predicts a positive relationship between AI use and wages, where the direction of causality runs from AI use to higher productivity and higher wages. Whether the total output effect, new tasks, and the remainder effect dominate the automation effect is an empirical question to which we turn in the next sections.

Basically, we are (and our DAIOE) is agnostic about how AI overall and in different sub-areas is impacting labour demand. AI technology may automate work tasks and/or complement workers in performing those tasks. Whether automation or complementation dominates in an occupation may differ across the three countries. It may also differ across jobs, i.e., across occupations in actual firms and jobs held by actual people, e.g., depending on firm productivity, location, and on worker characteristics.

4. Empirical approach

We want to investigate whether and how different types of AI affect labour demand over time. We therefore develop a dynamic AI occupational exposure measure (DAIOE), and bring it to micro-data. This section describes the exposure model, the micro data, and the regression model that we use to estimate labour demand.

4.1. DAIOE: construction of the index

To estimate how affected occupations are likely to be by AI, we combine information on AI progress and occupational work content, to arrive at a dynamic AI occupational exposure index (DAIOE). The index is a panel, meaning that we have a unique value for each occupation-year.[6] The index covers the years 2010-2023, a time period which has seen rapid progress across many areas of AI technology. The rest of this section describes in detail how the index is constructed.

Our method builds on the work of Felten *et al.* (2018, 2019, 2021). Felten *et al.* (2021) dub their forward-looking index *AIOE*, seeking to predict the likely future impact of AI on occupations. Our index is backward-looking, similar to Felten *et al.* (2018), and we add *dynamic* to emphasise that it is time-variant.

We use data from the Electronic Frontier Foundation (EFF) and Papers With Code (PWC) on AI progress across applications or sub-domains.[7] To the best of our knowledge, these databases are the most comprehensive, publicly available collections of data on AI re-

[6]The appendix contains additional information about the data used to construct the index.

[7]Data are available at: `https://www.eff.org/ai/metrics` and `https://paperswithcode.com`.

search.[8]

We categorise AI technology into nine main *AI applications*, see Table 1. These are the same as in Felten *et al.* (2021), except that we exclude *Instrumental track recognition* because of the lack of availability of metrics. The AI applications can in turn can be grouped into three overarching themes: games, language, and vision. The list of nine applications has been discussed with artificial intelligence researchers, who verified that overall, they provide a good representation of the main areas of AI research during the studied period.

Within each application, the PWC and EFF databases have data on several *metrics*, which are well-defined ways of measuring the performance of AI that have been used as benchmarks in AI research. For example, in the *image recognition* application, one metric is the well-known annual Imagenet contest (formally the known as the ImageNet Large Scale Visual Recognition Challenge (ILSVRC)), where teams of AI developers competed to correctly label images.[9] Another example is the *abstract strategy games* application, which contains the metric chess playing. For each metric, we have observations of the performance of a particular AI at a particular time.

Table 1
AI applications used

Area	*Application*	*Metric Examples*
Games	Abstract strategy games	Chess playing
	Real-time video games	Atari games
Vision	Image recognition	Imagenet Image Recognition competition
	Image comprehension	COCO Visual Question Answering real open ended
	Image generation	Generative models of CIFAR-10 images
Language	Reading comprehension	bAbi 20 QA reading comprehension
	Language modelling	Penn Treebank (Perplexity when parsing English sentences)
	Translation	En-De Translation BLEU scores
	Speech recognition	Word error rate on Switchboard trained against the HUB5'00 dataset

Notes: The table displays the *applications* (or sub-fields) of AI that we use. It also presents examples of specific metrics that are used to measure AI progress within each application. For the full list of metrics, see the appendix.

The metrics use different scales. Some, like Imagenet, are measured as percentage correct.

[8]Data from the EFF have been extensively used in various research fields, such as computer science, economics and management (Felten *et al.*, 2021), and PWC is widely used in the machine learning community (Martínez-Plumed *et al.*, 2021).

[9]The competition was last held in 2017, but the datasets from old competitions continue to be used as benchmarks.

Others may be in the form of absolute values, such as points in Atari games or ELO scores for chess. In order to make them comparable, we follow the methodology of (Felten *et al.*, 2018) and re-scale the metrics so that a *a linear increase in the metric corresponds to an exponential increase in performance.*[10]

We calculate a *best performance frontier* for each metric, which reflects the highest AI performance to date. The frontier (unscaled) for the metric *CIFAR-10 Image Recognition* is illustrated in Figure 3. Scaled frontiers for the full set of metrics within the application *Image recognition* are illustrated in Figure 4.

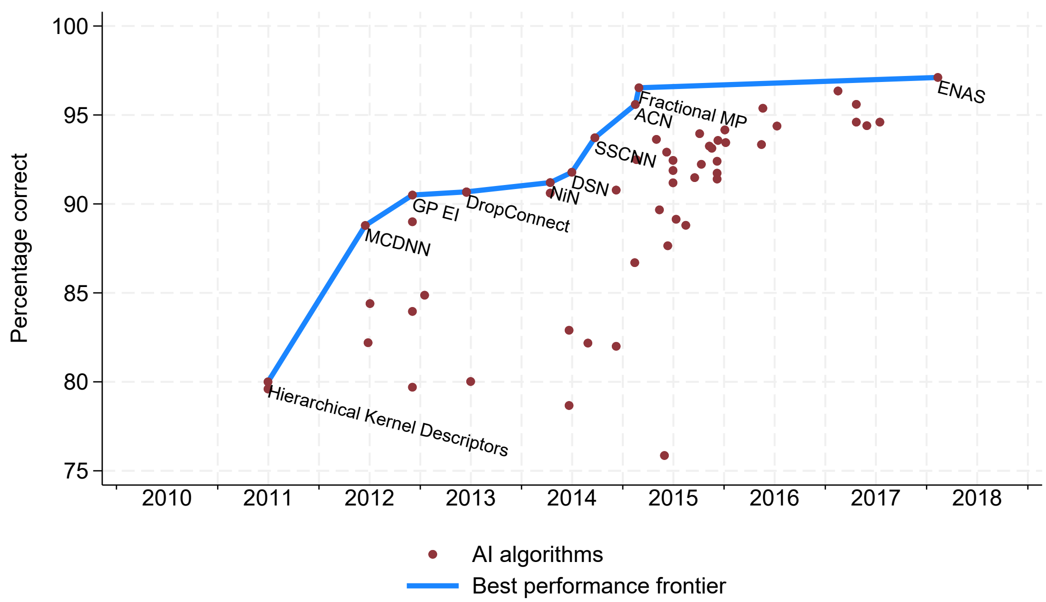

Figure 3: Observations and frontier for the metric *CIFAR-10 Image Recognition*

Notes: The best-performing AI algorithms are labelled with their names. The y-axis reflects the percentage of correctly labelled images.

Next, we aggregate the metrics to an overall progress curve for the application. Felten *et al.* (2018) fitted a linear regression model to the metrics to estimate an overall rate of progress for each application over the studied period. In order to obtain a more nuanced view of AI progress, we estimate year-by-year progress by taking the average slope of the frontier curves of the metrics during that year. The change in AI performance in application i at time t

[10]For details on the method for re-scaling, see the online appendix.

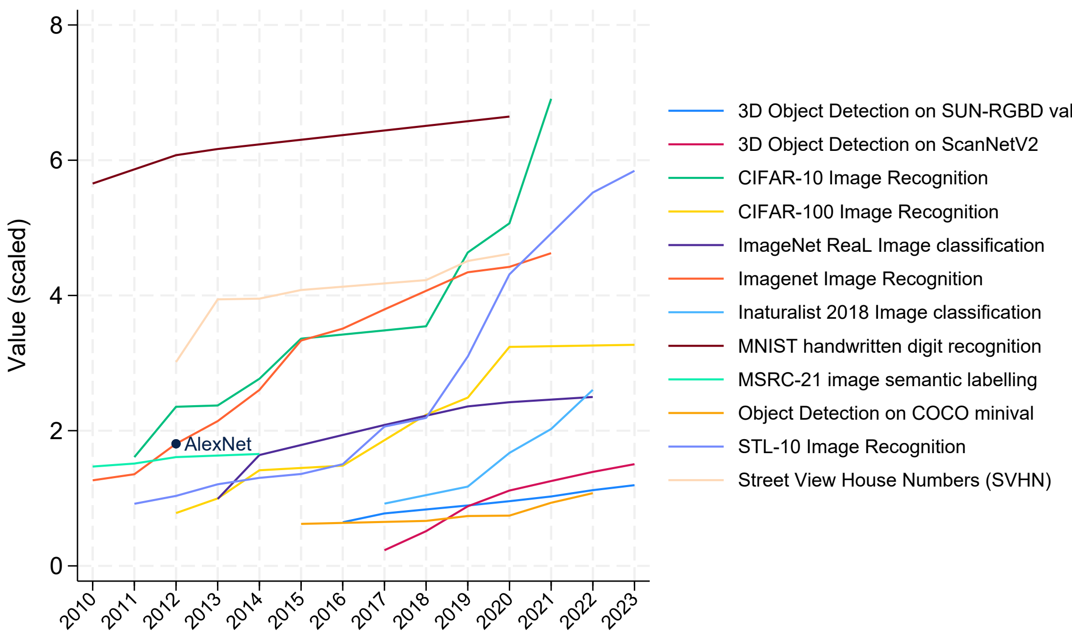

Figure 4: Frontiers for all metrics within the *image recognition* application

Notes: Scaled state-of-the-art frontiers for all 12 metrics within the image recognition application. The metrics have been re-scaled such that a constant rate of improvement corresponds to a linear slope. For example, Imagenet is originally measured as percentage error. We re-scale it using: $-ln(value/100)$. If the percentage error of the frontier was cut by half each year, then curve would be linear, with slope 0.693. The blue point marks the famous win of the AI named AlexNet in the Imagenet competition in 2012, which is considered a seminal moment for the deep learning architecture.

will henceforth be denoted as y_{it}. By summing the yearly changes we can obtain cumulative progress curves for all nine applications, illustrated in Figure 5.

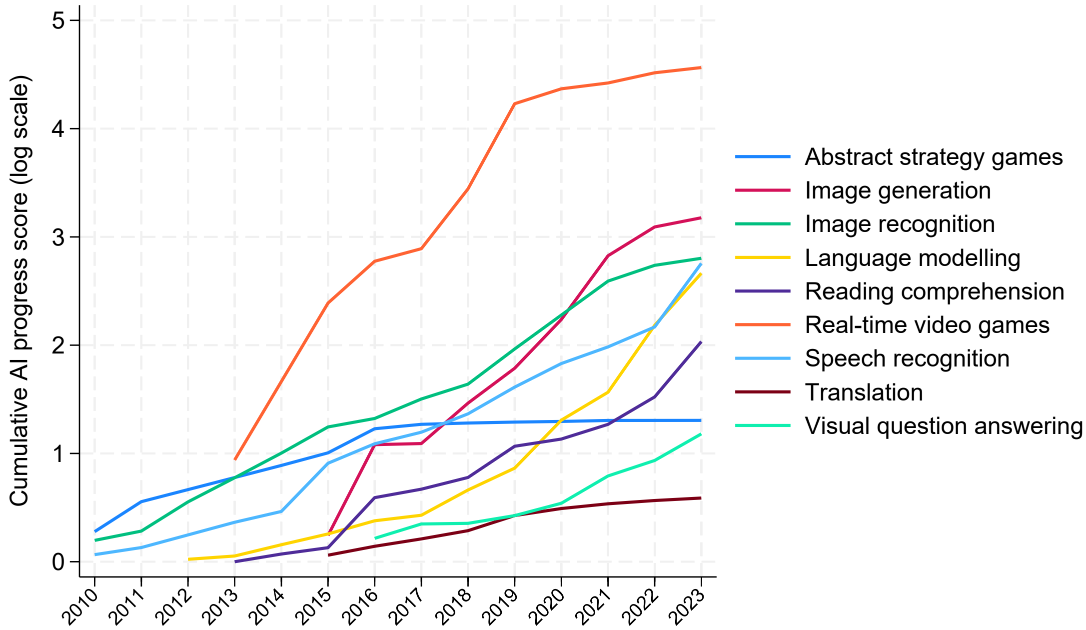

Figure 5: Progress curves for AI applications

Notes: An overall progress curve for each AI application is derived from the underlying metrics, based on the average slope of the metrics in each year. The application-level data is then fed into the *mapping matrix* which links AI applications to worker abilities.

To link AI progress to occupations, we use information about the work content of occupations from the Occupational Information Network (O*NET) database. O*NET is sponsored by the U.S. Department of Labour and is considered one of the world's most authoritative sources of occupational information (Handel, 2016). O*NET contains a set of 52 *worker abilities*, grouped into four categories.[11] This set of abilities is meant to capture fundamental individual characteristics that affect worker performance in an occupation, e.g. oral communication, reasoning, eyesight, or physical strength.

For each ability j and each eight-digit occupation o of the O*NET database we follow the procedure in Felten *et al.* (2021) by computing a measure of an ability's *relevance* for an occupation, r_{oj}, by multiplying the scores for the importance, i_{oj}, and level, l_{oj}, of that

[11]For the full list of abilities, including categories and descriptions, see the online appendix.

ability in that occupation.[12] We then divide the relevance scores by the sum of all relevance scores in the occupation, so that they sum to one for each occupation, in order to normalise for the fact that some occupations use a broader range of abilities than others.[13] These steps are represented by Equation 4:

$$r_{oj} = \frac{i_{oj} l_{oj}}{\sum_{j=1}^{52} i_{oj} l_{oj}} \tag{4}$$

The resulting ability relevance scores for an example occupation, *Nurse practitioners*, are illustrated in Figure 6. Key abilities for nurses relate to oral communication and problem solving. The occupation also requires some psychomotor and physical abilities, such as finger dexterity and trunk strength.

To link AI to occupations, we use the *mapping matrix* from Felten *et al.* (2018) to link each of the AI applications, i, to each of the *worker abilities*, j, in O*NET.[14] Each cell in the 9x52 mapping matrix contains a score between 0 and 1, x_{ij}, where a higher score indicates that AI application i has a higher degree of applicability to worker ability j. The entire matrix is printed in the appendix, see Figure C1. The most striking pattern is that, overall, it is the cognitive abilities that are classed as most strongly related to AI. Most of the AI applications are scored as being unrelated to physical and psychomotor abilities, the exception being *video games*. In our judgement, this as an accurate reflection of AI research during 2010-2023, where greater effort was put into advancing "pure thinking" capabilities,

[12] The respective questions used in the data collection underlying O*NET are: "How *important* is [ability, e.g., oral comprehension] to the performance of your current job?", on a 1-5 scale, and "What *level* of [ability, e.g., oral comprehension] is needed to perform your current job?" on a 1-7 scale, with a "2" illustrated as understanding a commercial and "6" understanding a lecture in an advanced topic. Because importance is scored 1-5, and level 1-7, we re-scale them by dividing by 5 and 7, respectively, to weight them equally in the overall relevance measure.

[13] Occupations that use a broader set of abilities, or a higher average skill level, would otherwise be modelled as more exposed to AI.

[14] The mapping matrix in Felten *et al.* (2018) was created based on the judgement of four computer scientists. Felten *et al.* (2021) provide an updated matrix, which was crowd-sourced by hiring MTurk workers. We choose to use the older matrix as a better fit for our model, because it was intended to reflect the capabilities of AI during the 2010s, whereas the 2021 matrix is forward-looking, intended to reflect likely future uses of AI.

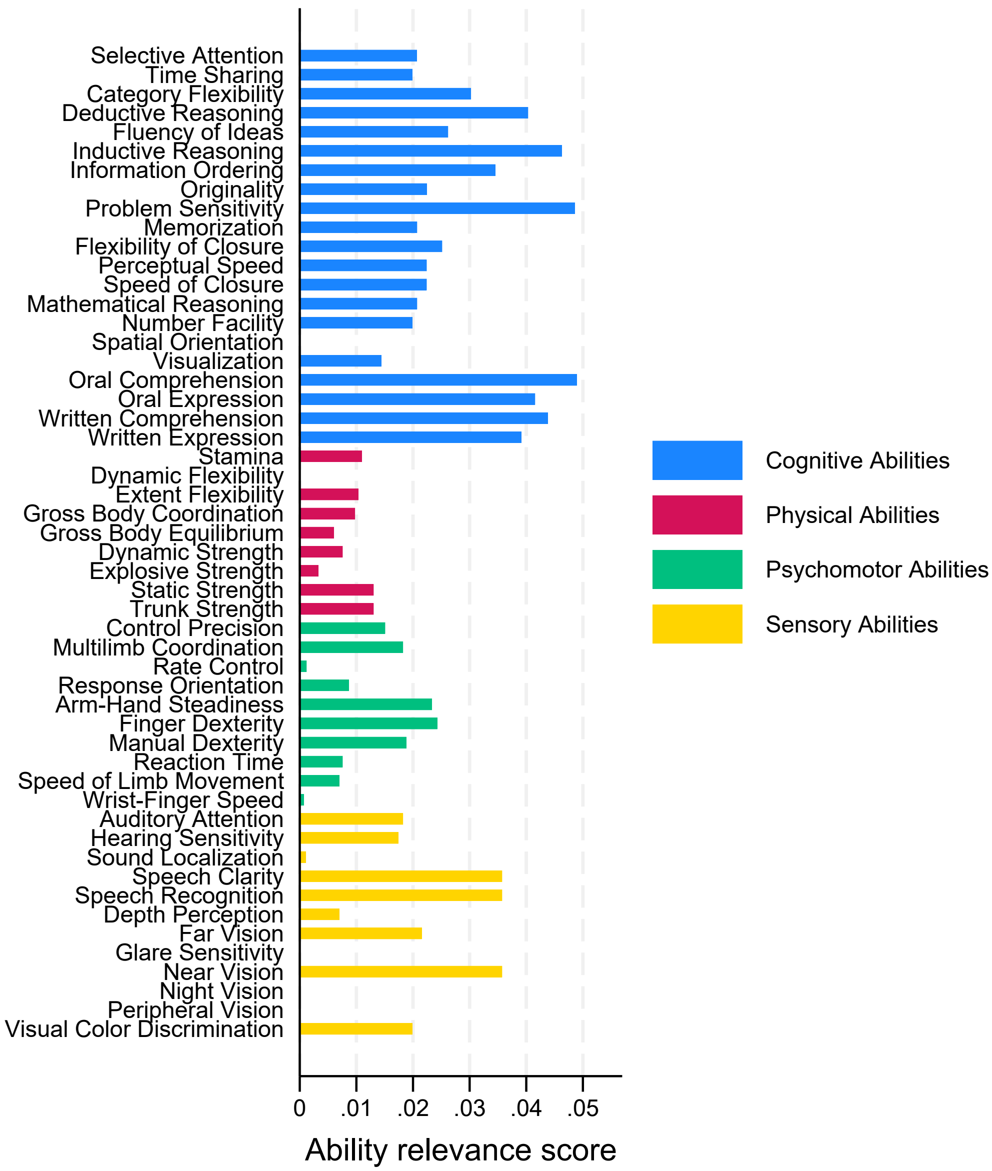

Figure 6: Ability relevance scores for the occupation *Nurse practitioners*

Notes: O*NET level*importance scores, re-scaled to sum to one, as per Equation 4. For more example occupations, see the online appendix.

as opposed to AI for moving in the physical world, i.e., robotics.

Following Felten *et al.* (2018), we input the AI progress data into the mapping matrix by multiplying each row by the estimated AI progress for that application during the year, y_{it}. This interaction of the AI progress and applicability scores yields an overall score for how much the ability's exposure was affected by progress within the AI application during the year. Next, we calculate the sum of the scores in each column, giving us a score, z_{jt}, for how much each ability's exposure was affected by all applications taken together. These steps are represented by Equation 5:

$$z_{jt} = \sum_{i=1}^{9} y_{it} x_{ij} \tag{5}$$

We obtain an overall score, w_{ot}, for the impact of the year's AI progress on the occupation's exposure by multiplying the ability exposure scores with the ability-occupation relevance scores and taking the sum, as shown in Equation 6:

$$w_{ot} = \sum_{j=1}^{52} z_{jt} r_{oj} \tag{6}$$

While the set of 52 abilities captures a great deal of the relevant work content across occupations, in our view it does not do justice to the importance of social interaction in jobs.[15] In order to incorporate the importance of social skills into our model of occupational work content, we make use of the *social skills* data which are available in O*NET. This includes six types of social skills (denoted s), such as *social perceptiveness*, *persuasion* and *instructing*, which like the abilities are scored according to level and importance.[16] We interact the level and importance scores in the same way as we did for the abilities, and then sum the relevance scores to get an overall score for the importance of social skills in the occupation.[17]

[15] The O*NET abilities that are arguably most closely related to social interaction are the four abilities that relate to oral communication.

[16] See the online appendix for the full list of social skills.

[17] In this case, we do not divide by the total social skill scores, thus allowing occupations that require a

Then, we divide the scores by the score of the most social occupation, giving us a score between zero and one, s_o, which indicates how social the occupation is, relative to the most social occupation. These steps are stated by Equation 7:

$$s_o = \frac{\sum_{s=1}^{6} i_{os} l_{os}}{max_{o \epsilon O}\left(\sum_{s=1}^{6} i_{os} l_{os}\right)} \tag{7}$$

We assume that social aspects of work are harder to replace with AI. For example, according to our score, the three most social occupations are *clergy*, *chief executives*, and *counselling psychologists*. It seems plausible to us that for the foreseeable future, a lot of people will continue to want human-to-human interaction for such services as spiritual guidance, leadership of organisations, and mental health counselling. We therefore *discount* the occupation-year AI exposure score (w_{ot}) using the formula in Equation 8:

$$\Delta DAIOE_{ot} = \left(w_{ot} \times \frac{1 - s_o + \delta}{max_{o \epsilon O}\left(1 - s_o + \delta\right)}\right)^2 \tag{8}$$

where δ is a parameter which determines how much weight will be given to social skills in the final exposure measure. Recall that the occupation's social score s_o is between zero and one, with $s_o = 1$ for the most social occupation. The value of the denominator will therefore be determined by the least social occupation, for which s_o is smallest, and $(1 - s_o + \delta)$ is hence the largest. If δ is set to zero, then the most social occupation will be modelled as having zero AI exposure; when δ goes to infinity, then s_o will have no impact on AI exposure. We have chosen to set δ equal to 2, which has the effect of reducing the AI exposure score of the most social occupation by 31 per cent. $\Delta DAIOE_{ot}$ represents the change in exposure for occupation o in year t.

As the final step in the construction of the index, we sum the yearly scores to generate a cumulative measure, where AI exposure increases over time:

broader range of social skills to be modelled as more socially demanding overall.

$$DAIOE_{ot} = \sum_{2010}^{t} \Delta DAIOE_{ot} \tag{9}$$

where exposure in the year t is equal to the sum of the yearly changes in exposure since 2010. We thus assume that the impact of AI on occupations was negligible prior to 2010.

Sub-indices for each of the nine AI applications, $DAIOE_{oti}$, are calculated in the same way, except that only the yearly change for a single application is fed into the mapping matrix in Equation 5. While Felten *et al.* (2023) build on Felten *et al.* (2021) to provide exposure measures for language modelling and image generation, we create indices for all nine AI applications, and as with the main DAIOE index, they reflect the changing exposure over time during 2010-2023.

4.2. DAIOE: descriptive analysis

This section provides a descriptive analysis of the DAIOE index.

In Table 2, we present the five most and five least exposed occupations in the year 2023, according to three versions of the index: AI overall, and for two of the nine sub-applications, namely image generation and speech recognition.

Figure 7 plots the AI exposure over time of seven occupations found at different parts of the distribution at the end of the period. The index indicates an acceleration of AI progress after 2012.

As a first robustness check, we compare DAIOE in the year 2018 with the backward- and forward-looking AIOE measures of Felten *et al.* (2018) and Felten *et al.* (2021), respectively, and the patent-cum-task-based measure of Webb (2020), all aggregated to the four-digit ISCO occupational level. Table 3 displays their correlations. DAIOE is strongly positively correlated with FRS18 and FRS21, as one might expect given that our method builds closely on theirs. There is a positive and statistically significant correlation between DAIOE and Webb19, although it is substantially weaker than with FRS18 and FRS21. FRS21 has no

TABLE 2

Top and bottom five occupations in the DAIOE ranking.

	DAIOE overall	
Rank	*Most Exposed*	*Least Exposed*
1	Proofreaders and Copy Markers	Dancers
2	Mathematicians	Fitness Trainers and Aerobics Instructors
3	Mathematical Technicians	Athletes and Sports Competitors
4	Statisticians	Choreographers
5	Technical Writers	Forest Firefighters
	Image Generation	
Rank	*Most Exposed*	*Least Exposed*
1	Poets, Lyricists and Creative Writers	Slaughterers and Meat Packers
2	Mathematicians	Graders and Sorters, Agricultural Products
3	Graphic Designers	Fitness Trainers and Aerobics Instructors
4	Fine Artists, Including Painters, Sculptors, and Illustrators	Orderlies
5	Technical Writers	Flight Attendants
	Speech recognition	
Rank	*Most Exposed*	*Least Exposed*
1	Telemarketers	Dancers
2	Proofreaders and Copy Markers	Structural Iron and Steel Workers
3	Credit Checkers	Manufactured Building and Mobile Home Installers
4	Telephone Operators	Pressers, Textile, Garment, and Related Materials
5	Medical Transcriptionists	Reinforcing Iron and Rebar Workers

Notes: The table presents the O*NET-SOC occupations that are most and least exposed in the year 2023, according to the DAIOE index. Results are presented for AI exposure overall, and for two AI applications, or sub-areas, image generation and speech recognition. See the online appendix for equivalent lists for all nine sub-indices.

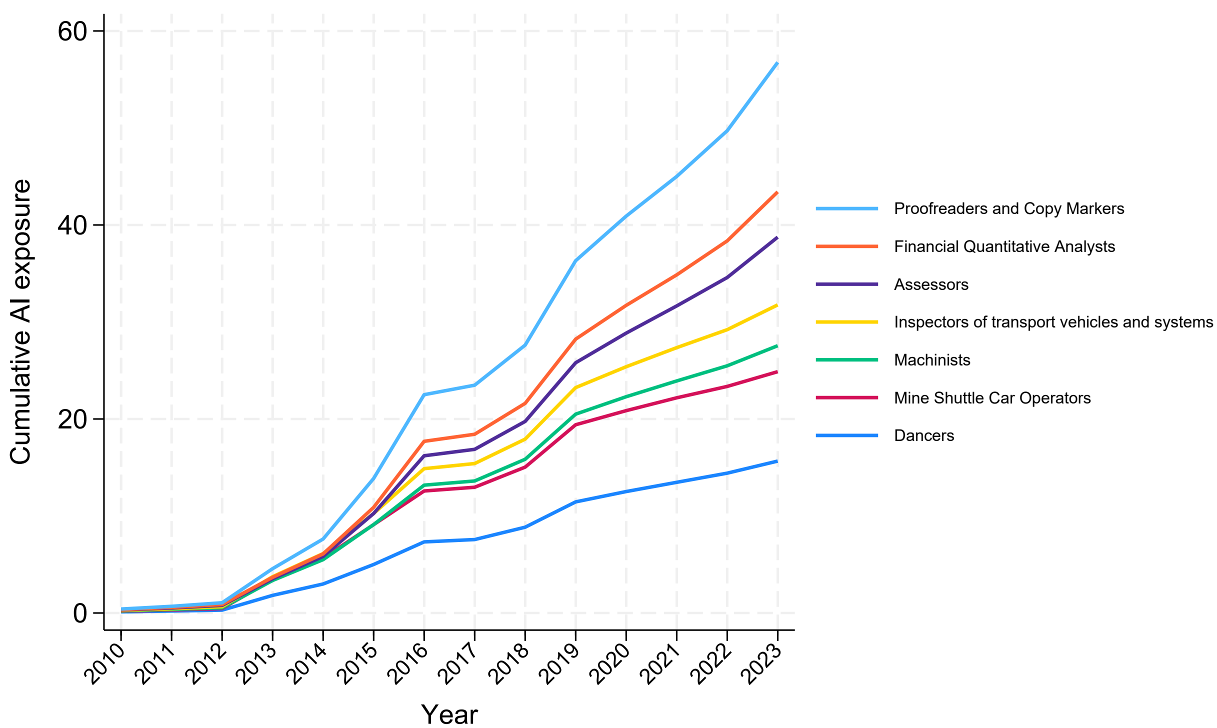

Figure 7: DAIOE over time for seven occupations

Notes: The occupations are at the 0, 10, 25, 50, 75, 100 percentiles in 2023.

significant correlation with Webb19.

TABLE 3
DAIOE vs other AI indices: correlations

	DAIOE	FRS18	FRS21	Webb19
DAIOE	1			
FRS18	0.869***	1		
FRS21	0.841***	0.965***	1	
Webb19	0.107**	0.110**	0.0310	1
Observations	771			

Notes: Correlations between DAIOE and alternative AI exposure indices. FRS18 = Felten *et al.* (2018); FRS21 = Felten *et al.* (2021); Webb19 = Webb (2020). One observation per SOC10 occupation. * p < 0.05, ** p < 0.01, *** p < 0.001.

To shed more light on the relation between the exposure indices and occupational content, Table 4 presents the estimates from a simple regression model, where the dependent variable is one of the AI indices, and the explanatory variables are the occupation's O*NET scores in terms of social skills, cognitive abilities, and physical abilities. In all four indices, AI exposure is positively related to cognitive abilities. The key distinction between DAIOE and FRS21 is that in DAIOE social skills are associated with less exposure, whereas the opposite is true for FRS21. Webb19 stands out as the only index where physical abilities are positively related to AI exposure, although the relation is not statistically significant. For DAIOE, FRS18 and FRS21, R^2 is very high, indicating that these three dimensions of occupations explain most of the variation in their AI exposure.

Figure 8 illustrates occupations' AI exposure by broad occupation groups/categories. While there is significant variation within occupation groups, a clear pattern emerges where white collar workers (groups 1-4) tend to be significantly more exposed, on average, compared to all other occupation groups. Groups 1-3 are the occupations that, according to the ISCO taxonomy, require higher education:[18] *managers*, *professionals*, and *technicians and associate professionals*. The occupations in group 4, *clerical support workers*, do not require higher education but are also associated with office work.

[18] See the explanation of the four *skill levels* in ISCO: https://www.ilo.org/public/english/bureau/stat/isco/isco08/.

TABLE 4

DAIOE vs other AI indices: relation to broad occupation characteristics

	(1) DAIOE	(2) FRS18	(3) FRS21	(4) Webb19
Social skills	-3.097***	0.232**	1.040***	-2.593***
	[-25.10]	[2.80]	[12.05]	[-8.77]
Cognitive abilities	3.315***	3.077***	1.451***	4.468***
	[19.59]	[27.11]	[12.25]	[11.08]
Physical abilities	-5.894***	-4.642***	-5.074***	0.238
	[-53.16]	[-62.42]	[-65.38]	[0.90]
R^2	0.849	0.932	0.926	0.145
Observations	772	772	772	771

Notes: OLS regressions of DAIOE and several alternative AI exposure indices against worker requirements in occupations. FRS18 = Felten *et al.* (2018); FRS21 = Felten *et al.* (2021); Webb19 = Webb (2020). The indices have been standardized (mean=0, SD=1) to make them comparable. The explanatory variables reflect the sum of the occupation's level*importance scores in O*NET, divided by the score of the highest-scoring occupation in the category. For example, if an occupation's overall score for physical abilities is half that of the most physical occupation, then the physical abilities variable will be equal to 0.5. The coefficients can thus be interpreted as the impact of moving from zero O*NET points in the ability category to the highest-scoring occupation in the category, on standard deviations in the index. t-statistics in brackets. One observation per SOC10 occupation. * p < 0.05, ** p < 0.01, *** p < 0.001.

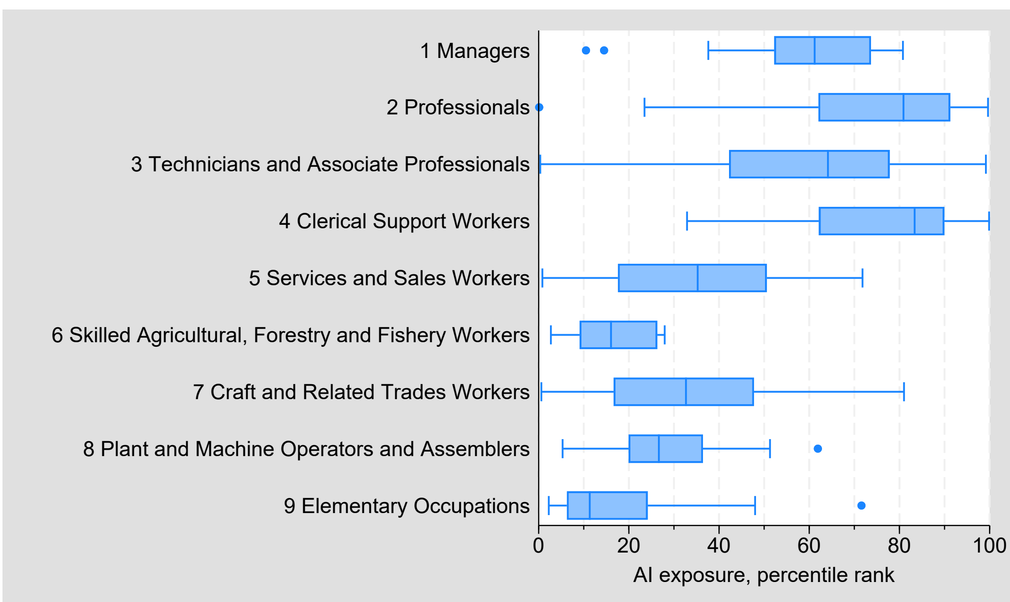

Figure 8: AI exposure by occupation group

Notes: The box plot illustrates how the percentile rankings of occupations in DAIOE are distributed in the year 2023, within one-digit ISCO-08 occupation groups. The three vertical lines in each box represent the quartiles, i.e., the 25, 50 (median), 75 percentiles. The endings of the whiskers represent the 0 and 100 percentiles, unless there are outliers, which are marked with points. Exposure could not be calculated for group 0, Armed Forces Occupations, because O*NET data are not available.

4.3. Register data

For our analysis of AI exposure and labour demand, we have acquired access to comprehensive and granular longitudinal register data for Denmark, Portugal and Sweden. Using unique identifiers of employers and employees we can exactly match firms and workers to arrive at linked employer employee data (LEED) for each country. Data are from the mid-1990s or early 2000s to the most recent year currently available, which for Denmark and Portugal is 2021 and for Sweden 2020. Restrictions of the respective countries disallows pooling the data into one database, why we estimate identical specifications but separately for each country.

The content of the LEED databases of the three countries is similar. Information on workers typically includes data on demographics, civil status, migration, education, family connections, occupation, employment, income, and allowances. Information on firms includes data from income statements, balance sheets, business, and earnings statistics, foreign trade, and labour market statistics. Survey data on firm ICT use and innovation is from Eurostat. (The specific registers used for the respective countries are described in the Online Appendix.) All monetary variables are deflated at 2015 level and converted to US Dollars.

Finally, we connect the DAIOE measure to firm employment, using administrative data on the pre-period workforce composition of firms in terms of employment per 4-digit occupation. We use the pre-period workforce composition to consider the potential endogeneity of firms' AI exposure, e.g., where changes in firms' skills composition make them more likely to adopt AI. Thus, firms with a large initial share of their employees in occupations where an AI application has made substantial progress in abilities that are important to that occupation will be more exposed than other firms.[19] We compute the measure both with fixed firm-specific occupational shares in the first year of the panel and with occupational composition which is allowed to change over time.

[19] When building the measure at the firm level, occupations with missing values of the measure are omitted and the weighted average is computed on the remaining ones.

In Table 5, we provide a snapshot of key statistics of the LEED for the three countries in the latest year. According to these statistics, most firms are small, bordering to being micro-enterprises. The firm-level statistics are similar for Denmark and Sweden, while the Portugese firms are markedly smaller, less human and capital-intense, and less internationalised in terms of trade values and foreign ownership.

The workforce composition by occupational group and by industry are displayed in Tables A1 and A2.[20] We note that the share of workers that are blue collar, low-skilled white collar and high-skilled white collar are roughly equal, with a third of the workers in each category. While Denmark and Sweden have a similar workforce composition in terms of blue and low-skill white collar workers, Sweden stands out regarding the share of high-skilled white collar workers. Portugal distinguishes itself by having the largest share of blue collar and low-skill white collar workers as well as the lowest share of high-skilled white collar workers.

The industrial distribution of the workforce is relatively similar. However, Sweden differs by having a smaller share in manufacturing, while being relatively heavy in business services and construction. Portugal has the largest manufacturing share of workers, but smaller shares in information and communication and also in business services.

For a stylised view of how firms with initially low and high exposure to AI are evolving in terms of their occupational composition, in Table A3, we present the 1-digit occupational shares in the first and last years of the period as well as in the first and fourth quartiles. We find that the initially high exposed firms have a substantially larger share of employees in occupational groups 1-4, compared to the lowest exposure firms.[21] For Denmark there is a general up-skilling, while in Portugal, some blue collar occupations increase for the most exposed firms. A general pattern is that the least exposed firms hire more workers in ISCO-08 category 3, while the most exposed reduce their hiring in that category. The latter

[20]We define blue collar workers as those in ISCO-08 categories 6-9, low-skilled white collar workers as those in 4-5, and high-skilled white collar workers as those in 1-3.

[21]The least exposed firms are predominantly in construction and trade, and the most exposed in other business services, e.g., consulting and advertising.

Table 5
Snapshot of Firms

Variable	Mean	Median	S.D.
		Denmark	
Workforce size	36.1	12.0	203.6
Firm age	18.1	14.0	15.2
Skilled worker share	0.23	0.13	0.26
Sales (1000 USD)	15,317.4	2,702.0	154,925.4
Value Added (1000 USD)	4,227.6	1,006.2	46,942.9
Capital intensity (1000 USD)	276.8	20.6	15,814.0
Export value (1000 USD)	5,054.5	0.0	104,211.0
Import value (1000 USD)	4,052.9	2.9	91,019.5
Foreign owned (D)	0.10	0.0	0.30
DAIOE index	12.467	13.074	9.202
		Portugal	
Workforce size	21.9	7.6	137.5
Firm age	19.2	16	14.5
Skilled worker share	0.16	0.0	0.24
Sales (1000 USD)	4,970.00	736.9	66,300.90
Value Added (1000 USD)	1,199.21	254	12,152.90
Capital intensity (1000 USD)	35.9	9.9	219
Export value (1000 USD)	1,067.76	0.0	24,028.96
Import value (1000 USD)	958.26	0,00	21,643.65
Foreign owned (D)	0.04	0.0	0.0
DAIOE index	12.436	13.118	9.029
		Sweden	
Workforce size	37.2	11.0	236.9
Firm age	17.0	16.0	9.5
Skilled worker share	0.20	0.11	0.24
Sales (1000 USD)	15,022.2	2,152.3	17,2749.3
Value Added (1000 USD)	4,030.3	872.0	36,156.4
Capital intensity (1000 USD)	211.5	23.4	5,927.9
Export value (1000 USD)	3,694.3	0.0	118,430.0
Import value (1000 USD)	3,269.0	0.0	78,351.4
Foreign owned (D)	0.08	0.0	0.28
DAIOE index	10.768	10.282	8.526

Notes: The table presents summary statistics for the three countries. Monetary values are in 1,000 USD. The DAIOE index is the standardised and weighted average AI exposure of the firm where the occupational composition is fixed at firm-specific pre-sample shares of 4-digit ISCO08 occupations. Skilled is defined as employment in ISCO08 1-digit codes 1-5. Capital intensity is defined as the book-value of physical capital per worker. Firms with any exports (goods or services) are considered as exporters, where manufacturing exports is comprehensive vis-à-vis third countries and weakly censored vis-à-vis EU countries, and services exports is survey-based while covering virtually all exports, with larger services exporters continuously and others semi-continuously included (for details, see the Online Appendix). The number of firms included are as follows: Denmark: 51,243, Portugal: 126,265 and Sweden: 94,684.

trend is strongest in Sweden, with the share of workers in that occupation decreasing by 5.9 percentage points, to 24.9 per cent. The reduction in category 3 would, e.g., be consistent with AI automating work of the least advanced of the white collar professions.

4.4. Empirical Specification

Next, we start to investigate the impact of AI on labour demand by estimating an equation with firm-level labour demand as the response variable and exposure to AI as the treatment variable. The log of firm f's employment at time t, L_{ft}, is related to the log of firm's exposure to AI application a at time $t-1$, AI_{fat-1}, and a set of covariates and fixed effects, i.e.,:

$$L_{ft} = \beta + \beta_{AI_a} AI_{fat-1} + \mathbf{X}_{ft-1}\boldsymbol{\beta_X} + \mathbf{D}_{ht}\boldsymbol{\beta_{ht}} + \mathbf{D}_{mt}\boldsymbol{\beta_{mt}} + \epsilon_{ft} \tag{10}$$

Our focus is on regression parameter β_{AI_a}. To control for pre-existing firm-level confounders, we include row vector $\mathbf{X}_{ft-1}$, which includes firm size (sales),[22] physical and human capital intensities (capital-workforce and post-secondary-educated-workforce ratios), firm age, firm exports and imports, and an indicator for being a multinational.[23] To pay attention to potential differences between industries and municipalities in AI exposure and AI use as well as in employment patterns, we include industry-year and municipality-year fixed effects, $\mathbf{D}_{ht}$ and $\mathbf{D}_{mt}$. ϵ_{ft} is the firm-period i.i.d. error term. To avoid noisy observations and ensure firms with an occupational heterogeneity, we study firms with at least five employees. Regressions at firm level are weighted using firm employment in the first year of the panel as weights. Standard errors are clustered at firm level.

5. Results

In Table 6, we present our baseline results from estimating Equation 10, using baseline firm employment as weights and standard errors robust to heteroscedasticity and serial correlation

[22]Our results are robust to removing sales or replacing it with sales per worker.
[23]Continuous covariates are in log.

at the firm level. Throughout, we control for confounding factors such as sales, the share of workers with college education, firm age and internationalisation, as well as include 3-digit industry-year and municipality-year fixed effects.[24] For each firm, the DAIOE measure is computed at the 4-digit occupational level, using the pre-sample occupational shares.

Our main interest is in the coefficient estimate for the DAIOE measure across the three countries. The estimates are negative for Denmark and Portugal, while positive for Sweden. However, the estimate is not statistically significant for Denmark. The divergent results between, on the one hand, Denmark and Portugal, and, on the other, Sweden could possibly be linked to differences in the relative importance of the automation, innovation and remainder effects in the three countries. This could be due to differences in industrial structure as well as differences in the skills composition of the labour force. To explore this, we now split the sample on occupation and skills levels.

How does AI exposure impact the demand for labour across different occupational groups? Since AI is able to solve cognitive problems and importantly not only routine but also non-routine cognitive types, we would expect AI to heterogeneously affect blue and white collar workers. Moreover, based on our conceptual framework and the stylised patterns in the previous section, we consider that AI could potentially complement or assist those employed in cognitive work, increasing the demand for their services. We therefore re-estimate Equation 10 for blue, low-skilled white collar and high-skilled white collar workers.

In Table 7, we display the results across the three groups of workers and countries. We find that the overall negative impact from Table 6 masks underlying heterogeneties. While there is a substantial negative and statistically significant link between the DAIOE measure and labour for blue collar work, the magnitude is lower and not statistically significant for low-skilled white collar workers and it is substantial, positive and statistically significant for high-skilled white collar workers. Hence, the up-skilling noted as a stylised fact holds, but it only applies to high-skilled white collar workers. This would be in line with a remainder-effect

[24] The results are robust to replacing sales with labour productivity or removing it altogether.

Table 6

Labour demand and AI exposure

	Denmark	Portugal	Sweden
DAIOE	-0.0086	-0.1609**	0.1452**
	(0.2028)	(0.0754)	(0.0657)
Sales	0.6980***	0.7260***	0.5525***
	(0.0398)	(0.0244)	(0.0386)
Share Bachelor	-0.2322***	-0.6997***	-3.1598***
	(0.0672)	(0.0831)	(0.2054)
Physical Capital Intensity	-0.0176	-0.0058***	-0.0307***
	(0.0135)	(0.0063)	(0.0062)
Firm Age	0.0023**	0.0041***	-0.0001
	(0.0011)	(0.0006)	(0.0013)
Foreign Owned	0.0427	0.1469***	0.0497*
	(0.0346)	(0.0514)	(0.0295)
Exports	0.0001	-0.0022	0.0316***
	(0.0020)	(0.0036)	(0.0054)
Imports	0.0350***	0.0067	0.0389***
	(0.0073)	(0.0054)	(0.0055)
Observations	303,294	774,097	528,782
R-squared	0.905	0.855	0.88
Within R2	0.801	0.775	0.755
No. of firms	51243	126,265	94,684

Notes: The table displays the estimated effect of firm AI exposure on log of firm total full-time-equivalent employment. The DAIOE index is the standardised and weighted average AI exposure of the firm where the occupational composition is fixed at firm-specific pre-sample shares of 4-digit ISCO08 occupations. All regressions include fixed effects at 3-digit NACE industry-year and municipality-year level, and they are weighted by baseline firm employment. All regressors are lagged at $t-1$ except for the contemporaneous firm age. All continuous variables are in log form. Standard errors are in parenthesis and clustered at the firm level. *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

for high-skilled white collar workers. As regards results across the countries, the results are the largest for Portugal and with a markedly larger negative association between AI exposure and demand for low-skilled white collar workers.[25]

[25] These results are overall robust to not using weights and to not using pre-period occupational composition, see Tables B2 and B4.

Table 7

Log of employment on firm AI exposure split by occupational group

	Denmark			Portugal			Sweden		
Dependent variables	*Blue collar*	*White collar low*	*White collar high*	*Blue collar*	*White collar low*	*White collar high*	*Blue collar*	*White collar low*	*White collar high*
DAIOE	-1.3209***	-0.0209	1.0932***	-0.8595***	0.09	0.9036***	0.2861**	-0.1344	0.4147***
	(0.2496)	(0.2512)	(0.2209)	(0.1781)	(0.1088)	(0.0983)	(0.1327)	(0.1118)	(0.0827)
Sales	0.6324***	0.6277***	0.6437***	0.5839***	0.6706***	0.6019***	0.4269***	0.4771***	0.4922***
	(0.0363)	(0.0348)	(0.0380)	(0.0514)	(0.0297)	(0.0206)	(0.0276)	(0.0306)	(0.0337)
Share Bachelor	-1.6826***	-1.1729***	0.9925***	-2.2776***	-1.3979***	1.2094***	-3.1598***	-1.5061***	1.1534***
	(0.1202)	(0.0904)	(0.0819)	(0.1572)	(0.1046)	(0.0866)	(0.2054)	(0.1211)	(0.1330)
Physical Capital Intensity	-0.0254	-0.0030	0.0005	-0.0465***	-0.0446***	-0.0283***	-0.0417***	-0.0212***	-0.0038
	(0.0156)	(0.0148)	(0.0139)	(0.0106)	(0.0087)	(0.0082)	(0.0077)	(0.0074)	(0.0062)
Firm Age	0.0037*	0.0032**	0.0024*	0.0066***	0.0051***	0.0050***	-0.004	-0.0038*	-0.0007
	(0.0019)	(0.0014)	(0.0013)	(0.0012)	(0.0007)	(0.0009)	(0.0026)	(0.0020)	(0.0016)
Foreign Owned	-0.1877***	0.0081	0.0695	-0.1395	-0.0121	0.2389***	0.1123*	0.1634***	0.1292***
	(0.0697)	(0.0435)	(0.0433)	(0.1352)	(0.0723)	(0.0761)	(0.0675)	(0.0356)	(0.0356)
Exports	0.0007	-0.0034	0.0089***	0.0145*	-0.0127***	0.0053	0.0318***	0.0203***	0.0375***
	(0.0042)	(0.0031)	(0.0029)	(0.0082)	(0.0047)	(0.0050)	(0.0054)	(0.0050)	(0.0045)
Imports	0.0205***	0.0406***	0.0371***	-0.0182	0.0129**	0.0075*	0.0290***	0.0363***	0.0493***
	(0.0070)	(0.0066)	(0.0072)	(0.0139)	(0.0063)	(0.0045)	(0.0055)	(0.0054)	(0.0055)
Observations	303,294	303,294	303,294	774,097	774,097	774,097	528,782	528,782	528,782
R-squared	0.770	0.836	0.872	0.701	0.816	0.811	0.785	0.806	0.865
Within R2	0.497	0.613	0.707	0.524	0.666	0.706	0.481	0.576	0.707
No. of firms	51,243	51,243	51,243	115,044	115,044	115,044	94,684	94,684	94,684

Notes: The table displays the estimated effect of firm AI exposure on log of employment split by occupational group. “Blue collar” include occupations in ISCO08 major groups 6, 7, 8, 9, "white collar low" include occupations in groups 4 and 5, while “white collar high” include occupations in ISCO08 major groups 1, 2, 3. The DAIOE index is the standardised and weighted average AI exposure of the firm where the occupational composition is fixed at firm-specific pre-sample shares of 4-digit ISCO08 occupations. All regressions include fixed effects at 3-digit NACE industry-year and municipality-year level, and they are weighted by baseline firm employment. All regressors are lagged at $t-1$ except for the contemporaneous firm age. All continuous variables are in log form. Standard errors are in parenthesis and clustered at the firm level. *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

So far, we have investigated the overall association between the occupational exposure of firms to AI and labour demand for categories of workers. However, our DAIOE measure is developed also to unbox the impact of occupational exposure to advances in subdomains of AI. As illustrated by the strong interest in generative AI, following the introduction of ChatGPT in November 2022, progress in AI research and dissemination differs both across time and areas of AI. Using our measure – or set of indices – we can now, as far as we know, for the first time measure and estimate the occupational exposure from differential trajectories and breakthroughs in AI.

In Table 8, we therefore display the results from estimating Equation 10 for the DAIOE from the nine AI subdomains and across firm employment overall as well as different types of workers, this across the three countries. All-in-all, the table displays the results from 108 firm-level labour demand regressions. The results illustrate the importance of unpacking the concept of AI when studying the impact on, e.g., different types of labour. Whereas the aggregate negative impact from the overall DAIOE measure on labour demand is largely consistent across types of AI applications, this is not true for the sub-groups of labour.

Starting with AI advances in the area of images and languages, the associations are negative and statistically significant for blue collar workers in Denmark and Portugal, while, for Sweden, the links are only present for languages. For those workers, the area of AI in videogames is however, substantially positively linked to demand for labour. The remainder effect could explain this result. In blue-collar work, advances in video game technology can be used for remote control of a host of tasks previously done manually, also now in a safer environment. An example is remote operating of machinery on construction sites and in mines, and operating drones related to cite inspection. In this way, AI can facilitate the work and therefore increase both the demand and attractiveness for those workers.

TABLE 8

Log of employment on firm AI exposure to specific AI technologies

	Denmark				Portugal				Sweden			
Dependent variables	*Full-time-equ. Empl*	*Blue collar*	*White collar low*	*White collar high*	*Full-time-equ. Empl*	*Blue collar*	*White collar low*	*White collar high*	*Full-time-equ. Empl*	*Blue collar*	*White collar low*	*White collar high*
stratgames	-0.0586	-0.7151***	-0.1226	0.5131***	-0.1013***	-0.4990***	-0.0819*	0.5440***	1.1455**	-1.0215	-1.1171*	3.8733***
	(0.0532)	(0.0925)	(0.0753)	(0.0639)	(0.0331)	(0.0830)	(0.0457)	(0.0444)	(0.4901)	(0.8043)	(0.6675)	(0.5324)
videogames	0.3414***	1.4184***	-0.5549***	0.0880	0.3477***	1.4844***	-0.7062***	0.0911	0.0171	0.6225***	-0.4541***	-0.0067
	(0.1217)	(0.1494)	(0.1725)	(0.1522)	(0.0545)	(0.1022)	(0.0714)	(0.0757)	(0.0382)	(0.0879)	(0.1063)	(0.0493)
imgrec	-0.0031	-0.9431***	-0.2075	0.9835***	-0.3342***	-08153***	-0.2583***	0.6900***	0.7882*	-0.6003	-1.8281***	3.6027***
	(0.1215)	(0.1715)	(0.1580)	(0.1377)	(0.0630)	(0.1462)	(0.0851)	(0.0833)	(0.4278)	(0.8615)	(0.6852)	(0.5549)
imgcompr	-0.1377	-1.3279***	0.0392	0.7353***	-0.3225***	-1.1926***	-0.1166	0.5671***	3.1616**	0.5558	0.8616	7.8135***
	(0.0948)	(0.1252)	(0.1164)	(0.1091)	(0.0589)	(0.1136)	(0.0819)	(0.0675)	(1.2817)	(2.7359)	(2.1893)	(1.6790)
imggen	-0.0858	-1.0794***	-0.1294*	0.5924***	-0.2036***	-0.8695***	-0.035	0.5132***	0.5466***	0.3997	-0.1214	1.4551***
	(0.0563)	(0.0981)	(0.0720)	(0.0681)	(0.0442)	(0.0861)	(0.0596)	(0.0546)	(0.2049)	(0.4044)	(0.3246)	(0.2597)
readcompr	-0.1742***	-1.0484***	0.1546***	0.3305***	-0.1901***	-0.8384***	0.2306***	0.2891***	0.7264**	-0.7537	1.6156**	1.7445***
	(0.0387)	(0.0664)	(0.0503)	(0.0477)	(0.0334)	(0.0548)	(0.0501)	(0.0408)	(0.3525)	(0.7513)	(0.7382)	(0.4277)
lngmod	-0.2263***	-1.3459***	0.2947***	0.3768***	-0.2010***	-1.0210***	0.4335***	0.3087***	1.0793*	-2.1674*	3.5877***	2.7239***
	(0.0600)	(0.0910)	(0.0717)	(0.0719)	(0.0483)	(0.0731)	(0.0717)	(0.0566)	(0.6410)	(1.3018)	(1.2593)	(0.7755)
translat	-0.2195***	-1.1731***	0.3302***	0.2372***	-0.2047***	-0.9309***	0.4234***	0.2040***	4.8221*	-10.1870*	18.1256***	9.1168***
	(0.0453)	(0.0787)	(0.0556)	(0.0565)	(0.0435)	(0.0656)	(0.0604)	(0.0572)	(2.7907)	(5.5275)	(5.2182)	(3.3765)
speechrec	-0.2126***	-1.3575***	0.5339***	0.2733***	-0.2313***	-1.0327***	0.5881***	0.1442*	0.3605*	-1.3803***	2.2310***	0.8540***
	(0.0435)	(0.0996)	(0.0574)	(0.0599)	(0.0494)	(0.1039)	(0.0620)	(0.0749)	(0.2156)	(0.4725)	(0.4233)	(0.2795)

Notes: Notes: Each cell contains a coefficient from a different regression. The nine DAIOE indices are the standardised and weighted average AI exposure of the firm where the occupational composition is fixed at firm-specific pre-sample shares of 4-digit ISCO08 occupations. All regressions include fixed effects at 3-digit NACE industry-year and municipality-year level, and they are weighted by baseline firm employment. All regressors are lagged at $t-1$ except for the contemporaneous firm age. All continuous variables are in log form. Standard errors are in parenthesis and clustered at the firm level. *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

Next, we consider white collar work and AI advances in the areas of images and languages. Here we find that high-skilled white collar worker demand is positively associated with the DAIOE across the three countries. The positive link between AI in the language area and demand is also true for low-skilled white collar work.

Finally, we study the link between advances in the AI areas of games and labour demand. Here we note a distinct pattern where workers in strategic positions – that is, high-skilled white collar work – are more highly demanded the more exposed their firms are to AI in the area of strategic games, while others are less demanded. As mentioned, for exposure to advances in AI in the area of video games, blue collar workers are more demanded, while this is not true for white collar workers. The remainder effect could explain the result on video games for blue-collar workers. Advances in video game technology can be used for remote control of a host of tasks previously done manually. An example is remote operating of machinery on construction sites and in mines, and operating drones related to cite inspection.

Summing up, overall, blue collar workers are mostly negatively impacted by advances in AI (with the exception of AI in the area of video games), low-skilled white collar workers are mostly negatively impacted, except for AI in the area of languages, while high-skilled workers are positively impacted by exposure to AI in all areas (except video games). To investigate if the overall effect is an up-skilling, we run a regression where the dependent variable is the share of skilled to unskilled workers. As displayed in Table 9, the estimates are relatively large, positive and statistically significant across all three countries. We cautiously interpret this as exposure to advances in AI leading to a higher share of skilled workers. This could either be due to AI complementing or assisting workers with higher education at work (the remainder effect), or to AI technology creating new tasks at the skills-intensive end of the task distribution (the innovation effect). We next probe this by employing our second set of DAIOE measures.

Table 9
High-to-low skill ratio and AI exposure

Dependent Variable: *high-low skill ratio*	Denmark	Portugal	Sweden
DAIOE	1.9298***	0.4306***	1.4252***
	(0.1669)	(0.0158)	(0.0782)
Sales	-0.0588***	0.003	-0.0224***
	(0.0155)	(0.0020)	(0.0085)
Physical Capital Intensity	-0.0102	0.0020***	0.0385***
	(0.0085)	(0.0007)	(0.0062)
Firm Age	-0.0016*	0.000	-0.0029**
	(0.0009)	(0.0001)	(0.0013)
Foreign Owned	0.0362	0.0425***	-0.0828***
	(0.0422)	(0.0069)	(0.0315)
Exports	0.0100***	0.0019***	0.0008
	(0.0021)	(0.0004)	(0.0026)
Imports	-0.0004	0.0018***	-0.0009
	(0.0031)	(0.0006)	(0.0020)
Observations	296,502	774,097	521,840
R-squared	0.454	0.548	0.372
Within R2	0.026	0.117	0.021
No. of Firms	50,460	126,265	93,803

Notes: Notes: The table displays the estimated effect of firm AI exposure on high-to-low skill ratio of the firm. The DAIOE index is the standardised and weighted average AI exposure of the firm where the occupational composition is fixed at firm-specific pre-sample shares of 4-digit ISCO08 occupations. All regressions include fixed effects at 3-digit NACE industry-year and municipality-year level, and they are weighted by baseline firm employment. All regressors are lagged at $t-1$ except for the contemporaneous firm age. All continuous variables are in log form. Standard errors are in parenthesis and clustered at the firm level. *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

With respect to heterogeneity across countries, we find that Sweden stands out in two regards. First, there is no negative association between exposure to AI progress related to images and demand for blue collar workers. Second, the links between AI exposure and demand for high-skilled white collar workers is substantially stronger in Sweden than in the other two countries. These patterns are possibly linked to the Swedish economy and manufacturing being highly servicified and having the highest share of employees with a tertiary education of the three countries (National Board of Trade, 2016).

6. Concluding remarks

AI technologies have made tremendous progress since the late 2000s and today a non-trivial and increasing share of firms use AI. We develop a novel measure to investigate the detailed changes in occupational exposure to AI, both overall and across subdomains of AI. Exploiting rich register data for three countries, we then estimate the impact of AI exposure on firm labour demand. We find that AI exposure is linked to an up-skilling in terms of increased demand for high-skilled white collar workers, and a decreased demand for blue collar workers. However, there is notable heterogeneity in impacts across subdomains of AI and countries. This highlights the importance of unboxing the impacts of AI across different AI technologies, time and across countries.

References

Acemoglu D. and Restrepo, P. (2018) 'The race between man and machine: Implications of technology for growth, factor shares, and employment' *American Economic Review*, 108 (6).

Acemoglu, D., Autor, D., Hazell, J. and Restrepo, P. (2022). 'Artificial Intelligence and Jobs: Evidence from Online Vacancies.' *Journal of Labor Economics*, 40(S1), S293-S340.

Aghion, P., Antonin, C. and Bunel, S. 'Artificial intelligence, growth and employment: The role of policy' *Economie et Statistique*, 510 (1).

Babina, T., Fedyk, A., He, A., and Hodson, J. (2022). 'Firm Investments in Artificial Intelligence Technologies and Changes in Workforce Composition.', manuscript.

Babina, T., Fedyk, A., He, A., and Hodson, J. (2022). 'Artificial Intelligence, Firm Growth, and Product Innovation.' *Journal of Financial Economics*, accepted.

Bessen, J.E., Denk, E., and Meng, C. (2022). 'The Remainder Effect: How Automation

Complements Labor Quality', Boston University School of Law Research Paper Series No. 22-3.

Carbonero, F., Davies, J., Ernst, E., Fossen, F.M., Samaan, D., and Sorgner, A. (2023). 'The Impact of Artificial Intelligence on Labor Markets in Developing Countries: A New Method with an Illustration for Lao PDR and Urban Viet Nam.' *Journal of Evolutionary Economics*.

Davis, J. M. V., and Heller, S. B. (2017). 'Using Causal Forests to Predict Treatment Heterogeneity: An Application to Summer Jobs.' *American Economic Review*, 107(5).

Eurostat (2022). 'Artificial intelligence by size class of enterprise', Table "isoc_eb_ai", accessed November 6, 2023.

Felten, E., Raj, M., and Seamans, R. (2018). 'A method to link advances in artificial intelligence to occupational abilities.' *AEA Papers and Proceedings*, 108.

Felten, E., Raj, M., and Seamans, R. (2019). 'The Occupational Impact of Artificial Intelligence: Labor, Skills, and Polarization.' NYU Stern School of Business. http://dx.doi.org/10.2139/ssrn.3368605

Felten, E., Raj, M., and Seamans, R. (2021). 'Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses.' *Strategic Management Journal*, 42(12).

Felten, E., Raj, M., and Seamans, R. (2023). 'Occupational Heterogeneity in Exposure to Generative AI'. Available at SSRN: https://ssrn.com/abstract=4414065.

Fossen, F. M., and Sorgner, A. (2022). 'New Digital Technologies and Heterogeneous Wage and Employment Dynamics in the United States: Evidence from Individual-Level Data' *Technological Forecasting and Social Change*, 175.

Frank, M. R., Autor, D., Bessen, J. E., Brynjolfsson, E., Cebrian, M., Deming, D. J., ... and

Rahwan, I. (2019). 'Toward understanding the impact of artificial intelligence on labor.' *Proceedings of the National Academy of Sciences*, 116(14), 6531-6539.

Gmyrek, P., Berg, J., and Bescond, D. (2023). 'Generative AI and Jobs: A global analysis of potential effects on job quantity and quality.', ILO Working Paper 96.

Handel, M.J. (2016). 'The O*NET content model: strenghts and limitations.' *Journal for Labour Market Research*, 49.

Hirvonen, J., Stenhammar, A., and Tuhkuri, J. (2022). 'New Evidence on the Effect of Technology on Employment and Skill Demand.' Unpublished manuscript, MIT.

Knaus, M. C., Lechner, M., and Strittmatter, A. (2021). 'Machine learning estimation of heterogeneous causal effects: Empirical Monte Carlo evidence.' *The Econometrics Journal*, 24(1).

Lane, M., and Saint-Martin, A. (2021). 'The impact of Artificial Intelligence on the labour market.' OECD Social, Employment and Migration Working Papers No 256.

Lundberg, S. M., and Lee, S. I. (2017) 'A Unified Approach to Interpreting Model Predictions' in Advances in Neural Information Processing Systems 30, pp 4765–4774, edited by I. Guyon and U. V. Luxburg and S. Bengio and H. Wallach and R. Fergus and S. Vishwanathan and R. Garnett, and published by Curran Associates, Inc. http://papers.nips.cc/paper/7062-a-unified-approach-to-interpreting-model-predictions.pdf

Martínez-Plumed, F., Barredo, P., Ó hÉigeartaigh, S., and Hernández-Orallo, J. (2021). 'Research community dynamics behind popular AI benchmarks' *Nature Machine Intelligence*, 3.

National Board of Trade (2016). 'The Servicification of EU Manufacturing', Report.

OECD (2019). ‘Recommendation of the Council on Artificial Intelligence.’ OECD/LEGAL/0449.

Seamans, R., and Raj, M. (2018). ‘AI, labor, productivity and the need for firm-level data.’, NBER Working paper w24239.

Tolan, S., Pesde, A., Martínez-Plumed, F., Fernández-Macías, E., Hernández-Orallo, J., and Gómez, E. (2021). ‘Measuring the occupational impact of AI: tasks, cognitive abilities and AI benchmarks.’ *Journal of Artificial Intelligence Research*, 71.

Webb, M. (2020) ‘The impact of artificial intelligence on the labor market’, manuscript.

Zeira, J. (1998) ‘Workers, machines, and economic growth’ *The Quarterly Journal of Economics*, 113(4).

Zhang, D., Mishra, S., Brynjolfsson, E., Etchemendy, J., Ganguli, D., Grosz, B., Lyons, T., Manyika, J., Niebles, J. C., Sellitto, M., Shoham, Y., Clark, J., and Perrault, R. (2021). ‘The AI Index 2021 Annual Report.’ AI Index Steering Committee, Human-Centered AI Institute, Stanford University, March.

Zolas, N., Kroff, Z., Brynjolfsson, E., McElheran, K., Beede, D. N., Buffington, C., ... and Dinlersoz, E. (2021). ‘Advanced Technologies Adoption and Use by US Firms: Evidence from the Annual Business Survey.’ NBER WP 28290.

Appendix

A Descriptive Statistics

Table A1

Workforce composition by occupational group

Isco 1 dig.	Occupation	Denmark	Portugal	Sweden
1	Managers	0.059	0.036	0.073
2	Professionals	0.143	0.104	0.15
3	Technicians and Assoc. Profes.	0.134	0.117	0.156
4	Clerical support workers	0.097	0.137	0.100
5	Services and Sales Workers	0.181	0.190	0.177
6	Skilled Agricultural Forestry and Fishery workers	0.003	0.009	0.006
7	Craft and related trade workers	0.144	0.165	0.133
8	Plant and Machine Operators and Assemblers	0.099	0.133	0.127
9	Elementary Occup.	0.138	0.11	0.078
Total		1.000	1.000	1.000

Table A2

Workforce composition by Industry

Industry	Denmark	Portugal	Sweden
Agriculture	0.000	0.015	0.025
Mining	0.003	0.004	0.002
Manufacturing	0.249	0.279	0.126
Utility services	0.014	0.017	0.008
Construction	0.103	0.083	0.161
Trade	0.333	0.279	0.278
Hotel. restaurants	0.039	0.079	0.071
Information & communication	0.075	0.042	0.053
Finance & Insurance	0.000	0.000	0.000
Real Estate	0.011	0.006	0.024
Other Business services	0.170	0.132	0.154
Public Administration	0.000	0.045	0.080
Other Services	0.002	0.019	0.015
Total	1.000	1.000	1.000

Table A3

Initial and final occupational composition by firm's initial AI exposure

	Denmark				Portugal				Sweden			
	Q1 - low initial expos		Q4 - high intial expos		Q1 - low initial expos		Q4 - high intial expos		Q1 - low initial expos		Q4 - high intial expos	
Isco 1 dig.	first year	last year	first year	last year	first year	last year	first year	last year	first year	last year	first year	last year
1	4.5%	4.7%	4.2%	5.0%	3.8%	3.8%	5.6%	5.2%	4.1 %	4 %	9.2 %	10.7 %
2	1.6%	2.3%	15.1%	16.7%	1.4%	2.2%	9.6%	9.7%	1.3 %	3.1 %	33.5 %	39.5 %
3	4.7%	4.8%	12.1%	12.6%	4.1%	4.9%	10.4%	10.3%	2.9 %	3.7 %	30.8 %	24.9 %
4	3.9%	5.8%	10.1%	11.0%	3.7%	6.0%	11.4%	11.6%	3.7 %	2.3 %	14.9 %	14.7 %
5	32.2%	33.4%	22.7%	19.7%	26.7%	25.8%	21.9%	21.7%	26.8 %	43.8 %	2.5 %	2.3 %
6	0.5%	0.6%	0.4%	0.4%	2.6%	2.3%	1.9%	1.8%	1.9 %	1.5 %	0.1 %	0.1 %
7	19.0%	17.8%	14.1%	13.6%	29.4%	28.0%	18.4%	18.3%	17.4 %	14 %	2.8 %	3.2 %
8	8.8%	8.8%	6.1%	6.0%	10.8%	10.3%	6.9%	7.0%	18.6 %	9.7 %	4.8 %	3.9 %
9	24.8%	21.8%	15.3%	14.9%	17.4%	16.8%	13.9%	14.4%	23.3 %	18.1 %	1.4 %	0.8 %
avg firm size	27.9	32.6	12.8	16.6	20.5	22.3	9.5	11.8	20.7	26.6	39.9	47.7

Notes: Initial AI exposure is determined by the quartile of AI distribution: low exposure firms are those in the first quartile, while high exposure firms are those in the fourth quartile of initial AI exposure.

B Robustness check

Table B1

Labour demand and AI exposure, no weighting

Dependent Variable: *log full-time-equivalent employment*	Denmark	Portugal	Sweden
DAIOE	-0.1675***	-0.1142***	-0.0552***
	(0.0204)	(0.0148)	(0.0149)
Sales	0.6028***	0.4059***	0.3993***
	(0.0111)	(0.0056)	(0.0092)
Share Bachelor	-0.0410***	-0.0275**	0.1548***
	(0.0136)	(0.0121)	(0.0176)
Physical Capital Intensity	-0.0078***	-0.0031***	-0.0165***
	(0.0016)	(0.0012)	(0.0012)
Firm Age	0.0029***	0.0065***	0.0026***
	(0.0002)	(0.0002)	(0.0003)
Foreign Owned	0.0524***	0.3404***	0.2008***
	(0.0128)	(0.0158)	(0.0130)
Exports	-0.0000	0.0033***	0.0179***
	(0.0006)	(0.0006)	(0.0009)
Imports	0.0103***	0.0168***	0.0182***
	(0.0010)	(0.0008)	(0.0009)
Observations	303,294	774,097	528,782
R-squared	0.701	0.523	0.585
Within R2	0.655	0.467	0.517
No. of firms	51,243	126,265	94,684

Notes: The table displays the estimated effect of firm AI exposure on log of firm total full-time-equivalent employment. The DAIOE index is the standardised and weighted average AI exposure of the firm where the occupational composition is fixed at firm-specific pre-sample shares of 4-digit ISCO08 occupations. All regressions include fixed effects at 3-digit NACE industry-year and municipality-year level. All regressors are lagged at $t-1$ except for the contemporaneous firm age. All continuous variables are in log form. Standard errors are in parenthesis and clustered at the firm level. *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

Table B2

Log of employment on firm AI exposure, split by occupational group, not weighted in the regressions

	Denmark			Portugal			Sweden		
Dependent variables	*Blue collar*	*White collar low*	*White collar high*	*Blue collar*	*White collar low*	*White collar high*	*Blue collar*	*White collar low*	*White collar high*
DAIOE	-0.9652***	-0.0964***	0.6496***	-0.7747***	0.1889***	0.5244***	-0.2947***	-0.1101***	0.3400***
	(0.0321)	(0.0302)	(0.0277)	(0.0170)	(0.0162)	(0.0157)	(0.0192)	(0.0183)	(0.0166)
Sales	0.4948***	0.4221***	0.5196***	0.2530***	0.2937***	0.2636***	0.2677***	0.2920***	0.3158***
	(0.0097)	(0.0092)	(0.0101)	(0.0040)	(0.0044)	(0.0040)	(0.0060)	(0.0070)	(0.0076)
Share Bachelor	-0.7684***	-0.5955***	0.8641***	-0.7974***	-0.6113***	1.2674***	-1.1350***	-0.4953***	1.1836***
	(0.0217)	(0.0213)	(0.0184)	(0.0285)	(0.0321)	(0.0350)	(0.0183)	(0.0179)	(0.0181)
Physical Capital Intensity	-0.0040**	0.0011	0.0025	0.0034***	0.0012	0.0031***	-0.0184***	-0.0050***	0.0030***
	(0.0018)	(0.0017)	(0.0017)	(0.0119)	(0.0011)	(0.0010)	(0.0011)	(0.0011)	(0.0011)
Firm Age	0.0061***	0.0027***	0.0047***	0.0063***	0.0067***	0.0056***	0.0025***	0.0018***	0.0022***
	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
Foreign Owned	-0.2356***	0.0649***	0.1191***	-0.0542***	0.2430***	0.4080***	-0.0093	0.0940***	0.2573***
	(0.0192)	(0.0174)	(0.0150)	(0.0199)	(0.0184)	(0.0163)	(0.0155)	(0.0143)	(0.0129)
Exports	-0.0016*	0.0002	0.0079***	0.0103***	-0.0059***	0.0052***	0.0150***	0.0139***	0.0247***
	(0.0009)	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0009)	(0.0009)	(0.0009)
Imports	0.0016	0.0169***	0.0121***	0.0076***	0.0225***	0.0149***	0.0078***	0.0185***	0.0267***
	(0.0011)	(0.0010)	(0.0010)	(0.0007)	(0.0007)	(0.0007)	(0.0009)	(0.0009)	(0.0009)
Observations	303,294	303,294	303,294	774,097	774,097	774,097	528,782	528,782	528,782
R-squared	0.574	0.519	0.674	0.532	0,462	0.546	0.582	0.529	0.652
Within R2	0.313	0.303	0.500	0,241	0,462	0.546	0.234	0.282	0.436
No. of firms	51243	51243	51243	126,265	126,265	126,265	94,684	94,684	94,684

Notes: The table displays the estimated effect of firm AI exposure on log of employment split by occupational group. "Blue collar" include occupations in ISCO08 major groups 6, 7, 8, 9, "white collar low" include occupations in groups 4 and 5, while "white collar high" include occupations in ISCO08 major groups 1, 2, 3. The DAIOE index is the standardised and weighted average AI exposure of the firm where the occupational composition is fixed at firm-specific pre-sample shares of 4-digit ISCO08 occupations. All regressions include fixed effects at 3-digit NACE industry-year and municipality-year level. All continuous variables are in log form. Standard errors are in parenthesis and clustered at the firm level. *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

Table B3

Labour demand and AI exposure, varying shares

Dependent Variable: *log full-time-equivalent employment*	Denmark	Portugal	Sweden
DAIOE	-0.2155	-0.2513***	-0.6010***
	(0.2052)	(0.0756)	(0.1654)
Sales	0.6981***	0.7258***	0.5518***
	(0.0398)	(0.0244)	(0.0385)
Share Bachelor	-0.1974***	-0.6777***	0.0941
	(0.0613)	(0.0850)	(0.0906)
Physical Capital Intensity	-0.0173	-0.0587***	-0.0293***
	(0.0137)	(0.0063)	(0.0063)
Firm Age	0.0023**	0.0041***	0.0000
	(0.0011)	(0.0006)	(0.0013)
Foreign Owned	0.0443	0.1466***	0.0509*
	(0.0342)	(0.0514)	(0.0293)
Exports	0.0003	-0.0021	0.0322***
	(0.0020)	(0.0036)	(0.0047)
Imports	0.0350***	0.0066	0.0392***
	(0.0073)	(0.0054)	(0.0061)
Observations	303,294	774,097	528,782
R-squared	0.905	0.855	0.88
Within R2	0.801	0.776	0.756
No. of firms	51243	126,625	94,684

Notes: The table displays the estimated effect of firm AI exposure on log of firm total full-time-equivalent employment. The DAIOE index is the standardised and weighted average AI exposure of the firm where the occupational composition is varing at firm-specific 4-digit ISCO08 occupations. All regressions include fixed effects at 3-digit NACE industry-year and municipality-year level. All regressors are lagged at $t-1$ except for the contemporaneous firm age. All continuous variables are in log form. Standard errors are in parenthesis and clustered at the firm level. *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

Table B4

Log of employment on firm AI exposure split by occupational group, with DAIOE index with varying shares

	Denmark			Portugal			Sweden		
Dependent variables	*Blue collar*	*White collar low*	*White collar high*	*Blue collar*	*White collar low*	*White collar high*	*Blue collar*	*White collar low*	*White collar high*
DAIOE	-2.0517***	0.0032	1.3151***	-1.2151***	0.3572***	1.0353***	-2.8442***	0.2702	0.6016***
	(0.2730)	(0.2552)	(0.2217)	(0.1733)	(0.1272)	(0.0979)	(0.2470)	(0.320)	(0.1722)
Sales	0.6321***	0.6276***	0.6442***	0.5831***	0.6710***	0.6024***	0.4234***	0.4773***	0.4936***
	(0.0364)	(0.0348)	(0.0380)	(0.0515)	(0.0296)	(0.0206)	(0.0268)	(0.0306)	(0.0340)
Share Bachelor	-1.5226***	-1.1764***	0.9240***	-2.1842***	-1.4508***	1.1566***	-2.6485***	-1.5719***	1.1216***
	(0.1243)	(0.0898)	(0.0794)	(0.1605)	(0.1058)	(0.0871)	(0.2007)	(0.1302)	(0.1368)
Physical Capital Intensity	-0.0226	-0.0030	-0.0013	-0.0459***	-0.0449***	-0.0287***	-0.0355***	-0.0219***	-0.0046
	(0.0159)	(0.0150)	(0.0141)	(0.0105)	(0.0087)	(0.0083)	(0.0076)	(0.0076)	(0.0063)
Firm Age	0.0036*	0.0032**	0.0025*	0.0066***	0.0050***	0.0050***	-0.0035	-0.0038*	-0.0007
	(0.0019)	(0.0014)	(0.0013)	(0.0012)	(0.0007)	(0.0009)	(0.0025)	(0.0020)	(0.0016)
Foreign Owned	-0.1830***	0.0079	0.0685	-0.1408	-0.0122	0.2405***	0.1148*	0.1627***	0.1295***
	(0.0691)	(0.0433)	(0.0429)	(0.1354)	(0.0721)	(0.0758)	(0.0676)	(0.0626)	(0.0360)
Exports	0.0019	-0.0034	0.0083***	0.0149*	-0.0129***	0.005	0.0340***	0.0200***	0.0375***
	(0.0042)	(0.0030)	(0.0029)	(0.0083)	(0.0047)	(0.0050)	(0.0052)	(0.0051)	(0.0046)
Imports	0.0208***	0.0406***	0.0369***	-0.0185	0.0130**	0.0077*	0.0306***	0.0361***	0.0491***
	(0.0070)	(0.0066)	(0.0072)	(0.0140)	(0.0063)	(0.0045)	(0.0053)	(0.0054)	(0.0056)
Observations	303,294	303,294	303,294	774,097	774,097	774,097	528,782	528,782	528,782
R-squared	0.773	0.836	0.873	0.702	0.816	0.811	0.79	0.806	0.866
Within R2	0.503	0.613	0.708	0.526	0.666	0.707	0.494	0.576	0.707
No. of firms	51,243	51,243	51,243	126,265	126,265	126,265	94,684	94,684	94,684

Notes: The table displays the estimated effect of firm AI exposure on log of employment split by occupational group. “Blue collar” include occupations in ISCO08 major groups 6, 7, 8, 9, "white collar low" include occupations in groups 4 and 5, while “white collar high” include occupations in ISCO08 major groups 1, 2, 3. The DAIOE index is the standardised and weighted average AI exposure of the firm where the occupational composition is varing at firm-specific 4-digit ISCO08 occupations. All regressions include fixed effects at 3-digit NACE industry-year and municipality-year level. All continuous variables are in log form. Standard errors are in parenthesis and clustered at the firm level. *, ** and *** represent statistical significance at 10%, 5% and 1% respectively.

C Mapping matrix

Figure C1 prints the *mapping matrix* from Felten *et al.* (2018), which maps the relevance of nine AI applications to the 52 worker abilities (divided into four categories and 14 sub-categories) in O*NET. A greener cell indicates a higher score.

Ability type 1	Ability type 2	Ability	Games: Strategy games	Games: Video games	Language: Language modelling	Language: Reading compre-hension	Language: Speech recog-nition	Language: Trans-lation	Vision: Image gene-ration	Vision: Image recog-nition	Vision: Image compre-hension
Cognitive Abilities	Attentiveness	Selective Attention	0.50	0.50	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Cognitive Abilities	Attentiveness	Time Sharing	0.25	0.75	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Cognitive Abilities	Idea Generation and Reasoning Abilities	Category Flexibility	0.50	0.50	1.00	0.50	0.50	0.50	0.25	0.75	0.75
Cognitive Abilities	Idea Generation and Reasoning Abilities	Deductive Reasoning	1.00	0.75	0.75	1.00	0.50	0.75	0.25	0.50	0.75
Cognitive Abilities	Idea Generation and Reasoning Abilities	Fluency of Ideas	0.25	0.50	0.50	0.50	0.25	0.25	0.75	0.50	0.75
Cognitive Abilities	Idea Generation and Reasoning Abilities	Inductive Reasoning	0.75	0.75	0.75	1.00	0.50	0.50	0.25	0.50	0.50
Cognitive Abilities	Idea Generation and Reasoning Abilities	Information Ordering	0.75	0.50	0.75	0.50	0.25	0.50	0.50	0.50	0.50
Cognitive Abilities	Idea Generation and Reasoning Abilities	Originality	0.75	0.50	0.75	0.50	0.25	0.25	1.00	0.50	0.50
Cognitive Abilities	Idea Generation and Reasoning Abilities	Problem Sensitivity	1.00	1.00	0.50	0.25	0.25	0.25	0.00	0.00	0.25
Cognitive Abilities	Memory	Memorization	0.75	0.50	0.50	0.25	0.25	0.50	0.25	0.50	0.50
Cognitive Abilities	Perceptual Abilities	Flexibility of Closure	1.00	0.75	0.50	0.50	0.50	0.25	0.50	0.75	0.75
Cognitive Abilities	Perceptual Abilities	Perceptual Speed	0.75	0.75	0.50	0.50	0.25	0.00	0.25	0.50	0.50
Cognitive Abilities	Perceptual Abilities	Speed of Closure	1.00	0.75	0.75	0.50	0.50	0.25	0.50	0.75	0.50
Cognitive Abilities	Quantitative Abilities	Mathematical Reasoning	0.75	0.50	0.50	0.25	0.50	0.50	0.50	0.50	0.50
Cognitive Abilities	Quantitative Abilities	Number Facility	0.25	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.25
Cognitive Abilities	Spatial Abilities	Spatial Orientation	0.25	0.75	0.00	0.00	0.00	0.00	0.50	0.50	0.50
Cognitive Abilities	Spatial Abilities	Visualization	0.75	0.75	0.25	0.25	0.25	0.25	1.00	0.25	0.50
Cognitive Abilities	Verbal Abilities	Oral Comprehension	0.00	0.25	0.50	0.25	1.00	0.50	0.00	0.00	0.00
Cognitive Abilities	Verbal Abilities	Oral Expression	0.00	0.00	0.25	0.00	0.50	0.50	0.00	0.00	0.25
Cognitive Abilities	Verbal Abilities	Written Comprehension	0.25	0.25	1.00	1.00	0.50	1.00	0.25	0.25	0.50
Cognitive Abilities	Verbal Abilities	Written Expression	0.25	0.25	0.50	0.50	0.50	1.00	0.50	0.25	0.50
Physical Abilities	Endurance	Stamina	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Physical Abilities	Flexibility, Balance, and Coordination	Dynamic Flexibility	0.25	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Physical Abilities	Flexibility, Balance, and Coordination	Extent Flexibility	0.25	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Physical Abilities	Flexibility, Balance, and Coordination	Gross Body Coordination	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Physical Abilities	Flexibility, Balance, and Coordination	Gross Body Equilibrium	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Physical Abilities	Physical Strength Abilities	Dynamic Strength	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Physical Abilities	Physical Strength Abilities	Explosive Strength	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Physical Abilities	Physical Strength Abilities	Static Strength	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Physical Abilities	Physical Strength Abilities	Trunk Strength	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Psychomotor Abilities	Control Movement Abilities	Control Precision	0.25	0.75	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Psychomotor Abilities	Control Movement Abilities	Multilimb Coordination	0.25	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Psychomotor Abilities	Control Movement Abilities	Rate Control	0.25	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Psychomotor Abilities	Control Movement Abilities	Response Orientation	0.25	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Psychomotor Abilities	Fine Manipulative Abilities	Arm-Hand Steadiness	0.25	0.75	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Psychomotor Abilities	Fine Manipulative Abilities	Finger Dexterity	0.25	0.75	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Psychomotor Abilities	Fine Manipulative Abilities	Manual Dexterity	0.25	0.75	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Psychomotor Abilities	Reaction Time and Speed Abilities	Reaction Time	0.25	0.75	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Psychomotor Abilities	Reaction Time and Speed Abilities	Speed of Limb Movement	0.25	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Psychomotor Abilities	Reaction Time and Speed Abilities	Wrist-Finger Speed	0.25	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sensory Abilities	Auditory and Speech Abilities	Auditory Attention	0.25	0.50	0.00	0.00	1.00	0.50	0.00	0.00	0.00
Sensory Abilities	Auditory and Speech Abilities	Hearing Sensitivity	0.25	0.50	0.00	0.00	0.75	0.50	0.00	0.00	0.00
Sensory Abilities	Auditory and Speech Abilities	Sound Localization	0.25	0.75	0.00	0.00	0.75	0.50	0.00	0.00	0.00
Sensory Abilities	Auditory and Speech Abilities	Speech Clarity	0.00	0.00	0.25	0.00	0.75	0.50	0.00	0.00	0.25
Sensory Abilities	Auditory and Speech Abilities	Speech Recognition	0.00	0.25	0.25	0.00	1.00	0.50	0.00	0.00	0.00
Sensory Abilities	Visual Abilities	Depth Perception	0.25	0.50	0.00	0.00	0.00	0.00	0.50	1.00	1.00
Sensory Abilities	Visual Abilities	Far Vision	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.75	0.75
Sensory Abilities	Visual Abilities	Glare Sensitivity	0.25	0.50	0.00	0.00	0.00	0.00	0.50	1.00	0.75
Sensory Abilities	Visual Abilities	Near Vision	0.25	0.50	0.00	0.00	0.00	0.00	0.50	1.00	1.00
Sensory Abilities	Visual Abilities	Night Vision	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.75	0.75
Sensory Abilities	Visual Abilities	Peripheral Vision	0.25	0.50	0.00	0.00	0.00	0.00	0.25	0.75	0.75
Sensory Abilities	Visual Abilities	Visual Color Discrimination	0.25	0.50	0.00	0.00	0.00	0.00	0.50	1.00	1.00

Figure C1: Mapping matrix from Felten *et al.* (2018)