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Artificial Intelligence and Worker Stress: Evidence from Germany

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Abstract

We use individual survey data providing detailed information on stress, technology adoption, and work, worker, and employer characteristics, in combination with recent measures of AI and robot exposure, to investigate how new technologies affect worker stress. We find a persistent negative relationship, suggesting that AI and robots could reduce the stress level of workers. We furthermore provide evidence on potential mechanisms to explain our findings. Overall, the results provide suggestive evidence of modern technologies changing the way we perform our work in a way that reduces stress and work pressure.

Keywords: Artificial intelligence technologies; Automation; Task content; Skills; Stress

JEL Codes: I31, J24, J28, J44, N34, O33.

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1. Introduction

New advanced technologies such as artificial intelligence (AI) change the way we perform our work, as they automate or assist in carrying out work tasks, thus increasing productivity, as well as creating new work content (see, e.g., Acemoglu and Restrepo , 2019, Bessen *et al*, 2022). In tandem with the rapid progress of AI research and development, companies are repeatedly emphasising their adoption of AI in earnings calls, and firms are also exponentially increasing their share of job ads requiring AI skills (Maslej *et al.*, 2023). Research on the impacts of new technologies is therefore burgeoning. While recent research focuses on the impact of new technologies on labour market outcomes such as wages and employment, this papers analyses how new technologies, and in particular AI, are related to stress and work pressure.[1]

Understanding the role of advanced technologies in workplace stress is important, as previous research has revealed a significant economic cost associated with stress, in addition to adversarial mental and physical health outcomes for workers, such as burnout and cardiovascular disease (LaMontagne *et al.*, 2010, Szeto and Dobson, 2013, ILO, 2016). Stress is commonly understood as the outcome of high work demands, little decision latitude and insufficient support or resources (Karasek, 1979, Karasek and Theorell, 1990, Bakker and Demerouti, 2007, Böckerman *et al*, 2020).

How new technologies such as AI affect work pressure and worker control as well as support is theoretically ambiguous. If workers in highly exposed occupations are left to perform fewer and less tedious tasks as well as at the same pace, one could expect a reduction in work demands, while if, e.g., work pace in remaining tasks increases or fear of unemployment mounts, pressure could increase. Likewise, the introduction of new tasks could either reduce work demands if those tasks are less exposed to automation pressure or more fulfilling and creative, or it could increase stress if the new tasks are more demanding and requiring

[1] For recent literature surveys on AI, the labour market and working life, see, e.g., Lodefalk (2024), OECD (2023), Lane and Saint-Martin (2021).

additional skills. Furthermore, new technologies that help workers do their job faster or with higher quality could reduce work pressure. Thus, how AI affects stress is ultimately an empirical question. So far, the evidence is mixed and it is mainly based on anecdotal and descriptive evidence (Cajander *et al*, 2022, OECD, 2023).

To investigate new technologies and stress, we use the two most recent waves of the large and representative German Qualifications and Career Survey (BIBB-BAuA 2012 and 2018). This labour force survey among employed individuals provides granular information on stress and technology adoption, along with rich information on worker and employer characteristics that may confound any relation between stress and technology adoption. Furthermore, we combine it with measures on occupational exposure to AI and robots, obtained from Engberg *et al* (2023a) and Webb (2020), respectively.

A first look at the data reveals a decline in the share of workers who report increased stress between 2012 and 2018. In this paper, we hypothesise that new technologies such as AI and robots can explain this decline. These technologies can alleviate work pressure by substituting workers in certain tasks, while evidence does not yet suggest that, e.g., AI has automated a large share of work task. They can also make workers more productive and autonomous in remaining tasks, as demonstrated in experimental studies on generative AI, while introducing new tasks that are more creative and less prescribed.

Using the rich survey data in combination with measures of AI and robot exposure, we estimate probit regressions, which confirm our hypothesis. The results indicate that new technologies are associated with a decrease in the likelihood that workers report increased work stress. This negative relation is obtained while including a large set of worker and plant controls. Separate estimates for the years 2012 and 2018 reveal that the negative relation between AI (robots) and stress is most pronounced for the year 2018 (2012), which is intuitive, as robot automation started to transform labour markets already in the early 2000s, while progress in AI has been made especially during the last years.[2] We also exploit

[2]Well-known breakthroughs in AI research in the last years include AlexNet (winning the ImageNet

survey questions in the BIBB-BAuA data on the adoption of new technologies, to ensure that workers exposed to new technology according to our exposure measures actually are experiencing them in the work place. Comfortingly, our results are only present in firms that adopt new technologies, while the results disappear in non-adopting firms.

We then proceed to investigate heterogeneous patterns across different groups of workers (occupation and education) and sectors, as well as to explore potential mechanisms. Throughout, we restrict the sample to workers in firms reporting technology adoption. First, we find that the link between new technologies and fewer workers reporting an increase in stress is present for STEM workers (e.g., science and engineering professionals, who are directly involved in monitoring and managing the manufacturing process), and support workers (e.g., labourers and clerks, who solve low-skilled manufacturing tasks or general office or data entry tasks). This is intuitive, as we expect AI and robots to assist or relieve these groups of workers in cognitive and physical tasks, respectively. Analysing sectoral differences, we find a negative relation between exposure to new technologies and stress for the manufacturing and the public sector, but not for the services sector. Turning to education, we find that robots are linked to less stress especially for workers with below median years of education, while stress reduction of AI exposure is prevalent among all educational levels.

To explore potential mechanisms, we first document how AI and robots are related to work content. We reveal pronounced differences. Higher exposure to AI (robots) is associated with, e.g., a weaker (stronger) presence of specific output requirements and meticulously prescribed work tasks, and a larger (smaller) likelihood of being confronted with new work tasks. In the next step, we show evidence indicating that the stress reduction linked to the new technologies is mediated by work characteristics. Reporting an increase in stress is less likely the more exposed workers are to new technologies, but this negative relation between stress and technologies is only prominent for workers that often need to perform new tasks

image recognition competition in 2012), AlphaGo (defeating the human world champion in the game of Go in 2016), or the publication of GPT-3 by OpenAI in 2020.

and it is stronger for those who perform many tasks in their job. Furthermore, we find that AI (robot) technology is associated with a lower likelihood of stress in jobs where work is less (more) prescribed in detail. Taking stock, this set of results is suggestive of a few patterns. Concerning new tasks, recent technologies could reduce stress, e.g., because they generate new tasks less susceptible to automation or more attractive to workers, or because the technologies assist in carrying out the new tasks. Regarding multitasking, being exposed to recent technologies could potentially automate some tasks and thereby reduce the pressure of additional new tasks. As regards the codifiability of work, it is possible that AI assists workers, and thereby reduce stress, in existing or new tasks that are less predefined in detail, while robots reduce stress in prescribed tasks by automating the same tasks.

Our research contributes to two different strands of the literature: one on well-being and health, including stress, and including technology impacts, and another on labour market outcomes, e.g., in terms of employment and wages. While workplace stress is a widely studied phenomenon and there is an increasing body of research on technological advancements and well-being and health, there is little evidence on how workers' stress is affected by advanced technologies such as AI (Cajander *et al*, 2022, OECD, 2023). Research on workplace stress reveals different causes, such as job demands, workload, and time pressure, the lack of control over work, little workplace support, job insecurity and fear of unemployment (see, e.g., Böckerman *et al*, 2020, Levy *et al.*, 2017).

A related strand of this literature investigates the impact of technological advancements on the well-being and health of employees. Research includes, for example, studies on the well-being and health effects of telecommuting (for a recent survey, see, e.g., Beckel and Fisher, 2022), and of so-called technostress - the psychological impact of technology use on employees, including issues like information overload, constant connectivity, and work-related stress (for important contributions, see Tarafdar *et al.*, 2007, Ayyagari *et al.*, 2011).

Evidence on AI and worker stress is mainly limited to cases and descriptive studies and the results are mixed, with some indicating a reduction in stress and others an increase. Milanez (2023) carried out 90 firm-level case studies in the manufacturing and financial sectors of eight countries to study the impact of AI on jobs. She found AI adoption to be associated with less repetitive work, enabling workers to focus on more valuable tasks. In 2022 and late 2010s, Lane *et al.* (2023) and Yamamoto (2019) performed surveys among workers in seven countries ($n = 5,334$) and Japan ($n > 10,000$), respectively. Both sets of surveys found workers to be more satisfied at work in the presence of AI. In Lane *et al.* (2023), AI was reported to enable, e.g., automation of tedious tasks and assistance in making decisions both faster and more accurately, as well as increasing control over how to carry out tasks. Additionally, experimental studies on generative AI suggest that AI assists more junior or new workers in entering and improving at work (e.g., Brynjolfsson *et al*, 2023, Dell'Acqua, 2023). Yamamoto (2019), however, found that while workers were more satisfied, they were also more stressed than before, performing more demanding and less routine tasks. Milanez (2023) also highlights that AI automation may result in a more complex and faster work environment that lacks the natural breaks with routine work and thereby increases stress. Our study contributes to the broader literature on worker stress and technology by investigating how advanced technologies such as AI affect workplace stress, using two waves of a large and detailed survey of workers in Germany ($n \sim 20,000$ in each wave) that capture a time of rapid technology development and adoption.[3]

Finally, by providing detailed evidence on the novel aspects of adopting modern technologies at the workplace, we speak to recent studies investigating how robots and AI affect labour market outcomes. For example, recent studies making use of firm-level data on robot adoption reveal mostly a positive impact of automation on employment (see, e.g., Acemoglu *et al.*, 2020, Humlum, 2019, Koch *et al*, 2021). Studies that focus on AI and labour market implications, include Acemoglu *et al.* (2022), Alekseeva *et al.* (2021), Babina *et al* (2022), Fossen

[3]AI may also be used to monitor, evaluate and micro-manage work as well as to automate work management ("algorithmic management") (OECD, 2023). Such practices could increase work pressure, limit control, and reduce the privacy of workers, contributing to stress.

et al (2022), and Engberg *et al.* (2023b), among others. Specifically, Acemoglu *et al.* (2022) employ data on US job ads to provide evidence that exposure to AI affects skill requirements and leads to a decrease in job postings for non-AI-related jobs, while they do not reveal any impact on occupational wages. In a related study, Alekseeva *et al.* (2021) use US job vacancy notes and find a strong increase in demand for AI skills and a wage premium, in particular for managers and in combination with, e.g., software, cognitive and soft skills. Babina *et al* (2022) looks at employment of workers with AI skills and reveal that this is associated with an up-skilling of the remaining workforce. Fossen *et al* (2022) use exposure to AI, software and robots of Webb (2020) and detect a positive (negative) relation between AI (software and robots) exposure and wage growth, while Engberg *et al.* (2023b) combine different data sources to investigate the dynamic influence of AI exposure on individual wages over time, exposing positive effects with nuanced variations across occupational groups. While previous studies look at the implication of AI and robots on wages and employment, our study is focused on a specific and important health outcome, namely stress, and thus provides novel and largely unexplored evidence on an implication of modern technologies.

2. Data

We make use of the two latest available waves of the German Qualifications and Career Survey for the years 2011/12 and 2017/18. This telephone survey is representative of the German labour force, e.g., in terms of age, gender, and occupation, and the sample includes approximately $20,000$ workers in each wave. The survey is carried out by the German Federal Institute for Vocational Education and Training (BIBB) and the German Federal Institute for Occupational Safety and Health (BAuA).[4] The BIBB-BAuA data is especially suitable for our analysis, as it includes questions related to stress and technology adoption, in addition to including detailed information on worker and employer characteristics. Previous waves have been used by DiNardo *et al.* (1997) and Spitz-Oener (2006) to investigate how

[4]Further details on the survey and how to access the data can be found at `https://www.bibb.de/en/15182.php`.

computerisation has affected wages and changed the demand for skills, respectively.

To measure stress at the workplace, we use the survey question "*Have stress and work pressure increased, have they remained the same or have they decreased?*" Based on this, we generate an indicator on work related stress which takes the value of 1 if the individual reports an increase in stress, or the value of 0 if the individual report no increase or a decrease in stress in the job.[5] Having a first look at this variable, we detect a decline in the likelihood that individuals report an increase in stress over time. While 48% of the respondents in the survey wave 2012 report that stress and work pressure have increased, only 42% do so in 2018.[6] Of course, this pattern varies greatly across individuals and occupations. Figure 1 plots the mean value of our stress indicator for 2012 against 2018 across different 3-digit ISCO-08 occupation groups. It reveals quite substantial heterogeneity in how stress levels differ between jobs and how workplace stress has changed between 2012 and 2018 within occupations. In our empirical analysis below, we will exploit occupational heterogeneity in exposure to AI and robots and relate it to individual stress outcomes for workers.[7]

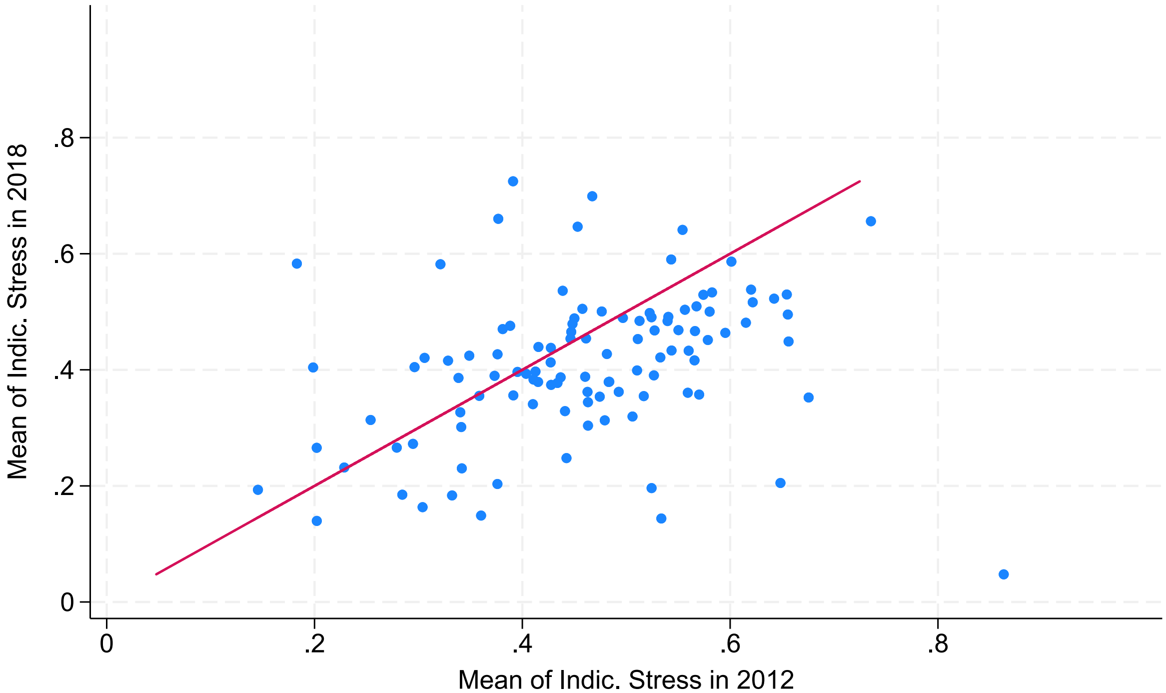
To measure exposure to new technologies, we combine BIBB-BAuA survey data with information on AI and robot exposure. The exposure to AI is from the dynamic occupational exposure to artificial intelligence (DAIOE) index (in 2017) of Engberg *et al* (2023a). Their measure builds on Felten *et al.* (2018, 2021), and estimates occupational AI exposure by mapping data on technological progress in AI to worker abilities in different occupations. Robot exposure is based on Webb (2020), who combines the similarity of robot patent texts and

[5]As an alternative, we only code the indicator variable as 0, if the individual response is that stress and work pressures remained the same. Yet, as another alternative we focus on the response "have stress and work pressures *decreased*", by generating an indicator variable equal to 1 if the individual reports a decrease in stress and 0 otherwise. Results using these alternative indicators are similar (more on this below). However, only few individuals (around 5-6% in each survey year) report specifically a decline in stress. As this hinders the analysis to investigate potential mechanisms in Section 3. below, we do not make use of this alternative indicator variable for our main analysis.

[6]Note, that the two surveys are conducted among *different* workers, i.e., the survey does not follow workers over time.

[7]If technologies substitute workers in all their tasks, stress might increase as a results of becoming unemployed. However, this is beyond the scope of this article, since the survey is restricted to *employed* individuals.

Figure 1: *Workplace stress in 2018 and 2012 across occupations*



Notes: The figure plots the mean value of our stress indicator for 2012 and 2018 across different 3-digit ISCO-08 occupation groups. The stress indicator variable is equal to 1 (0) if the individual reported that stress and work pressure increased (remained the same or decreased) over the past two years. Blue dots above (below) the red 45-degree line, indicate an increase (decrease) in the share of workers reporting augmented stress within a 3-digit occupation from 2012 to 2018.
Source: Authors' computations based on BIBB-BAuA survey waves 2012 and 2018 using inverse sampling weights.

occupational task profiles. Both measures are provided at the 4-digit ISCO-08 occupational level, and we aggregated them up to 115 different occupations at the 3-digit level, available in our survey data. Arguably, these external data might not provide a clear indication whether workers really are exposed to technologies, as the direct exposure at the workplace depends on the employer adopting and using new technologies. Therefore, we also make use of questions in the BIBB-BAuA survey about technological change at the workplace during the last two years. Specifically, individuals are asked if the firm introduced new computer programs, where it is explicitly mentioned that new versions of existing programs are not meant here. Furthermore, individuals are asked if the firm introduced new manufacturing or process technologies or new machines or plants in the last two years.

In our empirical analysis, we also use a set of worker and plant controls. Worker characteristics include the hourly gross wage (computed from information on the monthly gross wage and weekly working hours, following the methodology in Spitz-Oener (2006)), 3-digit ISCO-08 occupation classification, education (measured in years of schooling, incl. training), gender, age, marriage, type of employment (worker, salaried employee, or civil servant), and information on part-time work. Plant characteristics include the industry classification (61 different 2-digit NACE 1.1 industries), regional information (18 different NUTS 2 regions), and plant 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.).

Lastly, we also generate indicators on workplace characteristics based on survey questions. These are indicators on (i) performance pressure; (ii) prescribed work; (iii) repeated work steps; (iv) new tasks; (v) performance requirements; (vi) new work content; and (vii) multi-processes, as well as information on the number of different tasks (out of 18 different possible activities) a worker might perform in her job.[8] Summary statistics, including a definition of all variables, are provided in an Appendix Table A1.[9]

3. Empirical Analysis

This section describes the methodology we use to identify if new technologies, specifically AI and robots, affect stress at the workplace, and it presents and discusses the results.

[8]These 18 tasks follow previous work by Becker and Muendler (2015), who have used the BIBB-BAuA data for the survey years 1979, 1986, 1992, 1999 and 2006. We have extended their list of tasks to a total of 18, due to the availability of additional questions in the 2012 and 2018 surveys. 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.

[9]For our analysis below, we drop observations with missing information on the different variables introduced in this section.

3.1. *Empirical Methodology*

In the following, we estimate variations of the following equation using probit regressions:

$$\text{Indic.: Stress}_{ioj} = \alpha + \beta \text{AI-Exp}_o + \gamma \text{Robot-Exp}_o + \gamma' \mathbf{z_j} + \lambda' \mathbf{x_i} + \epsilon_{ioj}. \tag{1}$$

As defined in the previous section, the dependent variable indicates if stress and work pressure has increased for an individual i working in occupation o in firm j. We regress this indicator variable on AI and robot exposure, which measure technology exposure at the level of a worker's occupation. Thus, we identify how technologies are associated with workers' stress via the variation of our exposure measures across different detailed occupations. Arguably, beside technology exposure, stress depends on employer and employee characteristics, and we therefore include vectors of plant and worker controls, which are available in our dataset. Plant controls ($\mathbf{z_j}$) include fixed effects for the industry, region, plant size, and major occupational groups. Worker controls ($\mathbf{x_j}$) include a workers (log) hourly wage, years of education, gender, age, marital status, part-time status, gender, and type of employment. The plant controls capture the fact that stress varies across industries, regions, plant size and major occupations. E.g. workers in the major occupational group of managers within a large financial institution are likely to be more (or differently) stressed, than a services worker in a small hotel. The worker controls capture the fact the stress depends on individual characteristics, such as gender, education, and income. Put differently, by including the extensive set of plant and worker controls to isolate the variation in exposure to new technologies across narrow occupations from other stress related characteristics, we set out to investigate how AI and robot exposure affect the likelihood that stress and work pressure has increased.

3.2. New Technologies and Worker Stress

Table 1 presents our first evidence on how technology exposure is linked to workers' stress. This and the subsequent tables are organised as follows. We focus on estimates of β and γ from Eq. (1), i.e., coefficients reporting how AI and robot exposure affect the probability that an individual reports an increase in stress. The first set of estimates, in column 1, present simple correlations, as the probit regressions do not include plant or worker controls. In columns 2 and 3, we add plant and then worker controls. Columns 4 and 5 present results separately for the two sample years 2012 and 2018.

Table 1: AI, Robots and Worker Stress

	Indic.: Increase in stress				
	(1)	(2)	(3)	(4)	(5)
AI-Exposure	-0.0178	-0.0316***	-0.0312***	-0.0240*	-0.0384***
	(-1.81)	(-4.38)	(-4.74)	(-2.54)	(-4.28)
Robot-Exposure	-0.226***	-0.106*	-0.108*	-0.162***	-0.0608
	(-4.52)	(-2.12)	(-2.35)	(-4.99)	(-0.67)
Observations	28,052	28,052	28,052	28,052	28,052
Pseudo R-squared	0.003	0.017	0.031	0.032	0.033
Plant Controls	no	yes	yes	yes	yes
Worker Controls	no	no	yes	yes	yes
Year	2012/18	2012/18	2012/18	2012	2018

Notes: The dependent variable in all columns is an indicator variable that is equal to 1 (0) if the individual reported that stress and work pressure increased (remained the same or decreased) over the past two years. Occupational AI and Robot exposure is measured across 115 different 3-digit ISCO-08 occupations. Plant controls include controls for industry (2-digit NACE Rev. 1.1), regions (18 different NUTS-2 regions), plantsize (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.) and major occupations groups (according to the first ISCO-08 digit). Worker controls include the log hourly wage, education (measured in years of schooling incl. training), age, and indicator variables for married, part-time, gender, and type of employment (worker, salaried employee, or civil servant). Regressions that are based on both survey years, include year controls. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level. Standard errors (clustered at the 3-digit ISCO-08 level) are reported in parentheses.
Source: Authors' computations based on BIBB-BAuA survey waves 2012 and 2018. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). Occupational robot exposure is based on the index from Webb (2020).

The results displayed in Table 1 indicate a clear negative and statistically significant relation between the exposure to new technologies and worker stress. The relation is robust to the inclusion of plant and worker characteristics. Looking separately at 2012 and 2018, we detect that the negative relation between robots and stress only is present in 2012, while, for AI, the negative relation is present in both periods while being especially pronounced in the later survey wave of 2018.

As AI and robot exposure is measured at the occupation level, and we added both measures to the BIBB-BAuA data from different data sources, we do not know if individuals actually are exposed to these new technologies. Even though we include plant and worker controls to control for the fact that the availability, accessibility and exposure to new technologies can vary for example across industries and regions, as well as income, education, or occupational groups, we still do not know if a worker's employer has adopted these technologies. To consider this, we make use of additional survey information. Specifically, individuals are asked, if the firm has introduced new computer programs, new manufacturing or process technologies, or new machine or plants in the last two years. Using this information, we split our sample into groups of exposed workers and non-exposed workers. The results are presented in Appendix Tables A2 and A3. Reassuringly, the negative relationship between AI or robot exposure and workers stress vanishes if one restricts the sample to individuals that report that their employer did not adopt new computer programs or new machines or technologies (see Panels B in Appendix Tables A2 and A3). Contrary, looking at workers in technology adopting firms (see Panels A), the significance level of our estimates and the implied magnitudes have increased, compared to results from Table 1, where we pool across all (adopting and non-adopting) firms. These results thereby also confirm the validity of our exposure measures. If AI and robot exposure would also affect workers in firms that do not make use of new technologies, this might detect some indirect effects, e.g. the fear of being replaced by new technologies. However, we do not find such indirect effects. Contrary, we only find them for workers who are directly exposed to new technologies at their workplace.

In the following, we therefore restrict the sample to those individuals reporting that the firm introduced new computer programs and/or new manufacturing/process technologies and/or new machines/plants in the last two years.[10] Re-estimating Eq. (1), we display these results in Table 2. Again, the results – now for the group of workers in technology adopting firms – reveal a clear negative relationship between AI and robot exposure and stress at the workplace. Compared to Table 1, the significance and magnitude of our estimates have increased.

Table 2: AI, Robots and Worker Stress in Technology Adopting Firms

	Indic.: Increase in stress				
	(1)	(2)	(3)	(4)	(5)
AI-Exposure	-0.0290**	-0.0331***	-0.0326***	-0.0175	-0.0478***
	(-2.89)	(-4.89)	(-5.73)	(-1.56)	(-5.46)
Robot-Exposure	-0.281***	-0.165**	-0.160**	-0.236***	-0.0760
	(-5.30)	(-2.79)	(-2.95)	(-5.44)	(-0.69)
Observations	18820	18816	18816	9079	9730
pseudo R-squared	0.004	0.017	0.029	0.030	0.031
Plant Controls	no	yes	yes	yes	yes
Worker Controls	no	no	yes	yes	yes
Year	2012/18	2012/18	2012/18	2012	2018

Notes: The dependent variable in all columns is an indicator variable that is equal to 1 (0) if the individual reported that stress and work pressure increased (remained the same or decreased) over the past two years. Occupational AI and Robot exposure is measured across 115 different 3-digit ISCO-08 occupations. Plant controls include controls for industry (2-digit NACE Rev. 1.1), regions (18 different NUTS-2 regions), plantsize (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.) and major occupations groups (according to the first ISCO-08 digit). Worker controls include the log hourly wage, education (measured in years of schooling incl. training), age, and indicator variables for married, part-time, gender, and type of employment (worker, salaried employee, or civil servant). Regressions that are based on both survey years, include year controls. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level. Standard errors (clustered at the 3-digit ISCO-08 level) are reported in parentheses.
Source: Authors' computations based on BIBB-BAuA survey waves 2012 and 2018. The sample is restricted to individuals who report that the firm introduced new computer programs and/or new manufacturing/process technologies and/or new machines/plants in the last two years. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). Occupational robot exposure is based on the index from Webb (2020).

We also perform robustness analysis and look at variation across broad occupation groups, sectors, and years of education. Specifically, Appendix Table A4 uses the alternative indicator for stress, and Appendix Table A5 includes a measure of occupational software exposure. Furthermore, Appendix Table A6 re-runs estimates of A5, now with the variable indicating a

[10] Summary statistics for the restricted sample of exposed workers, are presented in columns 3 and 4 of Table A1 in the Appendix.

decline in stress, as dependent variable. Even though only few individuals specifically report a decline in stress, we find a positive and, mostly, statistical significant relation between our technology indicators and stress reduction. Thus, these results confirm our previous findings, and showing that our results are robust to using alternative codings for our stress indicator, and to the inclusion of an additional and different technology measure used in the literature.

Furthermore, in Appendix Table A7 we re-run the probit regressions separately for 5 broad occupation groups, namely managers, STEM professionals, support professionals, blue-collar workers, and support workers.[11] By doing so, we reveal that stress is reduced for more technology exposed workers, and especially for STEM workers and the group of support workers.[12] This is intuitive, as we expect AI and robots to take over some tasks and assist in other tasks and this especially for the group of science and engineering professionals and the group of support workers. These respective groups are involved in developing, monitoring and managing, e.g., manufacturing processes, and in carrying out manual and general office tasks, e.g., data entry work, that do not require post-secondary education. Beside occupational groups, we also exploit differences across broad sectors. We find a negative link to stress for workers in the manufacturing and public sectors but not in the services sector (see Appendix Table A8).

Finally, we also analyse AI, robots and stress for different educational groups. To do so, we make use of information on the years of schooling (and training) and split the sample according the median in our sample, which is 12 years of education. Results are presented

[11](1) Manager include corporate managers, directors and executives (defined by one-digit ISCO-08 = 1). (2) STEM professionals include science and engineering professionals, involved in the monitoring and management of the manufacturing process (defined by two-digit ISCO-08 = 21 or 31). (3) Support professionals include professionals such as human resource administrators, accountants and marketing advisers (defined by one-digit ISCO-08 = 2 or 3 and excluding 21 and 31). (4) Blue-collar core workers include operators and fitters, directly handling the manufacturing process (defined by one-digit ISCO-08 code 7 and 8 and excluding two-digit ISCO-08 codes >82). (5) Support workers include clerks and labourers, e.g. office clerks, data entry clerks, and hand packers (defined by the remaining ISCO-08 codes >3).

[12]We also tried to further split the group of support workers into groups of low-skilled and high-skilled support workers. Results do not differ among these two narrow groups, which might be also partly explained by the small sample size.

in Table 3. From inspection of Panel A, we reveal that robots are negatively linked to stress especially for workers with below median years of education, while the negative link to stress is more homogeneous for AI.

Table 3: AI, Robots and Worker Stress Across Years of Education

	Indic.: Increase in stress				
	(1)	(2)	(3)	(4)	(5)
PANEL A: Workers with below median years of education (i.e. <= 12 years)					
AI-Exposure	-0.00544	-0.0178	-0.0229*	-0.0117	-0.0475**
	(-0.46)	(-1.47)	(-2.09)	(-0.81)	(-2.83)
Robot-Exposure	-0.215***	-0.176*	-0.174**	-0.246***	-0.0840
	(-3.84)	(-2.40)	(-2.60)	(-4.07)	(-0.61)
Observations	8444	8440	8440	4818	3606
pseudo R-squared	0.004	0.022	0.031	0.033	0.042
PANEL B: Workers with above median years of education (i.e. > 12 years)					
AI-Exposure	-0.0415***	-0.0376***	-0.0330***	-0.0167	-0.0450***
	(-4.48)	(-3.74)	(-3.81)	(-1.08)	(-3.73)
Robot-Exposure	-0.441***	-0.169	-0.140	-0.293*	-0.0358
	(-6.25)	(-1.85)	(-1.74)	(-2.34)	(-0.28)
Observations	10376	10362	10362	4249	6100
pseudo R-squared	0.007	0.021	0.036	0.045	0.037
Plant Controls	no	yes	yes	yes	yes
Worker Controls	no	no	yes	yes	yes
Year	2012/18	2012/18	2012/18	2012	2018

Notes: The dependent variable in all columns is an indicator variable that is equal to 1 (0) if the individual reported that stress and work pressure increased (remained the same or decreased) over the past two years. Panel A (B) is restricted to individuals with less or equal (more) than 12 years of education. Occupational AI and Robot exposure is measured across 115 different 3-digit ISCO-08 occupations. Plant controls include controls for industry (2-digit NACE Rev. 1.1), regions (18 different NUTS-2 regions), plantsize (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.) and major occupations groups (according to the first ISCO-08 digit). Worker controls include the log hourly wage, education (measured in years of schooling incl. training), age, and indicator variables for married, part-time, gender, and type of employment (worker, salaried employee, or civil servant). Regressions that are based on both survey years, include year controls. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level. Standard errors (clustered at the 3-digit ISCO-08 level) are reported in parentheses.
Source: Authors' computations based on BIBB-BAuA survey waves 2012 and 2018. The sample is restricted to individuals who report that the firm introduced new computer programs and/or new manufacturing/process technologies and/or new machines/plants in the last two years. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). Occupational robot exposure is based on the index from Webb (2020).

3.3. *Potential Mechanisms*

While the previous subsection has revealed a statistically significant and negative relationship between AI, robots and stress at the workplace, we now proceed to investigate potential mechanisms. We start by exploring how exposure to AI and robot technology is related to different workplace characteristics. Specifically, we investigate how new technologies are related to the likelihood that workers report the work to be described by the different indicators introduced above, namely (i) performance pressure; (ii) prescribed work; (iii) repeated work steps; (iv) new tasks; (v) performance requirements; (vi) new work content; and (vii) multi processes. Therefore, we run 7 probit regressions, where we regress the probability of these workplace characteristics on AI and robot exposure separately, using the sample of 2018 for AI and the sample of 2012 for robot exposure.[13] Beside the two measures of occupational technology exposure, we include a set a set of plant and worker controls in the regressions.[14]

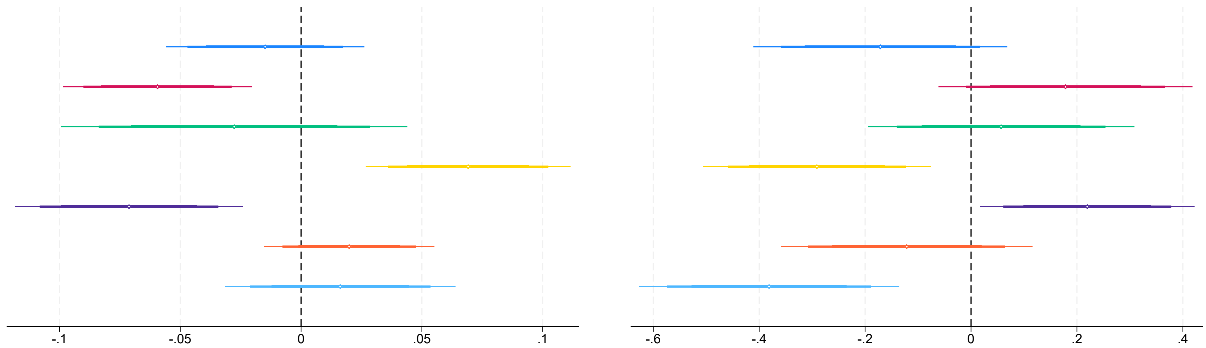
We present estimates of these 2*7 regressions graphically in Figure 2, where Panel a (b) presents coefficients for AI (robot) exposure. The figure reveals distinct links between different work characteristics and AI and robot technologies. Interestingly, the relationship between the character of work and AI technology is commonly a mirror image of the one for work and robot technology.[15] For example, according to the second red and the fifth purple plotted coefficients, carrying out explicitly prescribed work and work with strict performance requirements, respectively, is less (more) likely in occupations that are highly exposed to AI (robot) technology. Moreover, according to the fourth yellow plotted coefficients, workers are more (less) likely to be confronted with new tasks at the workplace if the occupation is

[13] We do so, as regression results from Table 1 and 2 revealed a strong link between AI and stress in 2018, and robots and stress in 2012. We have also verified that these results look similar if we pool across both years and if we include both technology measures simultaneously in the probit regressions.

[14] Specifically, we control for industry, regions, plant size, the log hourly wage, education, age, gender, married, part-time, and type of employment.

[15] In related work, Engberg *et al.* (2023b) unveils a distinctive relationship among occupational work content, skill requirements, and exposure to AI and automation. Specifically, they find that occupations with high AI exposure exhibit distinct activities and skill demands compared to those exposed to robots.

Figure 2: *Work Characteristics and Exposure to Technology*



(a) AI-Exposure

(b) Robot-Exposure

Notes: The figure plots the coefficients of AI-exposure (Panel a) or Robot exposure (Panel b) from estimating probit regressions on the probability on 7 different work characteristic indicators. These 7 indicators are equal to one if the individual reports: 1. to work under strong deadlines or performance pressure; 2. that the execution of the work is prescribed in every detail; 3. that one and the same operation is repeated in every detail; 4. that one is confronted with new tasks the work; 5. that an exact number of pieces, a certain minimum output or the time to do a certain task is prescribed; 6. that things are demanded which have not been learned; 7. that one has to keep an eye on different types of work or processes at the same time. All regressions include controls for industry (2-digit NACE Rev. 1.1), regions (18 different NUTS-2 regions), plantsize (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.) and worker controls, including the log hourly wage, education (measured in years of schooling incl. training), age, and indicator variables for married, part-time, gender, and type of employment (worker, salaried employee, or civil servant). Thick, medium, and thin lines represent the 99, 95, and 90 percent confidence intervals. Standard errors (clustered at the 3-digit ISCO-08 level) are reported in parentheses.
Source: Authors' computations based on a sample of 14,441 (13,567) individuals from the BIBB-BAuA survey wave 2018 (2012) for Panel a (b). Both samples are restricted to individuals who report that the firm introduced new computer programs and/or new manufacturing/process technologies and/or new machines/plants in the last two years. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). Occupational robot exposure is based on the index from Webb (2020).

highly exposed to AI (robots). Finally, according to the last light blue plotted coefficient in Panel b, workers are less likely to carry out simultaneous tasks if their occupation is exposed to robots. In sum, work characteristics associated with technology differ depending on the type of technology: characteristics linked to higher AI exposure include less prescribed and quantitatively specified work tasks, and a higher likelihood of being confronted with new tasks; while characteristics common with higher robot exposure include more prescribed and quantitatively specified work tasks, less multi-processing and a lower likelihood of carrying out new tasks.

Given these results, we now investigate how these workplace characteristics mediate the relationship between technologies and stress. To do so, we split the sample of individuals into groups according to the different indicator variables used in Figure 2 and using regressions akin to those of Table 2. The aim is to examine if the negative relationship between AI, robots and stress is heterogeneous for individuals with different work characteristics, and whether the heterogeneity is suggestive in how new technology reduce worker stress.

Technologies, new tasks, and multi-tasking: Existing research suggests that new technologies have the potential not only to automate tasks but also to generate new tasks. We therefore exploit information from our data about workers being confronted with new tasks and about multitasking.

First, we make use of our indicator variable for new tasks, and re-run regressions separately for the group of workers that report to face, or do not face new tasks. The results of this exercise are presented in Table 4 and provide a consistent picture. AI and robots are only linked to reduced stress for the group of workers confronted with new tasks. These results in combination with results in Figure 2 suggest that AI and robots are changing the activity content of work in a way that makes work less stressful. We interpret these results as new technologies reducing stress either because the new tasks are less exposed to automation, and/or because the new tasks are more attractive to the worker, e.g., being creative or stimulating.

An alternative explanation for the importance of new tasks could be that the introduction of new tasks also is correlated with the automation of other tasks. In this way, stress could be under control although new tasks are added. While we cannot establish the exact mechanism, we can explore whether new technologies are more strongly associated with reduced stress for workers that are exposed to substantial multitasking. For those workers, adding new tasks without automating others could increase rather than decrease stress. On the other hand, multitasking workers might have a higher likelihood that new technologies alleviate work pressure by automating some tasks. To investigate how the impact of AI on stress

Table 4: AI, Robots and Worker Stress – Mechanism Task Replacing

	Indic.: Increase in stress				
	(1)	(2)	(3)	(4)	(5)
PANEL A: Worker performing new tasks					
AI-Exposure	-0.0344***	-0.0342***	-0.0334***	-0.0212	-0.0465***
	(-3.38)	(-4.52)	(-5.08)	(-1.79)	(-4.69)
Robot-Exposure	-0.285***	-0.201**	-0.194**	-0.299***	-0.0901
	(-5.64)	(-3.05)	(-3.10)	(-4.49)	(-0.70)
Observations	16431	16429	16429	7884	8535
pseudo R-squared	0.004	0.017	0.030	0.033	0.033
PANEL B: Workers not performing new tasks					
AI-Exposure	-0.00177	-0.0242	-0.0248	0.0208	-0.0639
	(-0.12)	(-0.80)	(-0.82)	(0.71)	(-1.31)
Robot-Exposure	-0.177*	-0.0146	-0.00797	-0.0264	0.0290
	(-2.52)	(-0.14)	(-0.08)	(-0.29)	(0.20)
Observations	2389	2377	2377	1180	1174
pseudo R-squared	0.003	0.037	0.044	0.056	0.063
Plant Controls	no	yes	yes	yes	yes
Worker Controls	no	no	yes	yes	yes
Year	2012/18	2012/18	2012/18	2012	2018

Notes: The dependent variable in all columns is an indicator variable that is equal to 1 (0) if the individual reported that stress and work pressure increased (remained the same or decreased) over the past two years. Panel A (B) is restricted to individuals who (do not) report to be confronted with new tasks at the workplace. Occupational AI and Robot exposure is measured across 115 different 3-digit ISCO-08 occupations. Plant controls include controls for industry (2-digit NACE Rev. 1.1), regions (18 different NUTS-2 regions), plantsize (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.) and major occupations groups (according to the first ISCO-08 digit). Worker controls include the log hourly wage, education (measured in years of schooling incl. training), age, and indicator variables for married, part-time, gender, and type of employment (worker, salaried employee, or civil servant). Regressions that are based on both survey years, include year controls. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level. Standard errors (clustered at the 3-digit ISCO-08 level) are reported in parentheses.
Source: Authors' computations based on BIBB-BAuA survey waves 2012 and 2018. The sample is restricted to individuals who report that the firm introduced new computer programs and/or new manufacturing/process technologies and/or new machines/plants in the last two years. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). Occupational robot exposure is based on the index from Webb (2020).

depends on multitasking, we make use of survey questions related to the task content of jobs. The data allows us to distinguish between 18 different activities or tasks that workers need to (or not need to) perform in their job. Summing across these different activities then provides information about workers' number of simultaneous workplace tasks. The average and median number of tasks is 9, as shown in Appendix Table A1. Thus, we split our sample into workers performing more or less than 9 work activities. As shown in Appendix Table A9, the negative relation between stress and new technologies is more (less) pronounced for workers performing above (below) average number of job tasks. This could suggest that new technologies not only generate new tasks but also automate others, something which would alleviate work pressure for workers who perform a lot of multitasking.[16]

Technologies and prescribed work content: Previous research has highlighted that technologies are automating especially those task that can be easily prescribed in detail, while not automating other work, which is harder to code and automate because it is less prescribed in detail, more creative, etc. (see, e.g., Autor *et al.*, 2003). We could therefore expect less work pressure for workers who perform activities that are the easiest to automate, namely, those that are prescribed in detail. Our stylized result in Figure 2, showed that there is a negative (positive) relationship between the likelihood that the execution of work is prescribed in detail and AI (robots). This suggests a heterogeneous link between new techologies and stress depending on the potential for automation, something we would like to explore further.

We therefore split our sample of exposed workers according to whether or not the work is prescribed in detail, running estimations akin to (1). The results are presented in Table 5 and, as in Figure 2, reveal a differential picture for AI and robots. Specifically, from inspection of the coefficient estimates presented in Panel A (B), robots (AI) is associated with less likelihood to report an increase in stress for employees performing work that is (not) prescribed in detail.[17] A potential interpretation of these findings are that AI complements

[16]We also split the sample into four groups according to quartiles of the task number variable. Results are similar, indicating a negative relation between stress and new technologies especially for workers in the 3rd and 4th quartile of the task-number distribution.

[17]We also tested other workplace characteristics, but did not find clear differential effects there. For example, to the extend that workers might also face specific performance requirements, we split the sample into individuals reporting (or not reporting) that they need an exact number of pieces, have a certain minimum output or the time to do a certain task is prescribed. Results are presented in Appendix Table A10. The results display a negative link between new technologies and stress for both worker groups, however to a larger extend for those workers that do not have strict performance requirements. When splitting the sample into workers that work (or not work) under strong deadlines or performance pressure, we do not find

workers in less prescribed and more creative tasks, while robots automate codifiable tasks, and in these (different) ways therefore reduce worker stress.

Table 5: AI, Robots and Worker Stress – Mechanism Prescribed Work Content

	Indic.: Increase in stress				
	(1)	(2)	(3)	(4)	(5)
PANEL A: Workers performing work that is prescribed					
AI-Exposure	-0.0166	-0.0143	-0.0157	-0.00327	-0.0294
	(-1.35)	(-1.18)	(-1.39)	(-0.16)	(-1.87)
Robot-Exposure	-0.313***	-0.203*	-0.191*	-0.279***	-0.0998
	(-4.78)	(-2.10)	(-2.13)	(-4.24)	(-0.65)
Observations	9534	9530	9530	4912	4608
pseudo R-squared	0.006	0.022	0.040	0.048	0.047
PANEL B: Workers performing work that is not prescribed					
AI-Exposure	-0.0288***	-0.0427***	-0.0406***	-0.0240	-0.0552***
	(-3.46)	(-6.48)	(-5.99)	(-1.68)	(-4.77)
Robot-Exposure	-0.307***	-0.117	-0.108	-0.207	0.000800
	(-5.45)	(-1.90)	(-1.73)	(-1.90)	(0.01)
Observations	9286	9283	9283	4158	5113
pseudo R-squared	0.004	0.019	0.027	0.034	0.031
Plant Controls	no	yes	yes	yes	yes
Worker Controls	no	no	yes	yes	yes
Year	2012/18	2012/18	2012/18	2012	2018

Notes: The dependent variable in all columns is an indicator variable that is equal to 1 (0) if the individual reported that stress and work pressure increased (remained the same or decreased) over the past two years. Panel A (B) is restricted to individuals who (do not) report that the execution of the work is prescribed in every detail. Occupational AI and Robot exposure is measured across 115 different 3-digit ISCO-08 occupations. Plant controls include controls for industry (2-digit NACE Rev. 1.1), regions (18 different NUTS-2 regions), plantsize (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.) and major occupations groups (according to the first ISCO-08 digit). Worker controls include the log hourly wage, education (measured in years of schooling incl. training), age, and indicator variables for married, part-time, gender, and type of employment (worker, salaried employee, or civil servant). Regressions that are based on both survey years, include year controls. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level. Standard errors (clustered at the 3-digit ISCO-08 level) are reported in parentheses.
Source: Authors' computations based on BIBB-BAuA survey waves 2012 and 2018. The sample is restricted to individuals who report that the firm introduced new computer programs and/or new manufacturing/process technologies and/or new machines/plants in the last two years. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). Occupational robot exposure is based on the index from Webb (2020).

any differences.

4. Concluding remarks

This paper makes use of detailed worker level survey data in combination with recent occupational measures of AI and robot exposure to analyse how new and advanced technologies are associated with stress and work pressure. We find a persistent negative relation, suggesting that AI and robots could reduce the stress level of workers. We also investigate potential mechanisms. We find new technologies to be related to the work content of jobs. Exposure to AI and robot technology is especially linked to stress reduction in multi-tasking jobs. Workers who are more exposed to these technologies are also more likely to be confronting new tasks at the workplace. We interpret this as an indication that AI and robots are changing the way we perform our job, in a way that is easing our work, and thus making it less stressful. We also find some evidence suggesting that robots can reduce stress in jobs where parts of the work content are prescribed in detail, possibly by automating tedious tasks, while, for AI, stress is reduced for less codifiable work content. While the data for our analysis precede the introduction of powerful generative AI technologies of today, the data capture a period of important breakthroughs and adoption of advanced technologies by firms and public organisations, contributing to the limited evidence on AI and worker stress. Taking stock, our results provide suggestive evidence of the potential for modern technologies to be used to change the way we perform our work in a way that may reduce stress and work pressure.

Conflict of interest statement

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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A Appendix

Table A1: Summary statistics

Variable	Mean	St.Dev.	Mean	St.Dev.
	All workers		Exposed workers	
Indic.: Increase in Stress	0.450	0.497	0.485	0.500
Indic.: Increase in Stress (alt)	0.476	0.499	0.513	0.500
Indic.: Decease in Stress	0.055	0.229	0.055	0.228
DAIOE	15.276	2.036	15.380	2.051
Robot Exposure	0.378	0.384	0.385	0.373
Software exposure	0.411	0.174	0.426	0.178
Log hourly wage	2.970	0.500	3.021	0.481
Education	13.703	2.520	13.694	2.501
Age	46.984	10.472	46.973	10.411
Indic.: Plantsize	4.404	1.702	4.609	1.679
Indic.: Type of Employment	1.962	0.480	1.952	0.488
Indic.: Married	0.553	0.497	0.560	0.496
Indic.: Parttime	0.118	0.322	0.095	0.294
Indic. Female	0.511	0.500	0.460	0.498
Indic.: New computer programs	0.494	0.500	0.736	0.441
Indic.: New machines or technologies	0.469	0.499	0.699	0.459
Indic.: Performance pressure	0.875	0.331	0.898	0.303
Indic.: Prescribed work	0.492	0.500	0.507	0.500
Indic.: Repeated work steps	0.658	0.474	0.659	0.474
Indic.: New tasks	0.846	0.361	0.873	0.333
Indic.: Performance requirements	0.475	0.499	0.503	0.500
Indic.: New work content	0.387	0.487	0.418	0.493
Indic.: Multi processes	0.876	0.329	0.894	0.307
Number of tasks	8.684	3.219	9.008	3.161

Notes: Increase in Stress is an indicator variable equal to 1 (0) if the individual reports that stress and work pressure increased (remained the same or decreased) over the past two years. Increase in Stress (alt) is equal to 1 (0) if the individual reports stress and work pressure increased (remained the same) over the past two years. Decrease in Stress is an indicator variable equal to 1 (0) if the individual reports that stress and work pressure decreased (remained the same or increased) over the past two years. DAIOE, Robot and Software exposure measure occupational AI, robot or software exposure across 115 different 3-digit ISCO-08 occupations. Education is measured in years of schooling (incl. training). Age is measured in years. Plantsize is an indicator variable for 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. Type of employment distinguished among worker, salaried employee, or civil servant. Married and Parttime is 1 if the individual is married or in a part-time job, respectively. New computer programs is 1 if the individual reports the firm introduced new computer programs (new versions of existing programs are not meant here) during the last two years. New machines or technologies is 1 if the individual reports the firm introduced new manufacturing/process technologies and/or new machines/plants in the last two years. Indicators for 1. Performance pressure, 2. Prescribed work, 3. Repeated work steps, 4. New Tasks, 5. Performance requirements, 6. New work content, and 7. Multi processes are 1 if the individual reports 1. to work under strong deadlines or performance pressure; 2. that the execution of the work is prescribed in every detail; 3. that one and the same operation is repeated in every detail; 4. that one is confronted with new tasks the work; 5. that an exact number of pieces, a certain minimum output or the time to do a certain task is prescribed; 6. that things are demanded which have not been learned; 7. that one has to keep an eye on different types of work or processes at the same time. Number of tasks is the number of 18 possible tasks workers might perform in the job.
Source: Authors' computations based on BIBB-BAuA survey waves 2012 and 2018. The sample of all workers consists of 28,052 observations. The sample of exposed workers (defined if Indic.: New computer programs or Indic.: New machines or technologies are equal to 1) consists of 18,820 observations. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). Occupational robot and software exposure are based on the index from Webb (2020).

Table A2: AI, Robots and Worker Stress – Exposed and Non-Exposed Workers A

	Indic.: Increase in stress				
	(1)	(2)	(3)	(4)	(5)
PANEL A: Worker in firms that use new computer programs					
AI-Exposure	-0.0410***	-0.0369***	-0.0360***	-0.0275*	-0.0442***
	(-3.81)	(-5.24)	(-5.76)	(-2.47)	(-4.44)
Robot-Exposure	-0.249***	-0.215**	-0.206***	-0.318***	-0.0936
	(-4.25)	(-3.25)	(-3.29)	(-5.33)	(-0.89)
Observations	13850	13847	13847	6590	7244
pseudo R-squared	0.004	0.018	0.029	0.031	0.034
PANEL B: Worker in firms that not use new computer programs					
AI-Exposure	-0.00971	-0.0278*	-0.0292**	-0.0218	-0.0359*
	(-0.98)	(-2.45)	(-2.66)	(-1.58)	(-2.54)
Robot-Exposure	-0.168***	-0.0117	-0.0279	-0.0541	-0.00315
	(-3.32)	(-0.21)	(-0.53)	(-1.04)	(-0.03)
Observations	14202	14202	14202	6960	7222
pseudo R-squared	0.002	0.017	0.032	0.034	0.037
Plant Controls	no	yes	yes	yes	yes
Worker Controls	no	no	yes	yes	yes
Year	2012/18	2012/18	2012/18	2012	2018

Notes: The dependent variable in all columns is an indicator variable that is equal to 1 (0) if the individual reported that stress and work pressure increased (remained the same or decreased) over the past two years. Panel A (B) is restricted to individuals who (do not) report that the firm introduced new computer programs in the last two years. Occupational AI and Robot exposure is measured across 115 different 3-digit ISCO-08 occupations. Plant controls include controls for industry (2-digit NACE Rev. 1.1), regions (18 different NUTS-2 regions), plantsize (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.) and major occupations groups (according to the first ISCO-08 digit). Worker controls include the log hourly wage, education (measured in years of schooling incl. training), age, and indicator variables for married, part-time, gender, and type of employment (worker, salaried employee, or civil servant). Regressions that are based on both survey years, include year controls. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level. Standard errors (clustered at the 3-digit ISCO-08 level) are reported in parentheses.
Source: Authors' computations based on BIBB-BAuA survey waves 2012 and 2018. The sample is restricted to individuals who report that the firm introduced new computer programs and/or new manufacturing/process technologies and/or new machines/plants in the last two years. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). Occupational robot exposure is based on the index from Webb (2020).

Table A3: AI, Robots and Worker Stress – Exposed and Non-Exposed Workers B

	Indic.: Increase in stress				
	(1)	(2)	(3)	(4)	(5)
PANEL A: Worker in firms that use new machines and technologies					
AI-Exposure	-0.0205*	-0.0280***	-0.0272***	-0.0145	-0.0421***
	(-2.14)	(-3.37)	(-3.56)	(-1.03)	(-3.39)
Robot-Exposure	-0.264***	-0.153*	-0.161**	-0.245***	-0.0670
	(-5.11)	(-2.54)	(-2.80)	(-4.57)	(-0.54)
Observations	13158	13154	13154	6530	6610
pseudo R-squared	0.004	0.017	0.029	0.033	0.034
PANEL B: Worker in firms that not use new machines and technologies					
AI-Exposure	-0.0180	-0.0289**	-0.0291**	-0.0242*	-0.0308*
	(-1.36)	(-2.59)	(-2.67)	(-1.97)	(-2.14)
Robot-Exposure	-0.288***	-0.0981	-0.0880	-0.100	-0.0794
	(-4.45)	(-1.49)	(-1.39)	(-1.57)	(-0.85)
Observations	14894	14889	14889	7020	7849
pseudo R-squared	0.004	0.023	0.040	0.045	0.043
Plant Controls	no	yes	yes	yes	yes
Worker Controls	no	no	yes	yes	yes
Year	2012/18	2012/18	2012/18	2012	2018

Notes: The dependent variable in all columns is an indicator variable that is equal to 1 (0) if the individual reported that stress and work pressure increased (remained the same or decreased) over the past two years. Panel A (B) is restricted to individuals who (do not) report that the firm new manufacturing/process technologies and/or new machines/plants in the last two years.Occupational AI and Robot exposure is measured across 115 different 3-digit ISCO-08 occupations. Plant controls include controls for industry (2-digit NACE Rev. 1.1), regions (18 different NUTS-2 regions), plantsize (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.) and major occupations groups (according to the first ISCO-08 digit). Worker controls include the log hourly wage, education (measured in years of schooling incl. training), age, and indicator variables for married, part-time, gender, and type of employment (worker, salaried employee, or civil servant). Regressions that are based on both survey years, include year controls. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level. Standard errors (clustered at the 3-digit ISCO-08 level) are reported in parentheses.

Source: Authors' computations based on BIBB-BAuA survey waves 2012 and 2018. The sample is restricted to individuals who report that the firm introduced new computer programs and/or new manufacturing/process technologies and/or new machines/plants in the last two years. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). Occupational robot exposure is based on the index from Webb (2020).

Table A4: AI, Robots and Worker Stress in Technology Adopting Firms – Robustness A

	Indic.: Increase in stress (alternative indicator)				
	(1)	(2)	(3)	(4)	(5)
AI-Exposure	-0.0309**	-0.0337***	-0.0333***	-0.0181	-0.0473***
	(-2.98)	(-4.72)	(-5.44)	(-1.56)	(-5.17)
Robot-Exposure	-0.275***	-0.152*	-0.146*	-0.220***	-0.0648
	(-5.18)	(-2.33)	(-2.44)	(-5.22)	(-0.56)
Observations	17787	17783	17783	8524	9247
pseudo R-squared	0.004	0.018	0.029	0.029	0.032
Plant Controls	no	yes	yes	yes	yes
Worker Controls	no	no	yes	yes	yes
Year	2012/18	2012/18	2012/18	2012	2018

Notes: The dependent variable in all columns is an indicator variable that is equal to 1 (0) if the individual reported that stress and work pressure increased (remained the same) over the past two years. Occupational AI and Robot exposure is measured across 115 different 3-digit ISCO-08 occupations. Plant controls include controls for industry (2-digit NACE Rev. 1.1), regions (18 different NUTS-2 regions), plantsize (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.) and major occupations groups (according to the first ISCO-08 digit). Worker controls include the log hourly wage, education (measured in years of schooling incl. training), age, and indicator variables for married, part-time, gender, and type of employment (worker, salaried employee, or civil servant). Regressions that are based on both survey years, include year controls. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level. Standard errors (clustered at the 3-digit ISCO-08 level) are reported in parentheses.
Source: Authors' computations based on BIBB-BAuA survey waves 2012 and 2018. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). The sample is restricted to individuals who report that the firm introduced new computer programs and/or new manufacturing/process technologies and/or new machines/plants in the last two years. Occupational robot exposure is based on the index from Webb (2020).

Table A5: AI, Robots and Worker Stress in Technology Adopting Firms – Robustness B

	Indic.: Increase in stress				
	(1)	(2)	(3)	(4)	(5)
AI-Exposure	-0.0304**	-0.0331***	-0.0333***	-0.0187	-0.0477***
	(-2.82)	(-4.63)	(-5.53)	(-1.67)	(-4.96)
Robot-Exposure	-0.302***	-0.165*	-0.179**	-0.274***	-0.0740
	(-4.72)	(-2.22)	(-2.58)	(-5.44)	(-0.52)
Software-Exposure	0.0507	-0.000394	0.0437	0.0830	-0.00460
	(0.35)	(-0.00)	(0.40)	(0.85)	(-0.03)
Observations	18820	18816	18816	9079	9730
pseudo R-squared	0.004	0.017	0.029	0.030	0.031
Plant Controls	no	yes	yes	yes	yes
Worker Controls	no	no	yes	yes	yes
Year	2012/18	2012/18	2012/18	2012	2018

Notes: The dependent variable in all columns is an indicator variable that is equal to 1 (0) if the individual reported that stress and work pressure increased (remained the same) over the past two years. Occupational AI, Robot, and Software exposure is measured across 115 different 3-digit ISCO-08 occupations. Plant controls include controls for industry (2-digit NACE Rev. 1.1), regions (18 different NUTS-2 regions), plantsize (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.) and major occupations groups (according to the first ISCO-08 digit). Worker controls include the log hourly wage, education (measured in years of schooling incl. training), age, and indicator variables for married, part-time, gender, and type of employment (worker, salaried employee, or civil servant). Regressions that are based on both survey years, include year controls. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level. Standard errors (clustered at the 3-digit ISCO-08 level) are reported in parentheses.
Source: Authors' computations based on BIBB-BAuA survey waves 2012 and 2018. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). The sample is restricted to individuals who report that the firm introduced new computer programs and/or new manufacturing/process technologies and/or new machines/plants in the last two years. Occupational robot and software exposure is based on the index from Webb (2020).

Table A6: AI, Robots and Worker Stress in Technology Adopting Firms – Robustness C

	Indic.: Decrease in stress				
	(1)	(2)	(3)	(4)	(5)
AI-Exposure	0.00777	0.0116	0.0130	-0.000525	0.0320*
	(1.08)	(1.18)	(1.29)	(-0.03)	(2.19)
Robot-Exposure	0.272***	0.274***	0.308***	0.304**	0.340***
	(5.39)	(4.29)	(4.74)	(2.94)	(3.44)
Observations	18820	18755	18755	8990	9593
pseudo R-squared	0.003	0.019	0.026	0.038	0.031
Plant Controls	no	yes	yes	yes	yes
Worker Controls	no	no	yes	yes	yes
Year	2012/18	2012/18	2012/18	2012	2018

Notes: The dependent variable in all columns is an indicator variable that is equal to 1 (0) if the individual reported that stress and work pressure decreased (remained the same or increased) over the past two years. Occupational AI, and Robot exposure is measured across 115 different 3-digit ISCO-08 occupations. Plant controls include controls for industry (2-digit NACE Rev. 1.1), regions (18 different NUTS-2 regions), plantsize (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.) and major occupations groups (according to the first ISCO-08 digit). Worker controls include the log hourly wage, education (measured in years of schooling incl. training), age, and indicator variables for married, part-time, gender, and type of employment (worker, salaried employee, or civil servant). All regressions also include Software exposure as an control variable. Regressions that are based on both survey years, include year controls. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level. Standard errors (clustered at the 3-digit ISCO-08 level) are reported in parentheses.
Source: Authors' computations based on BIBB-BAuA survey waves 2012 and 2018. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). The sample is restricted to individuals who report that the firm introduced new computer programs and/or new manufacturing/process technologies and/or new machines/plants in the last two years. Occupational robot and software exposure is based on the index from Webb (2020).

Table A7: AI, Robots and Worker Stress Across Occupation Groups

	Indic.: Increase in stress				
	(1)	(2)	(3)	(4)	(5)
PANEL A: Managers					
AI-Exposure	-0.0292	-0.0453	-0.0206	0.0205	-0.0281
	(-0.43)	(-0.71)	(-0.33)	(0.17)	(-0.42)
Robot-Exposure	-0.629	-1.090	-0.926	-0.134	-0.978
	(-0.92)	(-1.53)	(-1.54)	(-0.11)	(-1.57)
PANEL B: STEM Professionals					
AI-Exposure	-0.0557***	-0.0462*	-0.0390*	0.0427	-0.128***
	(-8.41)	(-2.27)	(-2.05)	(1.31)	(-3.60)
Robot-Exposure	0.136	-0.218	-0.284	-1.660**	1.255*
	(1.43)	(-0.58)	(-0.83)	(-2.73)	(2.13)
PANEL C: Support Professionals					
AI-Exposure	-0.0467***	-0.0310**	-0.0239*	-0.0299	-0.0223
	(-3.91)	(-2.85)	(-2.39)	(-1.54)	(-1.49)
Robot-Exposure	-0.336	-0.266	-0.198	-0.312	-0.0994
	(-1.26)	(-1.17)	(-0.99)	(-1.34)	(-0.42)
PANEL D: Blue-Collar					
AI-Exposure	0.0670**	0.0164	0.0153	0.0889	-0.0860
	(2.86)	(0.50)	(0.45)	(1.70)	(-1.76)
Robot-Exposure	-0.168**	-0.144*	-0.154*	-0.224*	-0.0185
	(-2.58)	(-2.26)	(-2.47)	(-2.53)	(-0.15)
PANEL E: Support workers					
AI-Exposure	-0.00322	0.0139	-0.00290	0.0148	-0.0524**
	(-0.21)	(0.74)	(-0.18)	(0.68)	(-2.58)
Robot-Exposure	-0.193**	-0.0316	-0.0715	-0.187**	0.0227
	(-3.16)	(-0.37)	(-0.84)	(-2.93)	(0.14)
Plant Controls	no	yes	yes	yes	yes
Worker Controls	no	no	yes	yes	yes
Year	2012/18	2012/18	2012/18	2012	2018

Notes: The dependent variable in all columns is an indicator variable that is equal to 1 (0) if the individual reported that stress and work pressure increased (remained the same) over the past two years. Occupational AI, Robot, and Software exposure is measured across 115 different 3-digit ISCO-08 occupations. Plant controls include controls for industry (2-digit NACE Rev. 1.1), regions (18 different NUTS-2 regions), plantsize (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.) and major occupations groups (according to the first ISCO-08 digit). Worker controls include the log hourly wage, education (measured in years of schooling incl. training), age, and indicator variables for married, part-time, gender, and type of employment (worker, salaried employee, or civil servant). Regressions that are based on both survey years, include year controls. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level. Standard errors (clustered at the 3-digit ISCO-08 level) are reported in parentheses.
Source: Authors' computations based on BIBB-BAuA survey waves 2012 and 2018. The number of observations for Panel A-E are 1221, 2345, 7363, 2641, 5196. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). The sample is restricted to individuals who report that the firm introduced new computer programs and/or new manufacturing/process technologies and/or new machines/plants in the last two years. Occupational robot and software exposure is based on the index from Webb (2020).

Table A8: AI, Robots and Worker Stress Across Sectors

	Indic.: Increase in stress				
	(1)	(2)	(3)	(4)	(5)
PANEL A: Manufacturing					
AI-Exposure	-0.0120	-0.0287**	-0.0226*	-0.00485	-0.0477**
	(-1.12)	(-3.15)	(-2.47)	(-0.31)	(-2.90)
Robot-Exposure	-0.173***	-0.115	-0.125	-0.268***	0.0393
	(-3.34)	(-1.64)	(-1.78)	(-5.98)	(0.26)
PANEL B: Service					
AI-Exposure	-0.0198	-0.00413	-0.00464	0.00257	-0.0125
	(-1.23)	(-0.26)	(-0.33)	(0.13)	(-0.66)
Robot-Exposure	-0.354***	-0.271**	-0.255**	-0.268	-0.263
	(-3.58)	(-2.81)	(-2.69)	(-1.86)	(-1.75)
PANEL C: Public					
AI-Exposure	-0.0566***	-0.0712***	-0.0677***	-0.0592*	-0.0704**
	(-3.86)	(-4.48)	(-5.09)	(-2.32)	(-3.15)
Robot-Exposure	-0.390***	-0.350**	-0.327**	-0.462***	-0.186
	(-5.09)	(-2.67)	(-2.70)	(-4.09)	(-0.92)
Plant Controls	no	yes	yes	yes	yes
Worker Controls	no	no	yes	yes	yes
Year	2012/18	2012/18	2012/18	2012	2018

Notes: The dependent variable in all columns is an indicator variable that is equal to 1 (0) if the individual reported that stress and work pressure increased (remained the same) over the past two years. Occupational AI, Robot, and Software exposure is measured across 115 different 3-digit ISCO-08 occupations. Plant controls include controls for industry (2-digit NACE Rev. 1.1), regions (18 different NUTS-2 regions), plantsize (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.) and major occupations groups (according to the first ISCO-08 digit). Worker controls include the log hourly wage, education (measured in years of schooling incl. training), age, and indicator variables for married, part-time, gender, and type of employment (worker, salaried employee, or civil servant). Regressions that are based on both survey years, include year controls. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level. Standard errors (clustered at the 3-digit ISCO-08 level) are reported in parentheses.
Source: Authors' computations based on BIBB-BAuA survey waves 2012 and 2018. The number of observations for Panel A-C are 6716, 5434, 6248. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). The sample is restricted to individuals who report that the firm introduced new computer programs and/or new manufacturing/process technologies and/or new machines/plants in the last two years. Occupational robot and software exposure is based on the index from Webb (2020).

Table A9: AI, Robots and Worker Stress – Mechanism Task Replacing (alternative)

	Indic.: Increase in stress				
	(1)	(2)	(3)	(4)	(5)
PANEL A: Multi-tasking workers (i.e. > 9 tasks)					
AI-Exposure	-0.0324***	-0.0454***	-0.0410***	-0.0186	-0.0678***
	(-3.79)	(-5.40)	(-4.99)	(-1.40)	(-3.99)
Robot-Exposure	-0.285***	-0.209*	-0.211*	-0.326***	-0.117
	(-4.74)	(-2.39)	(-2.55)	(-3.61)	(-0.86)
Observations	8086	8077	8077	3916	4146
pseudo R-squared	0.004	0.022	0.035	0.040	0.045
PANEL B: Multi-tasking workers (i.e.<= 9 tasks)					
AI-Exposure	-0.0187	-0.0206	-0.0217*	-0.0129	-0.0280*
	(-1.20)	(-1.85)	(-2.16)	(-0.78)	(-2.27)
Robot-Exposure	-0.264***	-0.135*	-0.129*	-0.225***	-0.0403
	(-4.28)	(-2.08)	(-2.30)	(-3.81)	(-0.35)
Observations	10734	10728	10728	5153	5560
pseudo R-squared	0.004	0.021	0.034	0.039	0.038
Plant Controls	no	yes	yes	yes	yes
Worker Controls	no	no	yes	yes	yes
Year	2012/18	2012/18	2012/18	2012	2018

Notes: The dependent variable in all columns is an indicator variable that is equal to 1 (0) if the individual reported that stress and work pressure increased (remained the same or decreased) over the past two years. Panel A (B) is restricted to individuals who perform more (less or equal) than 9 task (out of 18 different activities) at the workplace. Occupational AI and Robot exposure is measured across 115 different 3-digit ISCO-08 occupations. Plant controls include controls for industry (2-digit NACE Rev. 1.1), regions (18 different NUTS-2 regions), plantsize (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.) and major occupations groups (according to the first ISCO-08 digit). Worker controls include the log hourly wage, education (measured in years of schooling incl. training), age, and indicator variables for married, part-time, gender, and type of employment (worker, salaried employee, or civil servant). Regressions that are based on both survey years, include year controls. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level. Standard errors (clustered at the 3-digit ISCO-08 level) are reported in parentheses.
Source: Authors' computations based on BIBB-BAuA survey waves 2012 and 2018. The sample is restricted to individuals who report that the firm introduced new computer programs and/or new manufacturing/process technologies and/or new machines/plants in the last two years. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). Occupational robot exposure is based on the index from Webb (2020).

Table A10: AI, Robots and Worker Stress – Performance Requirements

	Indic.: Increase in stress				
	(1)	(2)	(3)	(4)	(5)
PANEL A: Workers with strict performance requirements					
AI-Exposure	-0.0172	-0.0199	-0.0157	-0.00647	-0.0262*
	(-1.32)	(-1.77)	(-1.60)	(-0.38)	(-2.31)
Robot-Exposure	-0.220***	-0.0420	-0.0568	-0.169*	0.0912
	(-4.20)	(-0.71)	(-1.07)	(-2.09)	(0.72)
Observations	9467	9459	9459	4649	4797
pseudo R-squared	0.003	0.019	0.038	0.040	0.047
PANEL B: Workers without strict performance requirements					
AI-Exposure	-0.0348***	-0.0354***	-0.0367***	-0.0239	-0.0472***
	(-3.77)	(-4.18)	(-4.65)	(-1.85)	(-3.37)
Robot-Exposure	-0.423***	-0.330***	-0.311***	-0.361***	-0.267*
	(-7.01)	(-4.16)	(-3.98)	(-5.12)	(-2.10)
Observations	9353	9351	9351	4418	4916
pseudo R-squared	0.008	0.024	0.033	0.039	0.035
Plant Controls	no	yes	yes	yes	yes
Worker Controls	no	no	yes	yes	yes
Year	2012/18	2012/18	2012/18	2012	2018

Notes: The dependent variable in all columns is an indicator variable that is equal to 1 (0) if the individual reported that stress and work pressure increased (remained the same or decreased) over the past two years. Panel A (B) is restricted to individuals who (do not) report to have strict performance requirements at the workplace. Occupational AI and Robot exposure is measured across 115 different 3-digit ISCO-08 occupations. Plant controls include controls for industry (2-digit NACE Rev. 1.1), regions (18 different NUTS-2 regions), plantsize (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.) and major occupations groups (according to the first ISCO-08 digit). Worker controls include the log hourly wage, education (measured in years of schooling incl. training), age, and indicator variables for married, part-time, gender, and type of employment (worker, salaried employee, or civil servant). Regressions that are based on both survey years, include year controls. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level. Standard errors (clustered at the 3-digit ISCO-08 level) are reported in parentheses.
Source: Authors' computations based on BIBB-BAuA survey waves 2012 and 2018. The sample is restricted to individuals who report that the firm introduced new computer programs and/or new manufacturing/process technologies and/or new machines/plants in the last two years. Occupational AI exposure is based on the DAIOE measure from 2017 (Engberg *et al*, 2023a). Occupational robot exposure is based on the index from Webb (2020).

Data availability statement

The paper uses data from the BIBB/BAuA Employment Survey of the Working Population on Qualification and Working Conditions in Germany 2012 and 2018 (doi: 10.7803/501.18.1.1.10.) The surveys were conducted by the Federal Institute for Vocational Education and Training (BIBB), and the Federal Institute for Occupational Safety and Health (BAuA). For further details, see https://www.bibb.de/de/1386.php.

The data access was provided via Scientific-Use-Files of the Data Research Centre at the Federal Institute for Vocational Training and Education (BIBB-FDZ). The data are confidential, but not exclusive. To apply for data access, please follow the instructions at https://www.bibb.de/de/1386.php

To replicate the results reported in the paper, access to this data set must be obtained from the data provider.