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Who is afraid of AI? Who should be?

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Overview/Überblick

- Occupations that are highly cognitive, non-physical, and low in social interaction – typically higher-skill white-collar roles such as data analysts, software developers, and translators – turn out to be highly AI-exposed
- Occupations requiring manual dexterity or intensive interpersonal contact – such as construction labourers or nursing aides – remain among the least exposed to current AI technologies
- Aggregate occupational exposure to AI has risen markedly since 2010, with especially rapid gains in the late 2010s and early 2020s
- Our baseline estimates show no detectable effect of AI exposure on total firm employment, while it is associated with clear skill upgrading

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

- Berufe, die in hohem Maße kognitiv, nicht körperlich und mit geringen sozialen Interaktionen verbunden sind – typischerweise höher qualifizierte Angestelltenberufe wie Datenanalysten, Softwareentwickler und Übersetzer – sind offenbar in hohem Maße von KI betroffen
- Berufe, die manuelle Geschicklichkeit oder intensiven zwischenmenschlichen Kontakt erfordern – wie Bauarbeiter oder Pflegehelfer – gehören nach wie vor zu den Berufen, die am wenigsten von aktuellen KI-Technologien betroffen sind
- Die aggregierte berufliche Exposition gegenüber KI ist seit 2010 deutlich gestiegen, wobei die Zuwächse Ende der 2010er und Anfang der 2020er Jahre besonders rasch waren
- Unsere Basisschätzungen zeigen keine erkennbaren Auswirkungen der KI-Exposition auf die Gesamtbeschäftigung in Unternehmen, während sie mit einer deutlichen Verbesserung der Qualifikationen einhergeht

Schlüsselwörter: Künstliche Intelligenz, Arbeitskräftenachfrage, Daten auf Unternehmensebene aus mehreren Ländern

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Who is afraid of AI? Who should be?

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1. Introduction

Today's AI systems perform tasks once thought to require human intelligence – processing vast datasets under varying degrees of supervision, assisting decision-makers, generating content, and even making autonomous decisions (OECD, 2024). What are the consequences of the rise in AI for workers? Will AI create or destroy jobs? Conceptually, AI can both substitute for and complement human labour. Hence, empirical evidence is needed. This is what we set out to do in our research paper, Engberg et al. (2026), where we develop a novel *Dynamic AI Occupational Exposure* (DAIOE) index and apply it in a multi-country firm-level analysis to estimate the impact of AI on employment.

In the paper, we track advances in AI across nine AI subdomains (e.g., language modelling, image recognition, decision-making) from 2010 to 2023 to capture how frontier technology gains in AI evolve. We then map this into detailed information on occupational work content in order to generate a measure of exposure to AI by different occupations (such as, e.g., managers, labourers, nurses, etc.). Our measure unpacks AI into its components and developments over time, and builds on and expands the seminal work by (Felten et al., 2018).[1]

The DAIOE index reveals clear patterns in how AI's potential impact is distributed across jobs and over time. Occupations that are highly cognitive, non-physical, and low in social interaction – typically higher-skill white-collar roles such as data analysts, software developers, and translators – turn out to be highly AI-exposed. Given their interaction with AI, these may be the occupations that perhaps are most likely to "be afraid of AI". In contrast, occupations requiring manual dexterity or intensive interpersonal contact – such as construction labourers or nursing aides – remain among the least exposed to current AI technologies.

Aggregate occupational exposure to AI has risen markedly since 2010, with especially rapid gains in the late 2010s and early 2020s as breakthroughs in deep learning and large language models came online, e.g., as generative AI chatbots such as DALL-E and ChatGPT in 2022. Progress has also been uneven across subdomains: for example, image and speech recognition saw major improvements in the early 2010s, machine translation advanced in the mid-2010s (Zhang et al., 2021), and language modelling achieved breakthrough performance around 2020. Our dynamic measure captures these shifts.

Importantly, "exposure to AI" in this context indicates the potential applicability of AI to an occupation's tasks – it is *not* inherently a measure of substitution or complementarity with existing workers. Whether high exposure leads to labour displacement or augmentation is an empirical question that we look at separately in order to determine who, perhaps "should be afraid of AI". To do so, we merge the DAIOE indices with rich longitudinal employer–employee data from three countries (Denmark,

[1] The methodological details can be found in the Working Paper version (Engberg et al., 2026).

Portugal, and Sweden) to examine how variation in AI exposure – both in aggregate and by subdomain – relates to shifts in firms' employment and workforce composition over more than a decade. Because institutions and industrial structure differ, we do not expect identical estimates across countries; the value here is comparability, not uniformity.

Our baseline estimates show no detectable effect of AI exposure on total firm employment, alongside clear skill upgrading: firms with higher DAIOE scores raise their high-to-low skill employment ratios. This holds for all three countries. Across the three countries, firms more exposed to AI reallocate toward high-skill white-collar jobs and away from lower-skill clerical roles; effects on blue-collar workers are small. These patterns suggest that, whether or not you "should be afraid of AI" depends very much on the tasks you carry out in your job. AI may replace less complex, low-social-skill tasks but support more complex, higher-interaction roles.

2. Measuring AI Exposure: The DAIOE

To measure AI progress, we make use of data that have been used in AI research to test AI performance.[2] We classify AI technology into nine main AI applications (or subdomains), which are, in turn, categorised into three primary areas–games, vision, and language. These have been validated by AI researchers as representative of key AI research domains during the study period. Within each AI application, we calculate a state-of-the-art frontier, representing the highest AI performance to date. Summing these yearly changes yields cumulative progress curves for all nine applications, as shown in Figure 1.

To connect AI advancements to occupational tasks, we utilize the Occupational Information Network (O*NET) database (Handel, 2016). O*NET provides standardized information on occupational requirements, including worker abilities that capture key individual characteristics affecting job performance, such as oral communication, reasoning, vision, and physical strength. We use a mapping matrix from Felten et al. (2018) to link AI applications to worker abilities.[3] Cognitive abilities are most strongly linked to AI applications, followed by sensory abilities, while physical and psychomotor abilities show limited connections, except for video games, which notably combine perception and physical action. This pattern reflects AI research priorities from 2010 to 2023, which emphasised cognitive over robotic progress.

While the O*NET abilities provide a broad view of occupational content, they do not fully capture the role of social interaction. Hence, we incorporate information on

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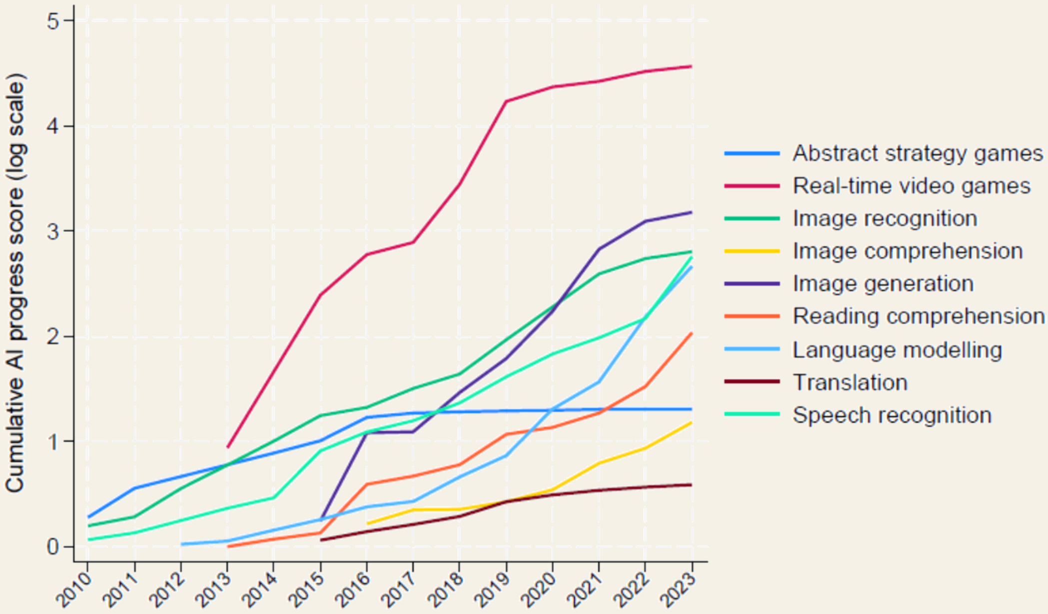
[2] Data on benchmarks are from the Electronic Frontier Foundation (EFF) and Papers With Code (PWC) on AI progress across applications or sub-domains. Data are available at: https://www.eff.org/ai/metrics and https://paperswithcode.com.

[3] This matrix assigns a relatedness score $x_{ij} \in [0, 1]$ between each application and ability, based on expert assessment.

social skills in O*NET, such as the occupational importance of persuasion and social perceptiveness. We thus assume that social tasks are more difficult to automate.

Figure 1: Estimated Progress Over Time by AI Application



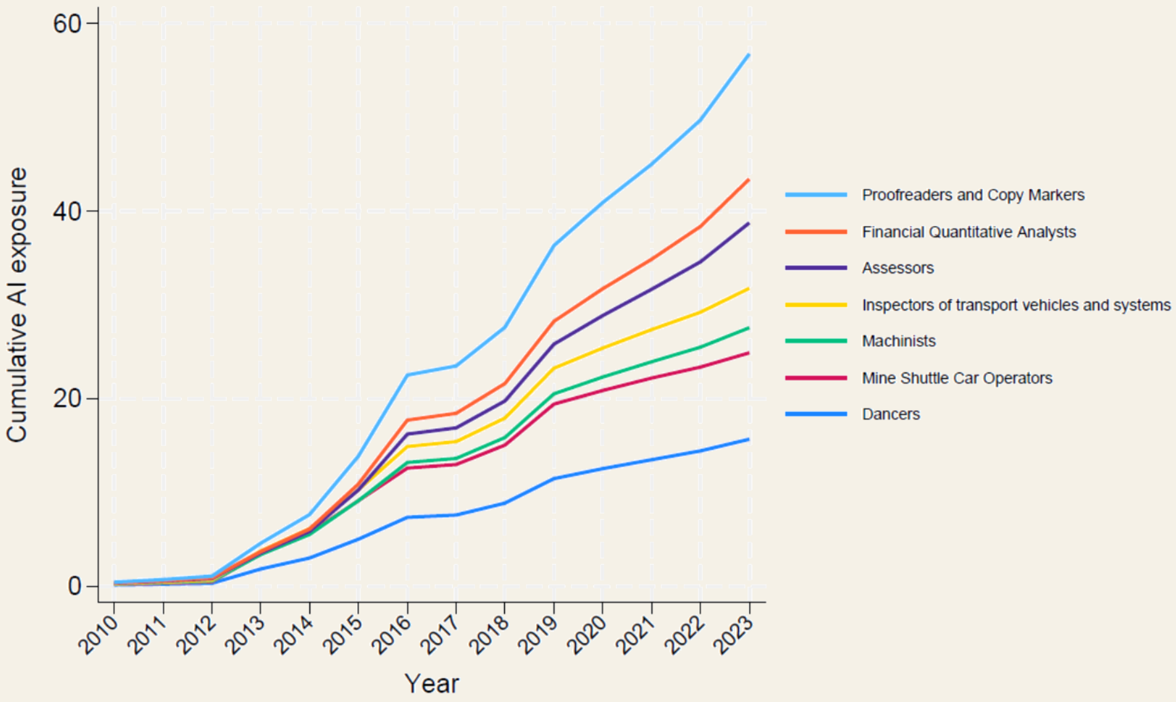
Notes: Progress curves for each AI application are derived from the underlying benchmarks, using the average slope of benchmark frontiers by year. The resulting application-level progress measures are subsequently linked to worker abilities through the *mapping matrix*.

Figure 2 traces the evolution of AI exposure from 2010 to 2023 for seven selected occupations, positioned across the exposure distribution. The figure reveals a widening dispersion over time and a clear acceleration of AI progress starting around 2012, coinciding with the rise of deep learning. A pivotal moment was the introduction of AlexNet in the 2012 ImageNet competition, which marked a leap forward in image recognition and helped catalyse rapid advances in multiple AI subdomains.

Looking more closely across major occupational groups, we find that white-collar occupations (ISCO groups 1–4) exhibit significantly higher average exposure to AI. Specifically, groups 1–3 – comprising Managers, Professionals, and Technicians and Associate Professionals – typically require higher education qualifications. Group 4, Clerical Support Workers, although generally not requiring tertiary education, are pre-dominantly associated with office-based tasks.[4]

[4] For more information on the skill levels in ISCO, see: https://www.ilo.org/public/english/bureau/stat/isco/isco08/.

Figure 2: DAIOE Trajectories Over Time for Selected Occupations



Notes: The figure shows AI exposure (DAIOE) over time for seven occupations, selected to represent the 0th, 10th, 25th, 50th, 75th, 90th, and 100th percentiles of the 2023 DAIOE distribution.

To further explore the relationship between AI exposure and occupational characteristics, we look at the occupations' scores for social skills, cognitive abilities, and physical abilities. We find that occupations with high cognitive demands and limited social or physical requirements tend to be the most exposed to AI. This pattern aligns with the top-exposed occupations listed in Figure 2; for instance, proofreaders and copy markers, and financial quantitative analysts are occupations that fit this profile. By contrast, the least exposed occupations, such as dancers and mine shuttle car operators, tend to involve highly physical and/or social tasks.

3. Employment effects

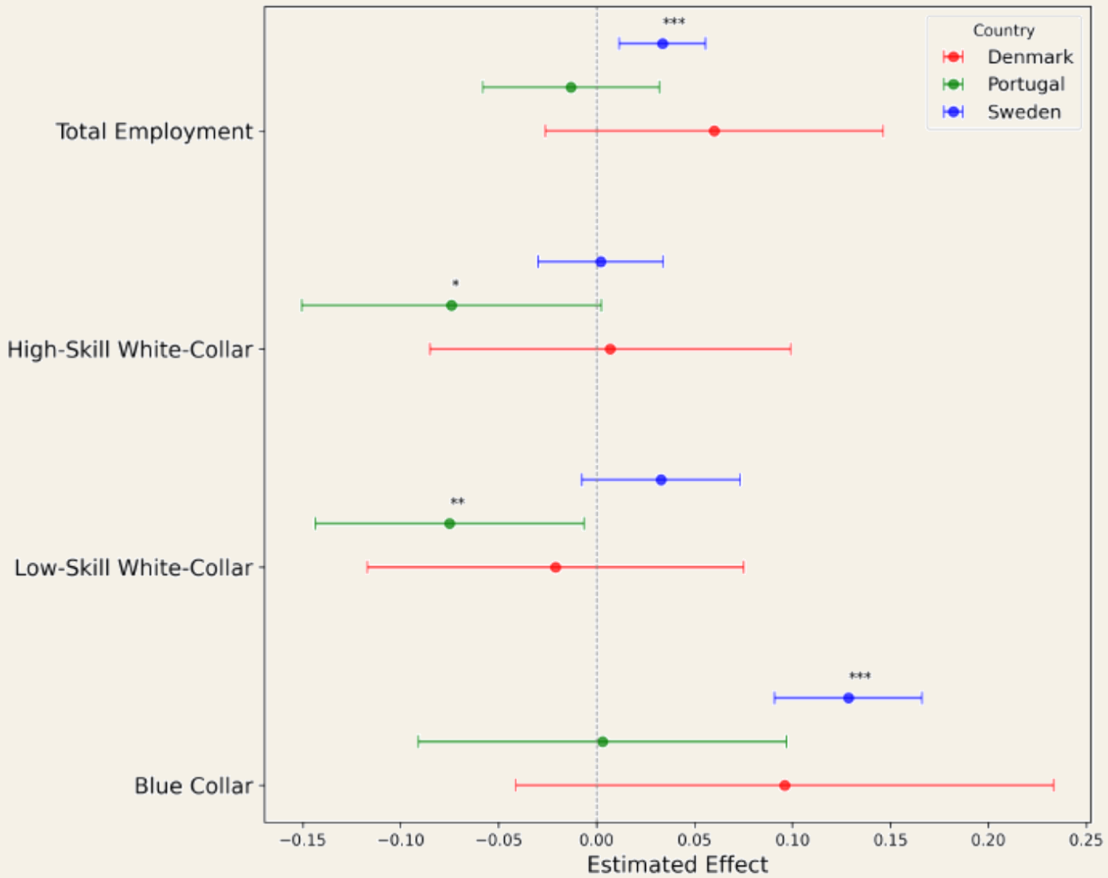
To investigate whether and how different types of AI affect labour demand over time, we apply our AI exposure measure to comprehensive micro-data from Denmark, Portugal, and Sweden – three relatively open economies that differ markedly in labour market characteristics, industrial structures, and digital adoption levels.[5] Regarding AI adoption, recent Eurostat data indicate that in 2024, approximately 25.2 percent of enterprises in Sweden and 27.6 percent in Denmark employed AI

[5] The data span from 2010 to the most recent available year: 2021 for Denmark and Portugal, and 2023 for Sweden.

technologies, compared to just 9 percent in Portugal (Eurostat, 2024). This disparity underscores the varying degrees of AI integration in these economies.

We present our baseline regression results in Figure 3. The figure visualises the coefficients and 95 percent confidence intervals for firm-level AI exposure on four firm-level employment outcomes across Denmark, Portugal, and Sweden. In addition to measuring the association between AI exposure and total employment, we examine heterogeneity across occupational groups by dividing a firm's workforce into three broad categories: "white-collar-high," encompassing occupations in ISCO-08 major groups 1 to 3; "white-collar-low," including groups 4 and 5; and "blue-collar," comprising groups 6 through 9.

Figure 3: Employment Outcomes



Notes: The whisker plot depicts the estimated associations between AI exposure and different employment outcomes (total employment, white-collar high-skill, white-collar low-skill, and blue-collar occupations) across Denmark, Portugal, and Sweden. The horizontal bars represent the coefficient estimates for each country, with whiskers showing the 95% confidence intervals. The DAIOE measure is the standardised and weighted average AI exposure of the firm where the occupational composition is fixed at firm-specific baseline-year shares of 4-digit ISCO08 occupations. All regressions include fixed effects at 3-digit NACE industry-year and location-year levels. All regressors are lagged at $t-1$ except for the contemporaneous firm age. All continuous variables are in log form.

Our baseline estimates show no significant link between AI exposure and *total* firm employment in Denmark or Portugal, and a small but positive association in Sweden. However, the heterogeneity of AI exposure's association becomes apparent when analysing employment effects across occupational groups and countries. As shown in Figure 3 the associations differ significantly across white-collar-high, white-collar-low, and blue-collar workers, and across countries.

These results thus far prompt a pertinent question: how does AI exposure relate to shifts in the overall skill composition of the workforce? In further analysis, we find that, across all three countries, there is a clear and statistically significant positive association between AI exposure and the skill ratio (a firm's ratio of high to low skill workers), indicating that firms exposed to advancing AI capabilities tend to increase the relative share of high-skilled workers. Hence, AI exposure is associated with a systematic shift in firm- level employment structures toward higher-skilled labour.[6]

One may reasonably expect that different AI applications or subdomains may have different employment implications. This is what we look at next.

Regarding total firm employment, we find that certain applications, in particular AI in reading comprehension, language modelling or speech recognition, exhibit positive and statistically significant associations with total employment, suggesting that AI technologies in this area are complementary to workers. This holds across all three occupational groups – white-collar-high, white-collar-low and blue-collar workers – though, interestingly, they are strongest for blue-collar workers.

Taken together, the results underline the importance of unpacking the nature of AI exposure across both occupational categories and technological applications.

4. Concluding Remarks

Should workers be afraid of AI? Our main finding is that firms with higher AI exposure show no systematic change in overall headcounts, but do shift their workforce mix towards a more skilled workforce. Disaggregated results reveal that AI exposure in reading comprehension, speech recognition and language modelling have the strongest positive effects on all skill groups.

These patterns underscore why it matters to unpack AI into its component technologies. As AI continues to evolve — especially with generative models — DAIOE offers a straightforward way to anticipate both broad up-skilling trends and more focused displacement risks.

In highlighting predominantly upskilling — rather than mass displacement — the results suggest that policy should prioritise helping workers adapt to technological change through training, re-skilling, and education so they can thrive in more AI-augmented roles.

[6] This also echoes recent U.S. evidence showing a shift toward general skill upgrading in the labour market (Deming et al., 2025).

At the same time, heterogeneity across AI applications that we highlight in our study, and differences in national contexts underscore that there is no one-size-fits-all impact of AI: policymakers and firms should monitor specific capabilities and target interventions to the areas of greatest disruption—whether assisting workers in occupations exposed to automation-prone technologies or fostering adoption where productivity lags.

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