On the Automation of Job Tasks: Occupational exposure to Artificial Intelligence and Software

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ai:conomics policybrief

On the Automation of Job Tasks

Occupational exposure to Artificial Intelligence and Software[1]

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Note: This policy brief is the extended version of IAB Kurzbericht 21/23. The original German text can be accessed here.

Abstract

While rapid advances in digital technologies transformed the occupational structures and workers‘ skill and task composition over the past decades, much less is known about how Artificial Intelligence technologies (AI) will shape future labour markets. As part of the "ai:conomics" project, we analyze the extent to which employees subject to social security contributions in Germany are potentially exposed to AI and software technology. Our results show that highly educated, high-income workers are most exposed to AI, while their exposure is lower to software. Overall, the findings suggest that given AI's far-reaching potential to carry out different sets of tasks, these technologies are expected to impact workers across a wider skill and wage spectrum, which previous automation technologies had limited impact on.

Key messages

- To what extent can artificial intelligence (AI) and software systems (without AI) affect employees in different occupational groups in Germany? Using indicators that measure the automation potential of job tasks, we characterize occupations that could be substituted given the patented innovations in their field (Webb, 2020). We refer to these indicators as relative exposure potentials, as they enable comparisons between occupations.
- We show that while the potential exposure to software is more likely to affect the job tasks of low or medium-educated employees, AI is more likely to have an impact on highly educated employees. This signals the distinct potential of AI in targeting different types of workers than other automation technologies.
- The exposure potential to AI and software is particularly high for workers in the manufacturing industry and in information and communication technologies.
- Occupations with a higher share of female employees appear to have lower AI and software exposure compared to those with a higher share of male employees.
- Furthermore, we find that AI and software have the potential to take over slightly more tasks in occupations with skilled labour shortages, compared to occupations without shortages.
- Nonetheless, our findings imply that even though the observed technologies can potentially automate certain tasks, not all tasks within an occupation can be carried out by AI.

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Over the past few decades, rapid advances in digital technologies have significantly transformed labour markets, occupational structures and workers' skills and task compositions. The IAB-Kurzbericht 13/2021 by Dengler and Matthes shows that the proportion of tasks that can be performed by machines has risen significantly between 2013 and 2019 in Germany, and that more complex occupational activities are more likely to potentially be substituted. In recent years, in addition to new software systems and robotics (e.g., software for cash registers, text and data processing, industrial robotics), a significant increase in the number of AI applications was also recorded. Due to its advanced capabilities in matching and classification tasks, AI can be applied in various sectors, e.g. in the insurance industry (e.g. automated processing of damage images); in the healthcare sector (e.g. diagnosis of X-ray images), in logistics (e.g. optimization of supply chains), in legal and administrative services (e.g. classification of text documents), and in e-commerce (e.g. chatbots in customer service) (Ernst et al, 2019; Mondolo, 2022). There are also numerous examples of AI applications in the manufacturing industry, including complex image processing and classification tasks for error detection and quality assurance, the use of neural networks for prediction and forecasting tasks, and the management of supply chains (Rammer et al., 2022). In addition, various applications of large language models (LLMs) are becoming more relevant in a wider range of economic sectors; particularly following the release of ChatGPT in November 2022 with strong public attention (OECD, 2023). The expectations on the steady increase in the use of (generative) AI has therefore fueled further discussions about whether and how AI might transform the labour market in Germany.

So far, US-based studies show that high-skilled workers are more exposed to AI (Lane & Saint-Martin, 2021). This is unlike the earlier findings on previous automation trends (such as computers, robotics or software) that favor highly educated workers at the expense of low- and medium-skilled workers in routine tasks (Autor et al., 2003; Goos et al., 2009). Studies also find that occupations most affected by AI experience small, positive changes in wages, if any; while there seem to be no employment effects at the industry or occupation level (Felten et al., 2019; Acemoglu et al., 2022).

The exposure potential of occupational tasks

As part of the "ai:conomics" project, we analyze the extent to which employees who are subject to German social security contributions[2] were potentially exposed to AI and software between 2012 and 2019 in Germany. To do so, we rely on patent-occupation-based indicators published in in 2020 which assess the extent to which tasks within occupations could potentially be automated (namely the "exposure measures" by Webb, 2020). Since the indicators enable a comparison between different occupations, we refer to them as relative automation potentials (for further details see Infobox 1).

In addition to existing indicators for the German labour market, particularly the *substitution potentials* of occupations by Dengler and Matthes (2021), the Webb (2020) measure enables us to distinguish whether the potential automation is due to AI or software. This allows us to better understand whether and to what extent different technologies potentially automate tasks in different occupational groups. Our analysis is therefore relevant for both the present and the (near) future, as the underlying patents (up to 2020) are valid for several years and some technological innovations will still need to prevail until they have an influence in future labour markets.

Throughout our policy brief, the term "software" refers to all systems and computer programs that follow manually written "if-then" rules and include applications that process and coordinate information and workload in an organization - which is very close to the definition of algorithmic management (Wood, 2021). In contrast, the term "AI" refers to predictive technologies that learn statistical correlations from data and react, derive or suggest measures for a specific purpose on this basis (Webb, 2020). In line with differences on their technical capabilities, the following analyses demonstrates significant variance in the potential exposure to AI and software across different employee groups. Regardless of whether new technologies are labour-enhancing or labour-replacing, it is important to note that even though automation potentials may not fully materialize due to economic, legal or technical reasons, a change in the future of work is expected, which will affect workers in various ways.

2. The term includes employees and workers in Germany who are subject to social security contributions, which means that those individuals, due to their wages in a certain band, must be a member of certain public insurance schemes like pension insurance, unemployment insurance, health and long-term care insurance and pay contributions to the social security systems, as do their employers.

Alongside the digital transformation, shortages of skilled workers are currently one of the most discussed topics among policy makers, academia, and the public. Naturally, the question of whether the lack of skilled workers could potentially be mitigated through targeted use of certain technologies arises. As part of our analysis, we therefore investigate the relationship of the occupational exposure scores with indicators that measure their extent of skilled worker shortages.

Infobox 1: Index of exposure potentials of occupations by Webb (2020)

Webb (2020) uses descriptions of job tasks and patents in specific technology fields to create a measure of the relative automation potential of occupational tasks. The job task description data is based on the O*NET database of occupations created for the US labour market, while the patent data that dates to 2020 come from Google Patents Public Data, provided by IFI CLAIMS Patent Services (Webb, 2020). Although latest AI technologies - such as large language models that reached market maturity only at the end of 2022 - are excluded in the database, it is possible that patents relating to these technologies already existed during the analysis period and possibly included in the construction of the measures.

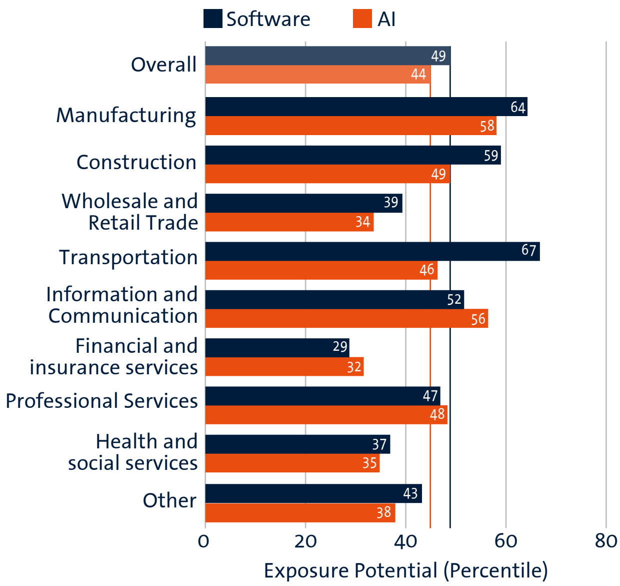
To construct the measures of exposure scores, Webb extracts verb-noun pairs found in patent and job tasks descriptions. He then quantifies the overlap between verb-noun pairs in the two text groups. For example, according to the job description, one of the tasks of doctors is to "diagnose the condition/disease of patients", where the verb-noun pair of this task would be: diagnose - condition/disease. On the patent side, the title of a technology patent might include "method of diagnosing disease", which in turn contains (diagnose - condition/disease) as a potential verb-noun pair, leading to an overlap between a specific occupation and a technology patent (Webb, 2020). Depending on the frequency of such verb-noun pair overlaps, Webb assigns a score to the (job) task and then aggregates these task-level scores to the occupational level. The resulting score is provided in the form of exposure percentiles with values ranging between 0 and 100.

Overall, the indicator records the capacity of a specified technology to substitute the tasks of specific occupations. Therefore, the higher the automation potential of an occupation, the more likely it is that the occupation consists of activities described in the technology patents and the more likely it is that activities in this occupation can be taken over by AI or software (Webb, 2020; see also Acemoglu et al. 2022 & Restrepo, 2023). Since the scores reflect the relative automation potential in an occupation, i.e. the exposure of the occupation compared to the average exposure of all occupations, a score of 0 indicates that none of the activities can be taken over and a score of 100 would mean that within this occupation – and compared to all other occupations – the highest number of activities can be taken over. However, this still does not imply that all activities can be performed by that technology.

The exposure percentiles are available for three different forms of technology: AI, software, and robotics. In this policy brief, we focus on AI and software exposure measures. The reason is that the robotics indicator, by construction, is limited to industrial robots, which are potentially nearly exclusively used in the manufacturing sector. AI, in contrast, is predicted to have a very broad range of applications and software has already become an integral part of most areas of work and life. Just like software, AI can also be used as a complementary tool: it can support workers in tasks that require training and specific expertise, and free-up time for other tasks, e.g. increased interaction with people or more informed actions and taking decisions based on the information compiled by the AI.

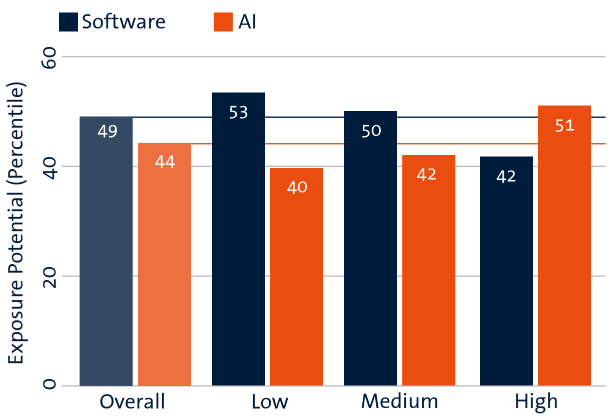
To investigate the occupational characteristics of exposed employees in Germany, we match the exposure scores with the 25% sample of the Integrated Employment Biographies (IEB, years 2012 to 2019) and construct a panel dataset on labour market biographies of employees subject to social security contributions across time. Since Webb's (2020) index is based on US occupations (Standard Occupational Classification, SOC), we use the crosswalk provided by Heß, Janssen, Leber (2023) to the German Classification of Occupations of 2010 (Kldb 2010) at the 5-digit occupational level. The conversion table for the allocation of occupations in KldB 2010 to ISCO-08 is provided by the Federal Employment Agency. As some occupational classifiers and task definitions within occupations may differ between the US and the German labour markets, inaccuracies might occur during the crosswalk. These inaccuracies can be particularly significant when observing individual occupations. However, since our study refers to occupational groups with the aim of deriving generalized statements, these inaccuracies are likely to be less significant. We cannot rule out the possibility that business models or the standard of services have changed since the indicators were calculated and that occupational task structures might therefore have to be weighted differently in the meantime.

Figure 1.
Exposure Potentials across industries, 2012-2019



Notes: Percentile values of the AI and software exposure on a scale from 1 to 100 (Webb 2020, see also Infobox 1), averaged across all industry-occupation observations. Wholesale and Retail Trade includes "Trade, maintenance, and repair of motor vehicles" (based on the German Classification of Economic Activities 2008, selected industries only).
Source: Sample of Integrated Employment histories 2012–2019, Webb (2020), own calculations. © IAB

Figure 2.
Exposure Potentials by qualification levels, 2012-2019



Notes: Percentile values of AI and software exposure on a scale from 1 to 100 (Webb 2020, see also Infobox 1), averaged across educational qualifications that relate to three different education levels; low qualification (employees without completed formal vocational education), medium qualification (employees with completed vocational training in the German apprenticeship system) and high qualification (employees with a university degree).
Source: Sample of Integrated Employment histories 2012–2019, Webb (2020), own calculations. © IAB

AI and software exposures across the German labour market

We now explore to which extent industries and groups of workers that differ in their socio-economic, demographic, or occupational characteristics can potentially be exposed to AI and software.

Potential exposure to AI is highest in the manufacturing industry

We start by documenting the distribution of average exposure scores across industries (see Figure 1). Our results suggest that employees in the transportation sector are most exposed to software whereas least exposure occurs for workers in the financial and insurance services. The exposure to AI appears to be largest in the manufacturing sector and lowest in wholesale and retail trade.

While employees in ICT, financial and insurance services and professional services have higher exposure to AI, the opposite pattern occurs for employees in the manufacturing, construction, wholesale and retail trade, transportation, healthcare and social services, where software exposure is higher. The biggest difference between the average AI and software exposure scores emerges for occupations in the transportation sector.

Figure 1 also shows that in none of the industries occupations have an exposure score close to the maximum value of 100; a score applicable to only a few occupations (Infobox 1). It is therefore more likely that the range of tasks within the occupations in an industry will be redistributed due to automation. Changes in the composition of tasks within an occupation or job molding are more likely than those entire professions being completely replaced by AI or software.

Highly qualified employees are most exposed to AI

When plotted against qualification levels, we find that AI exposure increases with qualification levels and that highly qualified employees appear to be most exposed to AI compared to employees with low and medium qualifications (see Figure 2). These findings are in contrast with earlier evidence on the impact of previous automation technologies, which showed that technology substitutes low and/or medium skilled employees (known as "skill-biased technological change" theory, Acemoglu & Author 2011). The results also confirm the findings of the US-based studies listed above (Felten et al. 2019) as well as recent findings on the potentially increasing use of technology in technical activities and complex specialist activities in Germany (Dengler & Matthes 2021). Software exposure on the other hand shows the opposite trend and is in line with previous findings; low and medium qualified employees are more exposed to software.

How can these findings be explained? We argue that occupations that require no formal vocational training (e.g. service staff, cleaning) generally do not require handling large amounts of data, which is a specific strength of AI applications. Particularly, tasks related to prediction, recognition, forecasting and analytical decision-making are the core of current applications of AI. These rather (non-routine) complex tasks are mainly performed by highly educated workers in certain sectors, as also demonstrated by increasing pattern of AI exposure with qualification levels. The findings emphasize the distinct potential of AI in comparison to existing technologies: even though current AI technologies are still far from reaching their full potential, they are already more capable of taking over a wider range of different complex tasks. The impact of AI-driven technological innovations on the labour market is therefore more likely to affect workers across a wider skill and wage spectrum that previous technologies had limited reach.

Software, in contrast, can execute or at least support the performance of repetitive, routine and rather low-medium-skilled tasks, for example in jobs in the manufacturing industry. In the social/services sector, however, there are similarly few applications for software as for AI, which is why the relative automation potential (e.g. process automation) is also low there. Yet there are other occupations requiring the same qualification levels, where standardized, repetitive tasks are more frequently performed and where software is more likely to be used to optimize and simplify processes, i.e. such as occupations in the administrative services sector (e.g. bank clerks). Thus, the applicability of software is lower in occupations with higher qualification requirements, as less standardized tasks are involved here.

AI exposure is lower for female employees

Turning to demographic characteristics, we analyze the distribution of exposure scores across occupations with different shares of female employees. The associated variation might occur since occupations with a particularly high proportion of women often have a different job structure than occupations with a high proportion of male employees. In Germany, for example, the share of female employees has increased mostly in non-routine cognitive and manual occupations while it declined in routine occupations (Bachmann & Gonschor 2022).

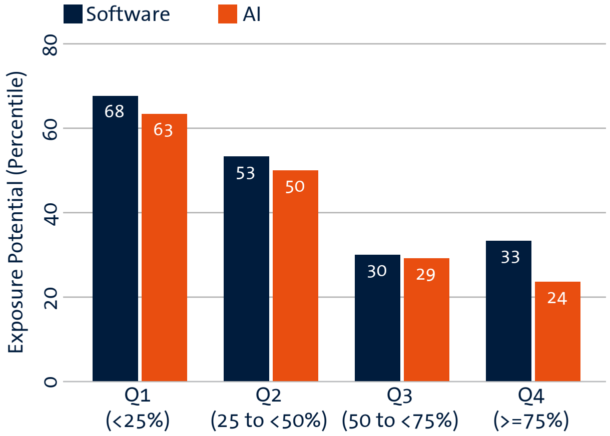
Our findings show that as the share of women within occupational groups increases, both AI and software exposure decreases (for the latter, occupations with highest female share being an exception, see Figure 3). The occupations with a share of female employees less than 25 percent include occupations in mechanical and industrial engineering, construction, warehousing and logistics as well as vehicle drivers in road traffic. The occupational group with the highest proportion of women includes occupations in cleaning, sales, office and secretarial work as well as occupations in healthcare and nursing, obstetrics and social work.

We can therefore argue that the share of women is particularly high in occupations that often require extensive social, interpersonal, and communication skills (i.e. ''human skills"), where the adoption of digital technologies has so far been relatively limited and where some bottlenecks to automation, even to AI, seem to persist.

High-income workers are most likely to be affected by AI

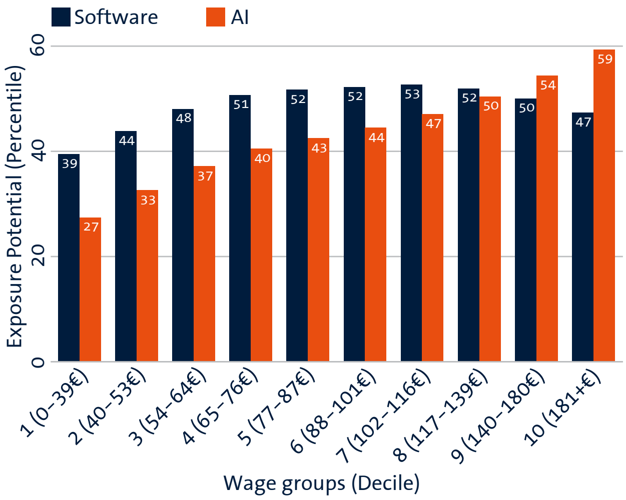
Next, we examine the distribution of the average exposure scores for employees' wages at different parts of the earnings distribution (see Figure 4). The results are consistent with the findings on the distribution of exposure scores against employees with different qualification levels. The analysis shows that AI exposure gradually increases with income levels, and peaks at the 10th decile, suggesting that high-wage employees appear to be most exposed to AI (i.e workers with daily wages of more than 181 euros and more). Occupations in the highest wage groups consist of mainly white-collar occupations in technical research and development, advertising and marketing, as well as IT professions (including IT system analysis, IT application consulting), and managers and directors in purchasing and sales. Middle-class workers (fifth decile, between 77 and 87 euros) include, for example occupations in mechanical engineering and industrial technology (without specialization) as well as in sales. Workers in the lowest group (first decile, up to 39 euros) are in occupations such as cleaning, catering, construction, and warehousing and delivery services.

Figure 3.
Share of female employees by exposure potentials, 2012-2019



Notes: Percentile values of the AI and software exposure on a scale from 1 to 100 (Webb 2020, see also Infobox 1).
Explanation: In occupations with a share of women of 25% to less than 50%, potential software and AI exposure is 53 and 50 respectively.
Source: Sample of Integrated Employment histories 2012–2019, Webb (2020), own calculations. © IAB

Figure 4.
Exposure potentials by income levels, 2012-2019



Notes: Percentile values of the AI and software exposure on a scale from 1 to 100 (Webb 2020, see also Infobox 1), averaged across real daily wages of employees in 10 wage groups (deciles). The salary ranges of the wage groups are shown in brackets. The average exposure potential is calculated for each wage group. It results from the occupations of the employees assigned to the wage group.
Explanation: For example, in wage group 7 with a daily wage between 102 and 116 euros, potential AI and software exposure is 47 and 53 respectively.
Source: Sample of Integrated Employment histories 2012–2019, Webb (2020), own calculations. © IAB

In contrast, as depicted in an inverted U-shaped relationship, software exposure is highest in middle-wage occupations and reaches its peak for workers at upper-middle wage segments (wage group 7, 102 to 116 euros). This pattern of software exposure is again in line with above-mentioned studies on job polarization, which document the decrease of the labour demand for middle relative to high-skilled and low-skilled occupations in response to "routine-task" replacing technological change (Goos et al., 2009; Acemoglu & Autor, 2011; Autor & Dorn, 2013).

AI exposure and occupations with skilled worker shortages

As a consequence of ongoing technological progress, globalization and aging of the population, certain professions in Germany have been experiencing shortages in skilled labour and implementing technological solutions is one of the most discussed potential strategies to compensate such shortages (BA, 2020; OECD, 2020).

Therefore, we examine the distribution of exposure scores across occupations with different degrees of skilled worker shortages (BA, 2020; see Infobox 2). Here we also observe a significant heterogeneity in exposure scores, particularly for occupations that require highly complex tasks. For example, occupations in geriatric care and occupations in software development have the same value of the skilled worker shortage indicator (2.83). Nonetheless, they differ significantly in their exposure potentials; while the exposure scores are very low for geriatric care (AI: 23; Software: 29), they are very high for occupations in software development (AI: 88; Software: 84).

Infobox 2: Analysis of skilled worker shortages

The skilled worker shortage indicators come from the Federal Employment Agency's "Engpassanalyse" (Analyses of labour shortages, BA 2020). The Agency annually evaluates the skilled worker shortages for different occupations and occupational groups in the German labour market. The indicator is available for three different required skill levels according to the German 2010 Classification of Occupations (5-digit code of the KldB 2010):

- Occupations with skilled tasks (which usually require a completion of formal vocational educational training of at least 2 years),
- Occupations with complex tasks (which require a qualification as master craftsman or technician or equivalent technical school or completion of university degree), and
- Occupations with highly complex tasks (which require a completion of a university studies of at least four years or similar and, beyond that, profound professional experience or further formal highly specialized qualification certificates like a doctorate).

The analysis excludes occupations with unskilled/ semi-skilled tasks that require no formal qualification or only short-term training as the labour shortage indicator is not available for this occupational group. In total, we obtain a shortage indicator for 236 occupations with skilled tasks, 135 occupations with complex tasks and 154 occupations with highly complex tasks (for more detailed information see BA, 2020).

At a given overall score, occupations are classified into occupations with different levels of shortages. Values between 2.0 and 3.0 indicate "bottleneck" occupations, thus occupations with large skilled worker shortages. Indicator values between 1.5 and 2.0 point out occupations that are in the "observation range", i.e. these occupations are considered as potential "bottleneck" occupations. Indicator values below 1.5 indicate that there is no shortage of skilled workers (BA, 2020).

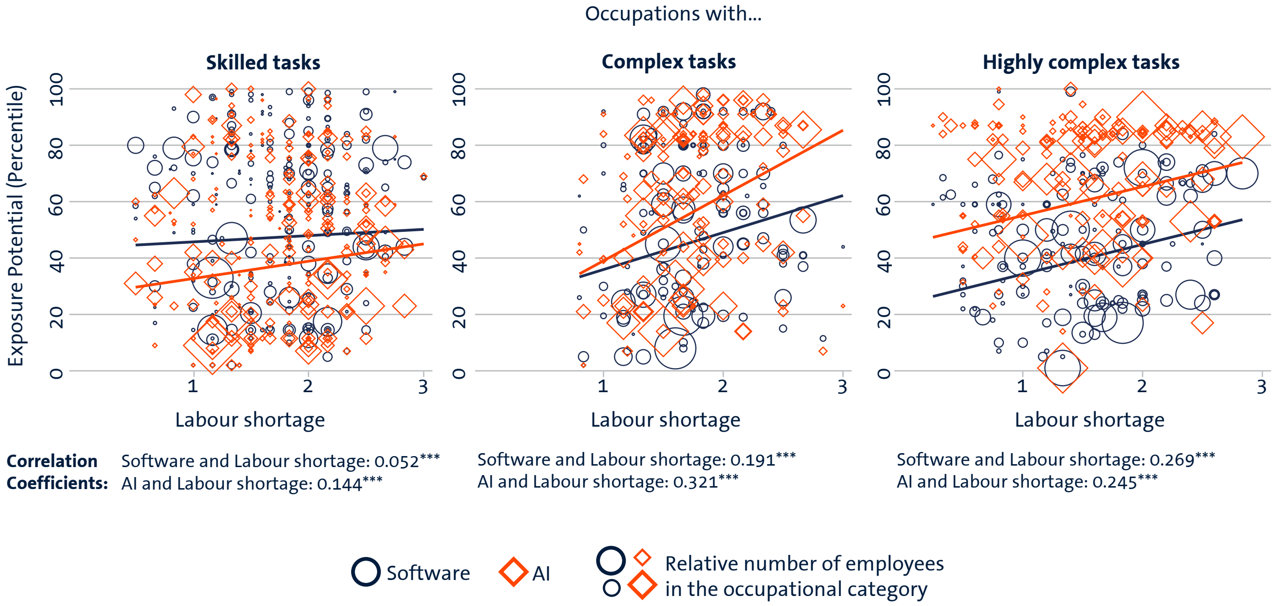
We use the indicator values available for 2019, which enables us to exclude any pandemic-related changes in the labour market in 2020 and consequent years from the analysis.

The labour shortage indicators are calculated for occupations at three different required skill levels as classified in the 2010 German Classification of Occupation: for occupations with skilled tasks (e.g. healthcare and nursing staff), occupations with complex tasks (e.g. specialist nurses), and occupations with highly complex tasks (e.g. doctors) (see Infobox 2 for further details).

When plotted against occupations with skill shortages, our results demonstrate that the use of AI and software seem to play a greater role for some occupations with high shortages relative to occupations with lower or no shortages (see Figure 5, particularly occupations with values at the top right of each of the three subgraphs). We find that the automation of tasks is most likely to be the case for occupations with complex and highly complex tasks, as indicated by the regression lines with positive slopes and the correlation coefficients of the exposure measures and the shortage indicators. The positive correlation is less pronounced for the occupations with skilled tasks. Overall, however, the results point to a rather weak relationship between AI exposure and skilled worker shortage; as shown by the strong scattering of the values and the flat positive slope of both the black and the red regression lines.

We can therefore suggest that the observed technologies can play a role in mitigating the shortage of skilled workers. However, our results also demonstrate that technologies alone could not completely take over the tasks for any of the "bottleneck" occupations and that technological change may reduce but cannot solve the acute shortage of skilled workers.

Figure 5.
Exposure Potentials plotted against skilled worker shortages at the occupational level by different required skill levels, 2012-2019



Indicator of the skilled worker shortage: less than 1.5 = no shortage; 1.5 to less than 2.0 = weak bottleneck; 2.0 and higher = bottleneck.

Notes: Percentile values of the AI and software exposure on a scale from 1 to 100 (Webb 2020, see also Infobox 1).
Explanation: The three graphics compare the exposure potentials of occupations with different levels of worker shortages. The vertical axis shows the exposure potential for software and AI. The horizontal axis shows the value for the skilled worker shortage indicator for each occupational category considered (5-digit classification of occupations 2010). The professions are grouped according to the required skill levels “Skilled tasks”, “Complex tasks” and “Highly complex tasks”. No shortage indicator is available for occupations with unskilled or semi-skilled tasks as well as for occupations with missing information (BA, 2020). Each occupation is assigned to a blue circle (Software) and an orange diamond (AI). Their size is proportional to the number of employees in the respective occupational category in 2019. The blue and orange lines represent the coefficient of the slope of a simple linear regression that models the employees weighted relationship between the exposure measures and the skilled worker shortage indicator. All lines reveal positive slopes, indicating (weak) positive relations. We report Pearson’s correlation coefficients below the graphs, which measure the strength of a linear relationship between the exposure potentials and skilled worker shortage indicators. The greater the value is above zero, as measured here consistently, the stronger the positive linear relationship, with 1 representing a perfect positive linear relationship.
Source: Sample of Integrated Employment histories 2012–2019, Webb (2020), BA (2020), own calculations. © IAB

Discussion

In this policy brief, we examine the extent to which groups of employees who are subject to social security contributions in Germany were exposed to artificial intelligence technologies (AI) and software systems (without AI). We use indices for automation potential through AI or software - the "exposure scores" by Webb (2020). These indices measure the capacities of AI and software systems to substitute for worker tasks and thus capture the automation potential of occupations. Note that the measures do not quantify the actual adoption of these technologies; consequently, we provide insights referring to their potential use.

Our results show that highly qualified workers appear to be most exposed to AI, unlike software, which is higher for workers with low and medium qualification levels. Occupations with a higher share of female employees, which often require more comprehensive social, interpersonal and communication skills are exposed to a lesser extent as shown in low levels of AI and software exposure scores. The results also point to heterogeneity in the distribution of automation potential across industries; AI and software exposure are particularly high in manufacturing and construction sectors and low in the healthcare sector, reflecting the increasing use of in AI applications in industries, e.g. for controlling robotics, detecting errors, recognizing patterns, and more.

We also investigate the distribution of exposure scores against occupations with skilled worker shortages and find that occupations with pronounced shortages are more likely to be exposed than non-shortage occupations. Nonetheless, our analysis also shows that none of the observed occupations can be fully automated. AI and software rather support or replace specific activities but not the whole set of conceivable tasks that typically have to be performed in an occupation. Technologies are (still) reaching their limits, particularly in social or creative processes and in tasks that are not standardized. The relative potential of automation is particularly high for occupations in the IT sector. Software applications can also take over less skilled tasks in occupations with shortages of skilled labour, while AI could potentially perform mainly highly skilled tasks.

Understanding the potential consequences of the use of AI and other forms of automation technologies has important implications for labour market policies. One key aspect is to acknowledge that different automation technologies can have varying effects on different groups of employees and sectors, potentially increasing social inequalities.

In principle, the use of AI and software can increase productivity in certain occupations. Companies and employees should be supported to maximise the impact of these benefits. Possible measures include the promotion of retraining and (further) education programmes. This would allow employees who are potentially affected by automation to adapt to the changing qualification requirements. Jobseekers could also benefit from such measures.

Regarding bottleneck occupations, i.e. with shortages of skilled labour, further research should examine the extent to which the development and use of AI and software can reduce the shortages by taking over tasks that can be automatized and respective rebundling of the remaining tasks (job molding). Employers and employee's representation commitees have an important role to play here. This holds particularly when it comes to the organization accompanying measures and welfare services such as further training and counselling. In the case of corresponding advisory approaches, it should also be borne in mind that the implementation of new technologies is often costly, especially for small and medium-sized enterprises.

Up to this point, our analyses have focused on the potential of AI and software for different groups of employees. It is open yet how high relative exposure potentials relate to the labour market outcomes of the affected employees. Further research is planned to address potential wage effects and quantitative employment effects. As the field of AI is currently developing rapidly, the fast-paced spread of technologies on the labour market and their consequences should be continuously monitored by ongoing research.

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