Artificial intelligence, tasks, skills, and wages: Worker-level evidence from Germany ☆

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ABSTRACT

This paper examines how new technologies are linked to changes in the content of work and individual wages. As a first step, it documents novel facts on task and skill changes within occupations over the past two decades in Germany. We furthermore reveal a distinct relationship between ex-ante occupational work content and ex-post exposure to artificial intelligence (AI) and automation (robots). Workers in occupations with high AI exposure perform different activities and face different skill requirements compared to workers in occupations exposed to robots, suggesting that robots and AI are substitutes for different activities and skills. We also document that changes in the task and skill content of occupations is related to ex-ante exposure to technologies. Finally, the study uses individual labour market biographies to investigate the relationship between AI and wages. By exploring the dynamic influence of AI exposure on individuals over time, the study uncovers positive associations with wages, with nuanced variations across occupational groups, thereby shedding further light on the substitutability and augmentability of AI.

1. Introduction

Advanced technologies are transforming labour markets, altering the nature of work and the skills required to perform it. While the effects of automation – particularly robotics – on employment and wages are well-documented, the labour market implications of artificial intelligence (AI) remain far less understood. Unlike earlier automation technologies such as industrial robots, which primarily replace routine tasks, AI has the potential to augment human capabilities, fundamentally altering how tasks are performed and redefining occupational skill demands. This raises a key question: Will AI mimic the implications of robot adoption, or will its dynamics and implications for labour market outcomes – including the content of work, skill requirements, and wage trajectories – differ in fundamental ways?

In this paper, we address these questions by examining the specific implications of AI for work and wages, contrasting its effects with those of robot exposure. Using longitudinal data from Germany spanning two decades, we uncover substantial differences in how these technologies reshape occupations. Workers in occupations with high AI exposure perform markedly different tasks and require distinct skill sets compared to those in robot-exposed occupations, highlighting that robots and AI target different facets of work. While robot exposure is predominantly associated with reductions in manual and routine tasks, AI exposure is linked to shifts towards knowledge-intensive and cognitively demanding activities. Furthermore, the changes in task and skill content are closely linked to the pre-existing characteristics of occupations and their exposure to these technologies. By leveraging individual labour market biographies, we find that AI exposure is positively associated with wages, though the magnitude and nature of these associations vary significantly across occupational groups. These findings provide a nuanced perspective on the broader question: unlike robots, AI's augmentative potential may fundamentally transform the distribution of tasks, skills, and wage dynamics in the labour market.

To gain a deeper understanding of the mechanisms through which technologies affect labour market outcomes, we draw on the task-based

model introduced by Autor et al. (2003) and extended by Acemoglu and Autor (2011) and Acemoglu and Restrepo (2019). This framework identifies three main effects of new technologies: the substitution of labour by capital for automated tasks (displacement effect), an increase in demand for labour for non-automated tasks (productivity effect), and the creation of new tasks (reinstatement effect). The relative importance of the three effects determines the impact of automation on wages. This modelling of automation provides valuable intuition, but empirical evidence on changes in the task content within narrowly defined occupations remains scarce. [1] By systematically analysing how AI, and its subdomains, reshape task content and skill requirements, this paper contributes to closing this gap and provides critical insights into the evolving nature of work and wage inequality in the age of AI.

For our descriptive analysis, we make use of the German Qualifications and Career Surveys (BIBB-BAuA) conducted over the years 2006, 2012 and 2018, which are highly suitable for our purposes. Several important previous contributions have used the previous waves of the BIBB-BAuA and their detailed survey questions on occupational work content (Acemoglu and Pischke, 1998; Spitz-Oener, 2006; Gathmann and Schönberg, 2010). Besides detailed information on employees and their employers, the survey asks individuals about the performance of 18 time-consistent defined tasks and 8 different skill requirements. While tasks and skills are closely related, they represent distinct dimensions of work. Tasks reflect the specific activities workers perform, often dictated by firm demand, while skills capture the underlying competencies workers acquire through education, training, and work experience. This distinction is crucial in interpreting how technological exposure influences occupational changes over time. While the average number of tasks workers perform in their jobs remains constant over the years, we reveal a considerable change in the importance of tasks and skills within occupations. Specifically, knowledge-intensive or advanced activities (e.g., research and organise) become more important over time, especially in more recent years, while manual tasks related to for example manufacturing (e.g., producing and repairing) have declined in importance. Importantly, we also document substantial variation across occupations, in the extent to which the within-occupation task intensity changes over time. These differences help to explain the differential effects of new technologies on wages across different occupation groups (see below).

In a second step, we combine the BIBB-BAuA data with different measures for AI and robot exposure at the occupation level, to investigate how these new technologies are related to the task and skill content of jobs. For AI technology, we use the Dynamic Artificial Intelligence Occupational Exposure (DAIOE) index by Engberg et al. (2024), and, for robot technology, we make use of the robot index by Webb (2020).[2] Using the BIBB-BAuA from 2006 and technology data from 2017, we inspect the task and skill mix of occupations before the emergence of new technologies, thereby revealing which tasks are most likely be susceptible for automation. Interestingly, a striking pattern emerges. The relationship between ex-ante work content and ex-post AI exposure is a mirror image of the one between ex-ante work content

and ex-post robot exposure. Put differently, workers in occupations that face a high AI exposure in the future perform different activities and face different skill requirements, compared to occupations that are exposed to automation (robots) in the future. These differences are persistent, even when controlling for differences in the task and skill content of jobs across regions and industries, and when including individual controls, such as education or wages. In the final step of our descriptive analysis, we reveal that changes in the task content and skill requirements of occupations can be explained by the ex-ante exposure to new technologies.

Finally, we provide indirect evidence on tasks change due to new technologies, by analysing the consequences of these technologies for wages. We employ the sample of integrated labour market biographies (SIAB) provided by the Institute for Employment Research (IAB) in Germany. Specifically, we exploit the time-variance of the DAIOE index to uncover the associations between changes in AI exposure over time and individual wages, overall, and within occupations. Importantly, variation in AI exposure across and within narrowly defined occupations, allows us to control for worker, establishment and occupational fixed effects. Moreover, to address the possibility of establishments and workers systematically sorting and matching with one another, we perform AKM wage regressions (Abowd et al., 1999), which include additive fixed effects for workers and establishments. Overall, we find indications of positive effects of an increase in AI exposure on individual wages between the years 2010 and 2017. Reassuringly, these effects are not driven by any single of the several sub-indices of the DAIOE index, which capture exposure to different types of AI. We also reveal heterogeneous effects of changes in AI exposure across occupational groups. Specifically, we document wage decreases for professionals (occupations with task replacement) when their occupation is more exposed to AI progress, while wages for non-professionals (occupations with an increase in skill requirements) increase in tandem with increased AI exposure.

Our main contribution is to demonstrate how AI is related to changes in the detailed content and remuneration of work by exploiting uniquely granular and representative worker-level data for Germany as well as a measure of AI occupational exposure from Engberg et al. (2024). Thereby, the paper directly speaks to the expected substantial effects of AI on jobs and wages, while using data that obviate additional assumptions and limitations when, e.g., using online job ads data (Eloundou et al., 2024; OpenAI, 2023; Autor et al., 2022). Empirical evidence has so far been limited in the absence of granular data on firms and individuals (Seamans and Raj, 2018; Frank et al., 2019; Zolas et al., 2021; OECD, 2023). Research on how AI changes the work content and wages has therefore mainly been restricted to aggregate or occupational and state-level studies for the USA (e.g. Felten et al., 2021; Eloundou et al., 2024), while some recent studies use US online job ads or event studies of firms or industries (Lane and Saint-Martin, 2021).[3] Acemoglu et al. (2022) use US job ads data (2010–2018) to document that exposure to AI in 2010 is related to a subsequent churning of skills and a decrease in vacancy postings for non-AI-related jobs while finding no impact on occupational wages. Alekseeva et al. (2021) also use US job vacancy notes (2010–2019). They find a strong increase in demand for AI skills and an AI wage premium, in particular for managers and in combination with, e.g., software, cognitive and soft skills.[4]

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[1] This is mainly due to data limitations. While the Occupational Information Network (O*NET) allows us to identify the task content of occupations, it is not well suited for studying time variation within occupations. However, Consoli et al. (2023) combine the predecessor of O*NET, the Dictionary of Occupational Titles (DOT), and two versions of O*NET to identify within-occupation task changes in the routine intensity.

[2] Building on Felten et al. (2018, 2021), DAIOE uses metrics on the state-of-the-art performance over time of AI across different sub-fields of AI, such as language modelling or image classification, from AI research papers. The data on AI progress are then mapped to those *worker abilities*, such as reasoning or vision, to which AI is deemed to be most applicable. To estimate robot exposure, Webb (2020) uses natural language processing (NLP) techniques to link descriptions of patented inventions related to robotics to descriptions of work tasks across occupations.

[3] Experimental and quasi-experimental studies have recently emerged on the effects of generative AI in limited tasks related to writing, coding, consulting, customer services and medical diagnostics (Brynjolfsson et al., 2023; Dell'Acqua et al., 2023; Fraser et al., 2023; Gaube et al., 2023; Harskamp and De Clercq, 2023; Noy and Zhang, 2023; Peng et al., 2023).

[4] In addition, Babina et al. (2022) find that having employees with AI skills is associated with an up-skilling of the workforce, using US job ads and resume data (2016–2018). Finally, Fossen et al. (2022) use the patent-based measure

Furthermore, by comparing AI to robots, our study resonates well with recent evidence on the differential applicability of AI and robots across industries. For example, Akcigit et al. (2023) emphasise crucial differences between these two technologies. While robots are limited to automating repetitive manual tasks, AI's application spans various industries and complex tasks, and it therefore has the potential to transform a wide range of job types and industries. Furthermore, Bonfiglioli et al. (2023) study the effect of AI on employment across US commuting zones over the period 2000–2020, using a proxy for AI adoption. Their study reveals employment effects of AI adoption while controlling for the adoption of industrial robots and shows that robots are more prevalent in manufacturing and affect these industries, while AI is mostly in services and affect the whole economy. Our study complements these recent contributions, by highlighting differences among robots and AI at the level of occupations, namely that AI and robots are substitutes for different tasks and skills.

Our paper also contributes to the broader literature on AI and the labour market. Conceptually, according to the framework of Acemoglu and Restrepo (2019), AI may automate work tasks, raise productivity, or create new tasks. AI may also augment or assist workers in remaining tasks, increasing labour demand and wages (Bessen et al., 2022). By examining how workers' tasks and skills change in relation to AI exposure, our findings are in line with anecdotal evidence from limited surveys, where workers are more inclined to see advantages with AI in terms of efficiency and new or more interesting tasks, rather than the threat of AI automating their work tasks (SACO, 2023).[5]

The rest of the paper is organised as follows. Section 2 introduces the different data sources we employ throughout our empirical analysis. In Section 3 we present novel facts on the task content and skill requirements of occupations and their relation to new technologies. Section 4 provides evidence at the worker level on the link between AI exposure and wages. Section 5 concludes by summarising the main findings of our analysis, discussing the limitations of our study, and providing policy recommendations.

2. Data

We employ different data sources that provide information on the task content and skill requirements of occupations, the exposure of occupations to advanced technologies, and granular worker-level characteristics, over time. A common variable in all these data sources is information on detailed occupation codes, specifically the ISCO-08 occupation classification at different levels of aggregation. Throughout the paper we use the following levels of aggregation: 1. major group (1-digit) such as '8 - plant and machine operator, and assemblers'; 2. sub-major group (2-digit) such as '81 - stationary plant and machine operators'; 3. minor groups (3-digit) such as '815 - textile, fur and leather products machine operators'; and 4. unit groups (4-digit) such as '8152 - weaving and knitting machine operators'. We also study potentially heterogeneous associations between technology and the content of work for broader occupational groups, and classify workers

as knowledge-intensive business services (KIBS) workers, blue-collar workers, and other non-professionals.[6] As shown in Miles et al. (1995), KIBS work performed by e.g. accountants, architects and software developers, is intense in cognitive skills and human capital more broadly and could therefore be particularly exposed to AI, as indicated in recent experimental studies.[7]

2.1. Survey data on tasks and skill requirements of occupations

To carry out an in-depth analysis of the task content and the skill requirements within occupations, we make use of the German Qualifications and Career Surveys conducted over the years 2006, 2012 and 2018. The surveys are carried out over the phone by the German Federal Institute for Vocational Education and Training (BIBB) and the German Federal Institute for Occupational Safety and Health (BAuA). Each survey is based on around 20,000 employed people aged 15 and over with regular working hours of at least 10 h per week. The BIBB-BAuA reports detailed information on worker and employer characteristics.[8] Most importantly, we observe workers' responses to survey questions about the tasks they perform (or not) and the skills that are required (or not) in their occupation. The data allows us to distinguish between 18 different tasks, such as: Program a Computer; Developing, Researching, Constructing; and Transport, Store, Dispatch. The data also includes information on 8 different skill requirements, such as: Knowledge of project management; Knowledge in mathematics, calculus, statistics; and Commercial or business knowledge.

Appendix Table A1 provides information on the share of workers that perform a specific task and report specific skill requirements in their job and the respective changes between 2006 and 2018, while Table A2 provides summary statistics on basic worker characteristics, such as age, education or wage. We also compute the sum of tasks workers perform in their jobs, i.e., a measure of multitasking. As shown in Table A1 the average number of tasks workers perform in their job is 8.73. Previously, Becker and Muendler (2015) have used the BIBB-BAuA data for the survey years 1979 to 2006 and documented a sixfold increase in the average number of tasks performed over their sample period when using a similar task classification that accounts for 15 different activities. From 2006 onwards, however, the average number of tasks performed by workers remains rather constant. Specifically, using our task classification, the average task number is 8.70, 8.75, and 8.75 for the years 2006, 2012, and 2018.[9] However, as we show in Section 3, the task composition of jobs has substantially changed while leaving the average number of tasks unaffected.

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[6] Our classification of KIBS workers follows Engberg et al. (2023).

[7] See Brynjolfsson et al. (2023), Dell'Acqua et al. (2023) and Noy and Zhang (2023). Studying KIBS is also motivated by the fact that employment in KIBS is larger than employment in manufacturing in several countries and by KIBS distinguishing themselves in terms of high start-up rates compared to manufacturing, being the basis for tomorrow's larger companies (Audretsch et al., 2020).

[8] Specifically, for worker characteristics we use information on hourly gross wage (computed from information on the monthly gross wage and weekly working hours), 3-digit ISCO-08 occupation classification, education (measured in years of schooling), gender, marriage, age, work experience (measured in years in employment using the worker's age information and the years of education incl. training), the type of employment (worker, salaried employee, or civil servant), and part-time. Employer characteristics include the industry classification (61 different 2-digit NACE 1.1 industries), regional information (18 different NUTS 2 regions), and size groups (1 person, 2 p., 3 - 4 p., 5 - 9 p., 10 - 19 p., 20 - 49 p., 50 - 99 p., 100 - 249 p., 250 - 499 p., 500 - 999 p., 1000 and more p.).

[9] Using the same classification of 15 tasks as in Becker and Muendler (2015), the average task number is around 7.

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of occupational exposure to AI, software and robots of Webb (2020) to study individual-level wage changes in the USA (2016–2021). Their results indicate a positive relation between exposure to patentable AI and wage growth and the opposite for software and robots.

[5] Finally, we contribute by providing micro-level evidence from the largest country of the European Union (EU). Germany was early to promote and adopt advanced technologies like artificial intelligence, due to the launch of the "Industrie 4.0"-program in 2013. Like US firms, German firms, and especially the larger ones, could therefore be expected to be early adopters of advanced technologies like AI. Indeed, according to a report conducted by Rammer (2022), the share of AI-adopting firms in Germany was between 6%–10% around 2020. Moreover, Giering et al. (2021) use individual-level German survey data from 2019 and finds that up to 45% of workers already engage with AI technologies.

2.2. Occupational exposure to AI and robots

We also use existing measures on AI and robot exposure of occupations. Data on robot exposure at the 4-digit occupational level is obtained from Webb (2020), which is based on the similarity of robot patent texts and occupational task profiles in O*NET. The robot exposure measure does not account for temporal changes in robot exposure, as it is based on pooled patent data , disregarding the timing of patents.[10] While we use (Webb, 2020)'s measure as the best available proxy for occupational exposure to robots, we recognise that it reflects long-run exposure rather than short-term fluctuations.

AI exposure is obtained from the Dynamic Artificial Intelligence Occupational Exposure (DAIOE) index of Engberg et al. (2024). Building on Felten et al. (2018, 2021), DAIOE estimates AI exposure by mapping data on technological progress in AI to *worker abilities* in O*NET. According to Engberg et al. (2024), high exposure in the DAIOE model suggests that AI is likely to be applicable to the occupation, but predicting whether the exposure is likely to lead to substitution or augmentation of human labour is beyond the scope of the model. Important for our study and contrary to robot exposure, AI exposure is estimated by occupation and year, and we will exploit this time variation in our empirical analysis in Section 4, thus providing insights on the substitutability and augmentability of AI.

Fig. 1 illustrates variation in exposure across and within occupational groups for the year 2017 and reveals that more cognitive-oriented occupations, such as professionals or technicians, are more exposed to AI.[11] DAIOE also includes nine sub-indices that reflect exposure to sub-fields of AI, such as language modelling or image recognition. Even though our study is restricted to the years up until 2017/2018 (the last available wave of the BIBB-BAuA survey), we still cover a period of major breakthroughs in AI. For example, Roser (2022) provides a timeline on the appearance of notable AI systems, showing that language and image recognition capabilities of AI systems have developed rapidly from 2010 onwards.[12]

In our subsequent analysis, we will combine the two technology measures with information on the task content and skill requirements of jobs from the BIBB-BAuA data. Both technology measures provide occupational-level information on technology exposure to robots and AI. It should be noted, however, that the robots and AI measures are based on occupational task and ability characteristics, respectively, for the U.S. economy, using the O*NET database. This raises potential concerns about the suitability of these measures for Germany. Arguably, the reliability of such cross-country adaptations relies among other things on the geographical invariance of occupational work content and technology adoption.[13]

The literature suggests that cross-country differences in the task and ability content of occupations are small, especially for the group of developed countries. Specifically, for many European countries, Handel (2012) provide evidence that country-specific measures of occupational task content are similar to those in O*NET. More recently, Caunedo et al. (2023) show that this pattern is persistent for the group of developed countries, overall.[14] As regards the ability content of occupations, Georgieff and Hyee (2022) use the OECD's Survey of Adult Skills (PIAAC) for 36 occupational groups and 23 countries. They find differences across countries to be relatively small, except for the least AI-exposed occupations, such as cleaners. Therefore, there is little variation in their PIAAC-based AI occupational exposure measure across countries. For example, the overall AI exposure for Germany is only slightly lower than that for the USA. We find this similarity in the ability content of work across developed countries to be reassuring for the AI occupational exposure measure, which exploits occupational information about abilities, using O*NET.

To further validate the suitability of the US based technology measures for the German context, we provide additional evidence on the similarity between the task content of occupations between US and Germany. This is especially relevant for our robot occupational exposure measure, which uses occupational information from O*NET about the task content of work. Here, we make use of the BERUFENET expert databases provided by Dengler et al. (2014), as an alternative to operationalising tasks through surveys. Crucially, according to Dengler et al. (2014, p.22), "the BERUFENET expert database for Germany is comparable with the US expert database *Dictionary of Occupational Titles* (DOT) used by, e.g., Autor et al. (2003)".

BERUFENET provides five task-measures at the level of 3-digit occupations for the years 2011, 2012, and 2013: (i) analytical non-routine tasks, (ii) interactive non-routine tasks, (iii) cognitive routine tasks, (iv) manual routine tasks, and (v) manual non-routine tasks. For the BIBB-BAuA data, we follow Spitz-Oener (2006) and generate five similar task-measures based on the 18 different task indicators. By doing so, we obtain two measures for the task content of occupations, one based on the German survey data, and one based on an expert database. We correlate this aggregated measure at the two-digit occupation level for the year 2012 and provide a graphical visualisation for the five measures across the different occupational groups in Appendix Figure A2. We find a relatively high correlation between the task measure from BERUFNET and the one from BIBB-BAuA, and this both for the two classes of manual activities and for two out of the three classes of non-manual activities. Since robots primarily are used to automate physically oriented work, such as welding and physically moving objects, this is reassuring.[15] Taking stock, this provides an indication for a task similarity between BERUFENET and BIBB-BAuA and, due to the similarity between DOT and O*NET, an argument for applying the O*NET based technology robot occupational exposure measure to the German data.

In addition, regarding the geographical invariance of technology adoption, we reassuringly note that since the 1990s, the adoption of the internet, broadband and investments in ICT more generally, as well as the global integration of value chains have promoted more rapid dissemination of information, including innovations. An illustration of how rapidly technologies nowadays may spread across countries is the launch of ChatGPT from the company OpenAI in November 30,

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[10] A more dynamic approach would involve exploiting the time-dimension of patent filings. This would better capture how robot exposure changes over time, provided there would be enough time-variation in patent data. In addition, it could be valuable to use longitudinal occupational task data, but this may not be consistently available.
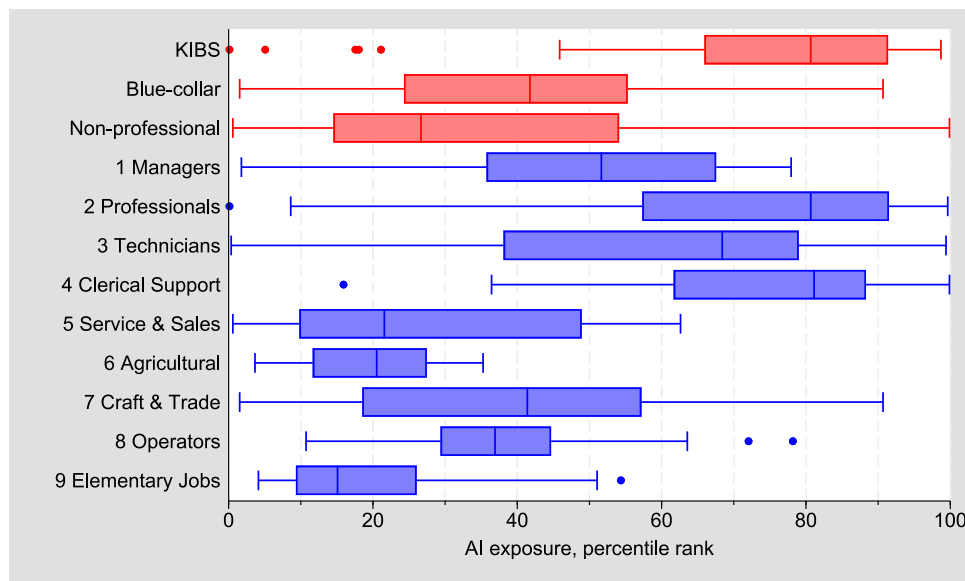
[11] A similar pattern for the occupational ranking in terms of AI exposure is observed for the year 2012 (see Appendix Figure A1).

[12] Further examples and evidence on the evolution of AI are provided in Chapter I. From GPT-4 to AGI: Counting the OOMs in SITUATIONAL AWARENESS: The Decade Ahead. See https://situational-awareness.ai/.

[13] To translate the exposure measures in Engberg et al. (2024) and Webb (2020) from the US occupational classification SOC 2010, to the less detailed international and EU equivalent ISCO-08, we take the simple average of occupations linked through the crosswalks. To analyse the impact of translation from more to less detailed occupational classifications, we have analysed the relationship between DAIOE and occupational characteristics at different aggregation levels. We find the results to be highly stable regardless of level of aggregation. This suggests that the structure of the occupation-level data is not significantly altered by the translation process.

[14] However, when comparing developed to developing countries, Caunedo et al. (2023) detect large differences in the task content of occupations, which likely are due to, e.g., differences in the adoption of new technologies among high- and low-income countries.

[15] The correlations are particularly high and positive for cognitive non-routine tasks and manual routine tasks. However, for cognitive routine tasks, the correlation is smaller (and negative). Specifically, the correlations between BIBB-BAuA and BERUFENET across 2-digit occupations are the following in the intensity of (i) analytical non-routine tasks: 0.634; (ii) interactive non-routine tasks: 0.561; (iii) cognitive routine tasks: −0.265; (iv) manual routine tasks: 0.618; and (v) manual non-routine tasks: 0.305.

Fig. 1. AI exposure by occupation group, 2017. *Notes:* The box plot illustrates the distribution of 4-digit ISCO-08 occupations' AI exposure (percentile rank) in the year 2017, according to the DAIOE index from Engberg et al. (2024), by occupation group. It includes (in red) the three broad occupation groups KIBS (Knowledge-Intensive Business Services), Blue-collar occupations, and Non-professional occupations; as well as (in blue) 1-digit ISCO-08 occupation groups. The vertical lines in each box represent the 25th, 50th (median) and 75th percentiles. Whiskers end at the minimum and maximum values, unless there are outside values, which if so are marked with points. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2022. ChatGPT was immediately made available in many countries, and within less than two months after having being launched, the company had more than 100 million subscribers to the new generative AI tool.[16]

2.3. Individual labour market data

In the final step of our analysis, we will provide worker level evidence on the implications of AI on wages. To do so, we employ the sample of integrated labour market biographies (SIAB), that is provided by the Institute for Employment Research (IAB). The SIAB is based on a 2% random sample of all individuals who have ever been registered in the German social security system. In combination with our time-varying AI exposure index, it will allow us to investigate the relationship between increasing AI exposure and individual wages, while controlling for a rich set of controls, such as worker-, plant-, and occupation fixed effects, and additive fixed effects for workers and plants following the estimation strategy introduced in Abowd et al. (1999). We follow Dauth and Eppelsheimer (2020) when preparing the SIAB, which, among other things, also includes that we deflate wages.[17] We restrict the sample to full-time workers liable to social security between the ages 20 and 60 and focus on those years that overlap with the BIBB-BAuA samples and with variation in our AI exposure index, i.e., 2010 to 2017. Summary statistics for the sample used in Section 4 are provided in Table 1.

3. Facts on skills, tasks, and new technologies

In this section, we make use of the BIBB-BAuA data in combination with the measures on occupational exposure to new technologies to provide novel facts on changes in the task content and skill requirements within occupations and how they are related to new technologies.

3.1. Task and skill changes within occupations

In a first step, we investigate how certain tasks and skill requirements become more or less important over time. To do so, we compute the relative change in the share of workers that report performing a specific task and report a specific skill requirement between the survey years 2006 and 2018 within different occupation groups. By separately documenting changes in both tasks and skills, we aim to highlight how the demand for work activities (tasks) and the human capital requirements (skills) evolve over time, potentially at different rates. Fig. 2 illustrates these changes for the 18 different activities and 8 skill requirements within the group of KIBS, blue-collar, and non-professional workers. In Appendix Figures A3, A4, A5, and A6, we repeat the exercise for 9 different ISCO-08 major groups and 35 different sub-major groups, by making use of inverse sampling weights (see Figures A7, A8, A9, A10, and A11)), and by restricting the analysis to the most recent period 2012 to 2018 (see Figure A12).

These figures document a considerable change in the importance of tasks and skills across and within occupations. For example, according to Panel (b) in Fig. 2, the share of blue-collar workers that report to organise, plan, or prepare (others' work), increased by close to 20% between 2006 and 2018, while the importance of manufacturing and producing goods declines by around 8%. Generally, tasks that are more knowledge-intensive or advanced, including information gathering, organising, and instructing, become more important over time, while manual tasks such as repairing and producing goods decline in importance. These figures also document substantial variation across occupations, in the extent to which the within-occupation task and skill intensity changes over time. For example, comparing Panel (a) and (c) in Fig. 2, it is evident that many tasks become less frequent for the group of KIBS workers, while for non-professional workers, the task displacement is offset as many other tasks become more important. To our knowledge, such changes in the task composition and skill requirements within and across narrowly defined occupations have not been documented so far in the literature.

What has caused such changes? An extensive literature argues that the emergence of new technologies, such as robots or AI, are the major driver. A common feature in theoretical contributions on these topics is that they build on the task-based framework, thereby modelling the

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Table 1
Summary statistics for regression samples on Section 4.
Source: SIAB 2010 to 2017.

Variable	Mean	Std. dev.	Min	Max
Log daily wage	4.7386	0.6957	2.6059	7.7855
Age	41.9219	10.6162	20	60
Experience	19.6219	9.8562	0	42
Indic.: Migrant	0.0724	0.2592	0	1
Indic.: Female	0.2961	0.4565	0	1
Indic.: Qual. for lower sec. school	0.6004	0.4898	0	1
Indic.: Qual. for FH or University w/o vocational qual.	0.0100	0.0993	0	1
Indic.: Qual. for FH or University with vocational qual.	0.1294	0.3357	0	1
Indic.: University of Applied Sciences (FH)	0.0303	0.1715	0	1
Indic.: University	0.1799	0.3841	0	1
Indic.: Switch plant	0.4010	0.4901	0	1
Indic.: Switch 4-digit occupation	0.6020	0.4895	0	1
Indic.: Rightcensored wage	0.1160	0.3202	0	1
Log plant employment	1.6017	0.4952	0	2.0794

Notes: The table reports summary statistics on individual outcomes for the sample used in regressions in Section 4. Daily wage is based on information in the data (daily wage/daily benefit) and deflated (base year 2015). As wages above the upper earnings limit for statutory pension insurance are right-censored, we replace right-censored wages with imputed wages, by following the methodology in Card et al. (2013). Age is computed from information on the year of birth. Information on education can be classified into The statistics are based on 2,508,165 observations.

displacement of tasks, the changing importance of remaining tasks, and the addition of new tasks.[18] Put differently, for this study, the task-based framework highlights that new technologies will change the task content of occupations as some activities are now performed, e.g., by robots, while workers can focus on the remaining non-automated and potentially new activities. Thus, it is crucial to understand (i) which tasks and skill requirements are potentially replaced by new technologies and (ii) how new technologies subsequently affect the task and skill mix of occupations. The following two subsections address these two questions.

3.2. New technologies and the task content and skill requirements of jobs

Advances in new technologies could be contributing to the changes documented in the previous subsection and we now investigate how technologies are related to the task content and skill requirements of jobs. Put differently, we link the task and skill mix of occupations before the emergence of new technologies, to the future exposure of these occupations to robots and AI. Thereby, we reveal which tasks are most likely to be susceptible to automation. While the literature argues that robots are most likely to replace routine manual tasks, less is known about which tasks might be replaced by AI, and how AI and robots differ in their ability to automate tasks. To address these questions, we combine information on AI and robot exposure with our BIBB-BAuA data from 2006, to investigate how new technologies (AI & robots) are related to the likelihood that workers perform specific tasks or are required to have specific skills. We therefore combine information on AI and robot exposure with our BIBB-BAuA data from 2006, to investigate how new technologies (AI & robots) are related to the likelihood that workers perform specific tasks or are required to have specific skills.[19] Specifically, we run $18 + 8$ probit regressions at the worker level. For each of these, we regress the indicator variable for worker i in occupation o performing a specific task or facing a skill requirement in 2006 (Indic. task/skill$_{io}^{2006}$) on occupational AI and robot exposure in 2017 (Exp$_o^{2017}$), including a set of worker $\mathbf{x_i}$ and plant $\mathbf{z_j}$ attributes:

$$\text{Indic. task/skill}_{io}^{2006} = \beta' \text{Exp}_o^{2017} + \gamma' \mathbf{x_i} + \lambda' \mathbf{z_j} + \epsilon_{io}. \quad (1)$$

Thus, we relate the task content and skill requirements of jobs in 2006, i.e., before new technologies changed occupational activities and skill requirements, with recent technology exposure. Variation comes from differences in AI and robot exposure across 3-digit occupations measured in 2017 and the coefficient β' reflects the correlation between AI or robot exposure and the likelihood of performing a specific task in 2006. A positive (negative) coefficient indicates that performing this activity or requiring this skill is related to a higher (lower) likelihood of exposure to AI or robots in the future and therefore a higher (lower) likelihood that AI or robots are substitutes or complements for these tasks and skills in the future.

We present estimates of these 26 regressions graphically. Fig. 3 reports coefficients for AI-exposure (Panel a and c) and robot exposure (Panel b and d) from estimating the probit regressions described above, while including industry, region, plant size and worker controls. In Fig. 3, we document associations between the likelihood of performing certain tasks or requiring specific skills and the level of occupational exposure to AI and robots. However, the relationship between work content and AI exposure is a mirror image of the one between work content and robot exposure. Whereas more knowledge-intensive tasks – tasks 1 to 9 – tend to be more prevalent in occupations that are more exposed to AI, they are less commonly observed in occupations with greater exposure to robots. Turning to skills, the ones that are more likely to be carried out with higher AI exposure include leadership, digital, advanced cognitive and language skills, as well as skills in the commercial or business domain. These skills are arguably typically associated with positions in the upper hierarchy of organisations, including management, but also specialists and analysts. Those are also the kinds of occupations that belong to the KIBS category. Once more, these patterns are the opposite of robot exposure. The more exposed the occupation is to robots, the less likely it is that skills in the area of, e.g., leadership and language, are required.

In the Appendix, we provide different versions. Figure A13 and A14 show estimates from regressions without all controls, or without worker controls, respectively. Figures A15, A16, and A17 is repeating the exercise for the groups of KIBS, Blue-Collar, or Non-professional occupations. Figure A20 is using the AI exposure from Felten et al. (2018). In Figures A18–A19, we also add the software exposure measure from Webb (2020) to check that the AI exposure measure does not only capture digitisation generally, and include 1-digit occupational fixed effects, respectively. Finally, we also use information available in the BIBB-BAuA survey 2006, about technological change in the workplace. Specifically, individuals are asked if the firm introduced new computer programs or new manufacturing or new machines or plants. By generating Fig. 3 for the group of non-exposed workers

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[18] See, Autor et al. (2003) and further developments of the task-based model by Acemoglu and Autor (2011) as well as Acemoglu and Restrepo (2019).

[19] As the BIBB-BAuA data only provides 3-digit occupation codes, we compute simple averages of the different technology measures across 4-digit occupations, to obtain exposure measures for 3-digit occupations.

(a) KIBS − Tasks (b) Blue-collar − Tasks (c) Non-professional − Tasks

(d) KIBS − Skills (e) Blue-collar − Skills (f) Non-professional − Skills

Fig. 2. Changes in the task composition and skill requirements. *Notes:* Panel a–c (d–f) illustrates the change in the share of workers that report performing a specific task (report a specific skill requirement) between 2018 and 2006 within the group of KIBS (knowledge intensive business services), Blue-collar, and Non-professional occupations.
The 18 different tasks are: (1) Program a Computer; (2) Computer use; (3) Developing, researching, constructing; (4) Gathering information, researching, documenting; (5) Organise, Plan, Prepare (others' work); (6) Purchase, Procure, Sell; (7) Consult & Inform; (8) Train, Teach, Instruct, Educate; (9) Advertise, Promote, Conduct Marketing & PR; (10) Protecting, guarding, monitoring, regulating traffic; (11) Repair, Maintain; (12) Entertain, Accommodate, Prepare Foods; (13) Nurse, Look After, Cure; (14) Cleaning, waste disposal, recycling; (15) Measure, Inspect, Control Quality; (16) Manufacture, Produce Goods; (17) Transport, Store, Dispatch; (18) Oversee, Control Machinery & Techn. Processes.
The 8 different skill requirements are: (1) Legal knowledge; (2) Knowledge of project management; (3) Knowledge in the medical or nursing field; (4) Knowledge in mathematics, calculus, statistics; (5) Knowledge of German, written expression, spelling; (6) Knowledge of PC application programs; (7) Technical knowledge; (8) Commercial or business knowledge.
Source: Authors' computations based on 14,722 individuals from BIBB-BAuA survey waves 2006 and 2018.

in 2006, we control for the fact that technologies (e.g., robots) have already changed the task composition of occupations in 2006. The resulting estimates in Figure A21 confirm the patterns revealed in Fig. 3.

Taking stock, by combining our task and skill data with occupational exposure to advanced technologies, our results reveal that workers in occupations with a high AI exposure have performed different tasks and had different skill requirements, compared to occupations with a high robot exposure. The probit analysis, thus, serves two purposes: first, it validates the hypothesis that the pre-existing task and skill content of occupations influences their susceptibility to new technologies. Second, it uncovers differences between AI and robots in their relation to specific tasks and skills, revealing AI's tendency to augment knowledge-intensive and cognitive activities, while robots are more closely associated with replacing manual and routine tasks. While AI and robots have distinct effects on tasks and skills, our findings show that these effects move in the same direction—AI exposure increases both knowledge-intensive tasks and the associated skill requirements, whereas robot exposure reduces manual tasks and related skills. This consistency suggests that firms adjust both the demand for tasks and the required skills in parallel, rather than one changing at the expense of the other. These insights bridge the descriptive evidence in Section 3.1 with the analysis of how technology-induced changes in tasks and skills evolve in the following section.
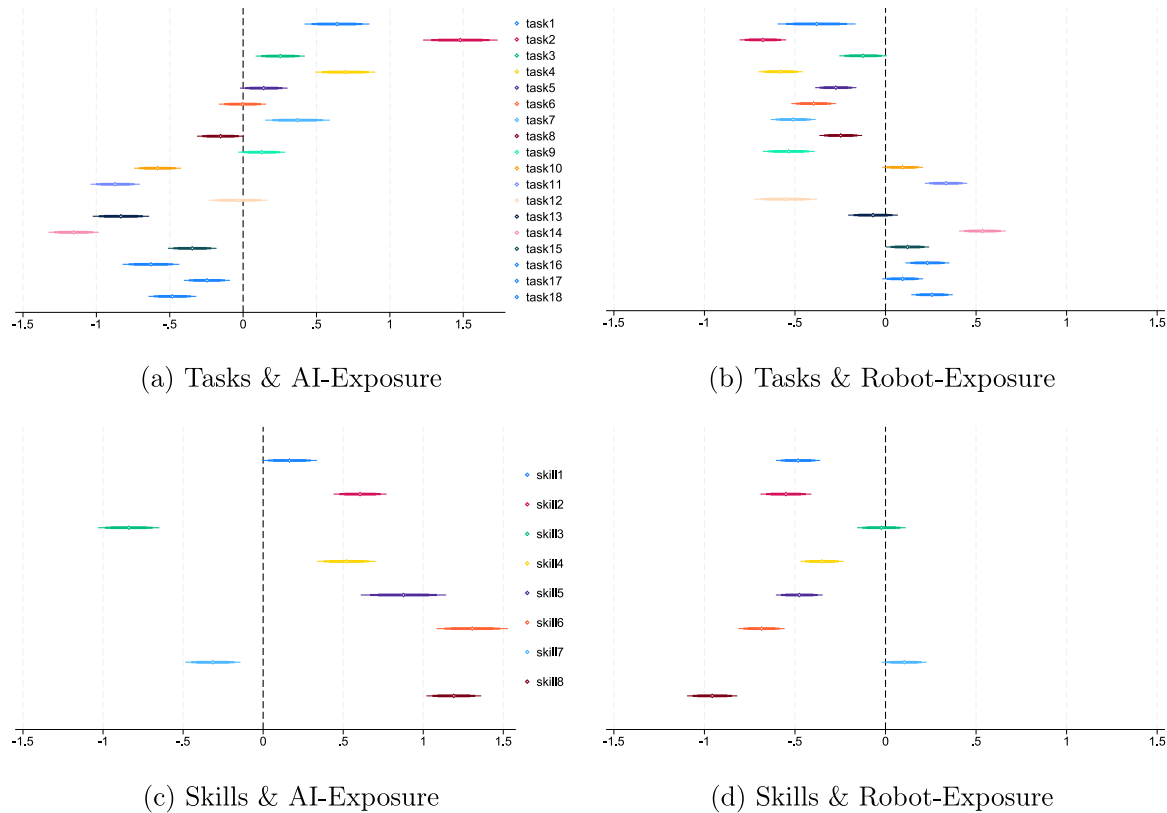
3.3. New technologies and changes in the task content and skill requirements of jobs

So far, our analysis has revealed substantial changes in the task content and skill requirements of occupations between 2006 and 2018

(see Section 3.1), and that AI and robots might be substitutes or complements for and complement workers in different tasks and skills (see Section 3.2). In a last step, we now aim to investigate if changes in the task content and skill requirements of occupations can be explained by the ex-ante exposure to new technologies. Therefore, we use the technology exposure from the beginning of the available period (2010) and relate it to subsequent changes in tasks and skills.

Ideally, one would track workers in the BIBB-BAuA data over time to see if the same worker is performing different activities and faces different skill requirements in the same job and relate this to technology exposure. However, the BIBB-BAuA data provides representative repeated cross-sections and we therefore aggregate the data to the 3-digit occupation level. Specifically, we compute the share of workers who reported to perform a specific task and face a specific skill requirement across 3-digit occupations in 2012 and 2018. Importantly, to compute the averages in 2012 (2018), we restrict the sample to workers in firms that did not (did) introduce new computer programs or new manufacturing or new machines or plants recently. We then compute the absolute relative change for each task and skill between 2018 and 2012 and add up these changes across the 18 tasks and the 8 skills. As one can meaningfully add up the different tasks to obtain a measure for multitasking, and as multitasking differs across occupations, we relate the task change to the average number of tasks within a job. For skills, we just divide the skill change by 8, to normalise it by the overall number of skill requirements. Formally, we derive the task change within occupation o as

$$tc_o = \frac{\sum_{i=1}^{18} \left[|task_{io}^{2018} - task_{io}^{2012}| / task_{io}^{2012} \right]}{\overline{task}_o}, \tag{2}$$

(a) Tasks & AI-Exposure

(b) Tasks & Robot-Exposure

(c) Skills & AI-Exposure

(d) Skills & Robot-Exposure

Fig. 3. Task, Skills, and ex-post exposure to technology. *Notes:* The figure plots the coefficients of AI-exposure (Panel a and c) and robot exposure (Panel b and d) from estimating probit regressions on the probability of 18 task performance and 8 skill requirement indicators, controlling for industry, region, plant-size and worker controls (incl. log hourly wage, education, age (-squared), experience (-squared, -cubic, - quartic), married, part-time, gender, and type of employment). Thick, medium, and thin lines represent the 99, 95, and 90 percent confidence intervals.
The 18 different tasks are: (1) Program a Computer; (2) Computer use; (3) Developing, researching, constructing; (4) Gathering information, researching, documenting; (5) Organise, Plan, Prepare (others' work); (6) Purchase, Procure, Sell; (7) Consult & Inform; (8) Train, Teach, Instruct, Educate; (9) Advertise, Promote, Conduct Marketing & PR; (10) Protecting, guarding, monitoring, regulating traffic; (11) Repair, Maintain; (12) Entertain, Accommodate, Prepare Foods; (13) Nurse, Look After, Cure; (14) Cleaning, waste disposal, recycling; (15) Measure, Inspect, Control Quality; (16) Manufacture, Produce Goods; (17) Transport, Store, Dispatch; (18) Oversee, Control Machinery & Techn. Processes.
The 8 different skill requirements are: (1) Legal knowledge; (2) Knowledge of project management; (3) Knowledge in the medical or nursing field; (4) Knowledge in mathematics, calculus, statistics; (5) Knowledge of German, written expression, spelling; (6) Knowledge of PC application programs; (7) Technical knowledge; (8) Commercial or business knowledge.
Source: Authors' computations based on a sample of 11,125 individuals from the BIBB-BAuA survey wave 2006. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg et al., 2024). Occupational robot exposure is based on the index from Webb (2020).

where $task_{io}$ is the share of workers that report performing task i in occupation o in a given year, and $\bar{task}_o$ is the average number of tasks workers perform in an occupation across the years 2012 and 2018.[20] In a similar way, we derive the skill change for occupations. The derived mean task (skill) change across all 3-digit occupations is 0.757 (0.334) with a standard deviation of 0.729 (0.130). These measures give us some indication about the extent of task and skill changes for different 3-digit occupations between 2012 and 2018 and we relate these changes to the technology exposure in 2010.[21] Results of this exercise are illustrated in Fig. 4.
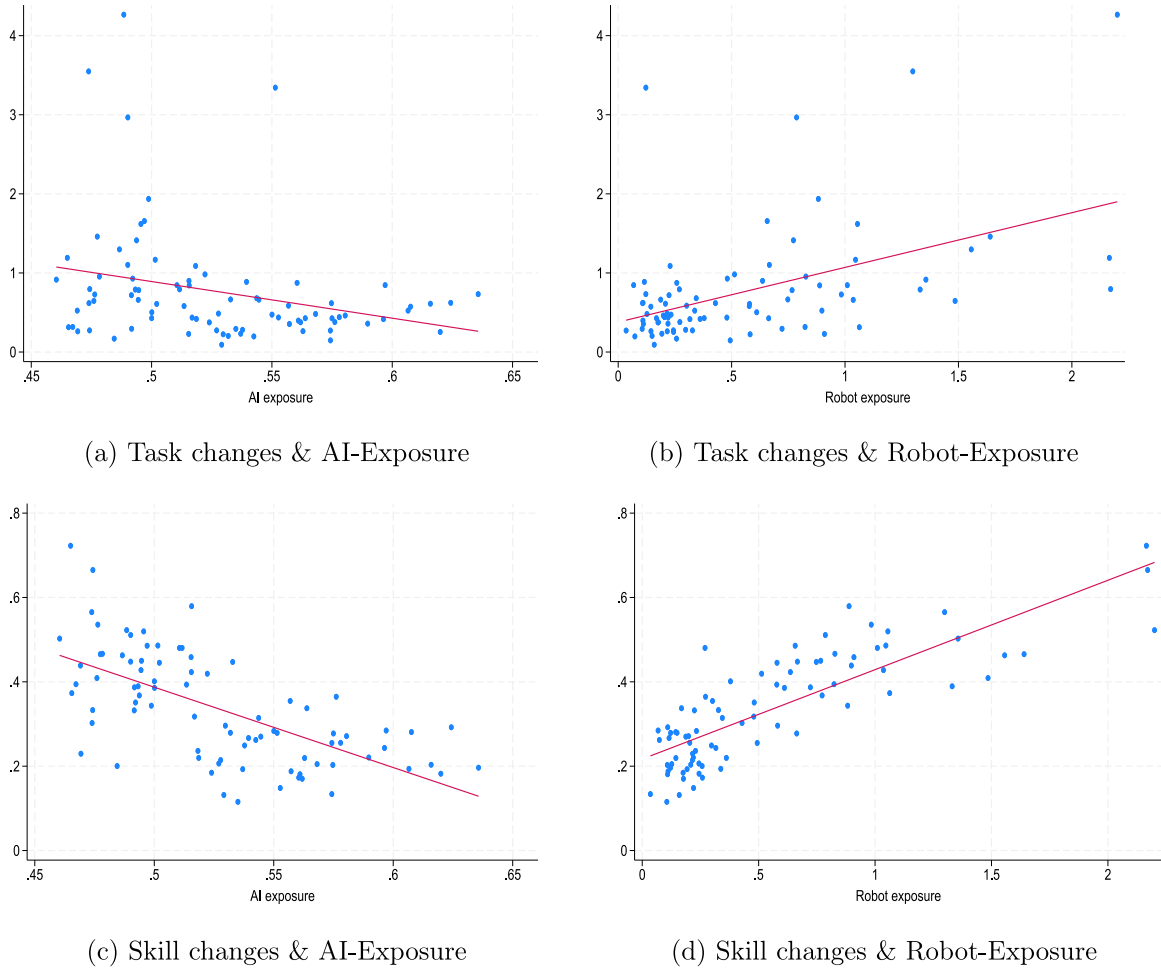
From inspection of Panel (a) and (b) in Fig. 4, we see that within-occupational task changes are weakly negatively (positively) related to AI (robot) exposure. A similar pattern emerges when examining changes in skill requirements: as shown in Panel (c) and (d), skill

changes follow the same directional relationship as task changes for each technology. However, changes in the skill requirements in occupations are less pronounced in occupations with initial high AI exposures. Looking at Panel (a) and (d), we see that occupations that are highly exposed to robots experience larger changes in both tasks and skills. The difference may arise because robots tend to replace entire tasks, leading to larger and more immediate occupational adjustments, while AI often may be integrated as an augmentative tool, resulting in more gradual changes in tasks and skills. Robot adoption is more common in routine, manual jobs, where automation can fully substitute tasks, whereas AI exposure (currently) is more prevalent in knowledge-intensive occupations, where adjustments possibly occur incrementally. Overall, while keeping in mind the data limitations that we face, these results would seem to support that changes in the task content and skill requirements of occupations are related to the exposure of occupations to emerging technologies.

According to the task-based framework, new technologies not only affect tasks done by labour but also individual wages. Wage increases (declines) are more likely if the productivity and reinstatement effect of automation outweigh (fall behind) the displacement effect. Thus, analysing the possible consequences of technologies on wages provides an additional perspective on the underlying task and skill changes, complementing our direct analysis of occupational shifts. This is the aim of the next section.

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[20] Note that, as discussed above, the number of tasks is constant across the years, and we therefore average the number of tasks across both survey years. Similar results are obtained when we only use 2012 to compute the average number of tasks for an occupation.

[21] The DAIOE index provides yearly information on AI exposure and we use the first year available in the data, i.e., 2010. This is, however, not possible for the time-invariant robot measure from Webb (2020).

Fig. 4. Technology exposure and ex-post changes in tasks and skills. *Notes:* Panel a and b (c and d) illustrate the average change in the share of workers that report performing a specific task (report a specific skill requirement) between 2018 and 2012 across 18 tasks and 8 skills. Each dot refers to one 3-digit occupation. The average change is then related to AI exposure (Panel a and c) or robot exposure (Panel b and d).
Source: Authors' computations based on BIBB-BAuA survey waves 2012 and 2018. Occupational AI exposure is based on the DAIOE measure from 2010 (Engberg et al., 2024). Occupational robot exposure is based on the index from Webb (2020).

4. AI and wages – Worker level evidence from Germany

In the final stage of our analysis, we now turn our attention to the dynamic nature of our AI exposure measure over time. Specifically, we examine how AI exposure has evolved from 2010 to 2017 within 4-digit occupations. This nuanced variation within and across narrowly defined occupations serves as a crucial factor in identifying the impact of AI on wages. To estimate the association between AI exposure and individuals' wages, we make use of the SIAB data set, as introduced in Section 2.3, in combination with the DAIOE measure to estimate the following Mincer wage regression:

$$\ln(\text{wage})_{iojt} = \beta' \text{Exp}_{ot} + \gamma \mathbf{x_{it}} + \lambda' \mathbf{z_{jt}} + \phi_t + \theta_o + \delta_j + \alpha_i + \epsilon_{iojt}, \quad (3)$$

where workers are indexed by i, occupations by o and plants by j. The outcome variable, $\ln(\text{wage})_{iojt}$ is the log daily wage of worker i employed by plant j at time t and the key independent variable, Exp_{ot}, refers to occupation-specific changes in the time-varying AI index (DAIOE). To isolate the effect of AI on wages we employ an extensive set of fixed effects, including time (ϕ_t), 4-digit occupation (θ_o), establishment (δ_j), and worker (α_i) fixed effects. Furthermore, all regressions include time varying worker ($\mathbf{x_{it}}$) and establishment ($\mathbf{z_{jt}}$) controls. The latter assist us in controlling for establishment exposure to other technologies, such as computer and cloud services use, which are known to be correlated, e.g., with establishment size (Acemoglu et al., 2023). The worker-fixed effect captures time-invariant characteristics,

such as productivity, task performance and skills. As our AI exposure varies across occupations, we cluster standard errors at the 4-digit occupational level. This comprehensive approach strengthens our ability to discern and quantify the influence of AI exposure on wage dynamics across different occupational categories.

Table 2 presents results where we exploit time-variation in AI exposure of occupations to estimate the influence on wages. More exposure to AI is positively and statistically significantly linked to a higher wage (Column 1). A one standard deviation (SD = 2.07) increase in exposure is approximately associated with an 1.96 percent increase in wage.[22] This benchmark result is, as mentioned, from an estimation where we control for a range of known factors that may confound results in Mincer-type regressions. However, adding further or alternative restrictions on the estimations only marginally affects the results. Even when we require the worker to remain in the same occupation (Column 2) or same occupation and plant (Column 3), as well as being in the sample for eight years (Columns 4 to 6), the results are virtually identical in magnitude and they remain statistically significant. Importantly, by additionally restricting the sample to plant and occupation-stayers, we mitigate potential confounding effects on wage

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[22] A one standard deviation increase is, e.g., equivalent to the difference in AI exposure between policy administration professionals and software developers.

Table 2
AI exposure and wages.
Source: SIAB 2010–2017 restricted to full-time workers, liable to social security.

	Log daily wage					
AI-Exposure$_t$	0.00936	0.0162	0.0166	0.00799	0.0104	0.00949
	(0.00187)	(0.00234)	(0.00250)	(0.00281)	(0.00376)	(0.00402)
Observations	2,433,676	973,680	755,523	1,072,298	343,213	260,488
R-squared	0.913	0.927	0.925	0.893	0.909	0.905
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Worker controls	Yes	Yes	Yes	Yes	Yes	Yes
Plant controls	Yes	Yes	Yes	Yes	Yes	Yes
Worker fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Plant fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
4-digit occupation fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Same 4-digit occupation	No	Yes	Yes	No	Yes	Yes
Same plant	No	No	Yes	No	No	Yes
8 years in sample	No	No	No	Yes	Yes	Yes

Notes: The dependent variable in all columns is the log daily wage (deflated to base year 2015). Occupational AI exposure is based on the DAIOE measure of Engberg et al. (2024). Worker controls include time-varying controls, such as experience (-squared, -cubic, - quartic), education, and age (-squared), and indicator variables for the same plant and same 4-digit occupation, and an indicator variable for right-censored wage. Plant controls include (log) number of workers, industry (3-digit NACE Rev.2) and region (NUTS 3) fixed effects. Standard errors clustered at the 4-digit occupation are given in parentheses.

shifts and employment turnover during the same period that may arise from other factors such as export growth, increased immigration, and the transition to renewable energy. In the Appendix, we also control for spell (i.e., worker-plant) fixed effects, and find similar associations (see Table A3). We interpret this finding of AI exposure being associated with an increase in worker wage as either the result of a strong productivity effect — where AI contributes to automation in the sense of task substitution — or from a reinstatement/augmentation effect, where AI enhances worker productivity by complementing existing tasks rather than replacing them.

We expect that the differential progress in AI across its subdomains during the study period also heterogeneously affects wages. Major breakthroughs occurred, for example, in image recognition, with AlexNet employing a neural network to win the ImageNet competition in 2012 (Krizhevsky et al., 2012), in strategy games, with AlphaGo defeating the human world champion in the game of Go in 2016 (Silver et al., 2016), and in machine translation, where major milestones were reached with the introduction of neural machine translation (Google, 2016). Benefiting from the availability of sub-indices of the DAIOE measure, we therefore rerun the wage regression from Table 2, with the results displayed in Table 3. First, we comfortingly notice that the positive and statistically significant association between AI exposure and wages is present also for most sub-indices.[23] Second, we also note a relatively large variation in the estimated coefficients. The largest coefficients are to be found for strategy games (0.0924), image recognition (0.694) and translation (0.0422), and the smallest ones for reading comprehension (0.0192) and video games (−0.00824). The results indicate that exposure to different AI-areas is heterogeneously affecting workers' wages, even when meticulously controlling for confounding factors at the worker and plant level. This could be because of differential progress in AI or differential adoption and usefulness of different types of AI.

In the Appendix, we also analyse the link between AI and wages separately for different occupational groups (see Table A5 for the group of KIBS, Blue-collar, and Non-professionals, and Table A6 for different 1-digit occupation groups). Analysing the association between AI exposure and wages for different occupational groups reveals distinct patterns, indicating varied outcomes for different workforce segments. Notably, among KIBS workers, there is an observed decrease in wages, while for blue-collar workers, there is no significant change. These findings speak to the task-replacement effect revealed for KIBS workers in Fig. 2. Conversely, non-professional workers, for whom we saw an

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[23] See Appendix Table A4 for p-values related to Table 3.

Table 3
AI subfield exposure and wages.
Source: SIAB 2010–2017 restricted to full-time workers, liable to social security.

	Log daily wage		
AI-stratgames$_t$	0.0947	0.0895	0.0924
	(0.0574)	(0.0574)	(0.0573)
AI-videogames$_t$	−0.0101	−0.00714	−0.00824
	(0.0199)	(0.0199)	(0.0199)
AI-imgrec$_t$	0.0756	0.0696	0.0694
	(0.0349)	(0.0349)	(0.0439)
AI-imgcompr$_t$	0.0287	0.0262	0.0265
	(0.0130)	(0.0130)	(0.0130)
AI-readcompr$_t$	0.0201	0.0185	0.0192
	(0.00968)	(0.00968)	(0.00967)
AI-lngmod$_t$	0.0326	0.0296	0.0307
	(0.0162)	(0.0162)	(0.0162)
AI-translat$_t$	0.0450	0.0407	0.0422
	(0.0208)	(0.0208)	(0.0208)
AI-speechrec$_t$	0.0233	0.0210	0.0217
	(0.0111)	(0.0111)	(0.0110)
Observations	559,686	539,920	528,530
R-squared	0.950	0.949	0.948
Year fixed effects	Yes	Yes	Yes
Worker controls	Yes	Yes	Yes
Plant controls	Yes	Yes	Yes
Worker fixed effects	Yes	Yes	Yes
Plant fixed effects	Yes	Yes	Yes
4-digit occupation fixed effects	Yes	Yes	Yes
Same 4-digit occupation	No	Yes	Yes
Same plant	No	No	Yes

Notes: The dependent variable in all columns is the log daily wage (deflated to base year 2015). Occupational AI exposure is based on DAOIE index and its respective subfields (Engberg et al., 2024). Worker controls include time varying controls, such as experience (-squared, -cubic, - quartic), education, and age (-squared), and indicator variables for same plant and same 4-digit occupation, and an indicator variable for right-censored wage. Plant controls include (log) number of workers, industry (3-digit NACE Rev.2) and region (NUTS 3) fixed effects. Standard errors clustered at the 4-digit occupation are given in parentheses.

increase in focus on some white-collar tasks, witness a wage increase. These are workers for whom AI exposure is associated with a marked up-skilling (see Figure A17). A more granular analysis reveals that technicians, clerical support and services, and sales agent workers experience a wage increase when their occupation is more exposed to AI progress. In contrast, professionals and operators see a decline in wages. Overall, these findings align with the findings of Babina et al. (2022), suggesting that increased investment in AI contributes to

organisational flattening, characterised by fewer middle-management layers. This shift occurs as workers, aided by technology, become more adept at independently solving problems.

Finally, we also split occupations according to the relative task change to investigate if the revealed wage effects are related to changes in the task composition of jobs, as documented in the previous section. Specifically, we use the BIBB-BAuA data to measure the absolute relative task change of occupations between 2006 and 2018 (similar to Section 3.3) and split occupations along the median into low and high task-churning occupations, i.e., into occupations in which the change in the task composition is minor or strong, respectively.[24] For occupations characterised by limited task changes, positive wage effects may be anticipated. With relatively stable work content, workers are more likely to accumulate experience that enhances their task performance. Moreover, these low-churn occupations may involve higher levels of non-routine cognitive or interpersonal skills, which are likely to complement AI technologies. By augmenting workers in these tasks, AI can increase productivity and potentially lead to higher wages.[25] Conversely, high-churn occupations may experience negative wage effects, as frequent changes in tasks can disrupt the alignment between workers' skills and job requirements. In addition, such occupations are likely characterised by tasks that are more routinised, repetitive, and easily automated. In these occupations, AI may function as a substitute rather than a complement, reducing the demand for workers performing these tasks.[26] Results of this exercise are shown in Table 4.

Comparing estimates in Panel A and Panel B for low- and high-task-churn occupations, respectively, reveals some interesting insights. In Panel A, the results for occupations with fewer task changes, as observed in the BIBB-BAuA survey data, largely resemble those presented in Table 2. Estimates presented in columns (1) to (6) are positive, statistically different from zero, and of a similar magnitude to those in Table 2. The picture, however, looks somewhat different in Panel B, which is for high-task-churn occupations. While estimates in Panels A and B are relatively similar when using the full sample of workers (columns 1 to 3), the result in column (6) of Panel B is different from that in Panel A. As discussed above, column (6) restricts the sample to workers who remain in the same plant and 4-digit occupation for the full observation period. This specification is designed to mitigate potential confounding from macroeconomic developments, such as export growth, immigration, or energy transition, that could otherwise influence observed wage dynamics. In Panel B, for this restricted sample of workers – those observed throughout the full sample period who remain in the same plant and occupation – AI is negatively associated with wages, as the

task content of these occupations changes substantially. This negative association appears only under the very restrictive requirements of column (6), where worker mobility is by construction limited. In high-churn occupations, where tasks evolve rapidly, this immobility likely leads to skill mismatches that are amplified by AI exposure. Lacking the option to adapt through job transitions or retraining, these workers may be increasingly substituted by AI, which puts downward pressure on wages. Arguably, this negative association is only present for a very specific sample of workers that abstracts from reallocation of workers across industries, firms, and occupations. In contrast, in the less restrictive samples (columns 1–5), such reallocation is possible, which may cushion the adverse wage effects. Still, it provides a first indication that the extent of the task adjustments might moderate the relation between AI exposure and wages.[27] A more in-depth analysis that investigates, for example, the impact of AI on movements across industries, firms, and occupations is beyond the scope of this paper, primarily due to data limitations. However, exploring the relationship between task adjustments and wage effects at a granular level, particularly in the context of modern technologies, presents a promising direction for future research.

5. Concluding remarks

This paper examines how new technologies affect the content of work and earnings, using granular, large-scale, and representative worker-level data for Germany as well as a measure of AI occupational exposure. It complements studies using online job ads data and event studies of certain firms or industries, typically for the USA. The study indicates differences in the way AI and robots substitute for different activities and skills within narrowly defined occupations. It further documents that changes in the task and skill content of occupations are related to ex-ante exposure to technologies. Finally, we explore how changes in occupational exposure to AI are associated with individuals' wages, finding an overall positive and yet heterogeneous link between AI exposure and individual wages. The findings in this paper highlight that AI and automation exposure is associated with both detailed changes in what workers do at work and changes in earnings.

Based on our findings, policymakers should focus on mitigating the negative effects of AI-driven task transformations by promoting reskilling and upskilling initiatives tailored to occupations with high AI exposure, particularly in professional, technical, and administrative services, where AI is reshaping work content but not necessarily displacing jobs outright. We identify cognitive and analytical skills (e.g., legal knowledge, project management), communication and language skills, and digital proficiency (e.g., PC application programs) as being positively associated with AI exposure. Targeted investments in these areas will be crucial for ensuring that workers can adapt to AI-driven task transformations and benefit from productivity-driven wage growth. Germany's "AI Strategy" (Künstliche Intelligenz Strategie) and the EU's "Digital Education Action Plan" already emphasise AI-related skills development, but expanding these efforts to include sector – and occupation-specific AI training – particularly for knowledge workers and administrative roles–could promote workers to more fully capitalise on AI-driven productivity gains. Given that AI exposure is associated with heterogeneous wage effects, targeted policies should also focus on reducing skill mismatches and ensuring that AI-driven productivity gains translate into broad-based wage growth. This may involve employer incentives to invest in AI-related workforce training,

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[24] The classification of occupations in the BIBB-BAuA data is based on minor ISCO groups (3-digit). We therefore classify all unit groups (4-digit) which are part of the higher level minor group in the SIAB data as low or high task-churning occupations. We also generate a similar measure for skill changes. However, the classification of occupations into low or high skill changes overlaps to a large extend with the low or high task-churning measure, why we present results only for the sample split based on the task-churning measure. We have also verified that the classification of occupations into low and high task churning looks similar when studying the period 2012 to 2018.

[25] This is in line with Felten et al. (2018), who provide evidence that AI enhances productivity in tasks that require non-routine cognitive skills. They discuss how AI complements jobs that involve creative thinking, decision-making, and complex problem-solving, particularly in sectors where AI is used to assist rather than replace human labour. Furthermore, Acemoglu et al. (2022) show that AI affects job tasks and wages by analysing job vacancy data. Here AI tends to complement high-skill, non-routine cognitive tasks, especially in managerial and professional roles, while having more disruptive effects on lower-skill, routine tasks.

[26] This is in line with Acemoglu and Restrepo (2019), where task displacement, particularly in routine-intensive occupations may occur. The displacement of workers from these tasks, without a corresponding increase in demand for complementary roles, would then exert downward pressure on wages.

[27] It is worthwhile to note again that the task data cannot be matched with the SIAB data at the individual level. Thus, we can only use task measures at the 3-digit occupational level stemming from the BIBB-BAuA data in our wage regressions. Investigating in greater detail whether task churning can be seen as a mechanism through which AI exposure affects wages, i.e., a mediator, rather than a moderator, is thus not suitable with our data.

Table 4
AI exposure and wages – Low- vs. High task churning occupations.
Source: SIAB 2010–2017 restricted to full-time workers, liable to social security.

	Log daily wage					
Panel A: Low task churning occupations						
AI-Exposure$_i$	0.00526	0.0153	0.0162	0.00502	0.0180	0.0191
	(0.00271)	(0.00314)	(0.00336)	(0.00397)	(0.00486)	(0.00520)
Observations	1,162,629	485,173	379,178	537,291	175,855	134,888
R-squared	0.910	0.924	0.922	0.889	0.907	0.904
Panel B: High task churning occupations						
AI-Exposure$_i$	0.00895	0.0165	0.0153	0.00958	−0.00769	−0.0137
	(0.00279)	(0.00368)	(0.00393)	(0.00425)	(0.00624)	(0.00666)
Observations	1,151,245	480,605	371,888	493,164	165,693	124,480
R-squared	0.921	0.930	0.927	0.901	0.912	0.906
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Worker controls	Yes	Yes	Yes	Yes	Yes	Yes
Plant controls	Yes	Yes	Yes	Yes	Yes	Yes
Worker fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Plant fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
4-digit occupation fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Same 4-digit occupation	No	Yes	Yes	No	Yes	Yes
Same plant	No	No	Yes	No	No	Yes
8 years in sample	No	No	No	Yes	Yes	Yes

Notes: The dependent variable in all columns is the log daily wage (deflated to base year 2015). Panel A (B) is restricted to occupations with low (high) task-churning between 2012 and 2018 according to the BIBB-BAuA data. Occupational AI exposure is based on the DAIOE measure of Engberg et al. (2024). Worker controls include time-varying controls, such as experience (-squared, -cubic, - quartic), education, and age (-squared), and indicator variables for the same plant and same 4-digit occupation, and an indicator variable for right-censored wage. Plant controls include (log) number of workers, industry (3-digit NACE Rev.2) and region (NUTS 3) fixed effects. Standard errors clustered at the 4-digit occupation are given in parentheses.

public–private partnerships to expand AI upskilling initiatives, and ensuring that vocational and higher education curricula evolve to equip workers with AI-complementary skills. Such programs may prove to be important in mitigating the potential consequences of AI adoption on inequality.

A natural next step for future research is to examine how AI exposure affects *within-firm wage inequality*, as recent studies suggest that technological change may exacerbate disparities within organisations (see, e.g., Domini et al., 2022; Barth et al., 2020). While our study provides valuable insights into wage dynamics across occupations and industries, our data are not ideally suited to address these within-firm dynamics comprehensively. Richer firm-level data capturing the full wage structure would offer deeper insights into how AI impacts both high- and low-wage earners within firms.

While combining data from different countries allows us to analyse AI exposure more comprehensively, this approach assumes that occupational structures and technology adoption patterns are sufficiently comparable across countries. Existing research suggests that key occupational characteristics and AI-related transformations exhibit cross-country similarities, yet institutional settings, education systems, and industrial compositions may still shape how AI adoption affects labour markets. Furthermore, our study focuses on an early period of modern AI where the overall implications are still relatively moderate. Thus, studying how the continuous increase in AI exposure will affect job security, firm or occupation switching, and other outcomes, is a promising avenue for further research.

We further acknowledge that establishing precise causal mechanisms in the context of this study is difficult, given that AI adoption is an evolving and complex process influenced by multiple factors. Future research could further strengthen identification strategies by leveraging firm-level AI adoption patterns or policy-driven variations in AI deployment that allow for more refined micro-level analyses.

Looking ahead, future research endeavours may expand on our findings by examining more recent periods characterised by a rapid acceleration in AI adoption. This exploration could encompass a broader spectrum of outcomes, including potential shifts in employment patterns and unemployment rates, as AI, for example, increasingly takes on tasks once performed by humans. By undertaking these future investigations, one would aim to achieve a more comprehensive understanding of how labour markets are influenced by the increasing adoption of AI.

CRediT authorship contribution statement

Erik Engberg: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Michael Koch:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Magnus Lodefalk:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Sarah Schroeder:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material provides additional descriptives, figures and robustness checks.

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.respol.2025.105285.

Data availability

The data that has been used is confidential.

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