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European Commission

SCIENCE FOR POLICY BRIEF

Labour, Education and Technology

Anticipating the impact of AI on occupations: a JRC methodology

HIGHLIGHTS

→ The Joint Research Centre developed a methodology to assess the relative impact of AI (artificial intelligence) on occupations.

→ It is based on a mapping between the amount of research in AI and occupations, linking them through cognitive abilities and work tasks.

→ The methodology was used to calculate an AI exposure score for 100+ occupations.

→ AI has the largest impact on occupations such as engineers, administration professionals (including policymakers), and teachers. In contrast, cleaners and construction labourers are much less impacted by AI.

→ With the fast advancement of AI, this score can be updated to anticipate the likely impact of emerging AI technologies on occupations.

'Together we must focus on the challenges facing the labour market' [including] 'the new challenges stemming from AI.'
(President von der Leyen, 2023 State of the Union)

INTRODUCTION

Over the past years, Artificial Intelligence (AI) has expanded its user base beyond specialists. Many non-experts now use AI applications, often without knowing it[1]. **AI** has also made its way into the **workplace**[2]. Employers have begun using AI applications to help them hire staff, monitor work performance, and deliver customer service. AI can help finance professionals analyse large datasets, security officers to process images, students to acquire new knowledge, or secretaries to generate meeting minutes.

How will these developments in AI affect the labour market? Which paid tasks can AI perform? On **which occupations** will AI have the largest impacts?

Policymakers, trade unions[3] and employers[4] alike are increasingly asking these questions. Businesses are aware that they may need to transform or reallocate tasks as a consequence of the deployment of AI, but envision that AI may also lead to employment creation[5].

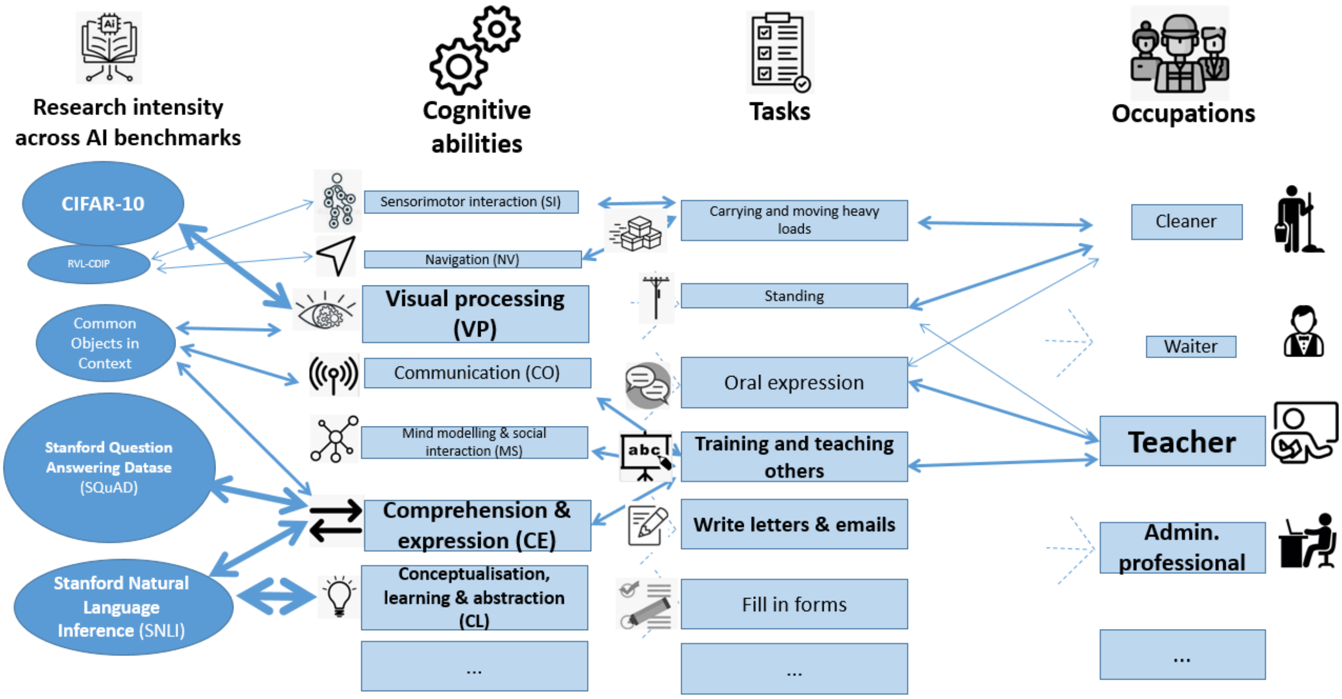
The **European Union** also acknowledges the importance of understanding the impact of AI on jobs. The Commission's Communication on fostering a European approach to AI[6], as well as the European Skills Agenda[7], mention both employment opportunities and potential job losses. The impact assessment of the AI Regulation[8] recognises that the net balance of AI job losses vs. creation is uncertain.

This policy brief presents an original method to assess the anticipated impact of AI on occupations. It results in an exposure score for each occupation, which was developed for a JRC research paper[9].

Joint Research Centre

THE MAPPING BEHIND THE AI EXPOSURE SCORE

Figure 1 – Mapping (qualitative illustration) between research intensity across AI benchmarks and selected occupations



The qualitative illustration shows the bidirectional path between research intensity across AI benchmarks and occupations. The size of circles losely represents the amount of AI research outputs across selected AI benchmarks. The size of the rectangles in the second column losely represents the AI research intensity in a selected number of cognitive abilities. The size of the rectangles in the last column are losely proportionate to the AI exposure score of the represented occupations.

THE METHODOLOGY

The score is based on an indirect matrix mapping between research in AI and occupations, through cognitive abilities and work tasks (see Figure 1). Its bidirectional nature means one can read the mapping both from left to right (starting from AI research intensity) and from right to left (starting from occupations).

Research intensity across AI benchmarks

Starting from the left of Figure 1, the first step consists in assessing how much research is conducted in specific AI benchmarks. Data on **AI research intensity** regarding each benchmark consists in the number of AI-related documents (e.g. blog entries, conferences, research publications) in Aitopics.org, an archive kept by the Association for the Advancement of AI. Alternatively, other platforms with data[10] on AI research intensity include Paperswithcodes.com, OpenML and Stanford University's AI Index annual report.

AI research intensity is measured across **AI benchmarks**[11] – i.e. standardised AI performance tests that provide an objective basis for capabilities comparison – just like academic tests do to evaluate student performance. For instance:

- the **CIFAR-10** dataset contains 80 million tiny images (e.g. airplanes, cars, birds, cats – see Figure 3) used to assess AI's ability to correctly recognise or generate visual objects;
- the Stanford Question Answering Database (**SQuAD**) is used to evaluate AI's ability to understand a passage (e.g. Wikipedia article) and extract relevant information to answer questions;
- the Stanford Natural Language Inference (**SNLI**) test assesses AI's performance to detect whether two texts logically contradict or entail each other (see Box 1 for examples);
- in the **RVL-CDIP** benchmark, the task consists in correctly classifying low quality scanned document images into the right category (e.g. letter, form, memo, questionnaire – see Figure 2).

Cognitive abilities

AI-specialised researchers then assess which are the **cognitive abilities** necessary to perform the operation of each AI benchmark. Examples of such abilities include visual processing, memory processing, logical reasoning, emotions and self-control.

For instance, comprehension and expression abilities are necessary to solve the task of the Stanford Question Answering Database (SQuAD). Correctly assessing contradiction or entailment between two sentences in

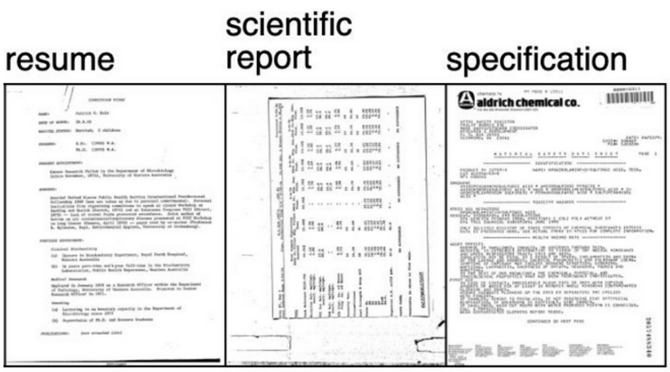
Box 1: solving the Stanford Natural Language Inference (SNLI) – an example of AI benchmark

The SNLI (Stanford Natural Language Inference) corpus[12] is a collection of more than 500,000 sentence pairs. The sentence pairs either logically:
- contradict each other
- are entailed from one another
- are neutral with respect to each other

The AI benchmark consists in assessing AI's performance in detecting the correct logical relation between these sentences.
Examples of sentence pairs:
- Contradiction: '*A black race car starts up in front of a crowd of people*' and '*A man is driving down a lonely road*'
- Entailment: '*A soccer game with multiple males playing*' and '*Some men are playing a sport*'.

the SNLI benchmark (see Box 1) requires abilities related to conceptualisation, learning and abstraction. Acing the classification of scanned document images in the RVL-CDIP dataset (see Figure 2) uses abilities such as visual processing, attention and search.

Figure 2 – Examples of scanned documents from the RVL-CDIP database and their correct classification



Source: A. W. Harley, A. Ufkes, K. G. Derpanis, "Evaluation of Deep Convolutional Nets for Document Image Classification and Retrieval," in ICDAR, 2015

Tasks involved in each occupation

In this step, starting this time from the right of Figure 1, a list of more than 100 occupations is drawn from the International Standard Classification of Occupations (ISCO-3). Examples of such occupations include administration professionals (e.g. policymakers, HR professionals, sales professionals), teachers, cleaners, and cooks.

Each occupation is described in terms of how frequently it involves performing certain **tasks**. Worker survey data (e.g. European Working Conditions Survey - EWCS) serve as basis for this mapping. For instance, legal professionals typically perform negotiation and conflict resolution. Mining and construction labourers, as well as fishery workers, perform strength, manual dexterity, and visual processing tasks.

Abilities required for each task

The final step to join AI research intensity with each occupation consists in **mapping each task with the cognitive abilities** required to perform it. Experts indicate whether each of the fourteen cognitive abilities is absolutely necessary to perform each task.

This allows linking occupations with abilities, through tasks. For instance, sensorimotor interaction is an ability needed for cleaners, heavy truck and bus drivers, but less so for teachers and office clerks. Social interaction abilities are on average less relevant for office clerks than for shop salespersons and waiters.

Computing AI exposure score

Finally, for each occupation, an AI exposure score is computed based on (1) the relative required intensity of each of the fourteen cognitive abilities for this occupation, (2) the relative AI research intensity for each of the (same) fourteen cognitive abilities.

CALCULATING THE EXPOSURE SCORE

AI research intensity on different cognitive abilities

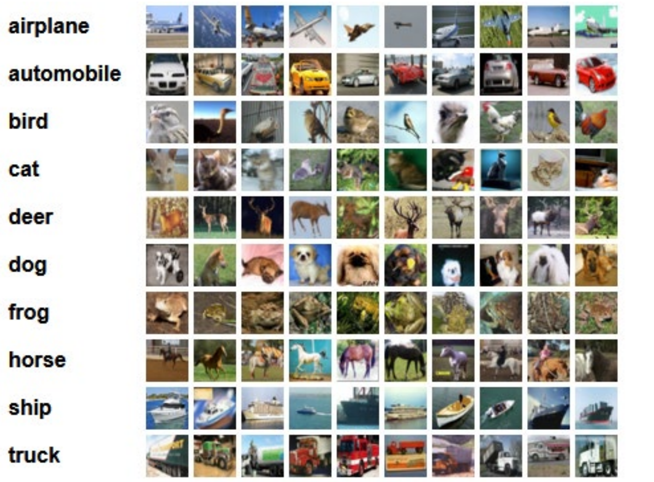
The methodology behind the occupation AI exposure score was first used in 2021. Data was gathered on the research intensity across 328 AI benchmarks, in the period between 2008 and 2018. This overall corresponds to the large increase in AI research that led to the advent of large language models.

During that time, most AI research concerned abilities dealing with **ideas**. Prominent ideas-related cognitive abilities covered by AI research included conceptualisation, learning and abstraction (e.g. being able to generalise from examples, receive instructions, accumulate knowledge); attention and search (i.e. focusing attention on the relevant parts of a stream of information), and comprehension and expression. For instance, a relatively high amount of research was conducted during that period regarding the SQuAD AI benchmark (i.e. Stanford Question Answering Database), which deals (as mentioned before) with comprehension and expression and quantitative and logical reasoning.

Another prominent area of AI research tackled the Stanford Natural Language Inference (SNLI), also strongly related to comprehension and expression, but also conceptualisation, learning and abstraction.

A prominent area of AI research during that time related to **visual processing,** i.e. the recognition of objects and symbols in images and videos. One of the main AI benchmarks that demonstrates this cognitive ability is the recognition of objects in the CIFAR dataset (see Figure 3).

Figure 3 – Examples of images in the CIFAR database



Source: A. Krizhevsky, A. (2009). Learning Multiple Layers of Features from Tiny Images

In contrast, there was very few AI research related to mind modelling and social interaction (e.g. anticipating someone else's actions), communication (i.e. exchange information with peers, understand messages) and emotion and self-control. All of these underrepresented AI abilities relate to dealing with **people**.

AI exposure score

How does this AI research regarding cognitive abilities translate into impact on occupations? Figure 4 shows the ranking of relative AI exposure scores for selected occupations during the period 2008-2018. This ranking indicates which occupations were most/least likely to be affected by AI research.

The **occupations most exposed to AI** were electrotechnology engineers, software developers, teachers, office clerks, and secretaries. For instance, teachers were more exposed to AI than 90% of workers. The impact that AI had on these occupations was mainly driven by AI-enabled 'ideas'-related abilities that are required for these occupations, such as comprehension and expression, attention and search, and conceptualisation, learning and abstraction.

Conversely, AI research **impacted** occupations such as cleaners and helpers, waiters and bartenders, and shop salespersons **relatively less**. This is because AI research in abilities required for these occupations – for instance, sensorimotor interaction and navigation – was still scarce.

Further analysis shows that there was a positive relationship between **wages** and AI exposure. AI research was more likely to affect high-income occupations (such as electro-technological engineers and medical doctors) than low-income occupations (e.g. street vendors, agricultural labourers, cashiers).

This AI exposure score was validated by comparing it with other similar indicators. Reasonable levels of correlation between this AI exposure score and the other indicators confirm the validity of the former.

Figure 4 – Ranking of selected occupations, from most to least exposed to AI (2008-2018 data)

Source: Tolan et al. (2021). Measuring the occupational impact of AI: tasks, cognitive abilities and AI benchmarks. *Journal of Artificial Intelligence Research.*

Box 3: the policymaker example

In the International Standard Classification of Occupations (ISCO) database, policymakers belong to the broader category of 'administration professionals'.
The **tasks** that these professionals usually perform involve ordering information, negotiating, coaching, induction and deduction. In contrast, strength-related tasks are not usually in the job description of policymakers.
These tasks, in turn, require **cognitive abilities** such as communication, conceptualisation, comprehension, expression, recognising and understanding emotions. Cognitive abilities like sensorimotor interaction are relatively less relevant for policymakers.
There is a lot of **AI research** linked to some of these abilities. For instance, comprehension and expression, as well as conceptualisation, are among the most researched AI abilities, as evidenced e.g. by the high number of research outputs around the Stanford Question Answering Database (SQuAD).
All in all, this explains why policymakers – and more generally administration professionals – are among the **top 20% most AI-exposed occupations**.

UPDATING THE SCORE

An ongoing JRC-funded project[13] gathers new AI benchmarks and the related number of research publications from 2020 to August 2024, giving a glimpse of the likely impact of more recent trends.

From 2020 to 2023, the number of scientific papers mentioning AI benchmarks almost **doubled**. During that period, the **main modalities** covered by these AI benchmarks were the processing and generation of **images, texts, videos and audios**.

Image-based AI benchmarks include CIFAR-10, MC COCO and ImageNet. These benchmarks are likely mainly related to visual processing. Tasks in AI **text processing and generation** include sentiment analysis, machine translation or text summarisation. Text-related AI benchmarks include those already mentioned earlier (such as SQuad and SNLI), but also previously not identified benchmarks. For instance, GLUE (General Language Understanding Evaluation) is used among others to assess AI performance in sentiment analysis. Overall, text-related AI benchmark are likely related to cognitive abilities such as comprehension, expression and conceptualisation.

The growth of AI research in these domains might reinforce the trends observe before 2020 in terms of exposure of occupations to AI.

DISCUSSION

Anticipating the impact of AI on occupations is crucial to prepare the workforce, foresee potential job displacements, and adapt curricula, to name a few. The methodology presented in this policy brief allows extracting data on research across different AI benchmarks, linking this research to cognitive abilities, and calculating an AI exposure score for occupations, through work tasks.

'Refreshing' the AI research part of the mapping, by monitoring AI benchmarks, allows easily updating the exposure score, thereby providing quick insights into the potential occupational effects of breakthroughs in AI. It may also be necessary to update the occupations and tasks part of the mapping to account for emerging trends in this field.

The application of this methodology prior to the widespread development of LLMs suggests that the potential **impact of AI seems different** than previous waves of technological progress. Doctors, teachers and engineers, for instance, were not particularly exposed to previous waves of technological outbreaks (e.g. robotisation), as much as cashiers, machine operators and assemblers, to name a few. AI has the potential to revert this pattern, by impacting **high-income occupations** more than low-income occupations. This is because AI has so far made progress on abilities related to ideas, such as conceptualising, learning, abstracting, comprehending and searching information… abilities that doctors, engineers and teachers particularly need to perform their job tasks. It is important to note that other, **non-AI based technological progresses** (for instance, self-checkout machines) may affect low-income occupations.

The fact that, say, teachers are exposed to AI does not necessarily translate into actual job impact. All it says is that AI could perform some of the tasks that teachers perform or assist them in performing these tasks better. Whether decision-makers will harness this potential or not depends on a number of factors. For instance, is the performance of these tasks by AI-enabled machines (including the associated restructuring of business processes) cheaper than labour costs for these tasks? Does the public and regulators trust AI to perform these tasks? What are the dynamics of AI diffusion in terms of labour income and the demand for goods and services?

This analysis does not consider **potential substitution or replacement effects** of AI on job. However, it is safe to say that AI will likely transform jobs rather than destroy them. This is because AI applications are unlikely to be able to perform all the range of abilities and tasks required to perform a job. Most occupations require good people-related abilities, for instance in terms communication, mind modelling and social interaction. These abilities are not well covered by AI, so far.

POLICY IMPLICATIONS

These findings can help policymakers in directing their response to AI progress, in the form of education and employment policies.

Policymakers may need to align **educational** curricula and training programmes to develop certain cognitive abilities. First, workers will need to develop skills to **use AI**, in terms of basic AI literacy (e.g. familiarity with AI tools), writing appropriate prompts, and critical analysis of AI-generated outputs. Second, finding the right **complementarity** between human and AI abilities will be key. Competing with AI on those abilities where it will likely perform better than humans (e.g. visual processing) is probably not the way forward. At the same time, workers in certain occupations will likely always need abilities such as conceptualising, learning and abstracting, despite AI performing well in this type of abilities. Investing in abilities (such as people-related abilities, i.e. emotions) where AI does not perform well could be a valuable strategy.

Employment policies may need to consider the labour market dynamics brought about by AI. These include potential impacts on income and gender inequality, occupational restructuring, shifts in demand for certain skills, and potential transformation of occupations. AI may have a positive impact on employment by performing tasks that are otherwise arduous, expensive and/or dangerous for humans to perform – for instance, content moderation tasks can cause mental issues for humans when exposed to e.g. violence. There is evidence[14] showing that AI, for instance ChatGPT, can increase workers' productivity. Encouraging workforce resilience and adaptability will help addressing the changing nature of labour market needs caused by the irruption of AI.

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DISCLAIMER

The section on policy implications was inspired by a chat with GPT@JRC. The opinions expressed in this policy brief are those of the authors and cannot be attributed to the European Commission.

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