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DISCUSSION PAPER SERIES

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Osea Giuntella
University of Pittsburgh, IZA and NBER

Johannes König
DIW and BSE

Luca Stella
Freie Universität Berlin, CESifo and IZA

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Artificial Intelligence and Workers' Well-Being

This study explores the relationship between artificial intelligence (AI) and workers' well-being and mental health using longitudinal survey data from Germany (2000-2020). We construct a measure of individual exposure to AI technology based on the occupation in which workers in our sample were first employed and explore an event study design and a difference-in-differences approach to compare AI-exposed and non-exposed workers. Before AI became widely available, there is no evidence of differential pre-trends in workers' well-being and concerns about their economic futures. Since 2015, however, with the increasing adoption of AI in firms across Germany, we find that AI-exposed workers have become less satisfied with their life and job and more concerned about job security and their personal economic situation. However, we find no evidence of a significant impact of AI on workers' mental health, anxiety, or depression.

JEL Classification: I10, J28, O30

Keywords: artificial intelligence, future of work, well-being, mental health

Corresponding author:
Luca Stella
Freie Universität Berlin
John F. Kennedy Institute for North American Studies
Department of Economics
Lansstraße 7-9
14195 Berlin
Germany

E-mail: luca.stella@fu-berlin.de

1 Introduction

Over the past few years, there has been a striking increase in the adoption of artificial intelligence (AI) by firms worldwide. The emergence of generative AI, like ChatGPT, has brought about a substantial surge in public interest in AI, shedding light on how this new technology has the potential to reshape our everyday existence as well as our cognitive and professional processes (The Economist, 2023). The level of investment in AI is increasing at high rates (Brynjolfsson et al., 2018). As of 2022, approximately 50% of companies reported using AI technologies in at least one business area (McKinsey, 2022). The global AI market is expected to grow at a rate higher than 37% between 2023 and 2030 (Grand View Research, 2022). AI may have transformative impacts on economic growth, health care, safety, and transportation and may reduce the costs and barriers to information access, education, and training (Aghion et al., 2018; Yu et al., 2018; Chen et al., 2020). Similar to other technological changes, AI can help reduce work-related risks (Ghasemi et al., 2023). Recent studies have investigated the impact of AI on labor market outcomes and productivity (see, for example, Brynjolfsson et al., 2018; Noy and Zhang, 2023; Raj and Seamans, 2018). However, to the best of our knowledge, no existing study has examined the impact of AI on workers' well-being and mental health using longitudinal survey data. This study therefore aims to address this gap in the literature.

Although previous studies have analyzed the effects of industrial robots and other types of automation technologies on life satisfaction and mental well-being (e.g., Gihleb et al., 2022; Nazareno and Schiff, 2021), we are not aware of any other studies examining the role of AI in affecting outcomes related to workers' well-being. The main difference between robotic technologies and AI is that robots require physical manipulation, whereas AI does not require physical manipulation but instead involves computer-based learning (Raj and Seamans, 2019). Scholars have suggested that the adoption of AI may lead to the automation of non-routine tasks (Autor et al., 2006; Felten et al., 2019). Thus, AI may lead to the automation of tasks that are not possible using robotics-based technology and expose relatively highly-educated workers to automation. Researchers have warned that AI could potentially aggravate the erosion of the middle class by diminishing opportunities for secure, high-paying employment that does not require advanced qualifications (Autor et al., 2019). AI may expedite task automation without simultaneously creating new roles for human workers. As noted by Agrawal et al. (2023), the distributional effects of technology depend on which tasks are automated and which workers perform those tasks rather than on automation per se. In this respect, Brekelmans and Petropoulos (2020) highlight that mid-skilled occupations are most likely to be negatively affected.

Evidence indicates that workers' attitudes towards AI in the workplace are mixed. While some surveys suggest that workers worldwide are increasingly concerned about the impact of AI on labor market opportunities (Neudert et al., 2020), a recent Pew study on workers in the US finds that workers in more exposed industries are not threatened by the effects of this new technology on their jobs (Rainie et al., 2023). AI has the potential to enhance workers' productivity and complement workers' skills; but also has the potential to replace the work of many individuals. Ultimately, as is the case with other technological revolutions, the labor market consequences of AI depend on the degree of complementarity and substitutability that emerges between AI and human labor (e.g., Acemoglu and Restrepo, 2022; Autor, 2022). AI also changes the nature of the tasks workers carry out, which may have direct effects on their job satisfaction and the sense of dignity and pride they have in their work (Bankins et al., 2022). Whether the positive effects of AI on labor market outcomes prevail over the displacement effects is an empirical question, especially in the short-run, as workers experience the transition and labor markets adapt to this revolution in production technology.

In this study, we investigate the impact of the adoption of AI technology in the workplace on workers' well-being and concerns about their economic future and mental health, using longitudinal data from the German Socio-Economic Panel (SOEP) and leveraging a new set of questions on AI-related technologies in the workplace, introduced for the first time in the 2020 SOEP wave. Germany provides an interesting context in which to study the implications of AI for workers as AI adoption has increased substantially since 2015. Rammer and Schubert (2021) document that before 2016 approximately 2% of the surveyed German firms reported the use of AI technologies, which grew to 10% in 2021. AI is a rapidly growing technology used in Germany with approximately 25% of all German firms in 2022 reporting that they intended to use AI in the coming years, whereas only 8% intended to do so in 2018 (Berg, 2021). Germany also offers a unique context for analyzing the impact of new technologies on the labor market, given the historical role of unions and extensive employment protection legislation (Dauth et al., 2021; Gihleb et al., 2022).

To conduct our analysis, we construct a measure of occupational exposure based on self-reported individual exposure to AI in the workplace. We define our measure of occupational exposure based on workers' initial occupations observed in the sample. To mitigate concerns that the rising importance of AI may have affected the self-selection of workers in their initial occupations, we restrict the sample to individuals who entered the labor market before 2000, well before the advent of AI technology in Germany. Having classified occupations according to their degree of exposure to AI, we employ an event study design and a difference-in-differences (DiD) approach by comparing workers in high- and low-exposure occupations before and after the significant increase in the adoption of AI across German firms in 2015. Our identification strategy hinges on the assumption of parallel trends in the outcomes of interest between AI-exposed and non-exposed workers prior to the significant roll-out of AI in Germany. Our analysis supports this assumption by showing no evidence of any significant differences in our outcome variables in the pre-trends, that is, during the period preceding the major wave of AI adoption (before 2015).

The results of our analysis suggest that since 2015, there is evidence of a divergence in the level of life satisfaction between AI-exposed and non-exposed workers. AI-exposed workers report lower life satisfaction compared to non-exposed workers (approximately 0.04 standard deviations). To put this magnitude into perspective, in our sample this point estimate would be comparable to approximately 16% of the positive effect of having a college degree on life satisfaction or approximately 13% of the negative effect of being unemployed. We also find evidence of a significant decline in job satisfaction among workers exposed to AI since 2015. When examining concerns about the economic future, AI-exposed workers are more worried about their job security and personal economic situation. In contrast, we find no evidence of significant effects on workers' mental health, anxiety, or depression. The effects on life satisfaction and job satisfaction are mainly driven by medium-skilled workers. This result is consistent with recent evidence suggesting that workers in medium-skilled jobs are most exposed to the displacement effects of AI (Brekelmans and Petropoulos, 2020; Raj and Seamans, 2019; Gathmann and Grimm, 2022).

Our study closely relates to a recent set of studies investigating the impact of AI on labor market outcomes (Acemoglu et al., 2022; Noy and Zhang, 2023; Kanazawa et al., 2022). Previous work has found no evidence of a significant relationship between exposure to AI and employment or wages at the occupation or industry levels (see, for example, Acemoglu et al., 2022; Albanesi et al., 2023). In fact, Felten et al. (2019) find evidence of a small positive effect on wages in AI-exposed occupations in the US, whereas Gathmann and Grimm (2022), using administrative data from Germany, find evidence of positive effects on employment, especially in the service sector. Scholars have also suggested that AI can reduce job performance inequalities (Noy and Zhang, 2023; Kanazawa et al., 2022). Specifically, we contribute to the growing body of literature on the impact of automation on job satisfaction and health. Using data from the US General Social Survey and the measure of automation exposure proposed by Frey and Osborne (2017), Nazareno and Schiff (2021) find that workers facing the risk of automation experience less stress but also poorer health. Similarly, Liu (2023) shows that US workers in highly automatable occupations report lower job satisfaction and health. Furthermore, previous evidence on the US found negative mental health effects from the introduction of robots, but there was no such evidence of negative effects in Germany (O'Brien et al., 2022; Gihleb et al., 2022). Gihleb et al. (2022) highlight the role of institutions and policies in mitigating the potential adverse effects of exposure to automation technologies on workers' mental well-being. In a recent study, Golin and Rauh (2022) find that workers are concerned about the threat of automation to their jobs within the next ten years. The authors also find that the fear of automation is linked to intentions to join a union, retrain, switch occupations, preferences for higher taxation, populist attitudes, and voting intentions. Crucially, while these studies considered either industrial robots or a general measure of the automatability of occupations, our study focuses specifically on direct exposure to AI technologies in the workplace.

AI-driven technologies have the potential to automate a wider range of tasks than robotics-focused technologies (Raj and Seamans, 2019). The increased use of machine learning may expose a larger share of middle- and high-skilled tasks and jobs to competition from automation technologies. Whether the positive effects of augmentation outweigh the negative effects of substitution requires further empirical investigation. Our study provides initial insights into how the AI revolution has affected workers' perceptions during the transitional phase. It is vital to comprehend the varied impact of AI on workers' well-being, as this knowledge may inform labor market policies and regulations that foster innovation and safeguard employees' dignity. Implementing labor policies designed to protect vulnerable workers, establishing effective retraining programs, and providing support to employees during technological transitions could play pivotal roles in mitigating the adverse consequences of new automation technologies on worker welfare.

2 Institutional Background and Data

2.1 AI in Germany

The roll-out of AI in Germany accelerated only recently. As noted by Gathmann and Grimm (2022), patent applications for AI technologies started to grow strongly only after 2015, and more significantly in 2017 and 2018. The innovation survey conducted by ZEW – Leibniz Centre for European Economic Research provides a consistent longitudinal perspective on AI adoption in Germany (Rammer and Schubert, 2021). Specifically, the most recent wave of the innovation survey contains information on AI adoption percentages for 2021. AI use was not widespread before 2010, and the rate of AI adoption was extremely low before 2016. AI adoption rates have increased substantially over the last few years. While only 2% of firms adopted AI before 2016, this number rose to 6% in 2019 and 10% in 2021 (Rammer et al., 2020). Regarding the diffusion of AI across industries, the leading adopters of AI technology in 2019 were finance (24%) and IT (21%), followed by skilled services (18%) such as legal, architecture, consulting, and research. Conversely, the laggards in AI adoption include mining (1.6%), miscellaneous business services (2.3%), and transportation (5.3%) (Rammer et al., 2020). These cross-sectoral differences in AI adoption are qualitatively reflected in our individual-level data on AI exposure from the SOEP, with IT and finance being the most exposed (see Figure A.1 in the Appendix). As shown in Figure 1, which is based on the data from the innovation survey (Rammer and Schubert, 2021), 75% of the firms in the finance sector that used AI technologies in 2019 began using AI in 2016. The share of the chemical and pharmaceutical sectors is 74%, whereas that of electronics and machines is 68%.

Increasing rates of AI adoption across German firms were accompanied by the German government's investment in AI. In 2018, the German Federal Government launched its Artificial Intelligence Strategy and pledged to invest approximately 5 billion euros by 2025 in AI development.[1] For these reasons, Germany is an interesting country for analyzing the effects of rising exposure to AI on the well-being and mental health of workers.

2.2 Data

The data source for our analysis comes from the German Socio-Economic Panel (SOEP). The SOEP is a representative longitudinal dataset that has surveyed households and individuals in Germany since 1984. The dataset contains a wide range of individual- and household-level information and is constructed to ensure the representativeness of the entire German population. For a detailed description of the survey, refer to Goebel et al. (2019) and Schröder et al. (2020).

The SOEP data have several unique features that make them particularly attractive for our analysis. First, the SOEP contains information on individuals' job characteristics and employment histories in the form of a long-running series of (four-digit) International Standard Classification of Occupation codes (ISCO). The availability of such information is essential because as detailed below, it allows us to create a pre-determined measure of AI exposure, which is based on job classification. Second, the dataset contains a set of self-reported indicators of satisfaction with respect to different life domains. In our study, we focus on life and job satisfaction as the primary outcome variables for workers' well-being. These measures are recorded on an 11-point Likert scale, ranging from 0 (very dissatisfied) to 10 (very satisfied). Respondents are also asked about several domain-specific concerns, including worries about job security and personal economic situation, which serve as our additional outcomes. They respond using a scale ranging from "not concerned at all", to "somewhat concerned", and to"very concerned".

[1] One of the goals of this initiative is to establish 12 centers for the development and use of AI technology as well as over 100 departmental positions for AI researchers at German universities. The German government's EXIST initiative intends to disperse roughly 2 billion euros to existing and new start-up companies in the AI field.

Furthermore, the SOEP has several metrics of mental well-being, including the Mental Component Score (MCS) derived from the SF-12 questionnaire (Andersen et al., 2007), as well as diagnoses of mental illnesses such as depression and emotional states (i.e., feelings of anxiety). Depression is a binary variable equal to one for doctor-diagnosed depression, while anxiety is measured on a 5-point frequency scale from "very rarely" to "very often".[2] Third, and most importantly for our purposes, the 2020 SOEP wave provides information on the use of automatic digital systems and their frequency of use. In 2020, the survey included a new module aimed at measuring individual-level exposure to AI in the workplace (Fedorets et al., 2022). Employed respondents are asked a battery of questions about their current exposure to various digital systems and are required to indicate the frequency of interaction with these systems on the job. Figure A.2 in the Appendix shows the question module which covers five broad areas in digital systems: 1) natural language processing; 2) image and video processing; 3) text processing; 4) information processing and evaluation; and 5) knowledge gathering. One of the advantages of the SOEP questionnaire is that workers are interviewed indirectly about their use of AI technologies, thereby avoiding potential measurement errors due to their familiarity with the notion of AI. The use-frequency categories are "several times a day"; "on a daily basis"; "on a weekly basis"; "less often"; "never." The answer distribution of these items is skewed; that is, most respondents reported that they never used these systems.[3] Using this information, we construct a broad measure of AI exposure at the individual level. In practice, we identify whether a person interacted with any type of digital system in their job, at least on a weekly basis. We then compute the average degree to which a two-digit ISCO occupation is directly exposed to AI technology. Our key explanatory variable is a dummy variable that indicates whether a worker is employed in an occupation with high (i.e., above the median) exposure to AI. Figure A.8 in

[2]Specifically, respondents were asked about their mental health score every other year since 2002; about their current depression status every other year since 2009; and about anxiety every year since 2007.

[3]The answer distributions are shown in Figures A.3 to A.7 in the Appendix. For these five items, positive exposure to AI (at least infrequent use) ranges from 20% to 30%.

the Appendix illustrates the predictive occupation categories for individual exposure to AI. Unsurprisingly, most AI-exposed occupations include programmers and IT workers. White collar workers and skilled professionals are among those most exposed to new technologies. To minimize the risk of AI driving the selection into occupations, we restrict the analysis to individuals who entered the SOEP data before 2000 and maintained their occupation in the first year fixed over time.

The working sample is constructed as follows. We consider the survey years 2000-2020 and restrict our attention to workers aged 25-65. As mentioned above, to mitigate concerns that the rising importance of AI in the early 2000s may have affected the sorting of workers into their initial occupations, we restrict the sample to individuals who entered the labor market before 2000, that is, well before the advent of AI technology in Germany. This restriction has consequences for the age distribution in our sample, particularly when focusing on the later years of our analysis and the impact of AI technology, which in Germany increased significantly only after 2015. Therefore, our results should be interpreted as the effects of AI exposure on middle-aged and older workers.[4] After these restrictions, we obtain a final longitudinal sample of approximately 166,000 person-year observations with non-missing occupational information resulting from approximately 16,000 individuals; the sample size varies depending on the outcome variable used in the regression model.

Table A.1 in the Appendix displays the descriptive statistics of the main variables used in our analyses. Approximately, 62% of workers in the sample report high exposure to AI in the workplace. The sample can be characterized as mid-career workers, as their average age is approximately 46. The sample is roughly balanced between males and females (51% females). Approximately 23% of individuals have a college degree, which identifies the high-skilled workers in our heterogeneity analysis by education. Approximately 68% are married, and the average number of children in the household

[4]As shown in Tables A.3 and A.4 in the Appendix, relaxing the restriction on the year of first occupation to 2005 yields similar results.

is close to 0.63. Although, as mentioned above, the sample is composed of slightly older workers, they are fairly representative of the German workforce. Average satisfaction with life and with job are both equal to approximately 6.8. The mean of the worries scales (job security and personal economic situation) is close to two, and thus centered on the response item indicating that they are "somewhat concerned". The MCS is close to its normed mean of 50, while the mean of the anxiety frequency is close to 2, which corresponds to the item "rarely feeling anxious." The proportion of ever being diagnosed with depression is approximately 8%.

3 Model Specification

To examine the relationship between AI exposure and workers' outcomes, we employ two complementary empirical approaches. First, we adopt an event study approach. Therefore, we estimate the following equation:

$$Y_{ijst} = \sum_{t=2000, t\neq 2009}^{2020} \gamma_t P_t + \sum_{t=2000, t\neq 2009}^{2020} \delta_t P_t \times \textit{AI-exposed}_{ijst} + \alpha X_{ijst} + \theta_i + \lambda_{st} + \epsilon_{ijst} \quad (1)$$

where the index $ijst$ denotes an individual i, who had their first job in an ISCO two-digit occupation j, resided in federal state s, and was interviewed in year t. Y_{ijst} denotes the outcome variable of interest: well-being (life satisfaction and job satisfaction); worries (concerns about job insecurity and personal economic situation); and mental health metrics (mental component score (MCS), anxiety frequency, and depression incidence). P_t is a set of calendar year dummies from 2000 to 2020 with the reference period being 2009. Before 2010, there was almost no exposure to AI technology in the workplace. As mentioned earlier, fewer than 1% of businesses were exposed to AI at the time. In the analysis, we also highlight a second period of interest (2015–2020), as AI adoption rates substantially increased after 2015 (Rammer and Schubert, 2021). $\textit{AI-exposed}_{ijst}$ is a dummy variable equal to one if individual i is highly exposed to AI in their (first) occupation, i.e., an indicator variable that equals one if the exposure to AI is above the median in this occupation. The coefficients of interest are δ_s, which capture the average difference in the outcomes of interest between AI-exposed and non-exposed workers over time. X_{ijst} is a vector that includes worker-level covariates such as interactions between a gender dummy and a full set of age dummies, the number of children, a binary variable indicating whether the worker is married, and indicators for their education. θ_i denotes the individual fixed effects, which absorb the influence of any time-constant individual heterogeneity. Our specification also includes federal state $\times$ year fixed effects, λ_{st}. The inclusion of these effects controls for all possible state-level time-varying factors, thereby accounting for the possibility that regions with different occupational structures may experience different time-varying shocks. Finally, ϵ_{ijst} represents an idiosyncratic error term.

We then integrate the event study analysis with the results from the DiD design. Formally, we estimate the following model:

$$Y_{ijst} = \beta Post_t \times AI\text{-}exposed_{ijst} + \gamma X_{ijst} + \theta_i + \lambda_{st} + \tau_t + v_{ijst} \tag{2}$$

where the variables Y_{ijst}, $AI\text{-}exposed_{ijst}$, X_{ijst}, parameters θ_i and λ_{st}, and the error term v_{ijst} are defined in the same way as in Equation (1). $Post_t$ is a dummy variable that equals one after 2015. As mentioned above, we consider 2015 as our reference year because Rammer and Schubert (2021) documented that the adoption of AI markedly increased from 2016, and as later shown in our event-study analysis, the effects of AI materialize only over the last few years in our sample. Equation (2) also contains survey year fixed effects (τ_t) to account for possible trends in the outcomes. The key coefficient in the DiD specification is β, which captures the difference in outcomes for AI-exposed workers after 2015, relative to non-exposed workers. The identifying variation for our coefficients of interest in both equations (δ and β) stems from changes in AI exposure within occupations and over time. We cluster standard errors at the individual level for all estimates.

At this stage, it is worth remarking that our analysis faces two main empirical challenges. First, it does not leverage any quasi-experimental variation in the allocation of workers across AI-exposed and non-exposed occupations. Second, we do not observe the counterfactual evolution of our outcome variables in the absence of AI. We attempt to address these issues in three ways. First, in both equations, we exploit the longitudinal design of the SOEP by including worker fixed effects (θ_i). These fixed effects cancel out the important time-invariant confounding factors that could bias our estimates. For example, individuals might sort themselves into occupations with different levels of AI exposure based on pre-determined characteristics, which could simultaneously affect their well-being, concerns about their economic future, and mental health. Individual fixed effects account for this selection bias. Second, our choice to assign exposure to AI of the initial occupation and to keep only individuals entering the sample before 2000,—well before the advent of AI technology in the German industry,—further alleviates selection concerns regarding the movement of workers across occupations in response to AI penetration. Finally, we show that there are flat pre-trends between AI-exposed and non-exposed workers, thereby suggesting that in our setting, the identification assumption of parallel trends in the absence of AI is plausible (see Section 4).

4 Results

4.1 Main Results

Trends in Well-being—Before presenting our estimation results, we document the trends in well-being and concerns about the economic situation for AI-exposed vs. non-exposed workers in Figure 2. Specifically, the figure visualizes third-degree polynomial smoothing of the residuals for our main outcomes after controlling for individual fixed effects, year fixed effects, federal state × year fixed effects, interactions between a gender dummy and a full set of age dummies, number of children, a binary variable indicating whether the worker is married, and indicators for education. Overall, across the various outcomes of interest, there is little evidence of large differences before 2015, whereas considerable differences emerge only after 2015. Regarding life satisfaction, both groups of workers start at approximately equal levels in 2000. At the beginning of our analysis period, workers exposed to AI have slightly higher life satisfaction, but this trend then reverses. From 2015 onward, AI-exposed workers show significantly lower life satisfaction than to non-exposed workers, and this pattern becomes more pronounced after 2015. Regarding job satisfaction, a divergence in trends materializes only after 2015. Regarding concerns about job security and personal economic situation, the patterns appear similar. Until 2015, both groups of workers exhibit similar levels of concern. After 2015, AI-exposed workers become more concerned about both dimensions than the non-exposed workers.

Event Studies— In Figures 3 and 4, we report the event study estimates of the effect of AI on well-being and mental health as described in Equation (1), namely, the series of estimated δ_t coefficients. These figures highlight the dynamic impact of AI diffusion during the three periods. The first period, 2000-2009, compares AI-exposed and non-exposed workers when AI was virtually absent. The second period, 2010-2014, identifies the early phases of AI adoption in Germany. The third period, 2015-2020, analyzes the differences between exposed and non-exposed workers in a period in which AI increased substantially among German firms. For all outcomes in Figure 3, we observe a flat pre-trend from 2000 to 2009, with the coefficients statistically insignificant and close to zero. However, there is no evidence of significant effects in the early stage of AI adoption between 2010 and 2015, a period in which less than 2% of German firms reported adopting AI technologies (Rammer and Schubert, 2021). Since 2015, we observe a decline in our measure of satisfaction outcomes and an increase in concerns about job security and personal economic situation.

Figure 4 displays the event study estimates for the mental health outcomes. For each outcome, we observe non-significant differences between AI-exposed and non-exposed workers between 2004 and 2009.[5] For these outcomes, we find no evidence of a significant change in trends throughout the study period, suggesting that AI has no effects on mental health. Notably, the event study coefficients for the mental health outcomes are small and close to zero.

In summary, our event study analysis of life satisfaction, job satisfaction, and concerns about job security and personal economic situation highlights a shift in the trend after 2015 between AI-exposed and non-exposed workers.

Difference-in-Differences—To gauge the overall effect of AI on our metrics of interest, we compare AI-exposed and non-exposed workers before and after the recent increase in AI adoption across German firms. As presented in our event study analysis, the effects of AI began to materialize after 2015, consistent with the data on firms' AI adoption (Rammer and Schubert, 2021). Therefore, we conduct a DiD analysis comparing AI-exposed and non-exposed workers before and after 2015. Table 1 reports the main estimates of the effect of AI on workers' well-being and concerns about their economic situations. The results show that from 2015 onward, AI-exposed workers report lower levels of life satisfaction than non-exposed workers (see column 1). The effect is relatively small, with 0.04 standard deviations, but is economically significant. To put this magnitude into perspective, in our sample this point estimate would be equivalent to approximately 16% of the positive effect of having a college degree on life satisfaction, or approximately 13% of the negative effect of unemployment. We also find that AI-exposed workers exhibit lower job satisfaction by approximately 0.05 standard deviations (see column 2). In our sample, this decline corresponds to approximately one-third of the positive effect

[5]For depression, we have no data before 2009.

of having a college degree on job satisfaction, or approximately 5% of the negative effect of unemployment. When examining workers' concerns about their economic future, AI-exposed workers are more concerned about job security and their personal economic situation (see columns 3 and 4). The estimated coefficients for concerns about job security and personal economic situation are approximately 16% and 9% of the protective effect of having a college degree on these concerns, respectively. Consistent with Figure 3, we do not observe significant differences in the pre-trends between AI-exposed and non-exposed workers (between 2000 and 2014). Indeed, when testing the hypothesis that the sum of all the pre-trend coefficients for the years preceding the first major wave of AI adoption is not significantly different from zero, we fail to reject the null hypothesis for all outcomes (see columns 1 to 4 of Table 1).

Table 2 shows the regression coefficients of exposure to AI on mental health outcomes. Taken together, the results in the table confirm the visual evidence from the event study (see Figure 4). For all outcomes, the estimated coefficients are not statistically significant and close to zero. Reassuringly, for these outcomes as well, we cannot reject the null hypothesis that the sum of all pre-trend coefficients for the years preceding the substantial increase in AI adoption is equal to zero.

In summary, our results suggest that AI exposure leads to a decline in life and job satisfaction, accompanied by an increase in concerns about personal economic futures. Interestingly, AI exposure had no effect on mental health metrics. This result aligns with previous research that found no negative effects on labor market outcomes (Acemoglu et al., 2022; Albanesi et al., 2023; Raj and Seamans, 2018). However, although labor market outcomes remain unaffected, workers may still be concerned about their economic prospects in this transition phase, potentially negatively affecting their overall life and job satisfaction.

4.2 Robustness Checks and Heterogeneity Analyses

To assess the robustness of our findings, we report the sensitivity of our DiD estimates for workers' well-being to the use of different samples or specifications.[6] First, in Panel A of Table A.2 in the Appendix we show that the effect of AI exposure remains mostly unchanged when we estimate Equation (2) using the initial state of residence when the individual entered the SOEP panel (instead of the individual's current state of residence). The results are similar when we exclude from the sample individuals who changed their county of residence (see Panel B), residential address (see Panel C) or postcode during the sample period (see Panel D). Second, as previously mentioned, we restricted the main analysis to workers entering the labor market prior to 2000. As discussed in the previous sections, this restriction had implications for the sample age. We show that the results are similar and remain statistically significant when we restrict the sample to workers who entered the labor market prior to 2005. We report the results of this analysis in Tables A.3 and A.4 in the Appendix. Third, we consider alternative metrics for the outcomes of interest. Specifically, for the satisfaction variables, we replace the continuous scales with dichotomous variables equal to one if the respondent indicates a level of satisfaction at or above the median. For concerns, we use dummy variables equal to one if the respondent indicated being very concerned. The results presented in Table A.5 in the Appendix tend in the same direction and remain statistically significant. We find that AI-exposed workers are 3% less likely to report life satisfaction at or above median and 5% less likely to report job satisfaction at or above median. Furthermore, they are 14% more likely to be very concerned about their job security, and 17% more likely to be very concerned about their personal economic situation. Finally, the inclusion of number of children, marital status, and education dummies as control variables might be problematic as they could potentially be affected by workers' well-being. Table A.6 in

[6] Evidence from the event study analysis confirms our main findings. For the sake of space, this analysis is not reported but available upon request.

the Appendix shows the robustness of our findings after excluding this set of controls.

In what follows, we present the heterogeneity analyses for workers' well-being along many dimensions. First, we explore the heterogeneity of the effects by gender (see Table A.7 in the Appendix). Taken together, we find evidence that the effect of AI exposure on well-being is similar among men and women, whereas the estimated effects on workers' concerns about job security and personal economic situation are significantly larger among men. This result is aligned with the findings of Anelli et al. (2021), who showed that men are more likely than women to be exposed to the negative effects of automation technology. Second, we examine whether the adoption of AI differentially affects workers' well-being and concerns based on their level of education. Panels A, B, and C of Table A.8 in the Appendix suggest that the effect of AI on life and job satisfaction is driven mainly by medium-educated workers (i.e., those with a high school diploma). This is consistent with previous evidence suggesting that middle-skill tasks may be the most exposed to the displacement effects of AI (Brekelmans and Petropoulos, 2020). Third, we explored the heterogeneity of the results by dividing the sample between East and West Germany (see Table A.9 in the Appendix). If anything, the effect of AI is associated with a larger negative effect on job satisfaction in East Germany. Similarly, we detect a larger effect on East German workers' concerns about their job security and economic situation.

5 Conclusion

Are workers concerned about the consequences of AI on their labor market opportunities? Recent advances in AI have led to fundamental shifts in daily life. A handful of studies have examined the impact of AI on labor markets and workplace productivity (Acemoglu et al., 2022; Albanesi et al., 2023; Raj and Seamans, 2018). However, little is known about how the AI revolution has affected workers' well-being and mental health. Using longitudinal survey data from Germany, this study estimated the effects of exposure to AI technology in the workplace on workers' well-being and mental health.

Comparing workers highly exposed to AI with workers employed in less exposed jobs before and after the significant increase in the adoption of AI across German firms in 2015, we found evidence of a relative decline in life and job satisfaction among exposed workers. The results on life and job satisfaction are stronger among medium-skilled workers, which is consistent with recent research suggesting that middle-skilled jobs may be more exposed to the displacement effects of AI (Brekelmans and Petropoulos, 2020). There is also an increase in workers' concerns about their job security and economic situation. These findings suggest that despite the lack of evidence on the negative effects of AI on labor market outcomes (Acemoglu et al., 2022; Albanesi et al., 2023; Raj and Seamans, 2018), workers may be concerned about their future economic prospects as a consequence of higher exposure to AI in the workplace. However, while concerns rose, we find no evidence of a significant effect on the metrics of mental health, depression, or anxiety.

Our study has a few limitations. First, a potential concern is that we use self-reported information on exposure to AI in the workplace to build our metric of occupational exposure. Second, although the diffusion of AI has substantially increased in the last five years, we are still in the early phases of the AI revolution; therefore, it may be premature to draw definitive conclusions about the impact of AI on workers. Third, because of our identification strategy, our study captures the effects on middle-aged and older workers. Thus, our results cannot be generalized to the effects of AI on young workers.

Although our study is explorative, it provides initial insights into the short-term consequences of the AI revolution on workers' perceptions during this phase of transition. Future research may shed further light on this topic by exploring larger datasets and using a more precise measure of AI exposure. Understanding the heterogeneous impacts of AI on the well-being of workers is crucial for shaping labor market policies and regulations that promote innovation, while protecting the dignity of workers. Labor policies aimed at safeguarding vulnerable employees, developing effective retraining initiatives, and providing assistance to workers throughout technological shifts could be instrumental in reducing the negative impacts of automation on workers' welfare.

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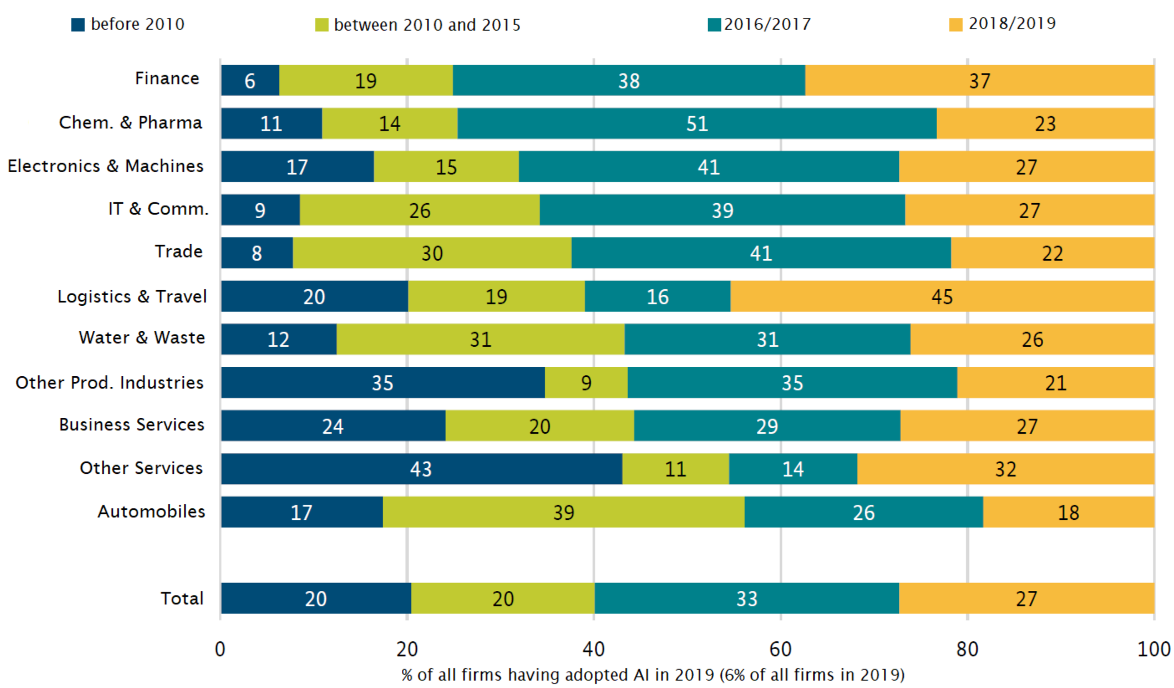
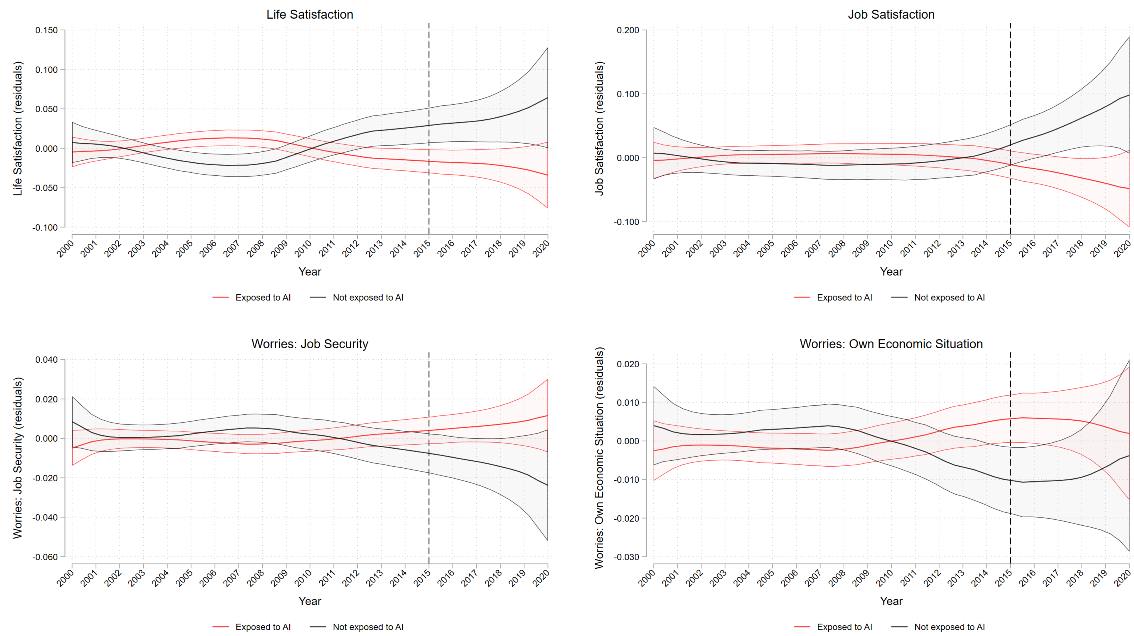
Figures and Tables

Figure 1: Share of AI Adoption by Industry – before 2010 to 2019



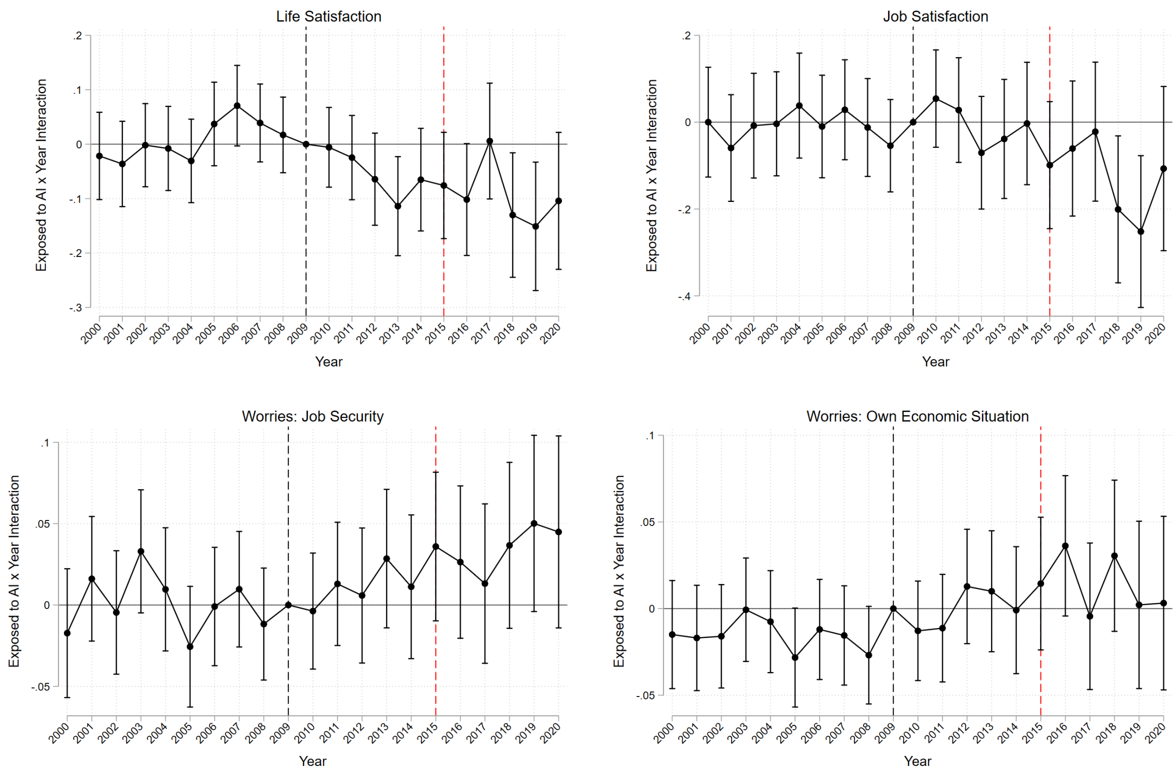
Notes - This figure is based on the one shown in Rammer et al. (2020). The figure provides the share of firms among AI adopters in 2019 from the point in time of first use between the period before 2010 and 2019. The results are based on the innovation survey conducted by the ZEW – Leibniz Centre for European Economic Research.

Figure 2: Exposure to AI and Workers' Well-being, 2000-2020 – Residualized Relationship



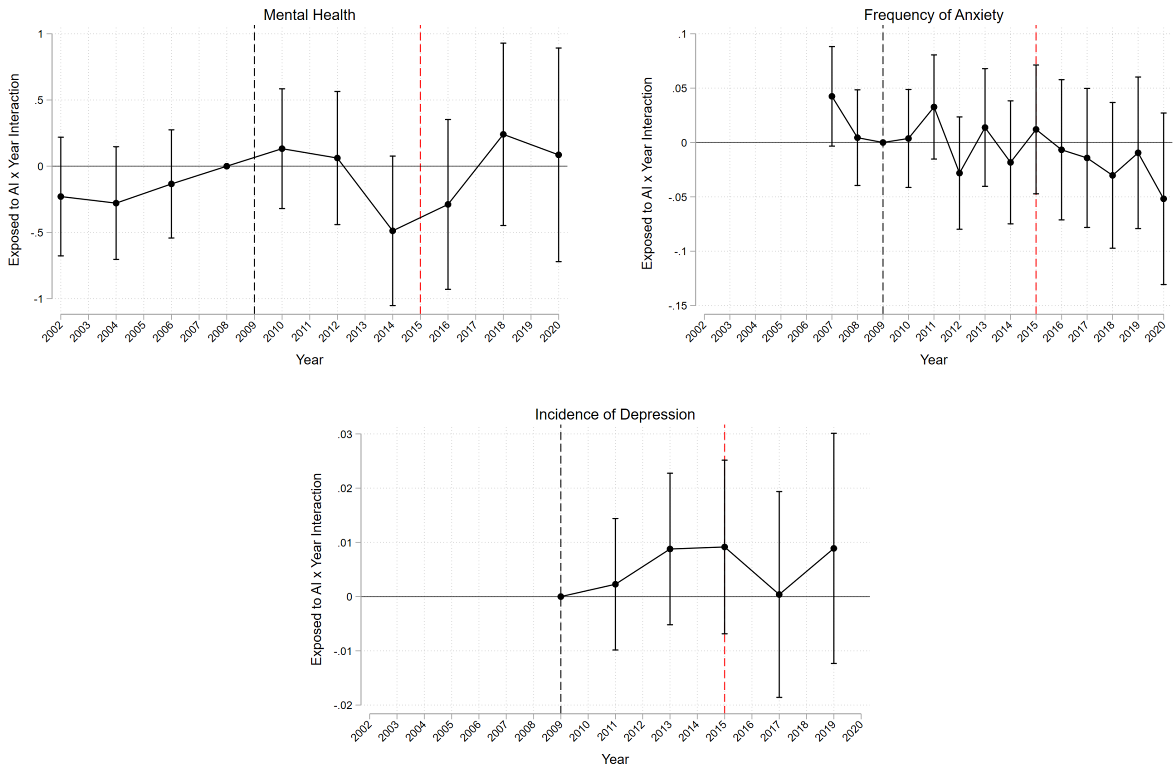
Notes - Data are drawn from the SOEP version 37. The figure documents the residualized evolution of workers' well-being and worries over the period 2000-2020 among individuals aged 25-65 (i.e., after controlling for interactions between a gender dummy and a full set of age dummies, individual fixed effects, year fixed effects, state-by-year fixed effects, as well as controls for the number of children, marital status and education). The dashed vertical line at 2015 indicates the beginning of a period in which AI increased substantially among German firms (see Section 2.1).

Figure 3: Exposure to AI and Workers' Well-being, 2000-2020 – Event Study Analysis



Notes - Data are drawn from the SOEP version 37. The figure shows the point estimates and 95% confidence intervals of the interaction terms between the exposure to AI and year dummies taking 2009 as the reference year when estimating the model in Equation (1). This figure highlights the dynamic impact of AI diffusion during the three periods. The first period, 2000-2009, compares AI-exposed and non-exposed workers when AI was virtually absent. The second period, 2010-2014, identifies the early phases of AI adoption in Germany. The third period, 2015-2020, analyzes the differences between exposed and non-exposed workers in a period in which AI increased substantially among German firms (see Section 2.1).

Figure 4: Exposure to AI and Workers' Mental Health Outcomes, 2000-2020 – Event Study Analysis



Notes - Data are drawn from the SOEP version 37. The figure shows the point estimates and 95% confidence intervals of the interaction terms between the exposure to AI and year dummies taking 2009 as the reference year when estimating the model in Equation (1). These figures highlight the dynamic impact of AI diffusion during the three periods. The first period, 2000-2009, compares AI-exposed and non-exposed workers when AI was virtually absent. The second period, 2010-2014, identifies the early phases of AI adoption in Germany. The third period, 2015-2020, analyzes the differences between exposed and non-exposed workers in a period in which AI increased substantially among German firms (see Section 2.1). The mental health outcome corresponds to the MCS.

Table 1: Effects of Exposure to AI on Workers' Well-being – DiD Estimates

	(1)	(2)	(3)	(4)
Dep. var.:	Life satisfaction	Job satisfaction	Worries: job security	Worries: own economic situation
Exposed to AI * 2015-2020	-0.073**	-0.105**	0.028**	0.024**
	(0.031)	(0.045)	(0.014)	(0.012)
Mean of dep. var.	6.895	6.885	1.663	1.971
Std. dev. of dep. var.	1.739	2.076	0.700	0.689
F-statistic (p-value) (2000+...+2014=0)	0.611	0.864	0.753	0.373
Observations	165,776	130,655	127,044	165,487

Notes - Data are drawn from the SOEP version 37. Standard errors are reported in parentheses and are clustered at the individual level. All specifications include interactions between a gender dummy and a full set of age dummies, individual fixed effects, year fixed effects, state-by-year fixed effects, as well as controls for number of children, marital status and education.
*Significant at 10 percent; ** Significant at 5 percent; ***Significant at 1 percent.

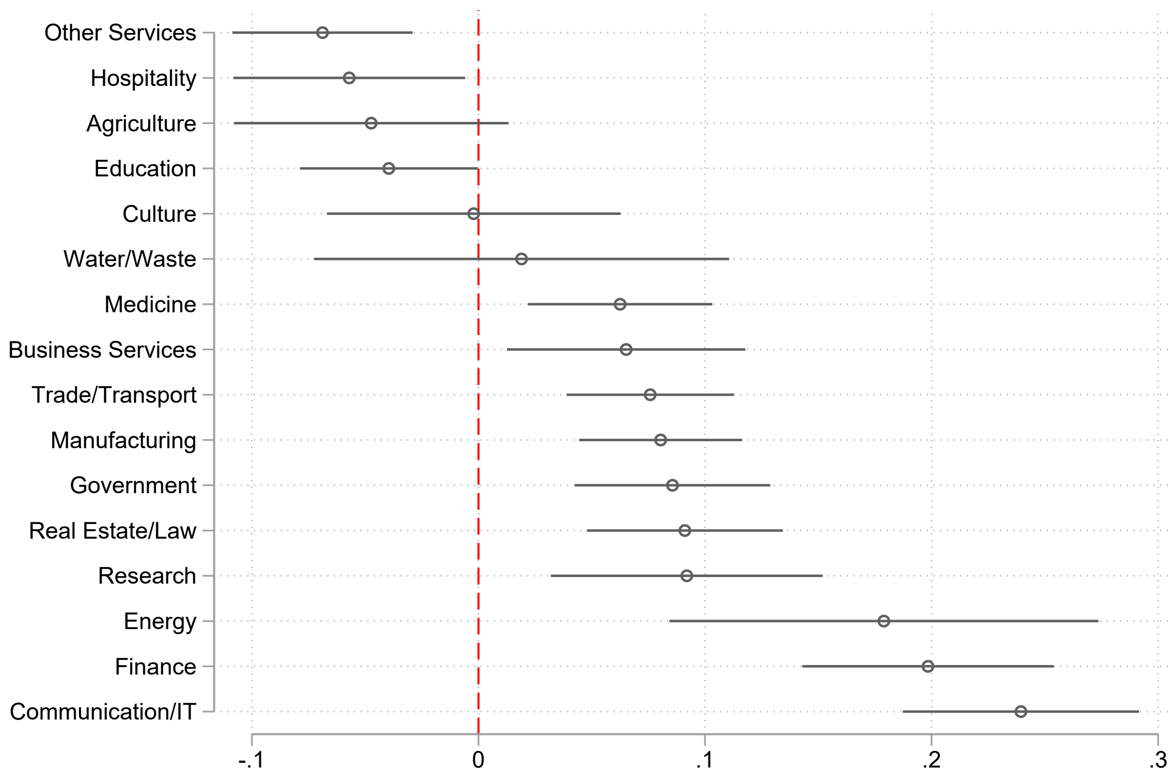
Table 2: Effects of Exposure to AI on Workers' Mental Health Outcomes – DiD Estimates

Dep. var.:	(1) Mental health	(2) Anxiety	(3) Depression
Exposed to AI * 2015-2020	0.104	-0.018	0.003
	(0.231)	(0.017)	(0.006)
Mean of dep. var.	49.53	1.982	0.0828
Std. dev. of dep. var.	9.867	0.978	0.276
F-statistic (*p*-value) (2000+...+2014=0)	0.367	0.695	0.332
Observations	69,206	77,467	30,018

Notes - Data are drawn from the SOEP version 37. Standard errors are reported in parentheses and are clustered at the individual level. All specifications include interactions between a gender dummy and a full set of age dummies, individual fixed effects, year fixed effects, state-by-year fixed effects, as well as controls for number of children, marital status and education. The mental health outcome corresponds to the MCS.
*Significant at 10 percent; ** Significant at 5 percent; ***Significant at 1 percent.

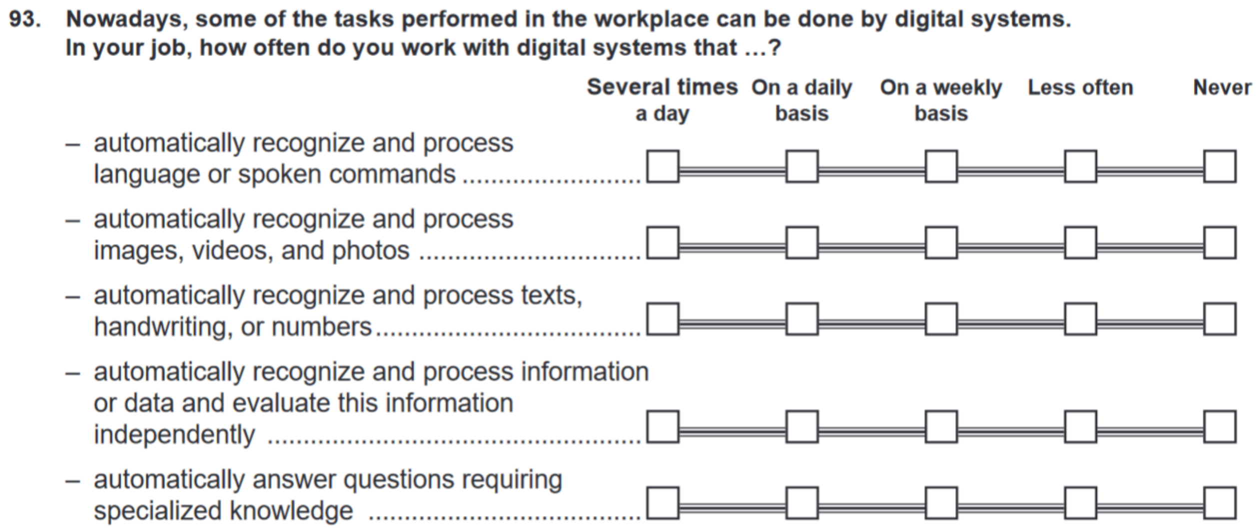
Appendix: Supplemental Figures and Tables

Figure A.1: AI Exposure by Industry based on Probit Predictions



Notes - Data are drawn from the SOEP version 37. The figure shows average marginal effects and 95% confidence intervals of industry dummies obtained in a Probit model that controls for basic socio-demographic characteristics (i.e., age, gender, migration status, marriage, education, and federal state fixed effects) and NACE classification dummies. The base category is construction.

Figure A.2: SOEP Questionnaire on Digital System Use in 2020

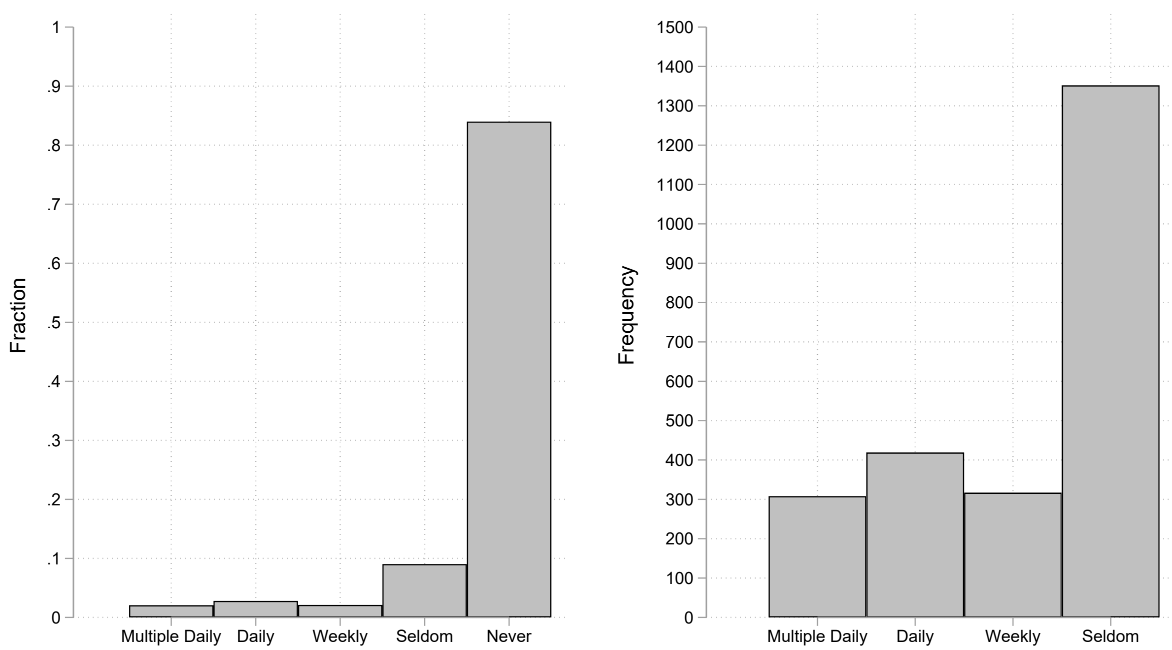


93. Nowadays, some of the tasks performed in the workplace can be done by digital systems. In your job, how often do you work with digital systems that ...?

	Several times a day	On a daily basis	On a weekly basis	Less often	Never
– automatically recognize and process language or spoken commands	☐	☐	☐	☐	☐
– automatically recognize and process images, videos, and photos	☐	☐	☐	☐	☐
– automatically recognize and process texts, handwriting, or numbers	☐	☐	☐	☐	☐
– automatically recognize and process information or data and evaluate this information independently	☐	☐	☐	☐	☐
– automatically answer questions requiring specialized knowledge	☐	☐	☐	☐	☐

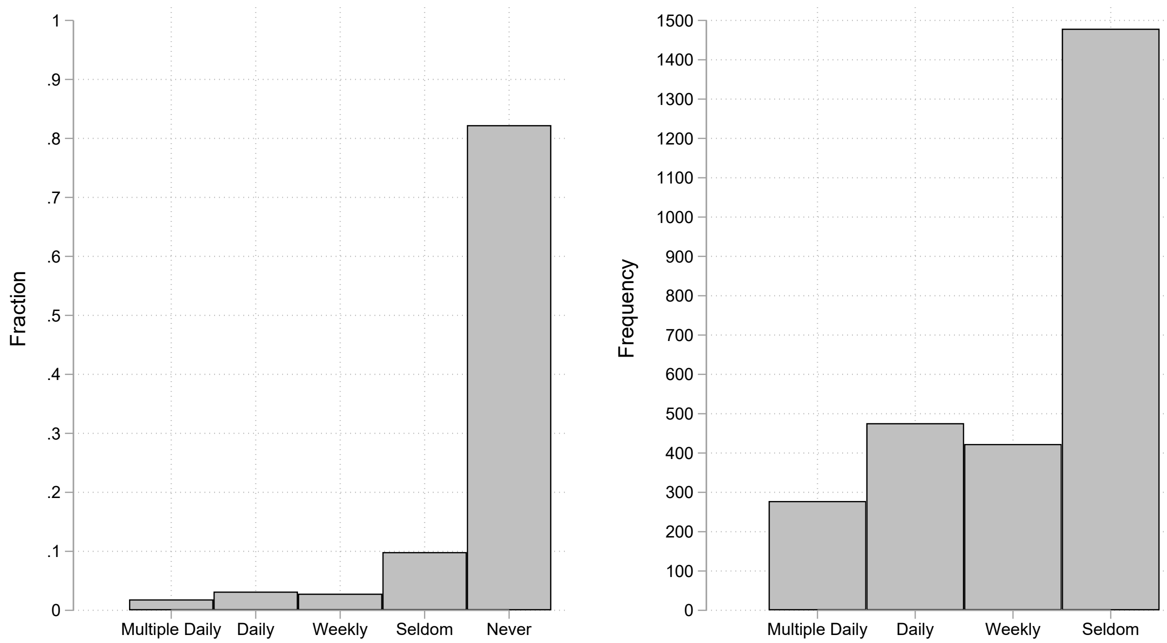
Notes - Excerpt from the SOEP questionnaire in 2020.

Figure A.3: Answer Distribution on Digital System Use: Language Processing



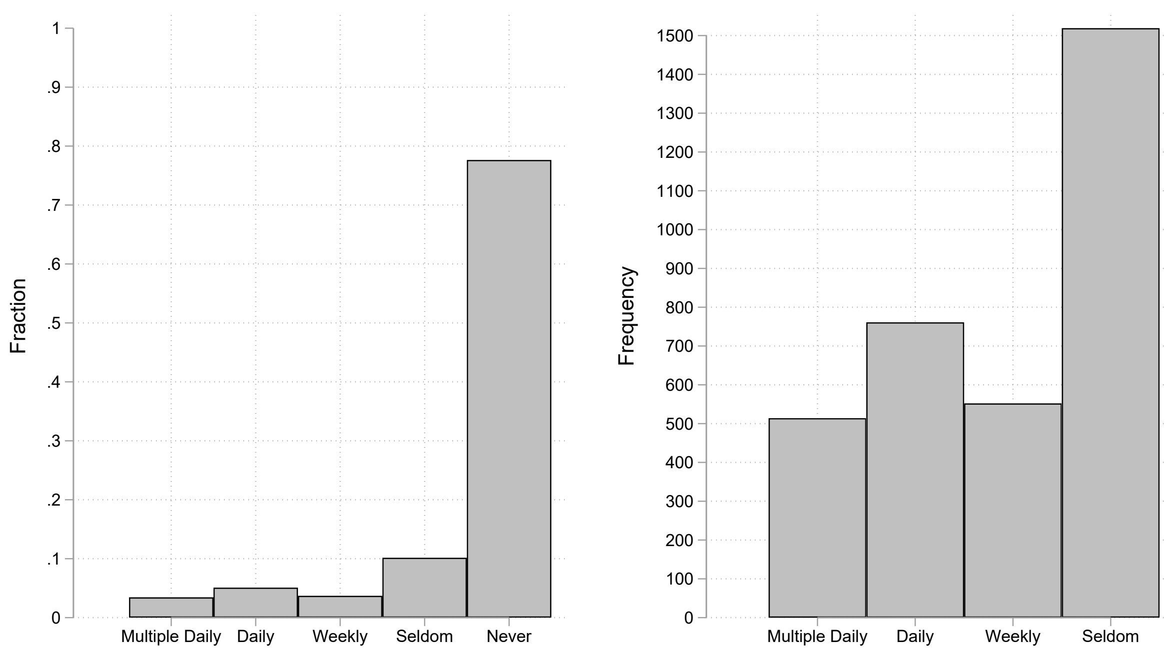
Notes - Data are drawn from the SOEP version 37. The figure shows the fractions of answers in the whole sample on the left-hand side and the frequency of answers (absolute cases) for respondents with at least infrequent use on the right-hand side.

Figure A.4: Answer Distribution on Digital System Use: Image Processing



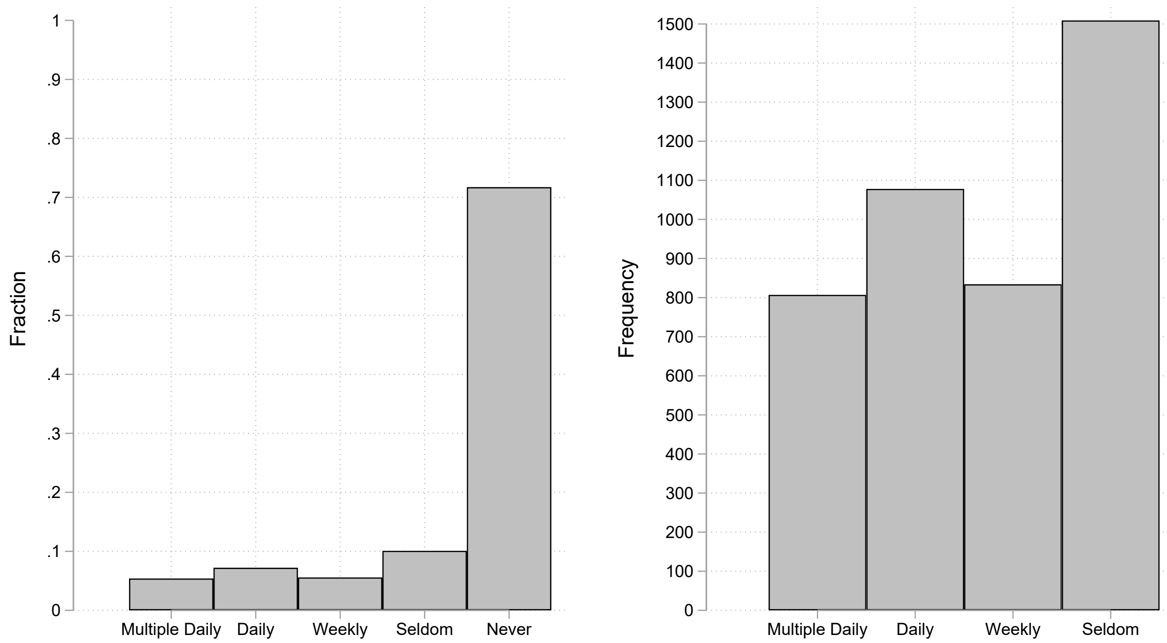
Notes - Data are drawn from the SOEP version 37. The figure shows the fractions of answers in the whole sample on the left-hand side and the frequency of answers (absolute cases) for respondents with at least infrequent use on the right-hand side.

Figure A.5: Answer Distribution on Digital System Use: Text Processing



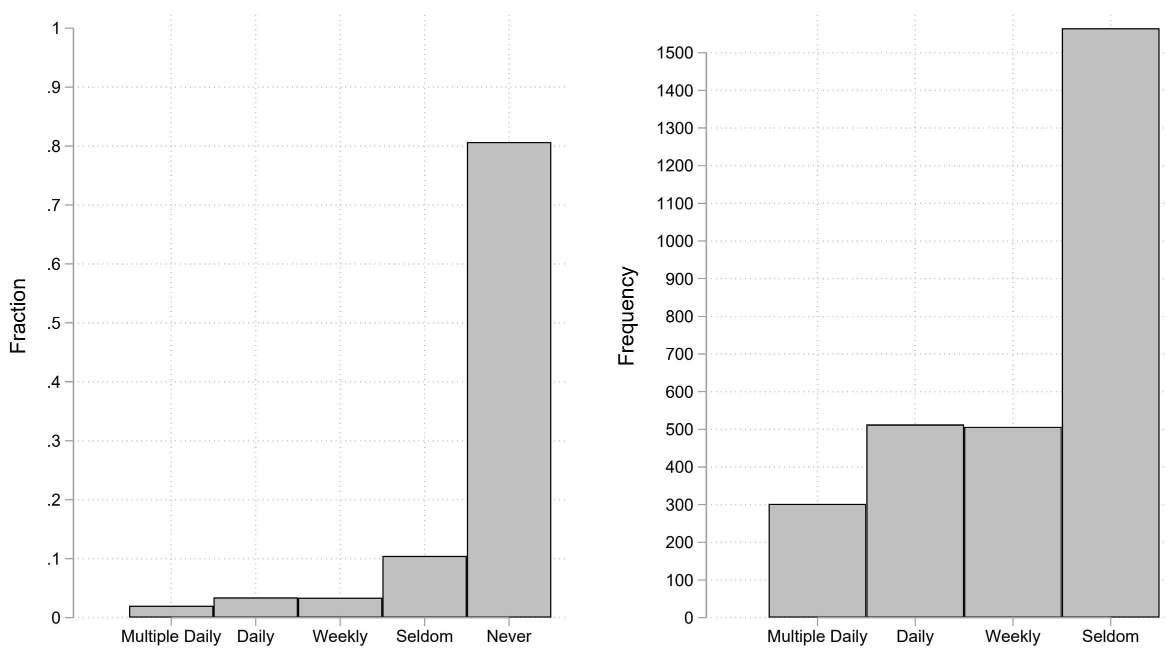
Notes - Data are drawn from the SOEP version 37. The figure shows the fractions of answers in the whole sample on the left-hand side and the frequency of answers (absolute cases) for respondents with at least infrequent use on the right-hand side.

Figure A.6: Answer Distribution on Digital System Use: Information Processing



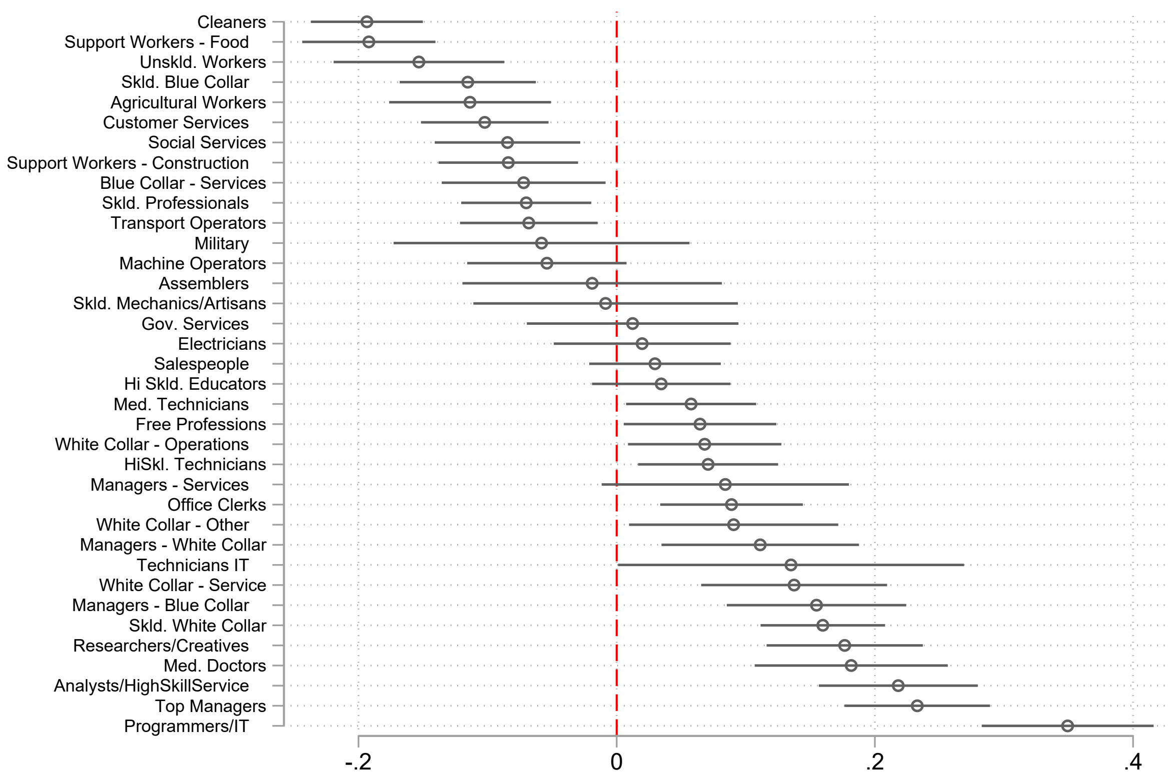
Notes - Data are drawn from the SOEP version 37. The figure shows the fractions of answers in the whole sample on the left-hand side and the frequency of answers (absolute cases) for respondents with at least infrequent use on the right-hand side.

Figure A.7: Answer Distribution on Digital System Use: Knowledge Gathering



Notes - Data are drawn from the SOEP version 37. The figure shows the fractions of answers in the whole sample on the left-hand side and the frequency of answers (absolute cases) for respondents with at least infrequent use on the right-hand side.

Figure A.8: AI Exposure by Occupation based on Probit Predictions



Notes - Data are drawn from the SOEP version 37. The figure shows average marginal effects and 95% confidence intervals of occupation dummies obtained in a Probit model that controls for basic socio-demographic characteristics (i.e., age, gender, migration status, marriage, education, and federal state fixed effects) and dummies for ISCO-08 classification. The base category is mechanics.

Table A.1: Descriptive Statistics

	Mean	Std. dev.
Panel A: Outcome variables		
Life satisfaction	6.897	1.740
Job satisfaction	6.885	2.083
Worries: job security	1.664	0.701
Worries: own economic situation	1.970	0.689
Mental health (MCS)	49.503	9.874
Anxiety	1.982	0.979
Depression	0.081	0.274
Panel B: Covariates		
Exposure to AI	0.622	0.485
Age	46.226	10.598
Female	0.510	0.500
Less than high school	0.077	0.266
High school diploma	0.696	0.460
College or more	0.227	0.419
Married	0.681	0.466
Number of children	0.632	0.930

Notes - Data are drawn from the SOEP version 37 for individuals aged 25-65 years (survey years: 2000-2020). All the samples contain individuals for whom information on all observables and the respective outcome variable are not missing.

Table A.2: Effects of Exposure to AI on Workers' Well-being, Migration Concerns – DiD Estimates

Dep. var.:	(1) Life satisfaction	(2) Job satisfaction	(3) Worries: job security	(4) Worries: own economic situation
Panel A: Using initial federal state of residence				
Exposed to AI * 2015-2020	-0.071**	-0.105**	0.028**	0.024**
	(0.032)	(0.045)	(0.014)	(0.012)
Mean of dep. var.	6.895	6.885	1.663	1.971
Std. dev. of dep. var.	1.739	2.076	0.700	0.689
F-statistic (p-value) (2000+...+2014=0)	0.600	0.890	0.765	0.361
Observations	165,776	130,655	127,044	165,487
Panel B: Excluding county movers				
Exposed to AI * 2015-2020	-0.072**	-0.105**	0.026*	0.023*
	(0.031)	(0.045)	(0.014)	(0.012)
Mean of dep. var.	6.876	6.866	1.663	1.978
Std. dev. of dep. var.	1.740	2.072	0.699	0.688
F-statistic (p-value) (2000+...+2014=0)	0.657	0.905	0.535	0.482
Observations	148,259	117,504	113,615	148,044
Panel C: Excluding residential movers				
Exposed to AI * 2015-2020	-0.063**	-0.105**	0.024*	0.022*
	(0.032)	(0.046)	(0.014)	(0.012)
Mean of dep. var.	6.876	6.865	1.660	1.973
Std. dev. of dep. var.	1.736	2.065	0.698	0.688
F-statistic (p-value) (2000+...+2014=0)	0.581	0.773	0.338	0.533
Observations	137,682	108,972	105,389	137,477
Panel D: Excluding postcode movers				
Exposed to AI * 2015-2020	-0.070**	-0.102**	0.026*	0.023*
	(0.031)	(0.046)	(0.014)	(0.012)
Mean of dep. var.	6.878	6.867	1.661	1.976
Std. dev. of dep. var.	1.738	2.069	0.699	0.688
F-statistic (p-value) (2000+...+2014=0)	0.721	0.993	0.449	0.445
Observations	145,044	114,885	111,097	144,835

Notes - Data are drawn from the SOEP version 37. Standard errors are reported in parentheses and are clustered at the individual level. All specifications include interactions between a gender dummy and a full set of age dummies, individual fixed effects, year fixed effects, state-by-year fixed effects, as well as controls for number of children and marital status.
*Significant at 10 percent; ** Significant at 5 percent; ***Significant at 1 percent.

Table A.3: Effects of Exposure to AI on Workers' Well-being, 2005-2020 – DiD Estimates

	(1)	(2)	(3)	(4)
Dep. var.:	Life satisfaction	Job satisfaction	Worries: job security	Worries: own economic situation
Exposed to AI * 2015-2020	-0.104***	-0.094**	0.034***	0.030***
	(0.028)	(0.041)	(0.013)	(0.011)
Mean of dep. var.	6.986	6.896	1.602	1.930
Std. dev. of dep. var.	1.725	2.055	0.685	0.694
F-statistic (p-value) (2000+...+2014=0)	0.494	0.697	0.977	0.530
Observations	122,823	99,215	95,915	122,733

Notes - Data are drawn from the SOEP version 37. Standard errors are reported in parentheses and are clustered at the individual level. All specifications include interactions between a gender dummy and a full set of age dummies, individual fixed effects, year fixed effects, state-by-year fixed effects, as well as controls for number of children, marital status and education.
*Significant at 10 percent; ** Significant at 5 percent; ***Significant at 1 percent.

Table A.4: Effects of Exposure to AI on Workers' Mental Health Outcomes, 2005-2020 – DiD Estimates

	(1)	(2)	(3)
Dep. var.:	Mental health	Anxiety	Depression
Exposed to AI * 2015-2020	0.130	-0.020	0.003
	(0.207)	(0.016)	(0.006)
Mean of dep. var.	49.84	1.963	0.079
Std. dev. of dep. var.	9.828	0.971	0.270
F-statistic (*p*-value) (2000+...+2014=0)	0.401	0.934	0.611
Observations	55,585	96,668	37,720

Notes - Data are drawn from the SOEP version 37. Standard errors are reported in parentheses and are clustered at the individual level. All specifications include interactions between a gender dummy and a full set of age dummies, individual fixed effects, year fixed effects, state-by-year fixed effects, as well as controls for number of children, marital status and education. The mental health outcome corresponds to the MCS.
*Significant at 10 percent; ** Significant at 5 percent; ***Significant at 1 percent.

Table A.5: Effects of Exposure to AI on Workers' Well-being, Alternative Definition of the Outcomes – DiD Estimates

Dep. var.:	(1) Life satisfaction	(2) Job satisfaction	(3) Worries: job security	(4) Worries: own economic situation
Exposed to AI * 2015-2020	-0.023***	-0.030***	0.019***	0.039***
	(0.008)	(0.010)	(0.007)	(0.007)
Mean of dep. var.	0.677	0.662	0.133	0.223
Std. dev. of dep. var.	0.468	0.473	0.340	0.417
F-statistic (p-value) (2000+...+2014=0)	0.216	0.260	0.315	0.073
Observations	165,776	130,655	127,044	165,487

Notes - Data are drawn from the SOEP version 37. Standard errors are reported in parentheses and are clustered at the individual level. Life satisfaction and job satisfaction are binary variables equal to one if the respondent indicates a level of satisfaction at or above the median. The outcomes related to worries are equal to one if the respondent reports to be "very worried". All specifications include interactions between a gender dummy and a full set of age dummies, individual fixed effects, year fixed effects, state-by-year fixed effects, as well as controls for number of children, marital status and education.
*Significant at 10 percent; ** Significant at 5 percent; ***Significant at 1 percent.

Table A.6: Effects of Exposure to AI on Workers' Well-being, without Socio-Demographic Controls – DiD Estimates

	(1)	(2)	(3)	(4)
Dep. var.:	Life satisfaction	Job satisfaction	Worries: job security	Worries: own economic situation
Exposed to AI * 2015-2020	-0.070**	-0.103**	0.028**	0.023*
	(0.032)	(0.045)	(0.014)	(0.012)
Mean of dep. var.	6.895	6.885	1.663	1.971
Std. dev. of dep. var.	1.739	2.076	0.700	0.689
F-statistic (p-value) (2000+...+2014=0)	0.552	0.854	0.745	0.396
Observations	165,776	130,655	127,044	165,487

Notes - Data are drawn from the SOEP version 37. Standard errors are reported in parentheses and are clustered at the individual level. All specifications include interactions between a gender dummy and a full set of age dummies, individual fixed effects, year fixed effects, and state-by-year fixed effects.
*Significant at 10 percent; ** Significant at 5 percent; ***Significant at 1 percent.

Table A.7: Effects of Exposure to AI on Workers' Well-being, by Gender – DiD Estimates

	(1)	(2)	(3)	(4)
Dep. var.:	Life satisfaction	Job satisfaction	Worries: job security	Worries: own economic situation
Panel A: Males				
Exposed to AI * 2015-2020	-0.094**	-0.106*	0.054***	0.061***
	(0.046)	(0.061)	(0.020)	(0.017)
Mean of dep. var.	6.864	6.881	1.693	1.953
Std. dev. of dep. var.	1.736	2.060	0.704	0.694
F-statistic (*p*-value) (2000+...+2014=0)	0.345	0.187	0.981	0.785
Observations	81,057	67,800	65,735	80,937
Panel B: Females				
Exposed to AI * 2015-2020	-0.068	-0.105	0.005	-0.005
	(0.043)	(0.067)	(0.020)	(0.017)
Mean of dep. var.	6.924	6.891	1.632	1.988
Std. dev. of dep. var.	1.742	2.094	0.694	0.684
F-statistic (*p*-value) (2000+...+2014=0)	0.678	0.200	0.817	0.392
Observations	84,719	62,855	61,309	84,550

Notes - Data are drawn from the SOEP version 37. Standard errors are reported in parentheses and are clustered at the individual level. All specifications include interactions between a gender dummy and a full set of age dummies, individual fixed effects, year fixed effects, state-by-year fixed effects, as well as controls for number of children, marital status and education.
*Significant at 10 percent; ** Significant at 5 percent; ***Significant at 1 percent.

Table A.8: Effects of Exposure to AI on Workers' Well-being, by Education – DiD Estimates

Dep. var.:	(1) Life satisfaction	(2) Job satisfaction	(3) Worries: job security	(4) Worries: own economic situation
	Panel A: Low educated			
Exposed to AI * 2015-2020	-0.040	0.032	0.068	0.011
	(0.174)	(0.226)	(0.079)	(0.056)
Mean of dep. var.	6.598	6.618	1.792	2.191
Std. dev. of dep. var.	1.878	2.269	0.731	0.678
F-statistic (*p*-value) (2000+...+2014=0)	0.226	0.622	0.901	0.954
Observations	12,559	7,932	7,638	12,501
	Panel B: Medium educated			
Exposed to AI * 2015-2020	-0.084**	-0.133**	0.020	0.023
	(0.037)	(0.054)	(0.017)	(0.014)
Mean of dep. var.	6.841	6.847	1.697	2.009
Std. dev. of dep. var.	1.756	2.106	0.708	0.681
F-statistic (*p*-value) (2000+...+2014=0)	0.381	0.607	0.790	0.183
Observations	115,301	90,120	87,608	115,124
	Panel C: High educated			
Exposed to AI * 2015-2020	-0.052	-0.057	0.019	0.024
	(0.076)	(0.106)	(0.030)	(0.029)
Mean of dep. var.	7.156	7.057	1.538	1.783
Std. dev. of dep. var.	1.605	1.924	0.653	0.676
F-statistic (*p*-value) (2000+...+2014=0)	0.403	0.065	0.765	0.686
Observations	37,752	32,408	31,627	37,699

Notes - Data are drawn from the SOEP version 37. Standard errors are reported in parentheses and are clustered at the individual level. All specifications include interactions between a gender dummy and a full set of age dummies, individual fixed effects, year fixed effects, state-by-year fixed effects, as well as controls for number of children and marital status.
*Significant at 10 percent; ** Significant at 5 percent; ***Significant at 1 percent.

Table A.9: Effects of Exposure to AI on Workers' Well-being, West and East Germany – DiD Estimates

	(1)	(2)	(3)	(4)
Dep. var.:	Life satisfaction	Job satisfaction	Worries: job security	Worries: own economic situation
Panel A: West Germany				
Exposed to AI * 2015-2020	-0.077**	-0.069	0.022	0.017
	(0.038)	(0.052)	(0.016)	(0.014)
Mean of dep. var.	7.019	6.951	1.611	1.927
Std. dev. of dep. var.	1.719	2.061	0.688	0.694
F-statistic (p-value) (2000+...+2014=0)	0.743	0.693	0.481	0.779
Observations	125,845	100,372	98,070	125,617
Panel B: East Germany				
Exposed to AI * 2015-2020	-0.078	-0.212**	0.055**	0.046**
	(0.056)	(0.090)	(0.027)	(0.022)
Mean of dep. var.	6.503	6.670	1.841	2.109
Std. dev. of dep. var.	1.742	2.112	0.709	0.654
F-statistic (p-value) (2000+...+2014=0)	0.584	0.309	0.407	0.167
Observations	39,863	30,206	28,901	39,801

Notes - Data are drawn from the SOEP version 37. Standard errors are reported in parentheses and are clustered at the individual level. All specifications include interactions between a gender dummy and a full set of age dummies, individual fixed effects, year fixed effects, state-by-year fixed effects, as well as controls for number of children, marital status and education.
*Significant at 10 percent; ** Significant at 5 percent; ***Significant at 1 percent.