GenAI@Work

Is generative AI the silver bullet for the tight labour market in the Netherlands?

pwc

www.pwc.nl

Glossary

AI: Artificial Intelligence (AI) refers to the simulation of human intelligence in machines that can perform tasks typically requiring human cognitive abilities, such as learning from data, reasoning, problem-solving, perception, language understanding and decision-making. AI systems use algorithms and computational power to analyse vast datasets, recognize patterns, make predictions, and adapt to changing circumstances.

Generative AI: It is a subset of AI that generates text, code, images, video and other content ('outputs') from data provided to it or retrieved from the internet ('inputs') in response to user prompts.[1] It can create new and original content, enabling machines to autonomously produce content that is often indistinguishable from human-created work.

Large Language Models (LLMs): LLMs refer to the development and utilisation of sophisticated artificial intelligence models, like GPT-4, that are trained on massive datasets using deep learning techniques. Such models are capable of various natural language processing tasks, including text generation, translation, summarization, and answering questions.

AI exposure: The exposure scores indicate how close, in terms of abilities required for specific tasks, different occupations are to AI capabilities.

'Artificial Intelligence (AI) has been having an impact for years. It is everywhere around us. Social media and streaming entertainment are such compelling experiences because predictive analytics (a form of AI) are so incredibly good at anticipating what we will like. From the search bar that completes your query about a product you want to buy to the distribution centre that handles your order and the optimization of your delivery, in so many seemingly quotidian yet revolutionary ways, AI in all its forms – machine learning, "deep" learning, text processing, speech recognition, image recognition, robotics, and real-time control – has transformed our lives. Through it all, we continue to enjoy its benefits while relying on specialists to bring them to us. For most of us, thinking about the uses, risks, implications, and imperatives of AI has been somebody else's job. That's not true anymore. The reason is language.'

PwC's Leaders Guide to Generative AI[2]

Our main conclusions

What did we find?

- We focused on language modeling generative AI (similar to ChatGPT, for example).
- We found that 44% of jobs in the Netherlands are either highly or very highly exposed to language modeling AI.
  - In some industries such as *financial institutions* and *education*, high or very high exposure applies to more than 75% of jobs.
  - In other industries, mainly those whose primary occupations involve more physical work, such as *accommodation and food serving*, exposure to language modeling AI is low.
- The occupations and industries that are highly exposed to AI tend to be those with a high probability of labour shortages.
- We found a very strong correlation between language modeling AI exposure and the technology adoption index.
  - Industries such as *information and communication* and *specialized business services* are not only very highly exposed to AI but also seem likely to adopt it.
  - This implies that language modeling AI can raise productivity in those industries and help to deal with labour shortages.

How did we do it?

- First, we created exposure scores to indicate how close, in terms of abilities required for specific tasks, different occupations are to the language modeling capabilities of AI.
  - We based our assessment on a recent study that analysed the exposure of different occupations to language modeling AI in the United States.[3]
    - This took into account the tasks that make up each occupation and the required abilities to perform them.
    - Those tasks are matched with the capabilities of language modeling AI.
    - We cannot directly tell whether a given occupation's AI exposure will lead to automation or augmentation.
  - We adjusted these occupations to the occupational classification used in the Netherlands, estimating the exposure to 113 occupation groups.
- Second, we incorporated specific labour market data.
  - We combined the impact of language modeling AI with expected labour market tightness indicators for those occupation groups.[4]
    - We are the first to consider this for the Netherlands.
  - We assessed the potential of AI to change the labour market for certain occupations and industries.
- Third, we constructed a technology adoption index and ranked the industries according to it.
  - The index is based on four factors retrieved from the academic literature.
  - This allowed us to assess the likelihood that a given industry will adopt AI rather than just assess how exposed it is.
    - How AI will ultimately affect the given occupations depends on the extent to which industries accept and adopt AI.
  - Finally, we studied the relationship between technology adoption, AI exposure and labour market tightness.
- We ended our analysis by looking at the broader implications of the results for society, governments and companies.

Why is language modeling AI expected to have a large impact on the labour market?

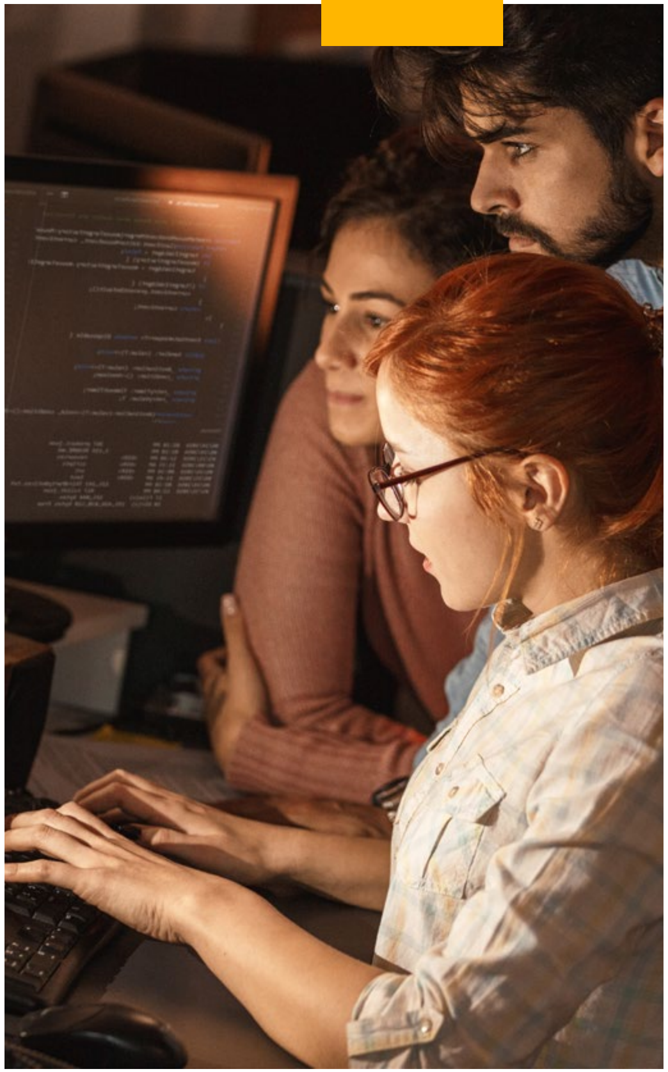
AI is a general-purpose technology. Such technologies provide a foundation for various applications and drive productivity improvements. The innovations fueled by them can lead to unintended positive changes in unrelated fields. Examples of general-purpose technologies in history include the steam engine, electricity, semiconductors and the internet. Crucially, they have the capacity to create long-lasting and sustainable changes in the economy and society.[5]

In addition, an important difference between AI and previous technologies is that **the impact of language modeling AI will be felt mainly by highly skilled workers in the service sector**. People in those jobs comprise the largest share of workers in modern economies: 84% of employees in the Netherlands, for example, work in commercial and public services.[6] So far, this group of workers has not been negatively impacted by technological advancements in terms of wages or employment.[7] However, recent developments in AI share similar capabilities to perform tasks found in non-routine and cognitive work that involve prediction after processing large amounts of complex input data, detecting patterns, making judgments, and optimising.[8]

To fully capture the current potential impact of language modeling AI on the labour market, we have to consider **labour shortages**. Labour shortages in the Netherlands have consistently been at very high levels and are expected to persist, mainly because of the demographic outlook.[9] To maintain economic growth and the standard of living, the Dutch economy will need to produce more with fewer human resources.

Accordingly, companies are incentivised to adopt technologies that can automate tasks, streamline processes and increase overall efficiency. And many are on their way to do so. **Ninety-eight per cent of companies** appear to think that **AI can help** with labour market challenges.[10] Automation and technology can help achieve higher levels of output with fewer human resources[11], leading to lower costs and higher revenue.[12] AI, especially language modeling AI, is expected to be at the core of this transformation.

Could language modeling AI be the silver bullet to reduce the pressure on the labour market?



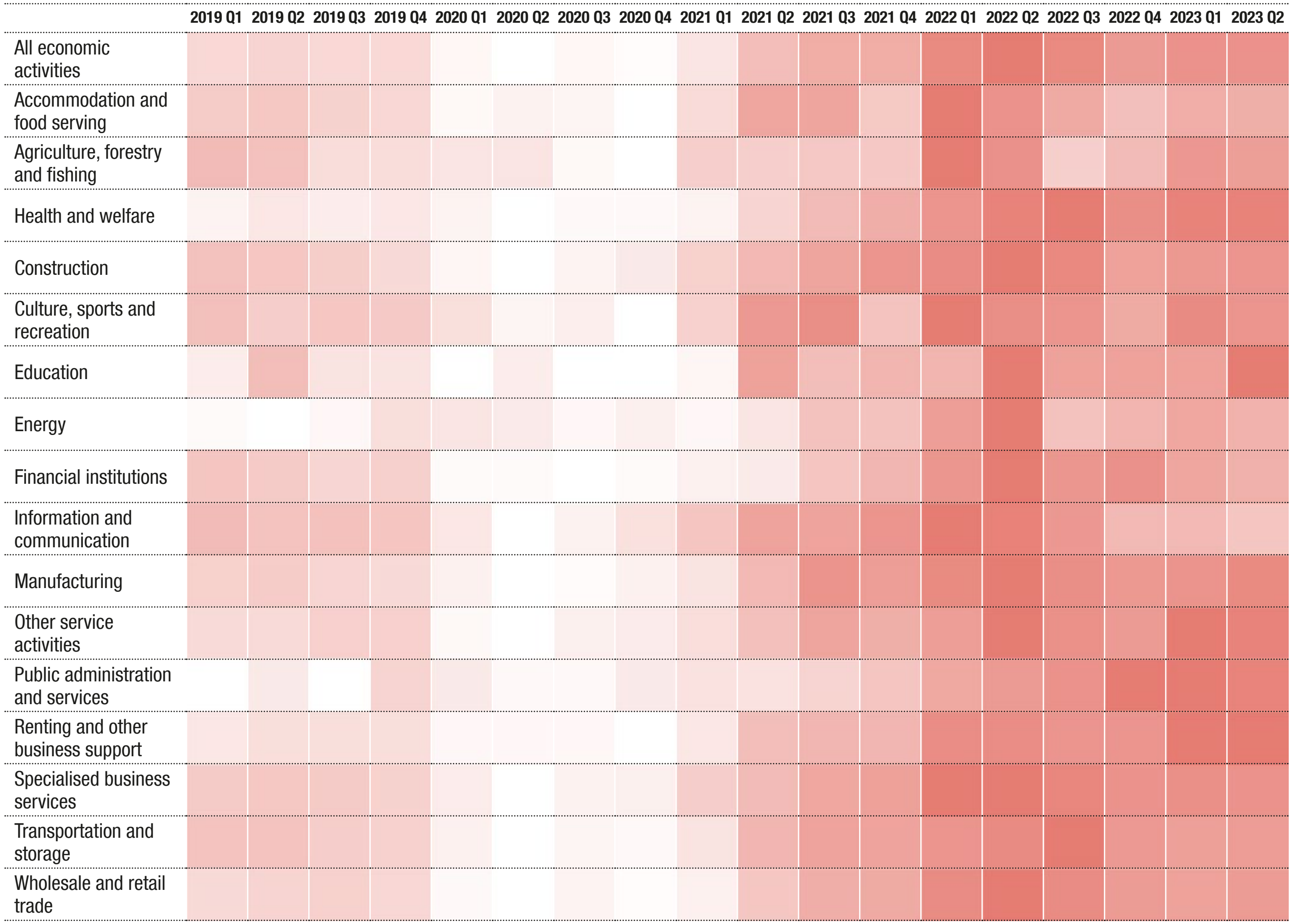
The future of the Dutch economy has structural challenges

Labour shortages are widespread in the economy

As of October 2021, there have been more unfilled vacancies than unemployed people, which is a phenomenon that has not occurred in the Netherlands in over 50 years.[13] The job vacancy rate in the Netherlands was the highest among EU countries in the first quarter of 2023.[14] Since the Covid-19 pandemic, this phenomenon has been widespread in all industries (Figure 1).

On one hand, this is in large part due to the structural features of the Dutch economy as the Netherlands has a large number of part-time workers. A previous report from PwC's Chief Economist Office showed that the Netherlands average working hours lag behind the EU's average.[15]

Figure 1 In all sectors vacancy rates are higher than before the Covid-19 pandemic



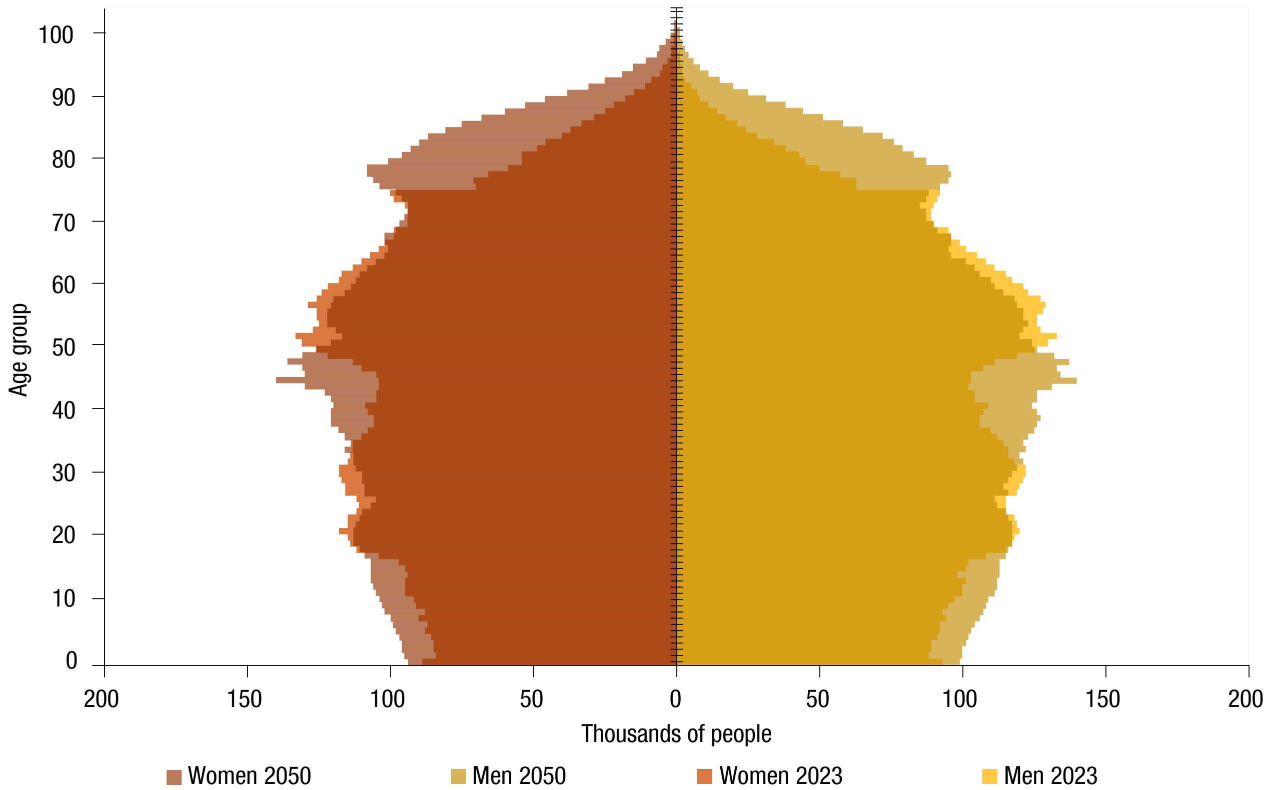
Source: CBS

Labour shortages are mainly driven by the demographic situation

On the other hand, a big part of the problem lies in the demographic trends of Dutch society. The number of elderly and inactive people in the Netherlands is increasing, while the increase in the working-age population is lagging behind (Figure 2).

In addition to the pressure on the labour market, the ageing population challenges public finances and the provision of basic services and public goods. Without productivity improvements, government expenditure, such as on healthcare, is expected to increase at a faster pace than the tax base.

Figure 2 Population ageing is expected to severely change the composition of the Dutch society



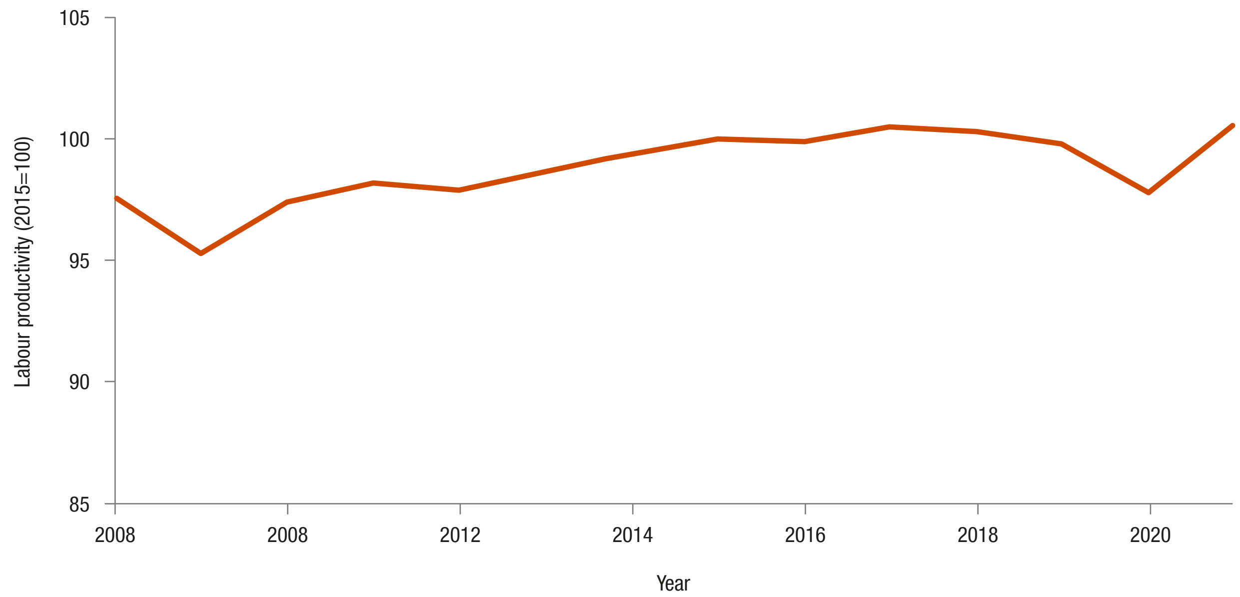
Source: CBS

Productivity has been stagnating

The level of productivity is the most important factor determining the standard of living.[16] To maintain its income growth and standard of living, the Netherlands will need to produce more with fewer workers. In other words, productivity needs to increase.

This is a challenge for the economy, especially if we consider that productivity has almost stagnated since 2015 and increased only marginally since the global financial crisis (Figure 3). Innovation and technology will play a key role if productivity rises in the coming years. Could AI be the technology to boost productivity and unlock future economic growth?

Figure 3 Labour productivity has barely increased since 2015



Source: CBS

Dutch labour market exposure to AI

In the Netherlands, 44% of jobs are highly or very highly exposed to language modeling AI

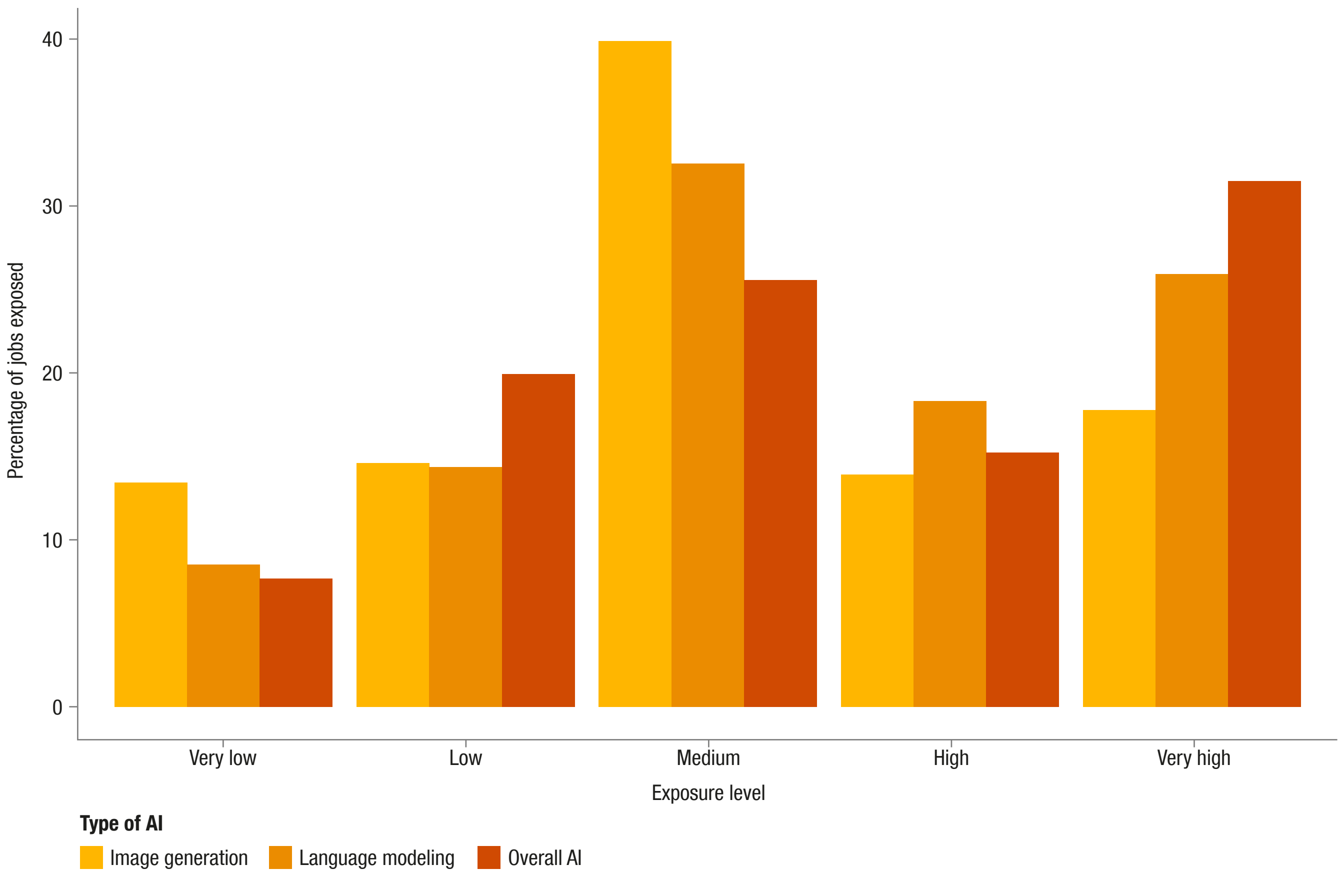
To evaluate the potential of AI to deal with labour shortages in the Netherlands, we combine an analysis of occupational exposure to different types of AI[17] with data about the Dutch labour market.[18]

Furthermore, we want to know not only what the exposure of an occupation is to AI but also how many people work in this occupation in the Netherlands and if this occupation is facing labour market constraints.[19]

- The exposure scores indicate how close, in terms of abilities required for specific tasks, different occupations are to AI capabilities.[20]
- A typical occupation consists of 20 to 30 distinct tasks, some of which are more similar to AI capabilities than others.[21] Tasks susceptible to the impact of AI tend to have objectives that can be clearly specified and are standardised.[22]
- We then count how many occupations out of the total labour force in the Netherlands have different AI exposure levels.

We find that the potential for AI in the Netherlands is immense: **44% of jobs are highly or very highly exposed to language modeling AI (Figure 4)**. Our results might change, potentially showing a larger share of jobs exposed, if considering the impact of language modeling AI in addition to other forms of AI, complementary software or robotics.[23, 24]

Figure 4 Percentage of total jobs exposed to AI in the Netherlands



Source: PwC analysis based on data from Felten et al. (2023) and Bakens et al. (2021)

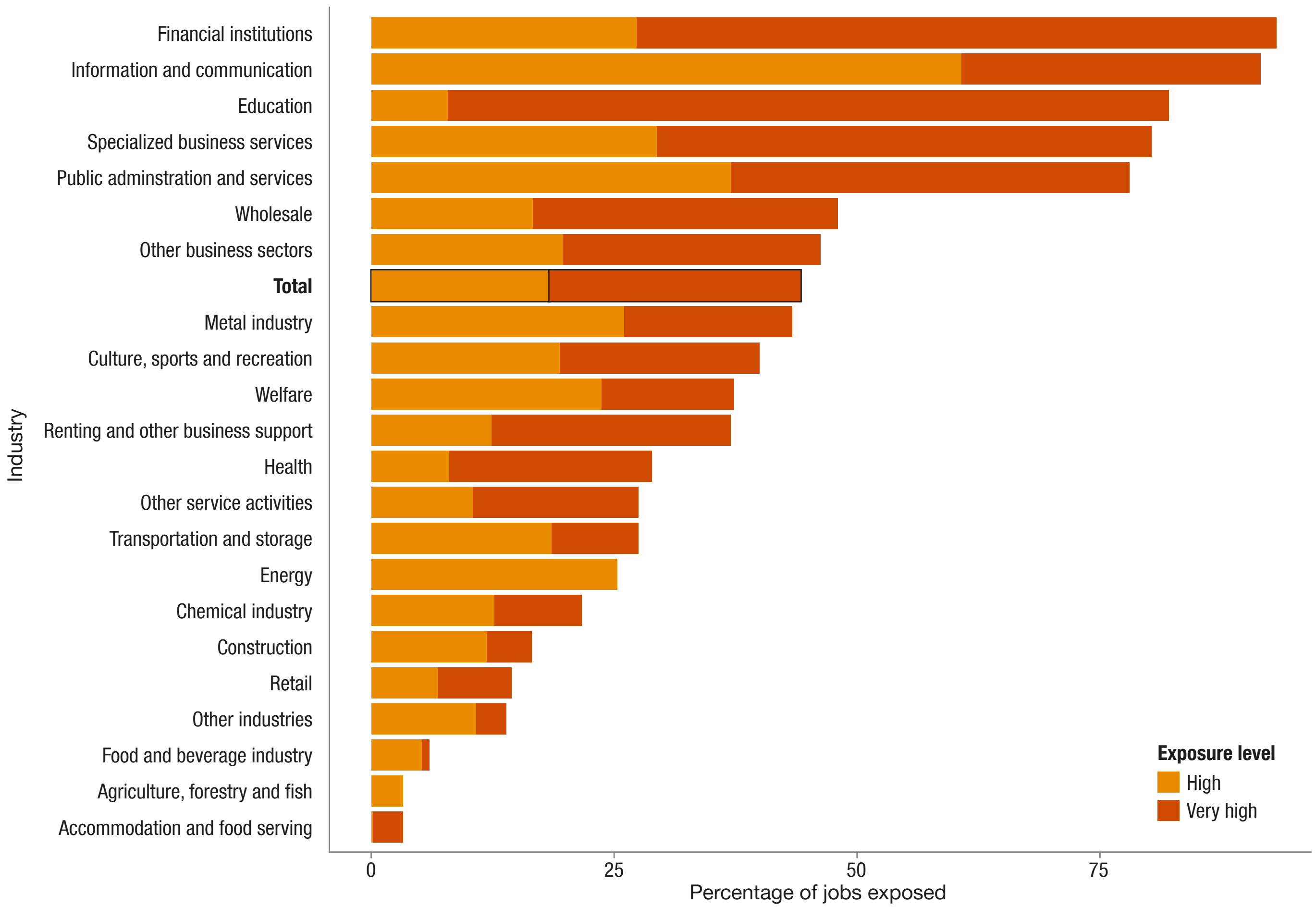
However, there is substantial variation in exposure to AI between industries

- Here we focus on language modeling AI, but our results are also available for other types of AI.
- In *specialised business services*, *public administration*, *information and communication*, *education* and *financial institutions* more than 75% of jobs are highly exposed to language modeling AI.
- On the other hand, less than a quarter of jobs are highly exposed in *retail*, *agriculture*, *forestry and fishing*, *construction* and in *manufacturing industries*. This is a clear reversal from previous technology waves, which had a larger impact on industries with a higher proportion of blue-collar jobs.[25]

Are the occupations with high AI exposure the same ones where we expect labour shortages?

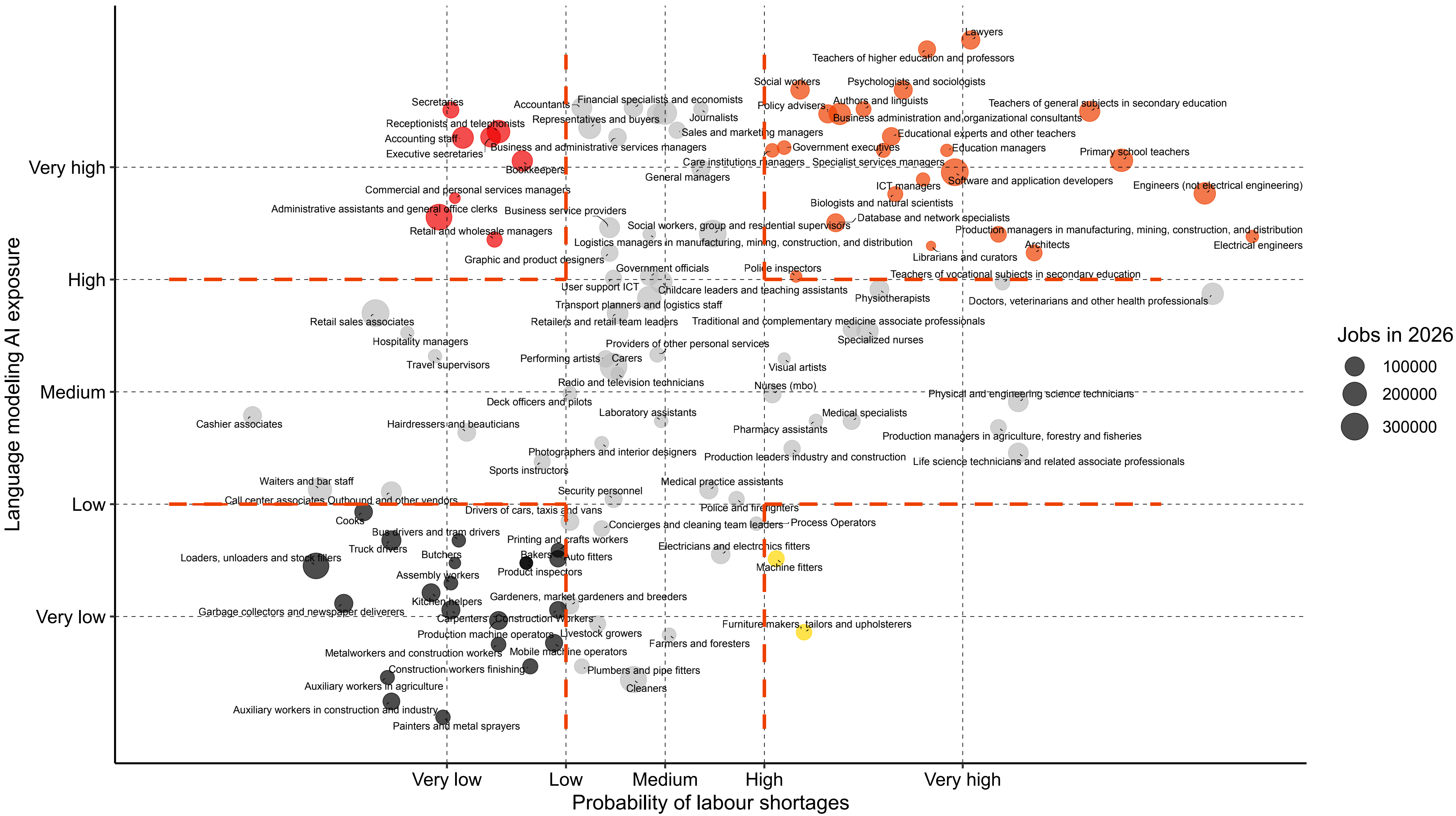
Next, we connect exposure to language modeling AI to labour market constraints.[26] Occupations with a high probability of labour shortages tend to have high language modeling AI exposure, indicating that such AI could make workers in those occupations more productive and help with expected labour shortages.

Figure 5 Percentage of highly or very highly exposed jobs to language modeling AI in the Netherlands by industry



Source: PwC analysis based on data from Felten et al. (2023) and Bakens et al. (2021)

Figure 6 The occupations with high language modeling AI exposure are the same ones where we expect



Souce: PwC analysis based on data from Felten et al. (2023) and Bakens et al. (2021)

Starting with occupations in black in Figure 6[27], there are occupations with low language modeling AI exposure, such as waiters, loaders or construction workers, that also have a low probability of labour shortages. We do not expect much impact on those occupations from this type of AI.

Following that, the bottom right corner is relatively empty. This implies that there are very few, if any, occupations with high expected labour shortages and low potential for AI to tackle those.[28]

In the upper half of the graph, occupations are more evenly distributed in terms of the probability of labour shortages. In addition, we see that those are occupations mainly in the services sector that tend to have high exposure to language modeling AI.

On the top right in orange are occupations such as engineers and teachers. They have very high expected labour shortages and very high exposure to AI. This implies that AI has the potential to play a large role in increasing the productivity of workers in those occupations.

In the top left corner coloured in red are occupations such as bookkeepers and administrative assistants. Those occupations are highly exposed to AI, but expected labour shortages are not that high. There might be a risk that some of these jobs end up either partially or fully automated as AI takes on some tasks and reduces the number of employed people required, leading people to relocate to other tasks or occupations.[29] Probably these occupations will not disappear completely, but employees will face the most pressure to adjust their skill set to the new composition of tasks that will be required to remain competitive. The commonly used phrase 'AI will not replace humans, but humans with AI will replace humans without AI' applies here.[30]

These results can be partly explained by the nature of this type of AI, such as LLMs. These models are trained on massive amounts of data. That is similar to a doctor or a lawyer who studies to become a specialist in a very narrow field of medicine or law and diagnoses rare diseases or takes on cases based on experience and technical knowledge. This type of AI is reducing the cost of specific cognitive expertise.[31] However, doctors and lawyers also do different tasks in their work, of which applying their narrow expertise is just one of them. For example, tasks that require more interpersonal contact would be much less likely impacted.[32]

At the same time, the probability of labour shortages shown here is based on the predicted supply of workers. This is usually more constrained where significant amounts of training are required, limiting the entrance of new workers into the labour market. That would mean both AI exposure and predicted labour shortages are positively correlated to education and training.

Box 1: How could financial analysts be affected by language modeling AI?

Financial firms have been using AI for many years.[33] By studying the current developments at the intersection of finance and AI, we can gather insights into the changing role of a financial analyst.

Which tasks do financial analysts perform now?
Financial analysts process large amounts of data and information to advise clients on investment decisions, usually within their own firm or in another company.

These are the main tasks that they perform:
- Gathering large amounts of high-quality financial data and information from different databases.
- Analysing the retrieved data using software.
- Modeling and forecasting a company's financial performance based on the gathered data, a set of assumptions and market sentiment.
- Interpreting the analysis output. For example, assessing whether the client should invest in the stock of the company whose performance was forecasted.
- Communicating these results to the client, usually in the form of a slide deck or a report that is presented in a meeting.

Which tasks could be affected by language modelling AI?
- **Data gathering and research:** given that the current versions of language modelling AI can organise and summarise large amounts of information rapidly, it can improve the data gathering process. There are already examples of this on the market, such as BloombergGPT, an AI launched by Bloomberg earlier this year that has made it easier to use the Bloomberg Terminal. Rather than writing queries in Bloomberg Query Language, which can be unintuitive, financial analysts can simply write questions in regular English, thereby making data collection more efficient.[34]
- **Financial analysis:** similarly, AI could speed up the financial analysis process itself by quickly breaking down financial statements and market sentiment to answer questions such as 'how is company 'A' doing relative to its competitors?'.[35]
- **Real-time trading:** quantitative financial analysis, which uses AI to process enormous amounts of data to then automatically profit off market inefficiencies, is becoming increasingly popular.[36, 37]
- **Creating reports and presentations:** generative AI could also help produce reports and slide decks faster, a task that is deemed time-consuming by financial analysts.

How could this affect jobs in the finance industry?
Some tasks, such as data collection, fundamental analysis and reporting, can be at least partially automated. However, not all roles will become AI-driven.

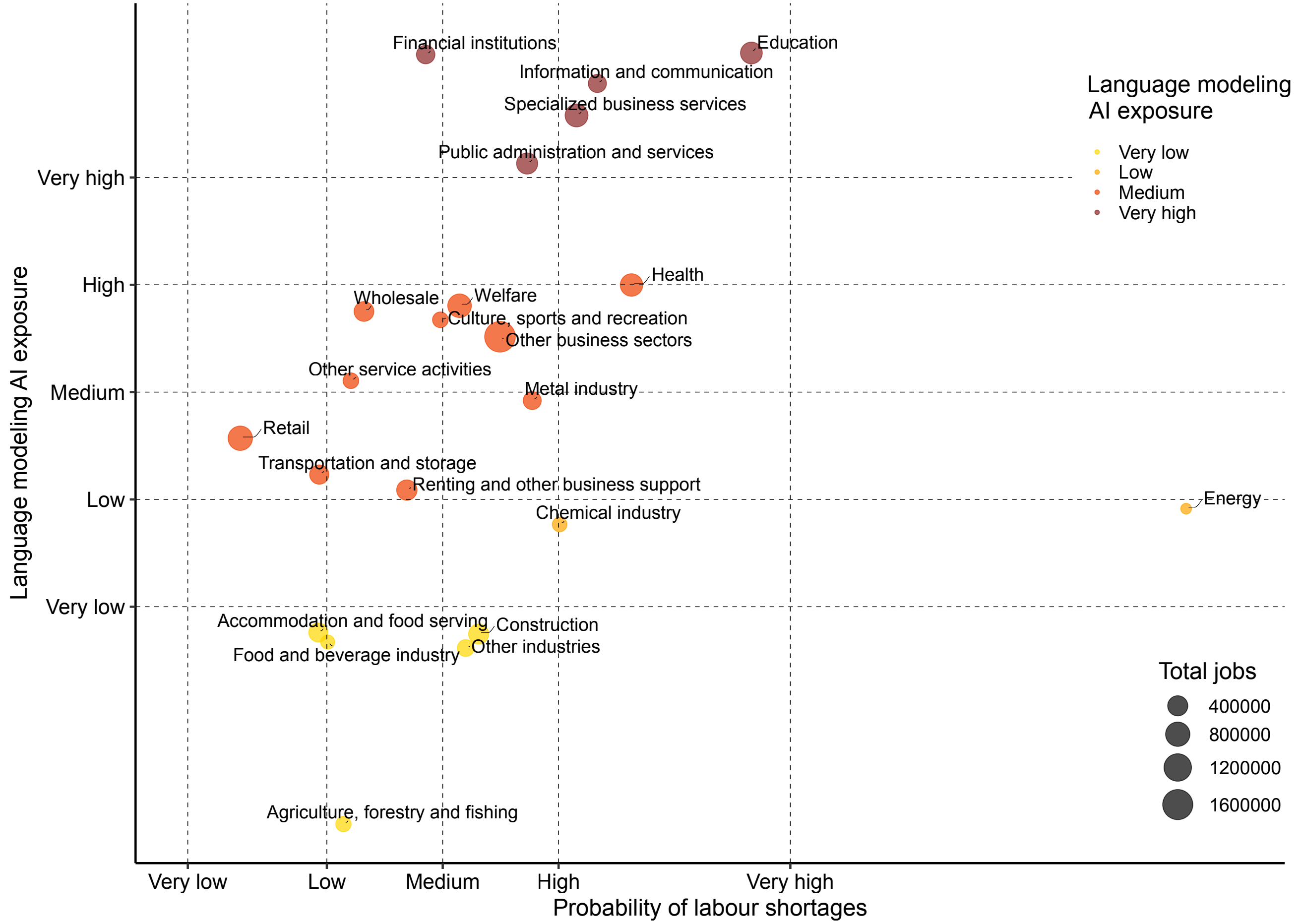
Output interpretation, communication and stakeholder management will likely remain human tasks. As Harvard University's Professor of Finance Mihir Desai points out, 'it appears that the client side of finance retains a preference for humans',[38] indicating that the communication between financial institutions and their customers might still be managed by people. Still, this will leave a large pool of highly skilled professionals with more time.

Accordingly, it could be that employers train current employees on digital skills that, in combination with their financial expertise, could help augment returns on human capital. Similarly, the financial industry's demand for quantitative skills in the labour market is likely to expand. The effect is already becoming clear, as seen by the inflow of people with STEM backgrounds into financial institutions.[39]

Moving from occupation to industry language modeling AI exposure

We reproduce the same analysis for all industries by incorporating data that captures how many different types of occupations exist in each industry. We see that of the five industries with the highest labour shortage probability, namely *energy*, *health*, *education*, *specialised business services*, and *information and communication*, the latter three also have very high language modeling AI exposure. This implies that language modeling AI has the potential to reduce labour shortages in those industries.

Figure 7 Many service industries have high language modeling AI exposure and high expected labour shortages



Source: PwC analysis based on data from Felten et al. (2023) and Bakens et al. (2021)

Box 2: Why is Energy an outlier among all industries in our analysis?

Figure 7 shows that the *energy* industry is a clear outlier: it has a very high probability of labour shortages but a low exposure to AI language modeling. Why is this the case?

- Most jobs in the *energy* industry, such as installing electric grid systems, demand manual labour skills, which by their nature cannot be performed by AI and require human involvement. Hence, almost half of the jobs in the *energy* industry have low or very low exposure to language modeling AI.
- However, the *energy* industry has a high probability of labour shortages because these occupations require technical skills that may not be readily available on the market.[40]

On the other hand, *financial institutions* have a very low probability of a labour shortage and a high exposure to AI.

- Most of the current tasks of financial analysts could be at least partially automated (see Box 1). This is because they revolve around gathering, categorising and analysing large amounts of (financial) data, something that AI can do really well. In addition, generative AI could develop the ability to generate the graphs and visuals needed to present analyses to clients.
- Yet, Economics and Business Administration remains the second most popular major in the Netherlands, which decreases the probability of labour shortages in *financial institutions*.[41] This is best seen through the famously competitive recruitment processes of *financial institutions*, as the large supply of human capital gives them the ability to be very selective.

Box 3: How could education be affected by language modeling AI?

Education is one of the most discussed industries in the context of AI. Experts have been monitoring the impact of AI in education for some time now, as seen in the UNESCO 2019 summit on the matter.[42] This prompts the question: what could education and educators look like in the age of AI? We look specifically at educators involved in teaching roles.

Which tasks do teachers perform now?

Teachers offer knowledge, guidance and mentorship during critical periods of students' lives. These are the main tasks that they perform:

- By setting learning goals and monitoring the learning process, teachers decide what concepts students should master and at what level of difficulty.
- Teachers design the curriculum and teaching materials by selecting the topics that will be taught in class, their respective teaching approaches and the academic literature.
- They communicate and reinforce knowledge with the help of teaching material and answer student questions throughout the course. These activities can take various forms, depending on the field of study, such as theoretical classes or hands-on laboratory work.
- Teachers assess the learning process of the students through formal evaluations, such as exams, presentations or research projects.
- Lastly, teachers also receive feedback from the students at the end of the education period to improve the teaching process.

Which tasks could be affected by language modeling AI?

Despite initial setbacks, many teachers are already developing ways to use language modeling AI and similar technologies in the classroom.[43]

- **Designing the curriculum and teaching materials:** generative AI can be used to assist in the design of the curriculum and the teaching materials, saving time for teachers. However, for now, human input would still be necessary to inform the AI about learning objectives and educational policy standards and detect possible mistakes.[44]
- **Grading:** additionally, generative AI could also help with grading. This could speed up a task that was previously very time-consuming for teachers, even outside of class hours.
- **Personal tutoring:** language modeling AI could also be used to help students with different learning styles.[45] For instance, it could output a variety of explanations of the same concept that tailor to the student's intuition, making the teaching process more efficient for both the teacher and the student.[46]
- **Learning evaluations:** surprisingly, AI could also help during learning evaluations. For instance, teachers could ask students to detect mistakes in AI output to assess their mastery of the subject.

How could this affect jobs in the education industry?

Since education is a fundamentally social process, the probability of AI completely substituting teachers is extremely low.[47] Even if curriculum design is entirely automated, there must be someone who can monitor, talk to, and, most importantly, guide students during these critical stages of life.

Nonetheless, it is crucial that teachers' training remains up-to-date with the latest technologies.[48] Policymakers must ensure that teachers (especially those who are less familiar with technology) know how to use language modeling AI and its detection software in the classroom. If this opportunity is worked out correctly, society could augment its return on investment in educators and enjoy a higher quality of human capital.

But is language modeling AI adoption actually going to happen? And where?

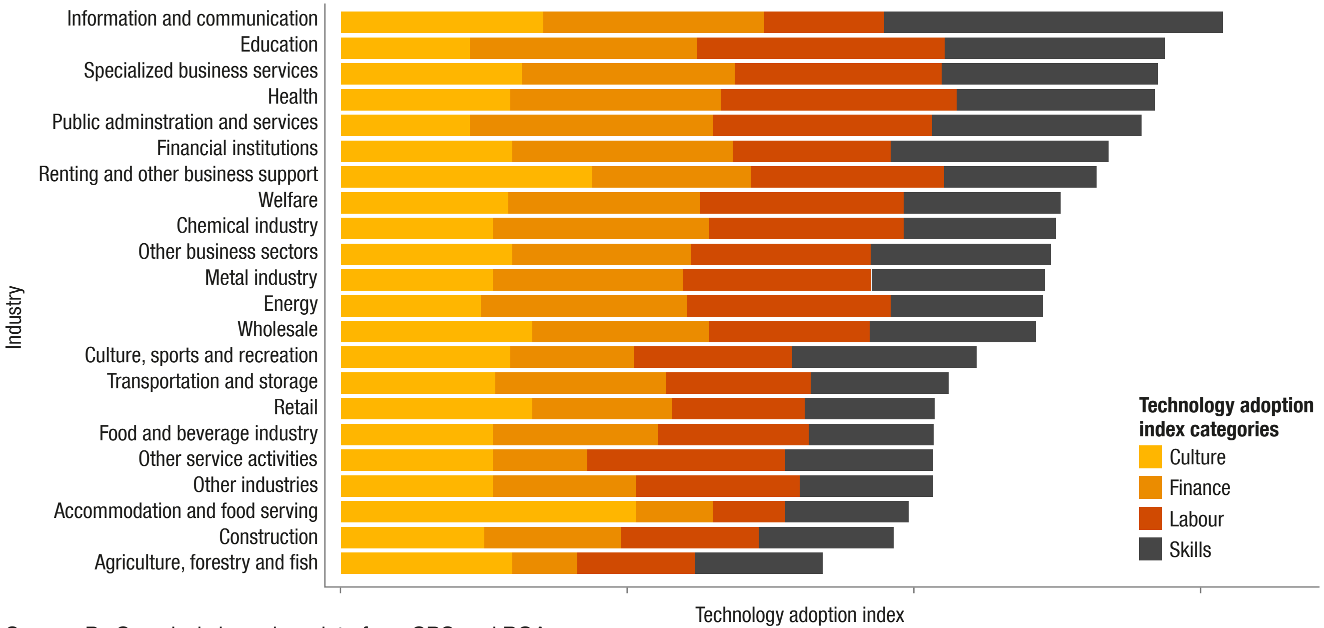
After identifying that the potential is there, we move to another question: will the potential be realised in the industries exposed to language modeling AI?

What are the factors behind technology adoption?

Acceptance and adoption of technology depend on the perception of its usefulness and ease of adoption.[49] A number of factors are behind these aspects on a firm and industry level, which we identify in four pillars:[50]

- **Culture:** In this category, we incorporate two metrics that capture how open industries are to new technologies: *the share of young companies in an industry* and *the share of companies with union relations.* Younger companies, which tend to be more innovative and less constrained by existing ways of working, tend to also have higher shares of AI use.[51] In addition, the higher the share of companies with union relations in an industry, the more bargaining and negotiation usually takes place before technology is adopted.[52] This can already be seen with the Screen Actors Guild strike in the United States.[53]
- **Finance:** Financial aspects play a critical role in the ease of adoption, especially if big investments are required. Previously, large[54] and more profitable companies were early adopters of technology.[55] Moreover, in the current age of AI, large companies have the advantage of conducting more research and training their own models with proprietary data instead of relying on generally trained tools.[56] We incorporate this aspect by looking at *the share of big firms* and *the average wage in an industry*.
- **Labour:** The need due to labour shortages affects the usefulness of technology implementation. Companies and sectors with more pronounced labour shortages can get a larger benefit from technology implementation to fill at least some of the required vacancies.[57] Hence, they have a greater motivation to adopt technology. To capture this aspect, we include *the average probability of labour shortages* and *vacancy rates in an industry*.
- **Skills:** Overall workforce skills and education level, especially in information and communications technology (ICT) fields, are important to acquire the skills to more easily use and implement novel

Figure 8 Industry ranking by the technology adoption index categories



Source: PwC analysis based on data from CBS and ROA.

technology. The prevalence of ICT professionals has been an indicator of technology adoption in the past.[58] In addition, more educated labour forces also tend to have better knowledge of the potential uses of technology.[59] To capture that, we look at *the share of ICT professionals* and *the share of occupations with higher education degrees*.

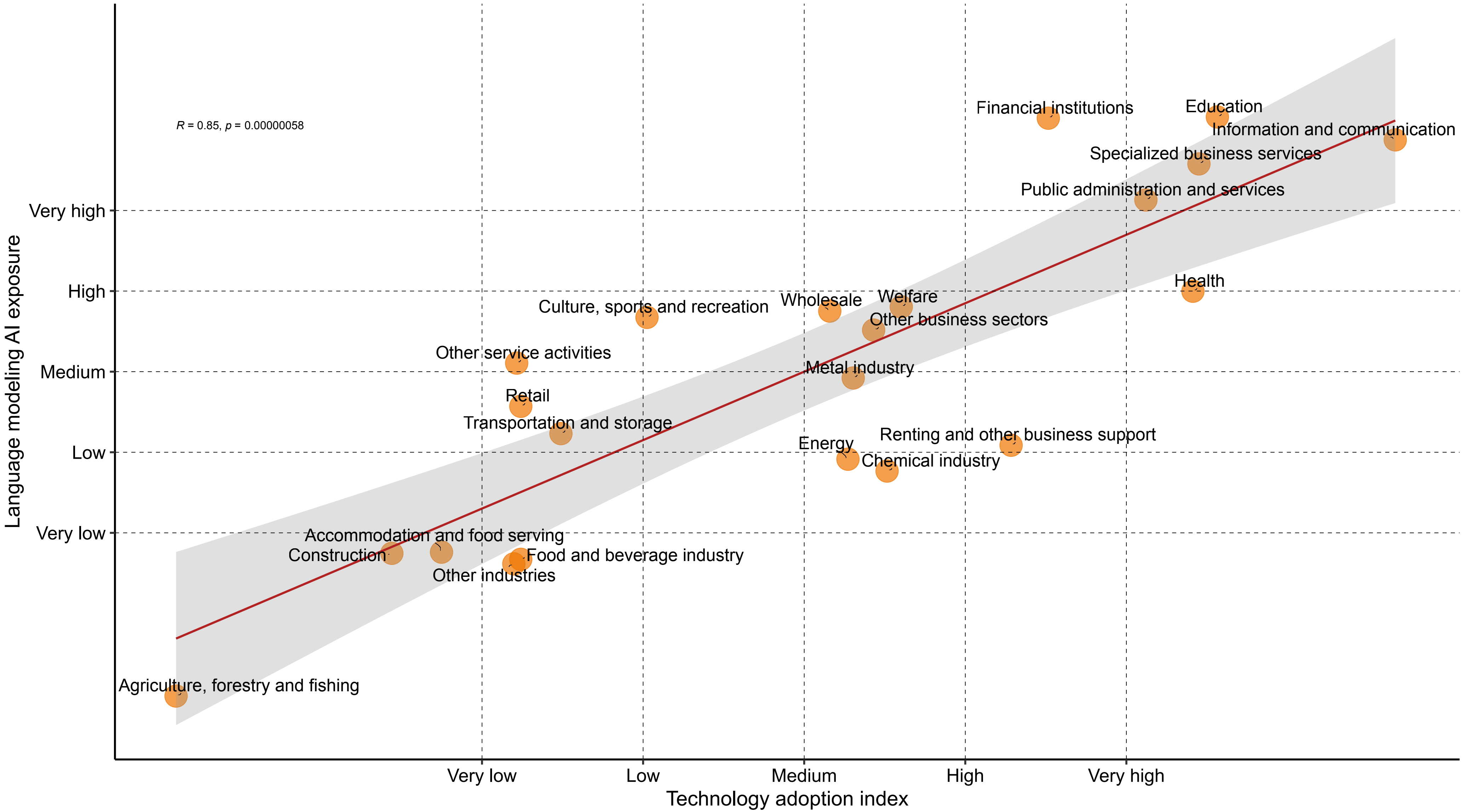
Industries highly exposed to language modeling AI also have the likely adoption conditions

Based on these four pillars, we construct a technology adoption index. Then we correlate and plot it with the industry language modeling AI exposure (Figure 9).

We find a strong and statistically significant correlation between our technology adoption index and language modeling AI exposure (we reach similar results for overall AI exposure, see Appendix B on page 30). This is encouraging, as it indicates that industries more exposed to language modeling AI also have the conditions to adopt the technology.[60]

Our results coincide with previous research on other forms of AI adoption in Europe and elsewhere, showing that industries more exposed to AI, such as *information and communication*, *specialised business services* and *financial institutions*, have also been the main adopters of AI and related technology so far.[61, 62]

Figure 9 Industries highly exposed to language modeling AI also have the likely adoption conditions



Source: PwC analysis based on data from Felten et al. (2023) and Bakens et al. (2021)

What should governments and society consider about the impact of AI on the labour market?

As AI technologies continue to advance and permeate various sectors of society, governments play critical roles in shaping their development, deployment, and impact. Here, we limit our reflections to labour market consequences.

Technology changes jobs but does not necessarily make them disappear

One of the largest sources of insecurity towards AI and technology in general lies in its potential to automate jobs, increasing unemployment. So far 54% of companies adopting AI have done so primarily for automation purposes.[63]

New technologies display two opposite effects on employment. On the one hand, substituting human labour in order to decrease production costs and increase productivity would lower employment. On the other hand, reduced production costs increase real incomes and demand. The latter effect fosters production and job creation.[64]

Until now, technological developments have mainly affected wages and wealth distribution, not how many jobs were available.[65] That does not mean jobs have not disappeared or largely changed in terms of tasks performed. The impact on task composition has been the main way technology has impacted occupations so far.[66]

In addition, new jobs have been created after major technological advancements, thanks to the complementarity between humans and technology. Sixty percent of employment in 2018 was in occupations that did not exist before 1940.[67]

Between 2011 and 2019, a period that coincides with the rise in deep learning applications, employment in jobs highly exposed to AI has actually increased in Europe.[68] There is also already evidence of a change in skill demands in companies more exposed to AI, but, at least until 2018, the effect of AI on employment demand or wage levels has been negligible.[69, 70] This, however, could change with recent and future advancements in AI.[71]

The economic equation is complicated

The number of ATMs in the US quadrupled between 1980 and 2010, but at the same time, the number of bank tellers increased by 10%. How is this possible? The rise of ATMs decreased the cost of running a bank branch, increasing the number of branches. So there were fewer bank tellers required to run a branch. But the increase in the number of branches more than compensated for that. The tasks performed by bank tellers changed as they became more involved in relationship management with clients instead of counting bank notes. That altered the nature of the job, which might not be appreciated by all bank tellers. To put this formally, workers might benefit more from technology if they provide tasks that are complemented by it. If they provide only tasks that are substituted, their labour market prospects will not be positive.[72]

But the complexity does not end here. If the tasks that relationship bankers supply can be easily performed by other workers, a flood of new workers might become relationship bankers, increasing the supply and mitigating any possible wage gains that would come from the complementarity between humans and technology.[73]

Finally, the elasticities of demand and the income elasticity of demand also have to be taken into account. If, for example, AI makes the work of lawyers more automated, reducing the need for labour, this could allow legal services to be offered at lower prices. It is likely that the demand for some types of lawyers will increase as a larger market can now afford certain legal services. However, for others, such as criminal lawyers, the demand should be less responsive to price changes. So, if, on one side, the reduction in prices would reduce the size of the legal business sector, on the other, the increase in demand might (at least partially) compensate for that. The effect on aggregate demand will depend not just on that but also on how clients who now have access to legal services at a lower price will spend their savings.

Innovations can impact income inequality

But looking only at how much human work could be replaced by AI misses a large part of the picture. Although past waves of technological innovation and automation did not lead to an increase in aggregate levels of unemployment, there has been a change in income distribution caused by job polarisation.[74]

Most of the benefits have been obtained by highly skilled workers, who have seen increasing incomes in the past decades. At the same time, workers in the lower and middle parts of the skill distribution had seen real wages decrease.[75]

As we discussed earlier, the tasks that language modeling AI can affect are different than in previous technological waves. Importantly, it can affect white-collar and high-wage occupations, what, in theory, could even reduce inequality.[76] However, in general, the distributional effects of technology depend more on which workers have tasks that get automated than on the fact of automation itself.[77]

It is also telling that the majority of the growth in inequality across workers so far has been due to increasing average wage differences between companies.[78] AI and similar innovations have the potential to further split companies into highly productive and less productive ones, making the earnings of workers employed in the latter suffer.

It is uncertain that AI will have a similar effect on the labour market as previous technologies

First of all, as the meteoric rise of LLMs showed, it is very difficult to anticipate where the future of AI will take us. Recently, a survey of around 30 economists showed that the majority believe that AI will not increase unemployment rates in high-income countries. However, the panellists expressed a great degree of uncertainty in their predictions, noting that 'we are still in the very early days of AI'.[79] A good heuristic to understand the potential impact of AI on specific occupations is to ask for whom AI is a substitute and for whom it is a complement.[80]

Preliminary evidence points out that, at least in terms of performance, AI could reduce inequality within firms by flattening their hierarchical structure.[81] Access to generative AI tools can increase productivity in customer service[82], professional writing[83] and software development roles[84], with the greatest impact coming from novice and low-skilled workers, who also seem more likely to adopt those tools.[85, 86]

However, although generative AI might indeed democratise access to certain white-collar jobs by reducing the costs of certain expertise[87], it might also be harmful for more junior employees in the long term. By prematurely relying on AI tools in their careers, junior employees might not learn the fundamental aspects of their jobs that come with dedicated effort and expertise.

What role do governments play in this labour market transformation?

In addition to regulation and ensuring an adequate social safety net, it is crucial that governments pay attention to AI developments and, if necessary, make changes to the tax system.[88, 89] Theoretically, if the productivity gains from AI are captured mainly by the owners of capital because the dominant effect is automation in relation to augmentation, our main problem would not be one of scarcity but one of distribution. In this case, there might be a strong case to increase the tax on capital gains and redistribute income.

AI increases the need for digital, analytical, and social skills.[90] Sixty per cent of workers will require training before 2027, but only half of them have access to adequate training opportunities today.[91] The good news is that only elementary digital skills and analytical thinking are sufficient to use and interact with AI applications.[92]

The responsibility rests with workers and companies to remain competitive and follow the latest technological developments. But if they fail to do so, governments can help provide the labour force with the education necessary to adapt. This could involve a combination of policy development, funding allocation and collaboration to ensure the workforce remains competitive and adaptable.

What should companies consider when thinking about AI and the workforce?

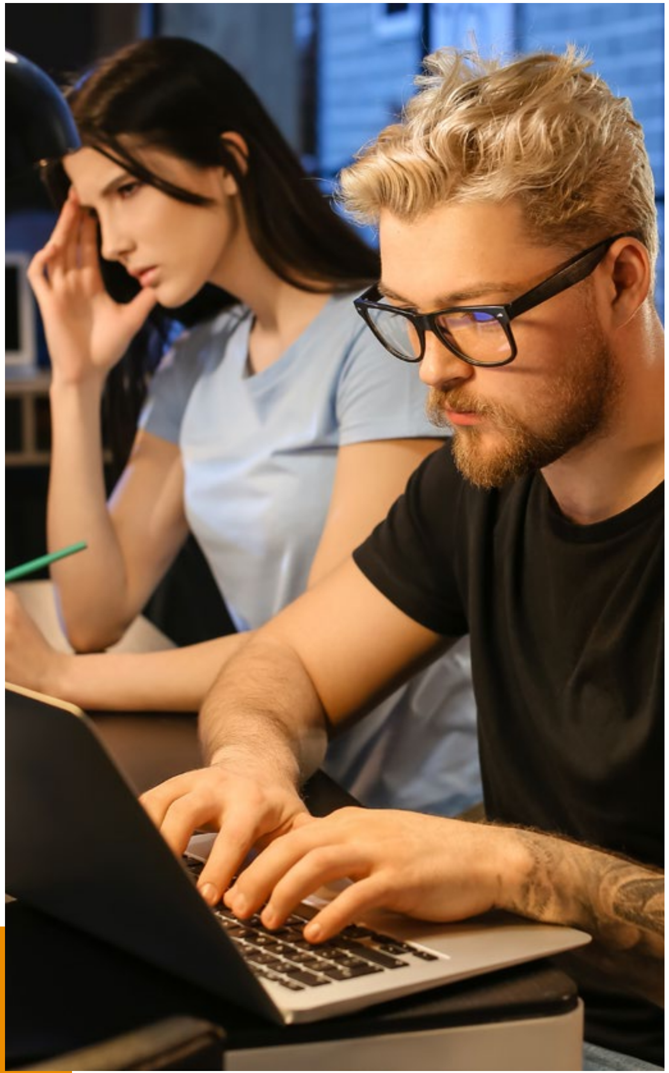
According to PwC's recent Hopes and Fears survey, the majority of workers have a positive view of the impact of AI on their jobs.[93] In addition, over 85% of organisations see the adoption of frontier technologies and broadening digital access as the most likely drivers of transformation in their organisation in the next few years.[94] Although there is a lot of potential and excitement, the diffusion of technological improvements is as important as innovation itself. It is possible that the effects of AI will not build up linearly but rather at different rates for different countries, industries, companies and employees.

Currently, few companies use generative AI tools at scale.[95] But there are big opportunities ahead, and it is the responsibility of companies and their leaders to harness the benefits of AI. At the center of that will be human and technology cooperation: the future is **human-led, tech-powered**. Companies that are able to leverage this collaboration will have the highest chance of success.

Companies must strategically position themselves to benefit from the disruption along the way. And this also includes making a **strategic evaluation** of the factors that might influence their AI adoption, including having the **skills required**, making the **needed investments** and **having employees onboard**.

Exposure to AI is not a management decision. It is unavoidable that business partners will start embedding generative AI in their processes and that employees will start experimenting with generative AI possibilities. This means that priority is not just about bringing this new technology and capability into the organisation, but also about **managing and directing what is already coming and preparing for what's next.**[96]

That is why it is important to **have an AI strategy that is clear, transparent** and communicated to employees about the available potential of AI and upskilling requirements. Generative AI has the potential to reinvent the way work is done in many organisations, but without the support and energy of all people, these efforts will fail to capture the benefits.[97] Realising the potential of AI might be challenging, but it will be well worth it.



Appendix A: Methodology

AI exposure scores

We use the AI exposure scores of Felten et al. (2023). This study attempted to determine the occupations most exposed to AI by linking ten AI applications (e.g., image generation, language modeling, abstract strategy games, real-time video games, etc.) to 52 human abilities (e.g., oral comprehension, oral expression, inductive reasoning, arm-hand steadiness, etc.).

An important caveat is that the term 'exposure' is used so as to be agnostic as to the effects of AI on the occupation, which could involve *substitution* or *augmentation* depending on various factors associated with the occupation itself.

ISCO to SOC occupation classification code crosswalk

Because the data in Felten et al. (2023)[98] is based on the United States, we had to perform a crosswalk from the Standard Occupation Classification (SOC) system to the International Standard Classification of Occupations (ISCO). This was necessary to link the AI exposure scores with Dutch labour market data. This crosswalking was done based on the method in Kouretsis and Bampouris (2022).[99] In addition, the 771 occupation groups[100] (SOC 4-digit) were aggregated to 113 (ISCO 3-digit) to match the labour market data.

The final result of this step is a data sheet with AI exposure scores for 113 occupations based on the ISCO 3-digit codes. The obtained AI exposure scores were standartised to have 0 as the mean across all occupations and 1 as the standard deviation. Hence, they show relative AI exposure between all occupations in the labour market. From there, we cannot tell exactly what share of each occupation group is exposed to AI, but we can understand which occupations in the labour market are most exposed. We classify each occupation's exposure scores from very low to very high as follows:

- Exposure scores less than -1 as 'very low'.
- Exposure scores between -1 and -0.5 standard deviations as 'low'.
- Exposure scores between -0.5 and 0.5 standard deviations as 'medium'.
- Exposure scores between 0.5 and 1 standard deviations as 'high'.
- Exposure scores above 1 standard deviation as 'very high'.

We apply the same classification for occupations and industries with their AI exposure scores and labour shortage probability.

Dutch labour market data

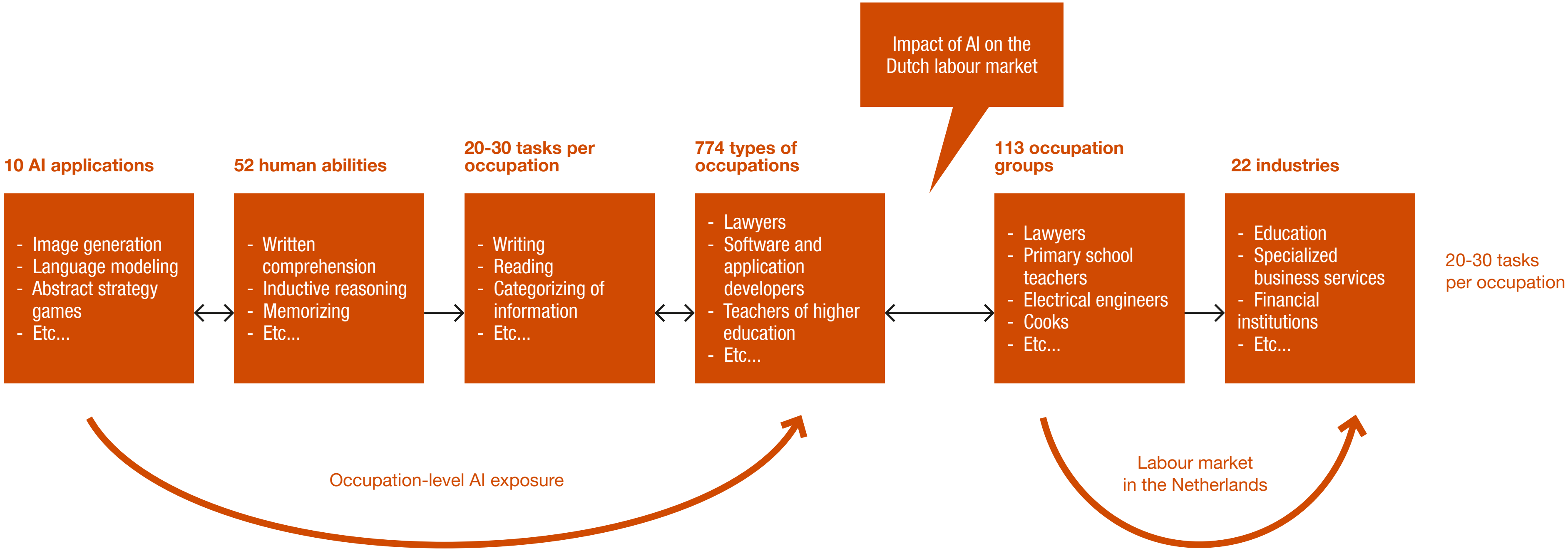
The labour market data used in this study comes from the Research Centre for Education and the Labour Market (ROA) of Maastricht University.[101] We use their industry classification. ROA uses an econometric model to forecast labour market data for the year 2026. For each occupation, the data includes the total number of employees in this occupation and how this occupation is distributed among industries.

To assess the probability of labour shortages, we use the Indicator for Future Staffing Bottlenecks by Occupation (*ITKB*). It reflects the expected labour market friction by occupation, giving the probability that this occupation will be able to match labour demand with supply. To obtain the probability of labour shortages in this occupation, we take 1-*ITKB*.

Merging the data

Next, the obtained generative AI exposure data and Dutch labour market data were merged based on the corresponding ISCO codes. There were minor discrepancies due to crosswalking in some occupations, and those were adjusted. Figure 10 summarises the methodology approach.

Figure 10 Summary of the methodology



Source: PwC analysis based on data from Felten et al. (2023) and Bakens et al. (2021)

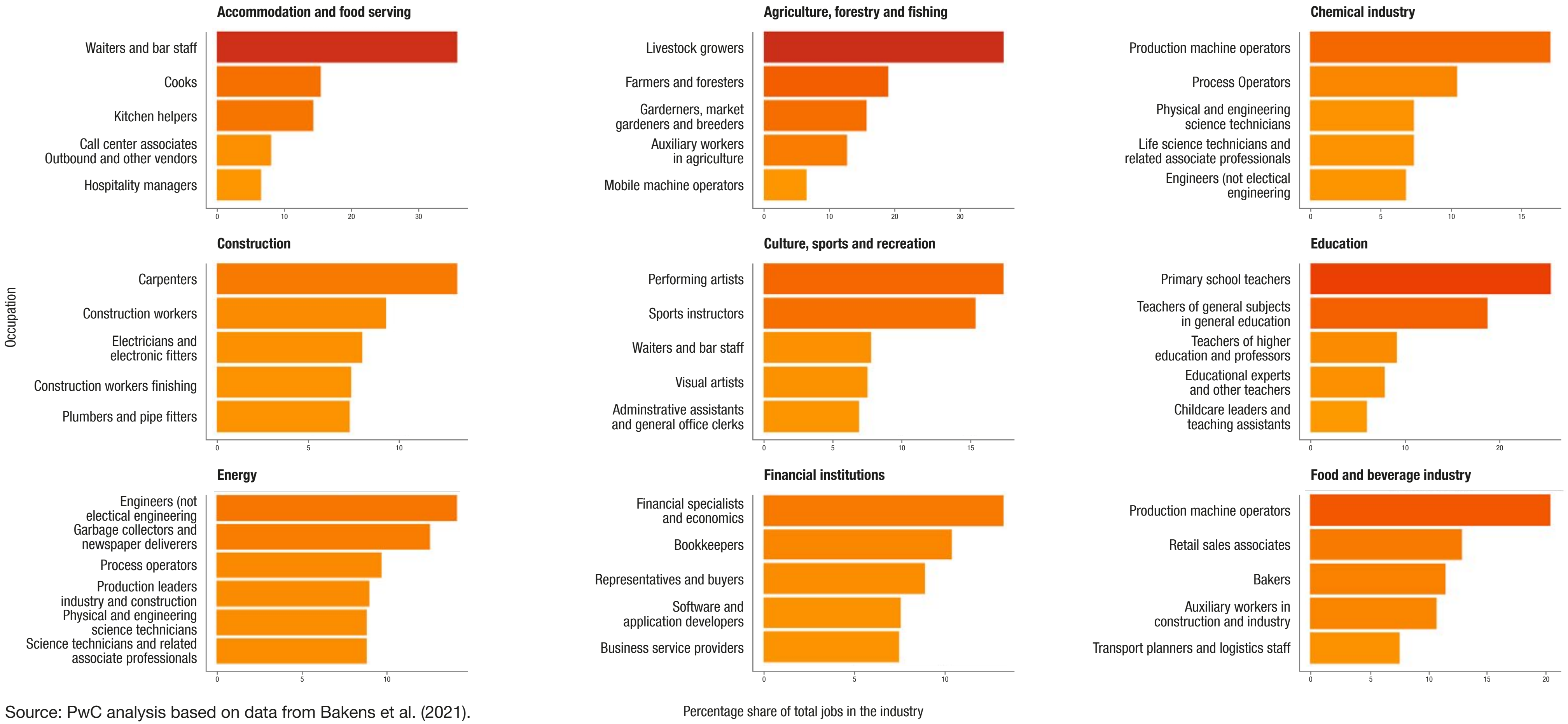
AI exposure analysis

Furthermore, to incorporate the occupational group exposure perspective we calculate the AI exposure scores as follows:

*Occupation AI exposure score * number of jobs* in this occupation in the Netherlands. We obtain occupation group AI exposure scores that we standardise to be able to classify them from ‘very low’ to ‘very high’. What we obtain is an economy-wide classification of occupation group exposure to language modeling AI. This is important as it not only looks at the technical AI exposure in terms of ability similarity but also at how prevalent this occupation is in the economy.

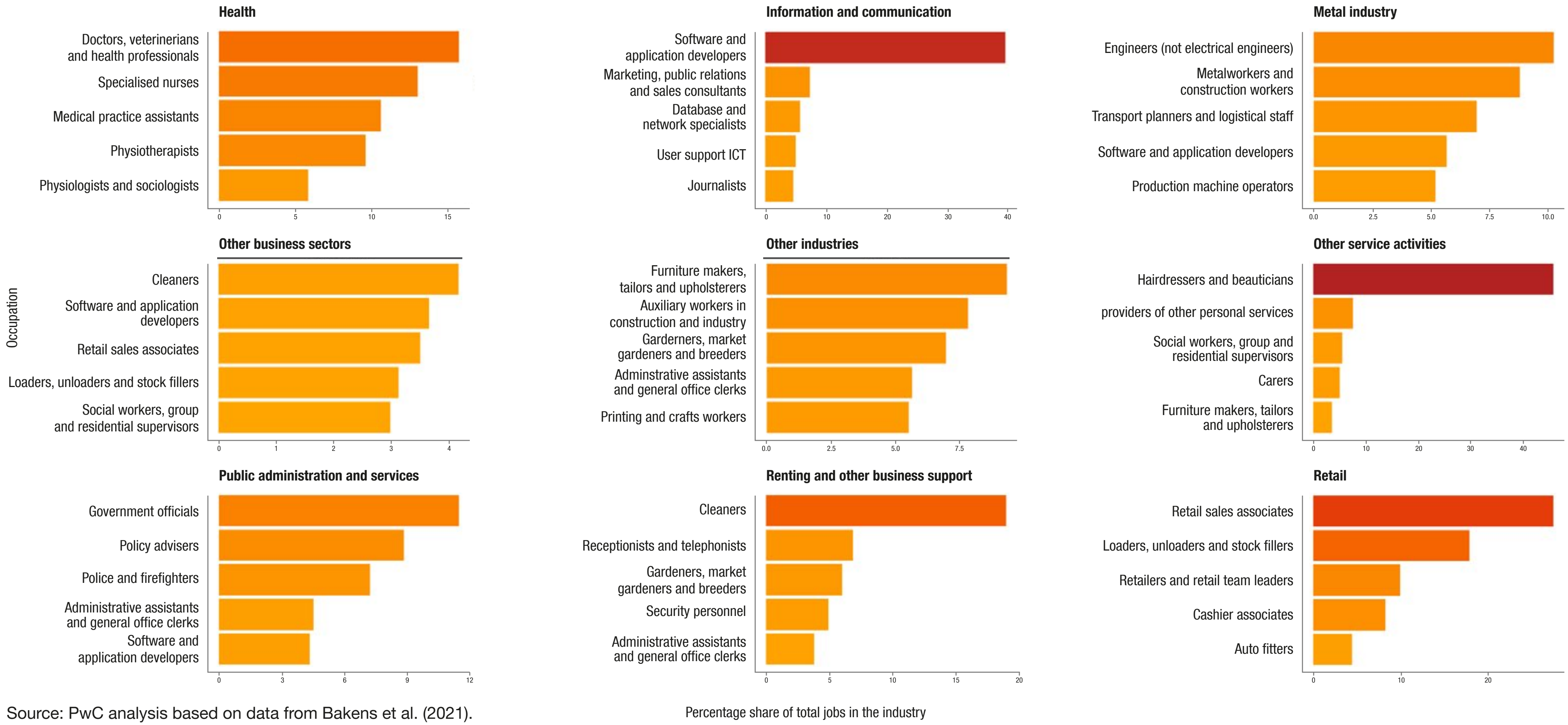
For industries, we do a similar analysis. We take the *occupation AI exposure score * number of jobs* in this industry, summing all relevant occupations to get the *total industry AI exposure score*.

Figure 11-1 Top five most relevant occupations in each industry



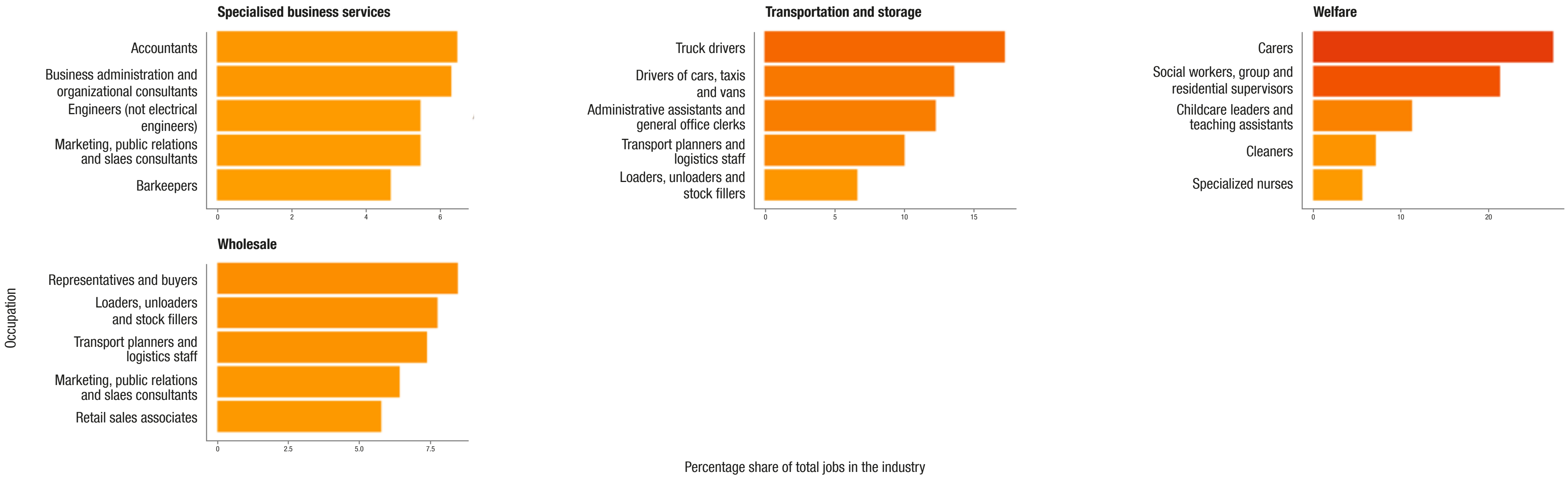
Source: PwC analysis based on data from Bakens et al. (2021).

Figure 11-2 Top five most relevant occupations in each industry



Source: PwC analysis based on data from Bakens et al. (2021).

Figure 11-3 Top five most relevant occupations in each industry



Source: PwC analysis based on data from Bakens et al. (2021).

Finally, we divide this score by the *total number of jobs* in this industry to obtain a *weighted industry AI exposure score*. Then we also standardise these scores to get exposure from 'very low' to 'very high' and calculate the share of jobs exposed in each category for all industries (Figure 12).

Figure 12 Percentage of total jobs exposed to AI in the Netherlands by industry

Source: PwC analysis based on data from Felten et al. (2023) and Bakens et al. (2021)

Incorporating technology adoption factors

We construct the technology adoption index in three steps:

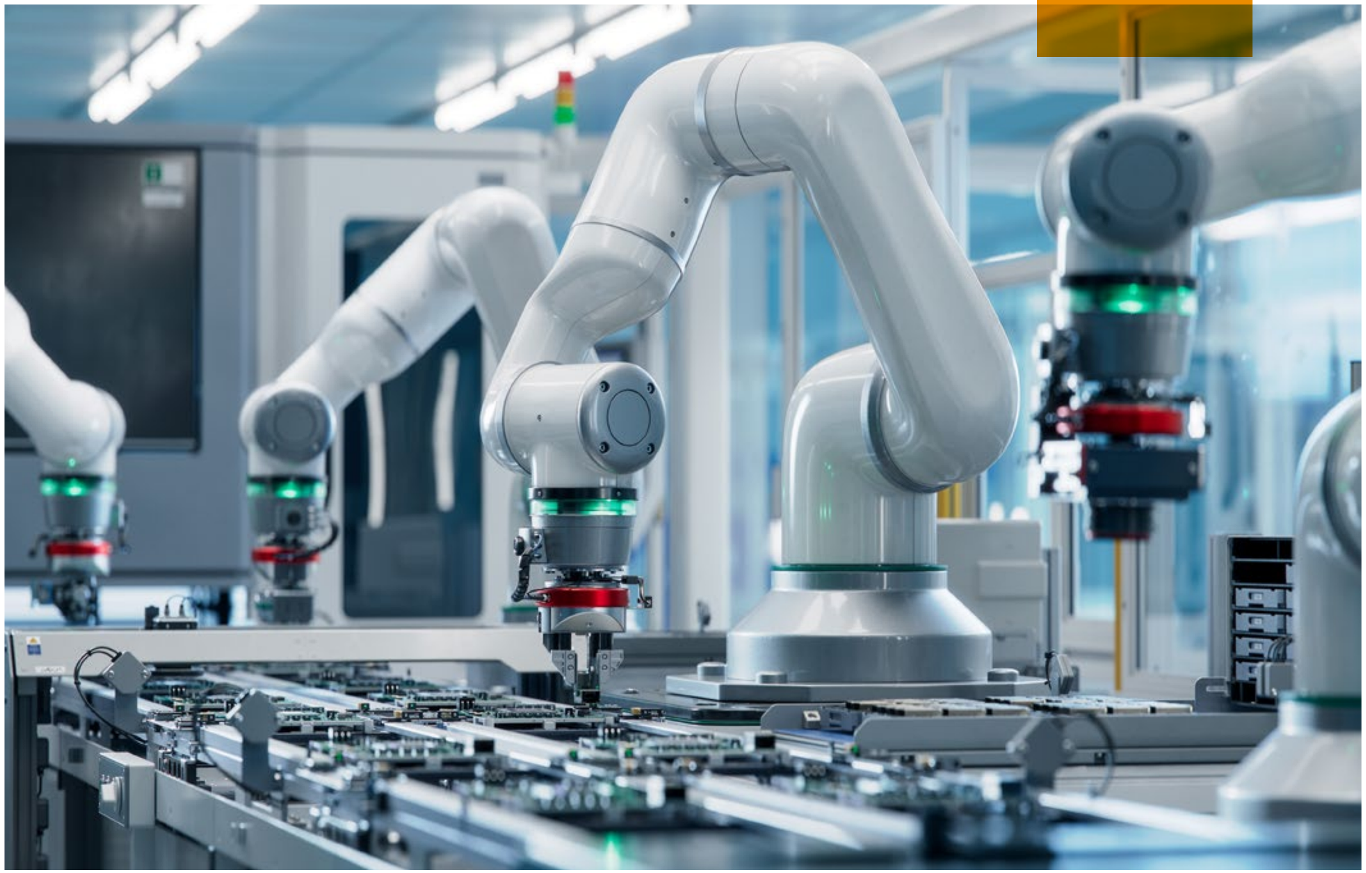
1. We aggregate data on eight different indicators, divided into four pillars:
   - **Culture:** *share of young companies* and *share of employees not unionised*, based on CBS data.
   - **Finance:** *share of companies with more than 50 employees* and *average wage*, based on ROA data.
   - **Labour:** *average probability of labour shortages*, constructed using the ITKB from ROA, and *vacancy rates*, CBS data.
   - **Skills:** *share of ICT professionals* and *share of occupations with higher education degrees* (bachelors level or higher), based on ROA data.

2. To create the individual pillar scores, we standardised the indicators and averaged the indicators inside each pillar, assigning equal weight to each indicator.

3. To construct the technology adoption index, we use a standardised average of the pillars.

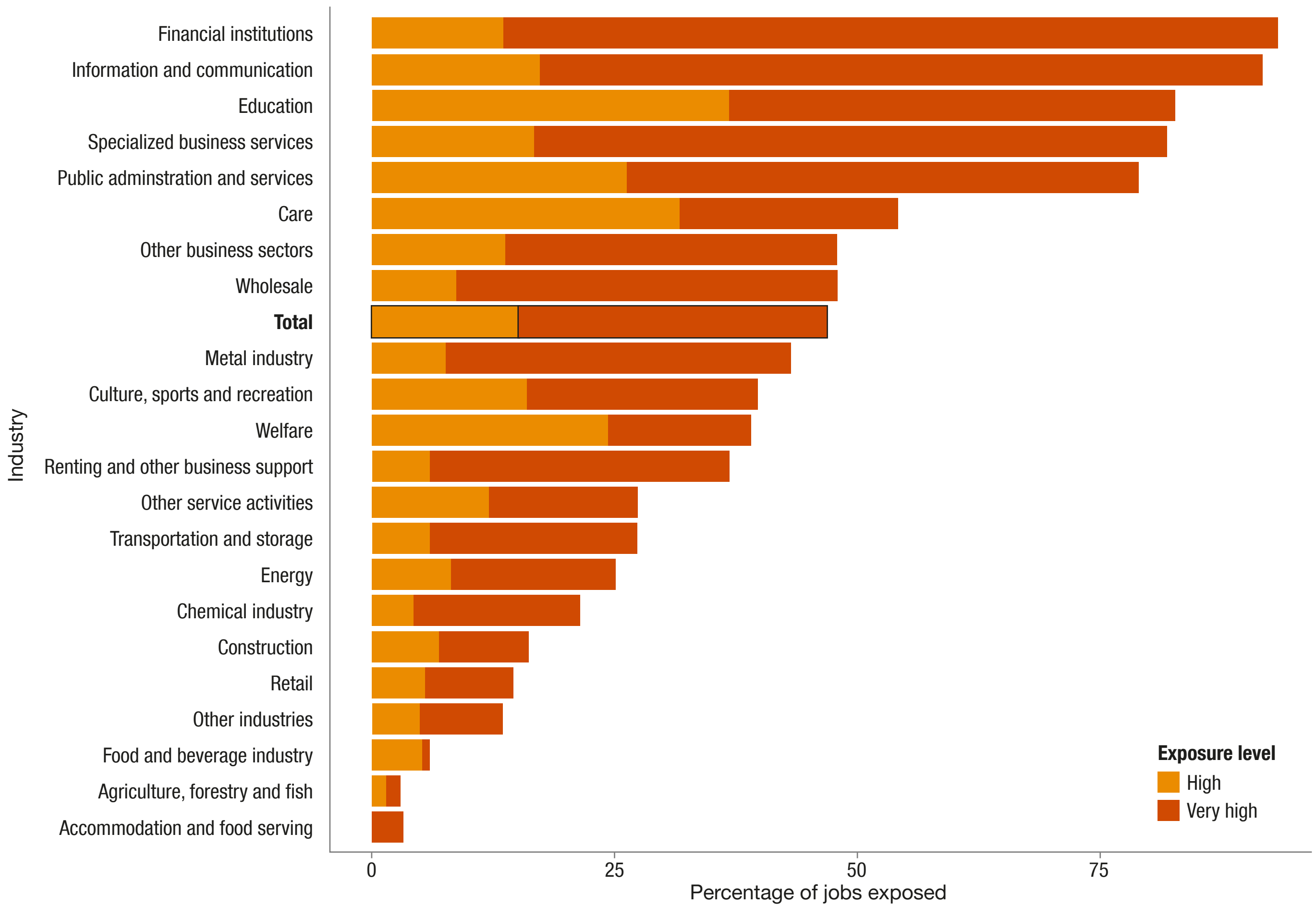
The industry classification differs slightly between CBS and ROA. For the indicators where the data source is CBS:

- We use the numbers for *manufacturing* for all manufacturing industries.
- The data for *wholesale and retail* for both *retail* and *wholesale*.
- The data for *health and social work activities* for both *health* and *welfare*.



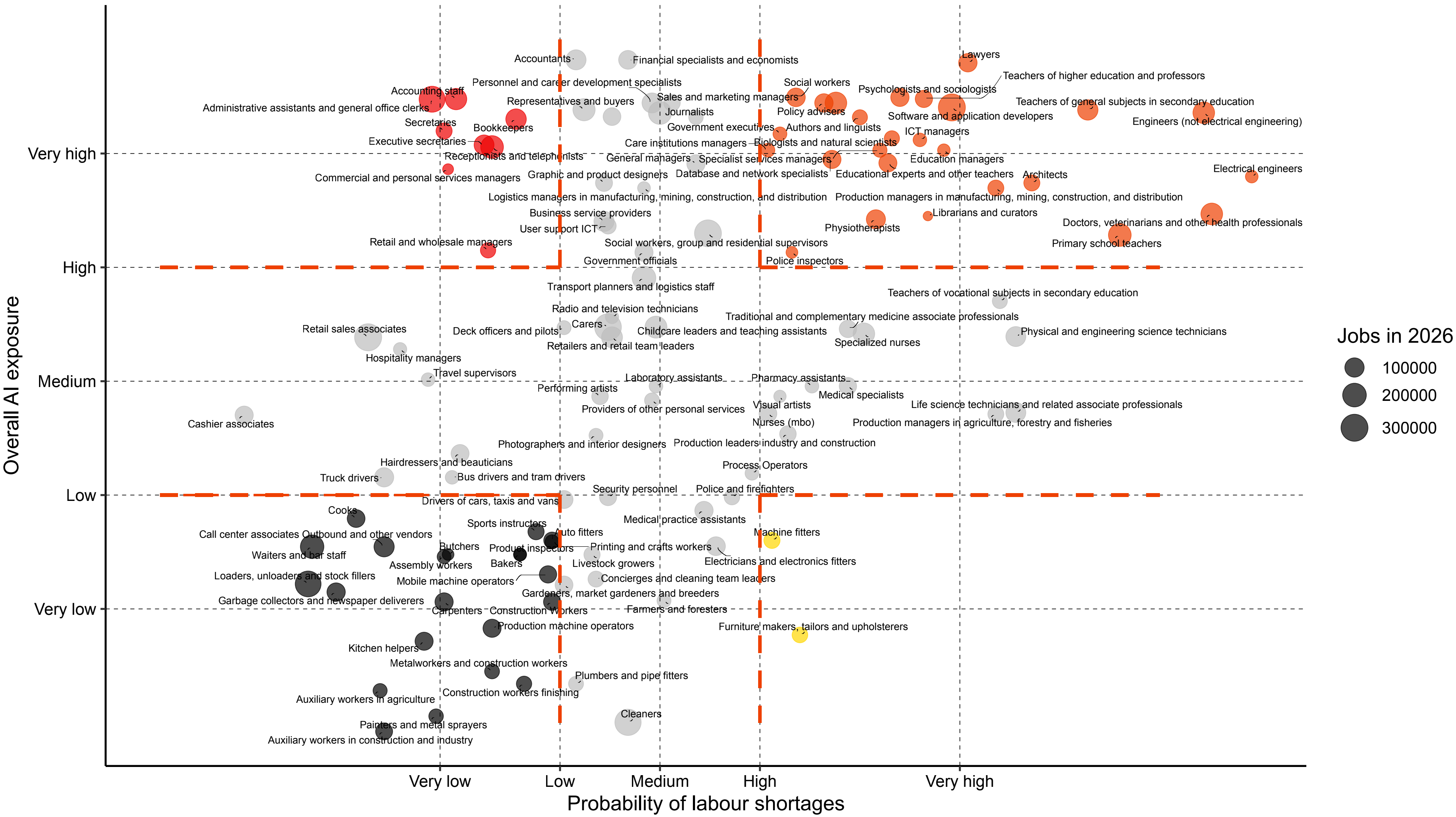
Appendix B: Main results for overall AI

Figure 13 Percentage of highly or very highly exposed jobs to AI overall in the Netherlands by industry



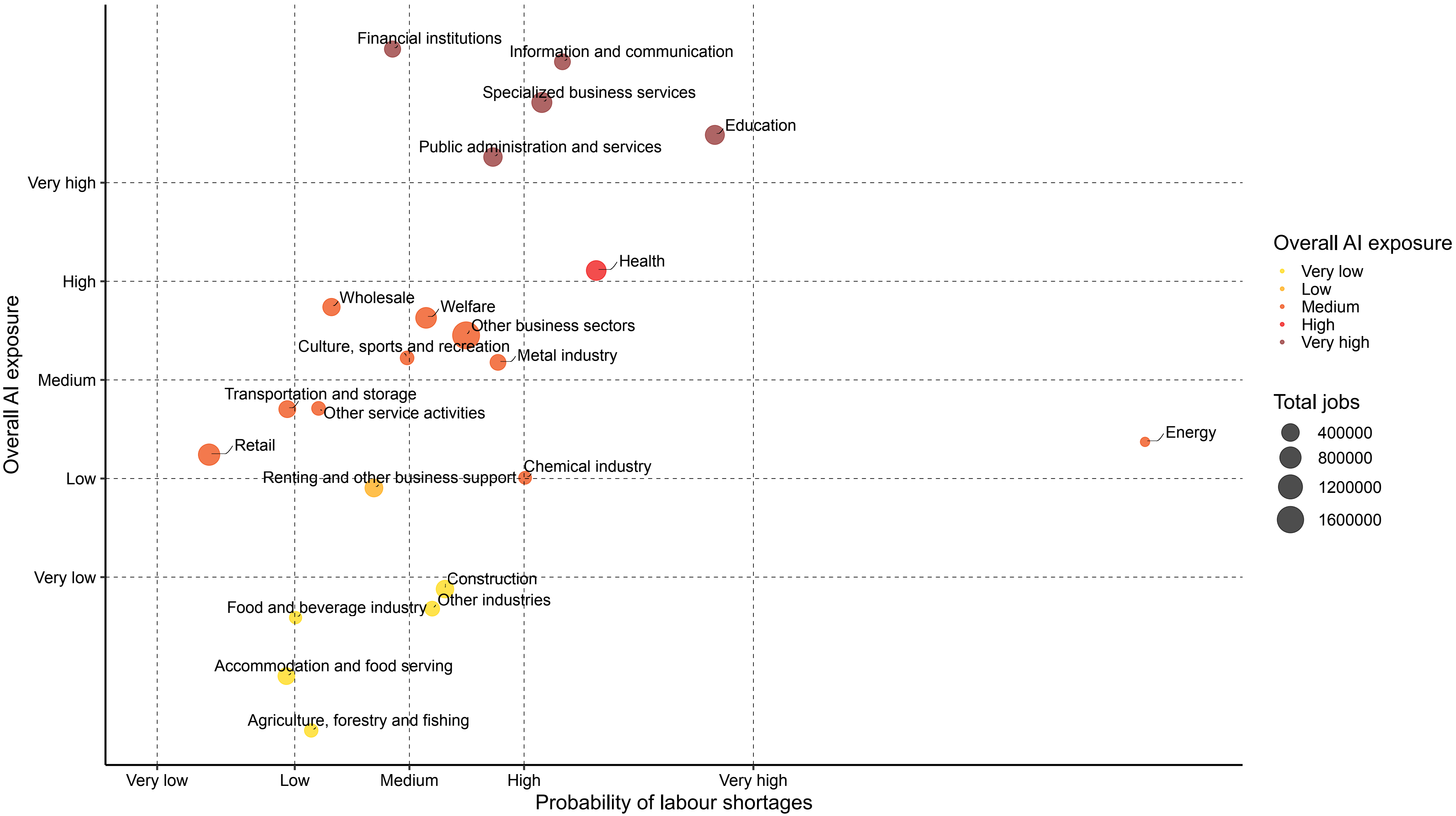
Source: PwC analysis based on data from Felten et al. (2023) and Bakens et al. (2021)

Figure 14 Occupation group distribution by overall AI exposure and labour shortage probability



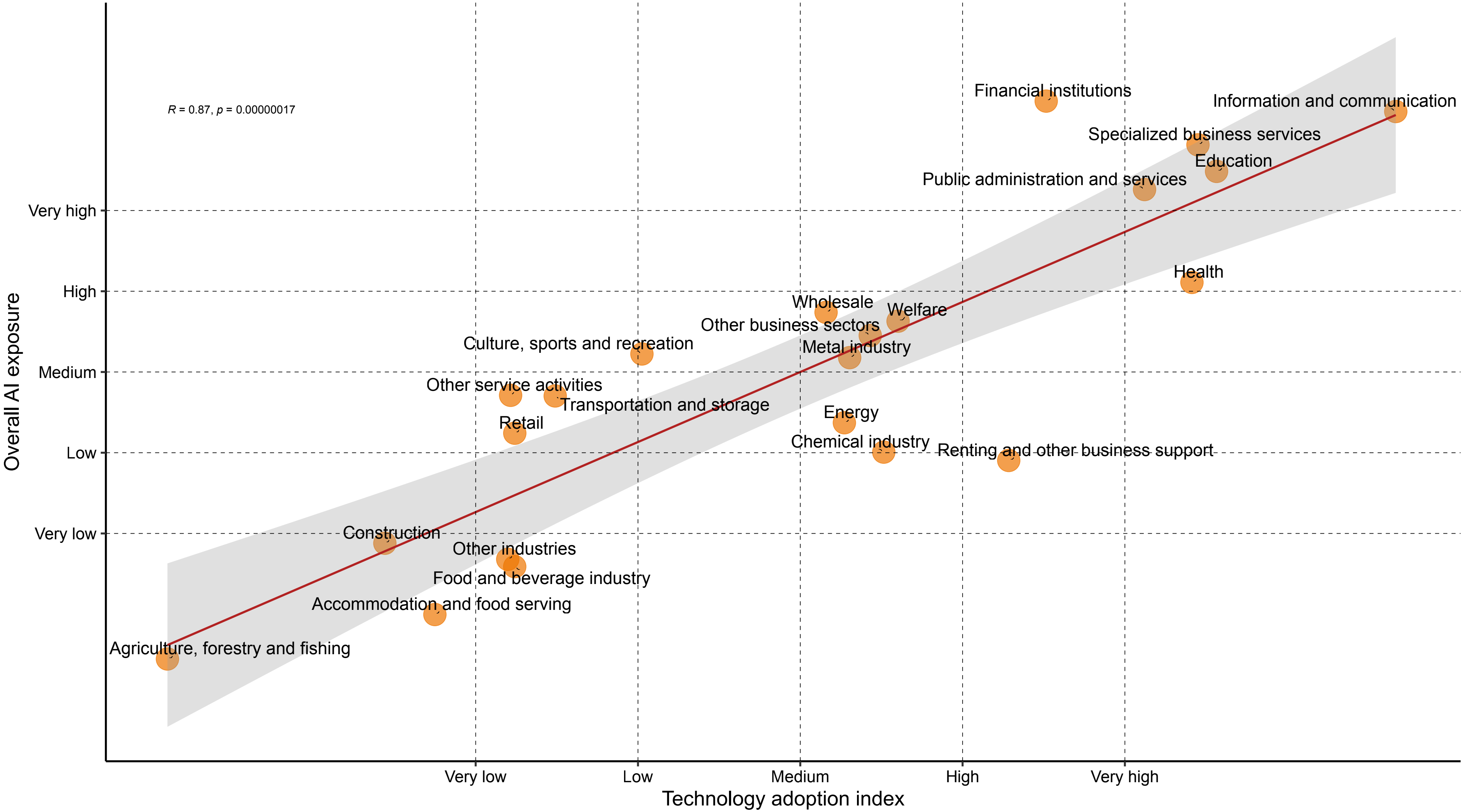
Source: PwC analysis based on data from Felten et al. (2023) and Bakens et al. (2021)

Figure 15 Industry distribution by labour shortage probability and overall AI exposure



Source: PwC analysis based on data from Felten et al. (2023) and Bakens et al. (2021)

Figure 16 Industry distribution by the technology index and overall AI exposure



Source: PwC analysis based on data from Felten et al. (2023) and Bakens et al. (2021)

Acknowledgements
(alphabetically)

Authors:

Guntars Upis	Chief Economist Office	PwC Netherlands
Ricardo Ribas Santolim	Chief Economist Office	PwC Netherlands

Editorial team:

Astrid van der Werf	Chief Economist Office	PwC Netherlands
Bastiaan Starink	Partner of Workforce	PwC Netherlands
Jan Willem Velthuijsen	Chief Economist	PwC Netherlands
Mona de Boer	Partner of Data & Technology	PwC Netherlands

Research support and contributions:

Bote Scholtens	Marketing & Communications	PwC Netherlands
Brenda Verberne	Marketing & Communications	PwC Netherlands
Christian Eistrup	Consulting	PwC Netherlands
Danny de Gier	Marketing & Communications	PwC Netherlands
Femke Alsemgeest	Marketing & Communications	PwC Netherlands
Joon Yang	Chief Economist Office	PwC Netherlands
Jose Castillo	Chief Economist Office	PwC Netherlands
Nicky Roelofsen	Clients & Markets	PwC Netherlands
Marcel Jakobsen	Chief Digital Officer	PwC Netherlands
Martine Roelfzema-Uitermark	Clients & Markets	PwC Netherlands
Monique de Jong	Marketing & Communications	PwC Netherlands
Richard Volbeda	Marketing & Communications	PwC Netherlands

Endnotes

1 PwC (2023): Policymakers focus on making generative AI safer for all
2 PwC (2023): Understanding the potential opportunities of generative AI
3 Felten et al. (2023): How will language modelers like ChatGPT affect occupations and industries?
4 Bakens et al. (2021): The labour market by education and occupation until 2026
5 Agrawal et al. (2023): Similarities and differences in the adoption of general-purpose technologies
6 CBS (2023): Where do most people work?
7 Bruegel (2023): A high-level view of the impact of AI on the workforce
8 White House (2023): The impact of artificial intelligence on the future of workforces in the European Union and the United States of America
9 NOS (2023): Never happened in 50 years: more vacancies than unemployed
10 PwC (2022): PwC 2022 AI Business Survey
11 Eisfeldt et al. (2023): Generative AI and firm values
12 HAI (2023): Artificial intelligence index report 2023
13 NOS (2023): Never happened in 50 years: more vacancies than unemployed
14 Eurostat: Job vacancies in number and percentage
15 PwC (2022): Unlocking the potential on the Dutch labour market
16 Economic Policy Institute (2000): The link between productivity growth and living standards
17 Felten et al. (2023): How will language modelers like ChatGPT affect occupations and industries?
18 Bakens et al. (2021): The labour market by education and occupation until 2026
19 For more details in the methodology, see Appendix A on page 22.
20 Exposure does not directly predict employment or wage loss but instead indicates where things could change in the economy and which workers are most likely to need to adapt. The exposure scores capture the technical feasibility of AI and are limited in their consideration of other factors. Additionally, 'least exposed' to AI does not necessarily mean that that occupation escapes any impact of AI. Lastly, we also do not incorporate new jobs in our calculations that could be created because of AI.
21 Santander (2023): Transformative potential of generative AI: innovation, impact, and implications for the future workforce
22 Webb (2020): The Impact of artificial intelligence on the labor market
23 Eloundou et al. (2023): GPTs are GPTs: An early look at the labor market impact potential of large language models
24 Strategy+Business (2023): Boston Dynamics wants to change the world with its state-of-the-art robots
25 We measure the industry exposure to AI based on the proportion of workers in each occupation employed in each industry and the occupational exposures. This leads to industry exposure based on workforce exposure. Some industries might have their business models highly impacted by AI, but this would not be measured in our exposure scores. Take retail, for example. AI is already having a very big impact on how product recommendations are made, but this might not be captured in changes in occupational tasks.
26 We measure labour market constraints using the probability of employers achieving the desired composition of personnel according to educational background within occupational groups, considering the supply-demand ratio for various types of training, based on Bakens et al. (2021): The labour market by education and occupation until 2026
27 In Appendix B on page 29, we report the results of a similar analysis, but this time focused just on the impact of overall AI. There are some small shifts, but the results are largely similar, indicating that the potential of overall AI comes largely from language modelling for many occupations.
28 We report the results for a grouping of 113 occupations. In practice, occupations and jobs are even more granular than that. If we could look at very specific groups, probably a few would fall into this category.
29 This will depend on the elasticity of demand and the income elasticity of demand, as increases in productivity can compensate for the employment effects of automation.
30 Harvard Business Review (2023): AI won't replace humans — but humans with AI will replace humans without AI
31 Ibid.
32 White House (2023): The impact of artificial intelligence on the future of workforces in the European Union and the United States of America
33 The Economist (2023): Lessons from finance's experience with artificial intelligence
34 Wu et al. (2023): BloombergGPT: A large language model for finance
35 IBM (2023): How to improve your finance operation's efficiency with generative AI
36 American Economic Review (2020): Processing the rise of quantitative investing
37 The Economist (2023): Lessons from finance's experience with artificial intelligence
38 Harvard Business Review (2023): What the finance industry tells us about the future of AI
39 Bloomberg (2017): A sign of the times – how the finance industry is embracing STEM professionals
40 FD (2023): Energy transition 'unfeasible' due to lack of personnel
41 CBS (2021): What are the most popular majors?
42 UNESCO (2019): Beijing consensus on artificial intelligence and education
43 Washington Post (2023): Artificial intelligence is already changing how teachers teach
44 Ibid.
45 Ibid.
46 Khan Academy (2023): World-class AI for education
47 Education Week (2023): Will artificial intelligence help teachers or replace them?
48 UNESCO (2023): Generative artificial intelligence in education: What are the opportunities and challenges?
49 Marangunić & Granić (2015): Technology acceptance model: a literature review from 1986 to 2013
50 For more details, see Appendix A on page 22. We focus our analysis on indicators for which data is available at the industry level in the Netherlands, but other aspects have differentiated companies and industries that adopt technology faster. These include higher productivity, engaging in innovative activities, aligning the organisational structure with the given technology and information spillovers and higher R&D intensity. There are also numerous more qualitative adoption factors for technologies that are difficult to measure, such as user acceptance, habit change, trust, legal requirements and time to mass market saturation.

51 CEPR (2023): Firms' use of artificial intelligence: Cross-country evidence on business characteristics, asset complementarities, and productivity
52 Kostøl & Svarstad (2023): Trade unions and the process of technological change
53 NBC News (2023): Actors vs. AI: Strike brings focus to emerging use of advanced tech
54 White House (2023): The impact of artificial intelligence on the future of workforces in the European Union and the United States of America
55 Babina et al. (2020): Artificial intelligence, firm growth, and product innovation
56 Santander (2023): Transformative potential of generative AI: innovation, impact, and implications for the future workforce
57 Eisfeldt et al. (2023): Generative AI and firm values
58 CEPR (2023): Firms' use of artificial intelligence: Cross-country evidence on business characteristics, asset complementarities, and productivity
59 Babina et al. (2022): Firm investments in AI technologies and changes in workforce composition
60 One limitation of this result is that our index is constructed as an average of the scores on each dimension. It can be that a specific dimension has a very large impact on technology adoption in a given industry. If Culture, for example, is more important than other dimensions, we are being overly optimistic about language modeling AI adoption in Education and in Public administration and services.
61 Eisfeldt et al. (2023): generative AI and firm values
62 Bruegel (2023): A high-level view of the impact of AI on the workforce
63 Acemoglu et al. (2022): Tasks, automation, and the rise in U.S. wage inequality
64 Lorenz et al. (2023): The future of employment revisited: how model selection affects digitization risks
65 Autor (2015): Why are there still so many jobs? The history and future of workplace automation
66 Brookings (2023): The Turing Transformation: Artificial intelligence, intelligence augmentation, and skill premiums
67 Autor et al. (2022): New Frontiers: The origins and content of new work, 1940–2018
68 Albanesi et al. (2023): New technologies and jobs in Europe
69 Acemoglu et al. (2022): Artificial intelligence and jobs: evidence from online vacancies
70 Babina et al. (2022): Firm investments in AI technologies and changes in workforce composition
71 OECD (2023): OECD Employment Outlook 2023: Artificial Intelligence and the labour market
72 Autor (2015): Why are there still so many jobs? The history and future of workplace automation
73 Ibid.
74 Webb (2020): The Impact of artificial intelligence on the labor market
75 Johnson & Acemoglu (2023): Power and progress: Our thousand-year struggle over technology and prosperity.
76 International Monetary Fund (2023): The power and perils of the "Artificial Hand": considering AI through the ideas of Adam Smith
77 Brookings (2023): The Turing Transformation: Artificial intelligence, intelligence augmentation, and skill premiums
78 Economist (2023): Machine dreams Your employer is (probably) unprepared for artificial intelligence
79 CEPR (2023): The impact of artificial intelligence on growth and employment
80 Financial Times (2023): David Autor: 'We have a real design choice about how we deploy AI'
81 International Monetary Fund (2023): The power and perils of the "Artificial Hand": considering AI through the ideas of Adam Smith
82 Brynjolfsson & Raymond (2023): Generative AI at work
83 Peng et al. (2023): The impact of AI on developer productivity: evidence from GitHub Copilot
84 Noy & Zhang (2023): Experimental evidence on the productivity effects of generative artificial intelligence
85 Stack Overflow (2023): Developer sentiment around AI/ML
86 Santander (2023): Transformative potential of generative AI: innovation, impact, and implications for the future workforce
87 Financial Times (2023): David Autor: 'We have a real design choice about how we deploy AI'
88 Abeliansky et al. (2023): Fostering a sustainable digital transformation
89 International Monetary Fund (2023): The power and perils of the "Artificial Hand": Considering AI through the ideas of Adam Smith
90 Ibid.
91 World Economic Forum (2023): Future of jobs report 2023
92 OECD (2023): OECD Employment Outlook 2023: Artificial intelligence and the labour market.
93 PwC (2023): Global hopes & fears survey
94 WEF (2023): Future of jobs report 2023
95 Bruegel (2023): A high-level view of the impact of AI on the workforce
96 PwC (2023): Leaders guide to generative AI
97 PwC (2023): Global hopes & fears survey
98 Felten (2023): Occupational heterogeneity in exposure to generative AI
99 Kouretsis and Bampouris (2022): Crosswalks Between Classifications of Occupations
100 Due to crosswalking difficulties Biologists (SOC code 19-1020), Door-To-Door Sales Workers, News and Street Vendors, and Related Workers (SOC code 41-9091) and Radio, Cellular, and Tower Equipment Installers and Repairers (SOC code 49-2021) were dropped from the analysis before the SOC to ISCO crosswalking.
101 Bakens et al. (2021): The labour market by education and occupation until 2026

Contacts

Bastiaan Starink
Partner of Workforce
PwC Netherlands
E: bastiaan.starink@pwc.com

Mona de Boer
Partner of Data & Technology
PwC Netherlands
E: mona.de.boer@pwc.com

Jan Willem Velthuijsen
Chief Economist
PwC Netherlands
E: jan.willem.velthuijsen@pwc.com