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From Efficiency to Illness: Do Highly Automatable Jobs Take a Toll on Health in Germany?

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Abstract

Automation transforms work at a rapid pace, with gradually increasing shares of the workforce being at risk of replacement by machines. However, little is known about how this risk is affecting workers. In this study, we investigate the impact of exposure to a high risk of automation at work on the subjective (self-reported health, anxiety, and health satisfaction) and objective (healthcare use and sickness absence) health outcomes of workers in Germany. We base our analysis on survey data from the German Socio-Economic Panel (SOEP) and administrative data from the Occupational Panel for Germany (2013-2018). Employing panel regression, we demonstrate that for workers, exposure to a high risk of automation at the occupational level is associated with lower self-reported health and health satisfaction, increased sickness absence, and, depending on how the risk is measured, anxiety. No effect on healthcare use is found. Our heterogeneity analysis provides evidence that none of the analyzed demographic and occupational groups is disproportionally affected by high automation risk. We also conduct several robustness checks (i.e., alternative model specifications and risk measures with different thresholds), with the results remaining largely consistent with our main findings.

JEL CODES: I10, I15, J21, J24, O33

Key words: automation risk, substitution potential, routine tasks, health, Germany

1. Introduction

Automation transforms labor markets, leaving workers at risk of being displaced by robots or artificial intelligence (AI). For instance, the share of jobs at high risk of automation has been estimated at 9% across the OECD countries, with peak values of around 12% observed for Austria, Germany, and Spain (Arntz et al., 2016). However, not all workers face the same risk, since automation "polarizes" labor markets by increasing employment of high- and low-skilled workers to the detriment of the medium-skilled segment (Goos et al., 2014; Dengler and Matthes, 2018; Frey and Osborne, 2017). The latter is overrepresented in occupations with a high prevalence of routine tasks that are more likely to be replaced by digital technologies in the future (Autor et al., 2003).

The social consequences of automation, and of the risk of being displaced due to automation, are not fully understood. By contrast, the economic outcomes of automation have been extensively studied over the past two decades, indicating that it is associated with total factor productivity and labor productivity (Graetz and Michaels, 2018; Kromann et al., 2020), wage inequality (Vannutelli et al., 2022; Fossen and Sorgner, 2022; Martins-Neto et al., 2024), and occupational shifts (Frey and Osborne, 2017; Balsmeier and Woerter, 2019). A recent strand of research has linked automation and the risk of displacement due to automation to psychological well-being and mental health outcomes (e.g., Lordan and Stringer, 2022; Zhao et al., 2022; Blasco et al., 2022; Giuntella et al., 2023), but the findings remain country-specific and inconclusive. For instance, earlier studies for Germany provided mixed evidence on the mental health outcomes of robot exposure, indicating that more research is needed in this area (Gihleb et al., 2022; Abeliansky et al., 2024).

This study aims to contribute to the growing body of literature on the "social costs" of technological change by investigating the impact of exposure to a high risk of automation at work on the subjective (self-reported health, anxiety, and health satisfaction) and objective (healthcare use and sickness absence) health outcomes of workers in Germany. We conduct a longitudinal analysis on survey data from the German Socio-Economic Panel (SOEP) combined with administrative data from the Occupational Panel for Germany (2013-2018). The SOEP contains detailed individual life course trajectories, as well as information on employment and various health measures. The Occupational Panel provides country-specific estimates of the share of routine tasks in occupations, which serve as a proxy for our automation risk measure. Our main findings are validated by a number of robustness checks, including alternative model specifications and modified automation risk measures, and are enriched by conducting the heterogeneity analysis with respect to various demographic and occupational characteristics.

Germany is an interesting case for studying the social outcomes of automation risk. On the one hand, the German economy relies heavily on the industrial sector, which has historically been characterized by a high proportion of automatable routine-intensive occupations. In 2023, manufacturing accounted for 20.4% of the gross value added generated in the German economy, compared to the EU average of 16.4% (Federal Statistical Office, 2024). As one of the top five countries in the world in terms of robot adoption, Germany accounted for 36% of the European robot market in 2022 (Müller, 2023). On the other hand, ongoing automation implies that the workforce must undergo occupational shifts and re-skilling, which could prove challenging in Germany, especially given its aging population, rigid certificate-based system of employment, and increasing number of migrants (and refugees) whose integration is likely to require substantial time and resources (Statista, 2024). These economic conditions suggest that the social outcomes of automation, and of the risk of being displaced due to automation, might be particularly pronounced in the German context.

We contribute to the literature in several ways. First, most of the existing evidence related to automation risk measured at the occupational (job) level comes from the US, while the European studies on automation risk mainly deal with robot exposure at the sectoral level. We fill this gap by adopting a country-specific task-based measure of automation risk defined at the occupational level by Dengler et al. (2014) for the German labor market. To the best of our knowledge, this is the first study that has applied this measure to the context of health and well-being in Germany. Second, the earlier studies on the health outcomes of automation mainly relied on cross-sectional data, whereas our findings arise from the longitudinal structure of the German Socio-Economic Panel and the Occupational Panel for Germany. Third, we enrich existing evidence by adding some objective health outcomes (healthcare use and sickness absence at work due to the respondent's own illness) to a standard set of subjective measures of health and well-being used in most of the earlier studies. In addition, we conduct a heterogeneity analysis with respect to several demographic and occupational characteristics that have been overlooked in the previous literature.

Finally, we address the question of what share of routine tasks in the occupation might be sufficient to have an impact on the health outcomes of the workforce in Germany.

2. Background

2.1. Previous research

The recent literature has mainly exploited three well-established objective measures of automation risk, with the exception of a few studies dealing with subjective indicators. The first measure, which was introduced by Frey and Osborne (2017), relied on data from an online service O*NET (2010) developed for the US Department of Labor. O*NET (2010) provides information on US occupations with respect to the knowledge, skills, and abilities they require and the variety of tasks they involve. By mixing expert opinions with advanced estimation algorithms, the authors computed the probabilities of computerization for the US occupations. The second measure of automation risk, robot intensity (also exposure, adoption, or penetration) estimated at the sectoral level, comes from statistics compiled by the International Federation of Robotics (IFR). Finally, the third measure of automation risk is routine task intensity (RTI), which is based on the distribution of different types of tasks within the occupation, and defines occupations with a high concentration of routine cognitive and routine manual tasks as being more susceptible to automation (Author and Dorn, 2013).

The US studies on automation risk often referred to the computerization probabilities of Frey and Osborne (2017), and mainly found a negative effect of automation risk on health outcomes. For instance, Patel et al. (2018) showed that workers employed in occupations with a higher automation risk are worse off in terms of their general, physical, and mental health. Nazareno and Schiff (2021) reported that higher automation risk is associated with decreasing levels of job stress and health. Finally, Liu (2023) found that an increase in the computerization score and higher software and robot exposure are related to a deterioration in self-reported health.

There are a few existing non-US studies that also relied on the computerization probabilities of Frey and Osborne (2017) and the assumption that the skills required to perform certain jobs are similar in the US and in the countries these studies focused on. For instance, Cheng et al. (2020) used the national survey of the working population conducted by the Ministry of Labor of Taiwan (2016) to show that employment in highly automatable jobs is associated with an increasing risk of work-related injury and disease prevalence. For the UK, Zheng et al. (2024) found a negative impact of automation risk on life satisfaction in the group of workers aged 30 to 49 (no effect is observed in the pooled sample).

The robot intensity measure is also used in the US context and has driven most of the evidence from the European studies, although the latter has been rather mixed and country-specific. For instance, Gunadi and Ryu (2021) found for the US that an increase in robot exposure is associated with a reduction in the share of low-skilled individuals reporting poor health (due to a reduction in physical tasks), work disability, and quitting a job in the past for health reasons. O'Brien et al. (2022) provided evidence for the US that the predicted increase in industrial robots per 1,000 workers is positively related to all-cause mortality among the population aged 45-54 and among women aged 20-29 (mainly due to increases in drug overdose deaths, suicide, homicide, and cardiovascular mortality).

In a comparative study of the US and Germany, Gihleb et al. (2022) investigated the impact of industrial robot adoption on workers' safety, health, and well-being. The authors reported that a one standard deviation increase in robot exposure is associated with a reduction in work-related injury rates in the US (the results are mainly driven by manufacturing firms) and a decline in the risk of reporting any disability in Germany. The findings indicated that in the US, an increase in robot exposure tends to worsen mental health outcomes, and to be positively related to an increase in drug- and alcohol-related deaths and in the number of days during the previous month when the respondent felt mentally unwell. By contrast, no significant effect of robot exposure on high psychological burden and life satisfaction was found for Germany. Meanwhile, Abeliansky et al. (2024) provided evidence that higher robot intensity is associated with a mild deterioration of mental health in Germany, reporting that a 1% increase in robot intensity leads to a decline of 0.0047 points in the mental health index of an average worker.

In contrast to the findings for Europe, Yang et al. (2022) observed that in China, an increase in robot intensity is related to a significant improvement in workers' mental health outcomes. Finally, Zhao et al. (2022) showed based on a sample of 137 countries over the 2005-2018 period that increases in the yearly stock of industrial robots and the yearly number of AI-related publications are negatively related to the current and future well-being of workers (proxied by self-reported feelings about life).

To the best of our knowledge, there is only one existing study, Lordan and Stringer (2022) for Australia, that has applied the routine task intensity (RTI) measure of automation risk in the context of health outcomes. The authors provided evidence that having an automatable job (the top third of the employment-weighted distribution of RTI across occupations) is negatively related to physical health and body pain, while a positive relationship was observed for vitality and satisfaction with free time. However, no effect of automation risk on overall mental health and life satisfaction was found in the pooled sample.

There are also a few previous studies that exploited a subjective measure of automation risk. For instance, self-reported high exposure to automation at work was found to be associated with an increase in major depressive episodes or generalized anxiety disorder among French workers (Blasco et al., 2022) and with a deterioration in life satisfaction in Germany, but to have no effect on mental health, anxiety, and depression (Giuntella et al., 2023).

To sum up, the findings of the recent literature on the health and well-being outcomes of workers affected by automation risk are inconclusive due to differences in the dependent variables considered and in the ways the main predictors are constructed. This is particularly true for Germany, where the evidence is quite mixed. Furthermore, findings for European countries on the impact of automation risk measured at the occupational level on health and well-being are lacking. Finally, only a few of the studies mentioned above are able to claim causality, since most of the evidence comes from cross-sectional data.

2.2. German context

The case of Germany is particularly interesting for studying the social outcomes of automation risk. First, in the European context, Germany is recognized as the driving force in the adoption of new technologies. In 2022, the German stock of installed industrial robots accounted for 415 units per 10,000 employees, compared to the EU average of 208 units, making Germany the leading robot market in Europe (Müller, 2023). Moreover, in 2024, the level of digital transformation of businesses in Germany exceeded the EU average in the areas of electronic information sharing, use of social media, performing data analytics, and use of any AI technology (DESI statistics, 2024).

Second, the economic and institutional frameworks of Germany have some specific features that distinguish them from those of other European countries, and that might enhance the impact of automation on society. To begin with, the German labor market has been characterized by a relatively low unemployment rate in recent years (e.g., it dropped from 6.9% to 5.2% between 2013 and 2018 and was 5.7% in 2023), with moderate skills shortages observed in some occupational fields (e.g., science, technology, engineering, and math (STEM) and health-related occupations) and regions (e.g., southern and eastern Germany), and low occupational mobility of the workforce (Statista, 2024). Furthermore, Germany's production sector, which is mainly driven by the automotive, mechanical engineering, chemical, and electrical industries, and has historically been dominated by routine-intensive occupations, is mostly concentrated in the western part of the country. Under these conditions, ongoing automation may widen the existing socioeconomic gap between the eastern and the western federal states of Germany.

Third, in recent decades, the German population has been steadily aging. For instance, in 2023, almost 23 million people, or 22.7% of the German population, were aged 40-59, making them the largest age group in the country (Statista, 2024). Since the health of older workers tends to be more vulnerable to the impact of new technologies (Abeliansky et al., 2024), the German healthcare system may face a number of challenges in the very near future.

Finally, the massive inflow of migrants that Germany has experienced over the past decade has the potential to cover the needs of the German labor market. However, employment for non-EU nationals, which is regulated by the provisions of the German Residence Act (AufenthG), remains quite rigid and certificate-based. Admission to the labor market for foreigners requires the approval of the Federal Employment Agency, which relies on the assumption that native job candidates have a preferential status. Apart from these bureaucratic challenges, the adaptation and re-skilling of migrants (along with the re-skilling of the native population in the context of ongoing automation) will require substantial funding, which is unlikely to be prioritized in the federal budget.

2.3. Research aims

Our study has three aims. First, we investigate to what extent high automation risk defined at the occupational level contributes to the subjective and objective health outcomes of workers in Germany. Second, we conduct a heterogeneity analysis by splitting our sample into relatively homogeneous groups with respect to several demographic and occupational characteristics. The earlier studies on this topic mainly considered the age-, gender-, education-, and sector-related differences in the health and well-being outcomes of workers affected by automation (O'Brien et al., 2022; Gihleb et al., 2022; Lordan and Stringer, 2022; Abeliansky et al., 2024). We also compare estimates for male and female subsamples, given the gender-related segregation of the German labor market (i.e., men are mostly concentrated in heavy production industries and tend to have full-time employment contracts, while women are more likely to work in services and to have part-time jobs). In addition, we consider differences in effects with respect to migration background and region of settlement, as Germany has a substantial share of residents with a migration background (the share of foreigners in the population increased from 8.7% to 12.2% between 2013 and 2018, and accounted for 15.2% in 2023), and there are persistent socioeconomic disparities between the western and the eastern federal states of Germany (Statista, 2024). Furthermore, we compare effects between groups with various types of employment (part-time vs. full-time), sectors (automation-prone vs. other), company sizes (small and medium, large, and very large), and occupational classes (low-, medium-, and high-skilled), which have not been widely investigated in the previous literature. Finally, we address the question of to what extent our findings depend on how the risk of automation is measured. We do so by varying the threshold for the share of routine tasks in an occupation, which is used to distinguish between individuals in occupations at high risk of automation and those in occupations at no or low risk of automation. We also conduct several other robustness checks to find out whether our estimates depend on various modeling choices and change once potential statistical issues are addressed.

3. Data and methods

3.1. Sample

Our analysis builds on two sources of longitudinal data. First, we use the most recent version of the German Socio-Economic Panel (SOEP), SOEP-Core v38, which is collected by the German Institute for Economic Research (DIW Berlin). The SOEP is a nationally representative survey conducted at the individual and the household level that includes a wide range of questions on the social and demographic characteristics, employment histories, health, and well-being of the German population (Goebel et al., 2019). Our main explanatory variable, high risk of automation, comes from our second data source, the Occupational Panel for Germany conducted by the

Institute for Employment Research (IAB). The latter contains administrative data on the demographic and employment-related segregation of the German population specified at the occupational level, along with the shares of routine and non-routine tasks in these occupations (Grienberger et al., 2022).

We merge these datasets based on the occupational group (three-digit level) combined with the requirement level (fifth digit) of the German Classification of Occupations 2010 (KldB2010) and survey year, since this is how the data are structured in the Occupational Panel. The three-digit code of KldB2010 defines occupational groups, which are similar in terms of required skills, abilities, and knowledge, while the fifth digit distinguishes occupations according to the degree of complexity of the work activities (i.e., unskilled and semi-skilled, specialist, complex specialist, and highly complex activities) (Paulus and Matthes, 2013). The resulting dataset is defined at the individual level with added yearly information on the share of routine tasks in each occupation.

We consider only currently working individuals; thus, respondents on maternity leave, students, and retired respondents are removed from the sample. In addition, we exclude civil servants and members of the armed forces, along with marginally employed, self-employed, and disabled respondents, due to the very specific characteristics and labor market regulations applied to these occupational groups. Our final sample consists of 18,283 regularly employed individuals aged 18-65 with non-missing values in the variables of interest (58,196 observations spread over the 2013-2018 period).

3.2. Dependent variables: health outcomes

To ensure consistency with earlier studies, we use a set of subjective health outcomes as dependent variables. Self-reported health (SRH), which is considered to be a reliable measurement of general health, is based on the question "How would you describe your current health?" and is measured on a categorical scale, increasing from one ("bad") to five ("very good") (Bombak, 2013). As a proxy for mental health, we use the feeling of anxiety. In the SOEP survey, respondents are asked to evaluate how often they have felt worried in the last four weeks on a scale from one ("very rarely") to five ("very often"). Finally, health satisfaction varies between zero ("completely dissatisfied") and 10 ("completely satisfied").

We additionally consider two objective health outcomes: healthcare use and sickness absence. We do so to enrich the evidence, and to avoid the reporting heterogeneity bias that might occur in self-assessed ordinal outcomes due to the fact that individuals vary in terms of how they understand and use ordinal response categories, and, as a result, place the cut points between adjacent response categories in different ways (King and Wand, 2007). The objective measures arise from the number of doctor appointments respondents have made in the last three months (healthcare use) and the number of days off work respondents have taken due to their own illness in the last year (sickness absence), respectively. We restrict these continuous variables to binary measures, equal to one if the original variable takes positive values and to zero otherwise, indicating whether there was any healthcare use or any sickness absence.

3.3 Key independent variable: high risk of automation

Our main explanatory variable, high risk of automation, derives from the measure of substitution potential for occupations proposed by Dengler et al. (2014) for the German labor market. The scholars adopted the task-based approach of Author et al. (2003) and used data from the BERUFENET database to construct the distribution of five task types (i.e., routine cognitive, routine manual, non-routine manual, non-routine analytic, non-routine interactive) within occupations in Germany. BERUFENET is compiled by the German Federal Employment Agency to provide up-to-date detailed descriptions of the competencies and skills that are required to perform certain occupations in Germany. The share of routine tasks in the occupation, the so-called substitution potential, was considered as a proxy for automation risk.

Since we focus our analysis on highly automatable occupations (which are likely to be replaced by new technologies in the next two decades), we construct our main explanatory variable by dichotomizing the original substitution potential measure in such a way that it takes a value of one if the occupation contains more than 70% of routine tasks, and a value of zero otherwise. This well-established threshold was used in the earlier studies of Arntz et al. (2016) for the OECD countries and of Frey and Osborne (2017) for the US. In addition, we conduct a sensitivity analysis with alternative downward positions of the threshold to tests whether our findings remain stable over such a change (see section 4.4 for a detailed description of variables and results).

Figure 1 represents the dynamics of the substitution potential and the share of occupations with high automation risk over the 2013-2018 period. As shown on the graph, both indicators are relatively time-invariant over the time spans of 2013-2015 and 2016-2018, which is due to the way the substitution potential measure was constructed. It was first introduced in 2013, and was updated in 2016. Moreover, the respondents in the sample seem to be rigid in terms of occupational change, tending to stick to their current occupations. Nevertheless, the increase in both indicators between 2015 and 2016 provides evidence that the automation-driven transformation of the German labor market tends to gather pace over time.

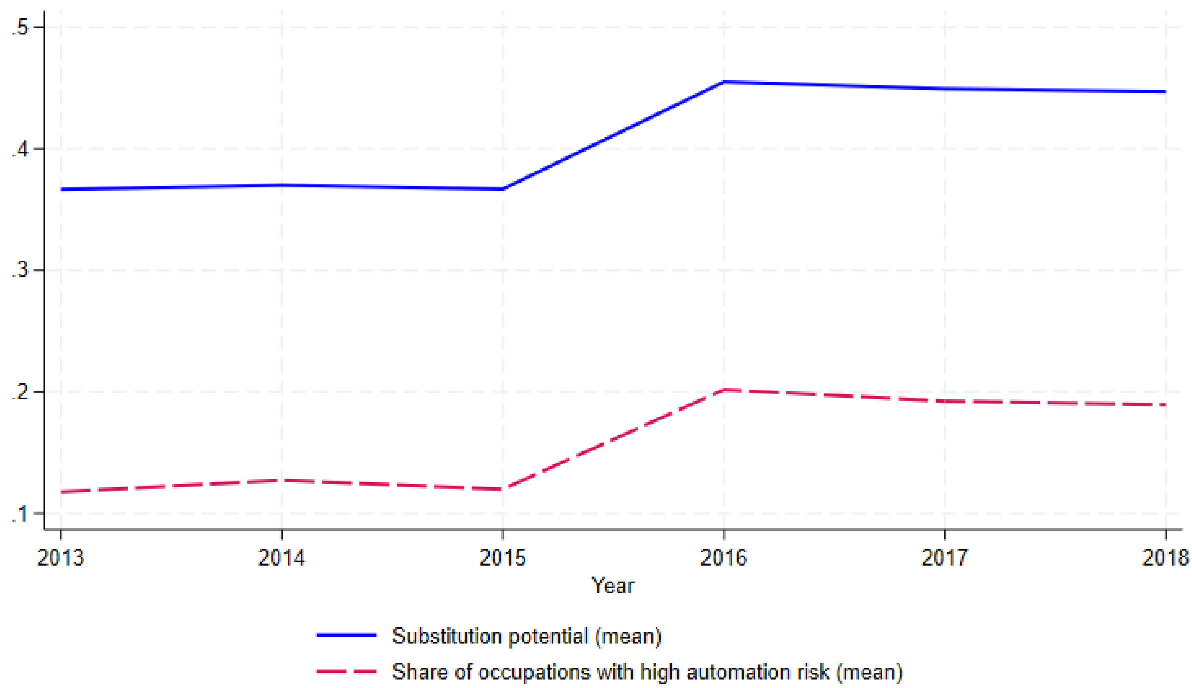

Figure 1 – Dynamics of the substitution potential and the share of occupations with high automation risk over the 2013-2018 period

The list of the 20 most frequent occupations with high automation risk is provided in Table S1 in the supplementary materials. As shown in Table S1, the highly automatable occupations in our sample are mainly concentrated in heavy industrial sectors (e.g., manufacturing, electric industry, automotive industry), although a few of the occupations are in service sectors (e.g., banking and insurance, logistics, information technology).

3.4 Control variables

We use a standard set of demographic control variables in our main models that includes age, squared age, gender, marital status (married or cohabiting vs. otherwise), educational attainment (low (level 1-2 of ISCED-97), medium (level 3-4 of ISCED-97), and high (level 5-6 of ISCED-97)), natural log of the yearly net household income in thousands of euros adjusted for inflation and household size (Modified OECD Equivalence Scale), migration status (no or indirect migration background vs. direct migration background), and region of settlement (west Germany vs. east Germany). Since earlier studies found substantial gender-, region-, and migration-related disparities in the health outcomes of the German population, we also use these variables for a sample stratification in our heterogeneity analysis (Breckenkamp et al., 2007; Sperlich et al., 2019; Stawarz et al., 2021). In addition, we use a set of occupational characteristics for stratification, including type of employment, company size, sector of employment, and professional class, as most of these characteristics are related to the future probability of robot adoption in Germany (Deng et al., 2023).

A descriptive overview of all of the variables used can be found in Table S2 in the supplementary materials. The distribution of responses on the subjective dependent variables suggests that our respondents chose “good” health, a “very rare” feeling of anxiety, and the eighth category of health satisfaction more frequently than the other options. The share of respondents who previously used healthcare and took days off work due to their own illness is around 65% and 63%, respectively. The share of occupations in our sample at high risk of automation does not exceed 16%, which is consistent with the estimate for the whole German labor market (Dengler and Matthes, 2018). Table S3 in the supplementary materials displays the results of a t-test of equal means, which shows statistically significant differences between automation risk groups in reporting anxiety and objective health outcomes.

3.5. Estimation strategy

We exploit the longitudinal structure of the data and estimate individual-effects linear regressions:

$$y_{it} = \alpha_i + x_{it}\beta + \varepsilon_{it},$$

where i is the number of individuals in the sample, t is the number of waves of the survey, y_{it} is a set of outcome variables, α_i is an individual-specific and time-invariant random component, x_{it} is a set of regressors, β is a set of estimated coefficients, and ε_{it} is an idiosyncratic error term.

We treat our categorical dependent variables as cardinal, since the evidence from methodological studies confirms convergence between the estimates from linear and ordered latent response models (Dudel et al., 2016; Ferrer-i-Carbonell and Frijters, 2004). In addition, this approach was implemented in earlier studies on work-related determinants of health and well-being (e.g., Nazareno and Schiff, 2021; Kühn et al., 2023).

We rely on the random effects (RE) specification due to the way our automation risk measure is constructed. As described in section 3.3, it is quasi-time-invariant (only 3.47% of respondents in the sample change their status with respect to automation risk). Other control variables also show limited within variation: 0.28% and 0.14% of respondents change their educational status or relocate between east and west Germany, respectively. Estimating fixed effects models with these data would drop almost all the variation in our main explanatory variable, and would lead to unreliable estimates.

Nevertheless, we estimate fixed effects and population-averaged models as robustness checks, and, in addition to the linear probability models, we address the binary nature of our objective health outcomes via panel probit models. Furthermore, since healthcare use and sickness absence are reported retrospectively, we lag our main explanatory variable by one year and re-estimate models for these health outcomes. Finally, assuming that our measure of automation risk might be endogenous, i.e., determined by other variables that also have an impact on our health outcomes, we adopt the instrumental variable approach and estimate the G2SLS models (Balestra and Varadharajan-Krishnakumar, 1987).

A few earlier studies on health outcomes of automation addressed potential endogeneity bias by instrumenting robot intensity in the country of interest by robot intensities in other nearby countries (e.g., Gihleb et al., 2022; Yang et al., 2022). While dealing with automation risk at the occupational level, we adopt the approach of Cornelissen et al. (2011), who used the share of workers receiving performance pay within industries and firm size categories to instrument the individual worker's probability of having a performance pay job. Our instrument comes from the Occupational Panel for Germany and is derived as the year- and sector-specific share of the German population employed in highly automatable occupations (the G2SLS models estimates and instrument statistics are provided in Table S4 and Table S5 in the supplementary materials, respectively).

4. Results

4.1. Baseline models

Table 1 provides a summary of the estimated coefficients on high risk of automation for various health outcomes using our main specification and control variables. Since our dependent variables are measured on different scales, the coefficients are not directly comparable. Our results suggest that respondents employed in highly automatable occupations are 0.022 (on the scale from one to five) and 0.049 (on the scale from zero to 10) points worse off in terms of SRH and health satisfaction than their counterparts working in less automation-prone occupations, respectively (consistent with Nazareno and Schiff, 2021).

Table 1 – Estimated coefficients on high risk of automation (RE)

Dependent variable	Coef.	SE	95% CIs	p-value
SRH	-0.022**	0.011	[-0.044 -0.000]	0.047
Anxiety	0.013	0.012	[-0.011 0.036]	0.293
Health satisfaction	-0.049*	0.025	[-0.099 0.000]	0.052
Healthcare use	-0.002	0.006	[-0.015 0.011]	0.780
Sickness absence	0.049***	0.007	[0.035 0.062]	0.000
Number of observations	58,196			
Number of individuals	18,283			

*Note. *p-value<0.10, **p-value<0.05, ***p-value<0.01*

All models include controls for age, squared age, gender, marital status, educational attainment, income, migration background, and region of settlement. Robust standard errors are clustered at an individual level.

Overall, our estimates are slightly lower in absolute terms than the estimates of the impact of employment status and job insecurity on self-reported health and health satisfaction in Germany from the earlier studies based on the SOEP data and using similar scales in their health outcomes. For instance, Otterbach and Sousa-Poza (2016) showed that low job security is associated with a decline of -0.138 and -0.059 points (-0.078 and -0.021 points) in health satisfaction and self-reported health in the male (female) subsample of German workers, respectively. Furthermore, Kühn et al. (2019) reported that part-time employment is associated with a 0.08- and 0.14-point increase in health satisfaction in west and east Germany, respectively. Thus, compared to the previous evidence, the negative effect of high automation risk on the subjective health outcomes of workers seems to be relatively moderate in the German context.

Furthermore, employment in highly automatable occupations is associated with a 4.9-percentage-point increase in the probability of reporting sickness absence, and is also positively related to anxiety, though the latter coefficient is not statistically significant (consistent with Gihleb et al., 2022). Since no significant effect is found for healthcare use (the coefficient is relatively small and negative), we conclude that the observed detrimental effect of automation risk on the health of workers in Germany is driven by minor physical and mental issues that do not require a visit to the doctor, rather than by serious chronic conditions, injuries, and psychological disorders.

4.2. Differences by demographic characteristics

Figures 2a and 2b show how the effect on health of high risk of automation varies over several demographic groups. Since our dependent variables are measured on different scales, the estimated coefficients for SRH and anxiety in Figure 2a and for health satisfaction and sickness absence in Figure 2b are not directly comparable. In addition, the analyzed groups overlap, e.g., west Germany includes both men and women.

Figure 2a shows no striking differences in SRH between and within the considered groups. Women employed in highly automatable occupations are more likely to suffer from anxiety (the magnitude of the coefficient is almost twice as large for women as for men), but neither coefficient is statistically significant, perhaps due to the reduction of the sample size. Differences in the direction and the magnitude of the effect on anxiety are also found between the native population and migrants, and between west and east Germany, but again, the coefficients are not statistically significant.

Figure 2b indicates that employment in highly automatable occupations is negatively related to health satisfaction in both gender groups and regions of settlement, with a slightly higher magnitude for men and for those settled in east Germany (-0.068 and -0.120 points, respectively). In contrast to the native population, migrants employed in highly automatable occupations appear to be better off in terms of health satisfaction (although the coefficient is not statistically significant).

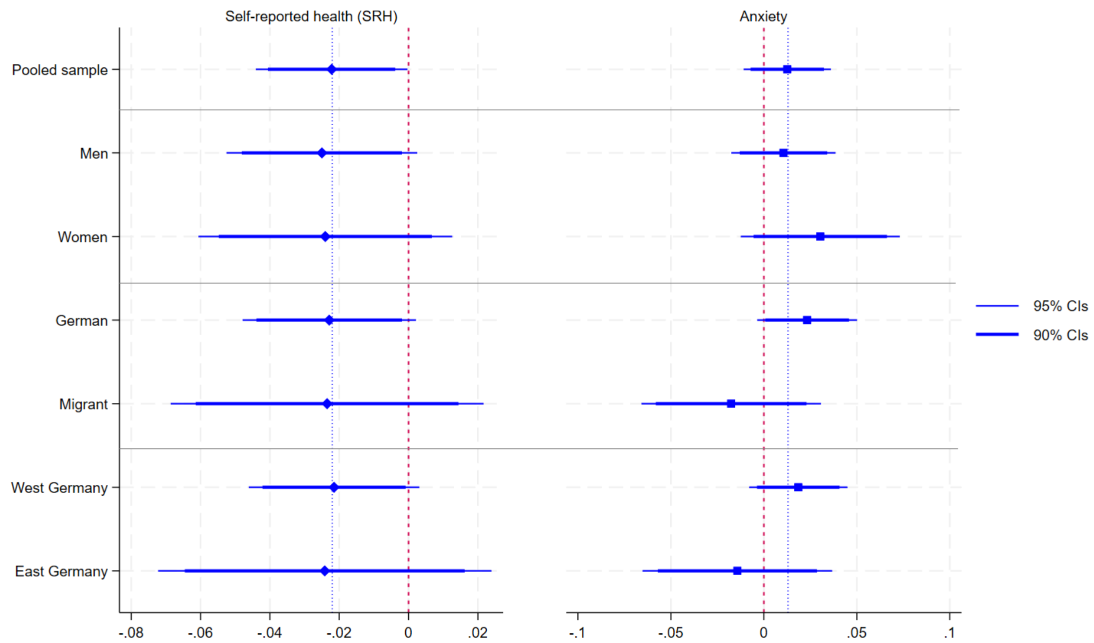

Figure 2a – Estimated coefficients on high risk of automation for SRH and anxiety stratified by demographic characteristics

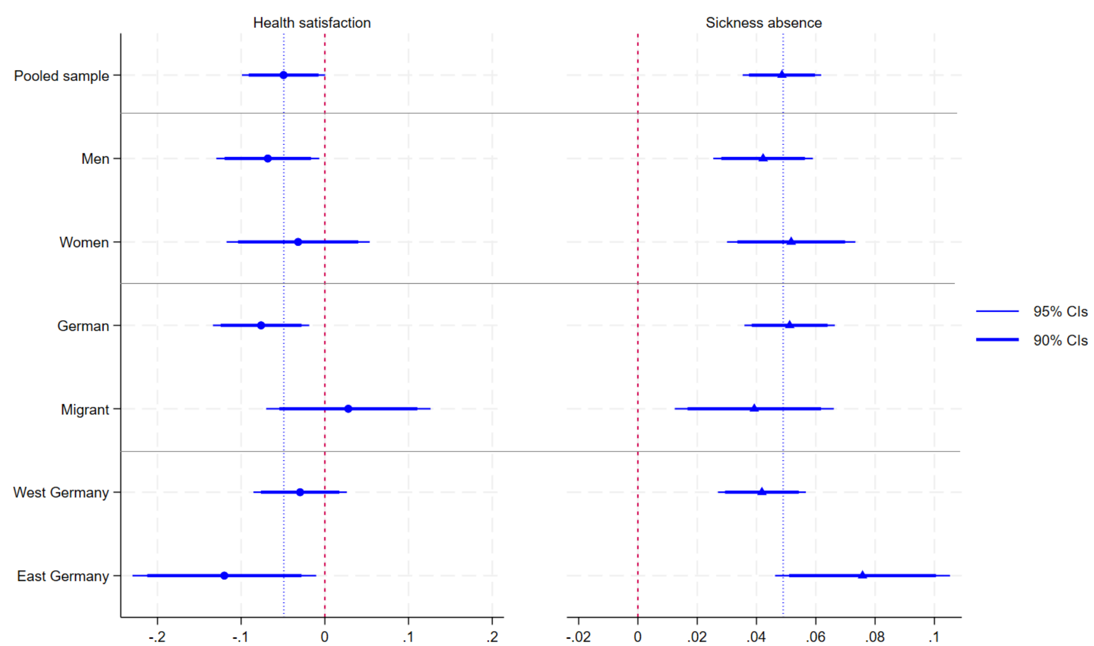

Figure 2b – Estimated coefficients on high risk of automation for health satisfaction and sickness absence stratified by demographic characteristics

Similar to the pooled sample, the effect on sickness absence of high automation risk is positive and statistically significant in each of the considered demographic groups, but its magnitude tends to vary. The highest estimated coefficients are observed for east Germany (7.6 percentage points), female workers (5.2 percentage points), and the native population (5.1 percentage points). No statistically significant effect on healthcare use is detected for any analyzed demographic group.

Overall, our findings from the heterogeneity analysis indicate the presence of some mild heterogeneity, with several subgroups deviating from the evidence observed for the pooled sample; however, in most cases, our estimates face a statistical power issue.

4.3. Differences by occupational characteristics

Figures 3a and 3b indicate whether the effect on our health outcomes of high automation risk changes between and within several occupational groups. Similar to the previous section, the analyzed groups overlap, and the x-axis varies between figures. Thus, the estimated coefficients are not directly comparable.

As shown in Figure 3a, the most pronounced negative effect of high automation risk on SRH is observed for the low-skilled occupational class (-0.059 points) and for sectors that are not automation-prone (-0.040 points). As for anxiety, the highest positive statistically significant effect is found for part-time and low-skilled workers (0.051 and 0.052 points, respectively) and for workers employed in small and medium enterprises and in automation-prone sectors (0.037 and 0.032 points, respectively).

Figure 3b indicates that the health satisfaction of workers employed in small and medium enterprises and less automatable sectors is more vulnerable to the negative impact of high automation risk (-0.086 and -0.095 points, respectively vs. -0.049 points for the pooled sample). The effect on sickness absence for those respondents employed in small and medium enterprises (5.6 percentage points) and in low-skilled and medium-skilled occupations (8.1 and 6.0 percentage points, respectively) exceeds the value estimated for the pooled sample (4.9 percentage points). However, the opposite pattern is observed for part-time workers and respondents employed in very large companies (3.8 and 2.4 percentage points, respectively). The effect on sickness absence of high automation risk in the group of high-skilled workers tends toward zero.

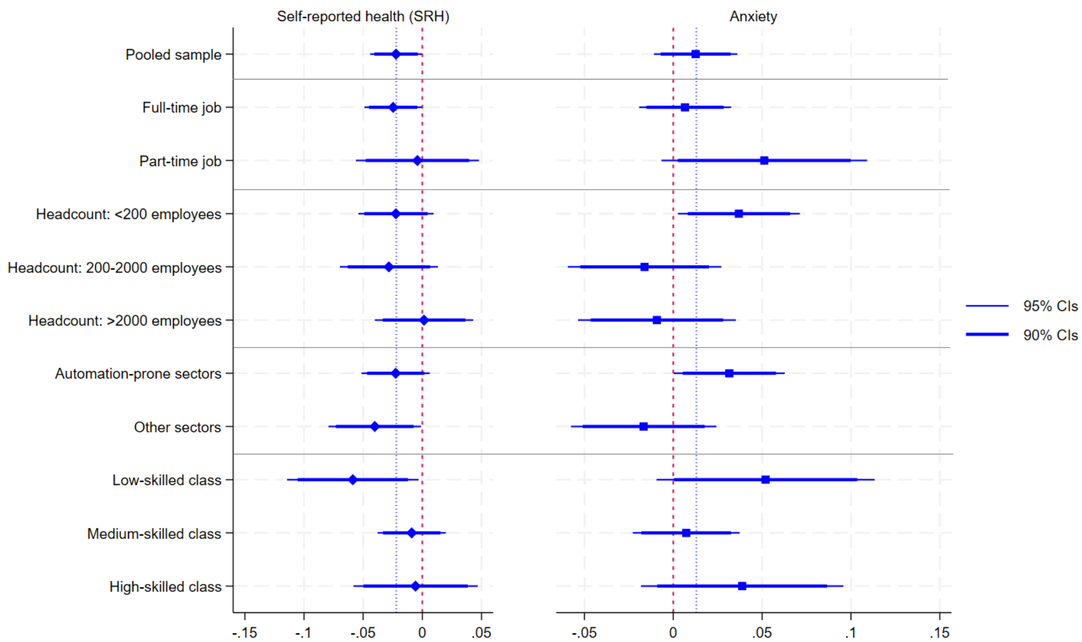

Figure 3a – Estimated coefficients on high risk of automation for SRH and anxiety stratified by occupational characteristics

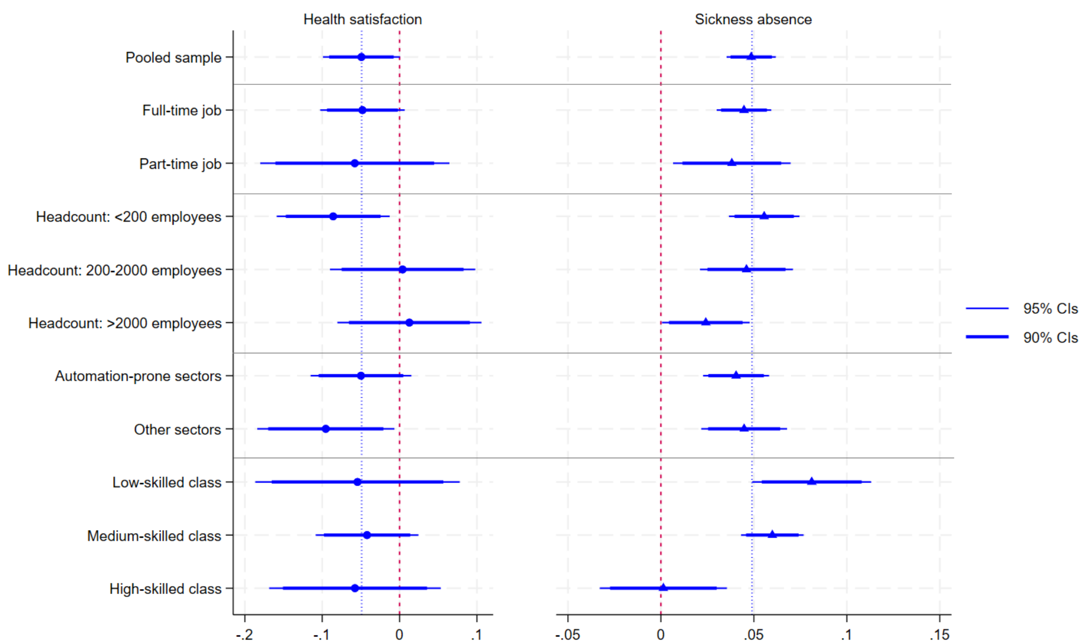

Figure 3b – Estimated coefficients on high risk of automation for health satisfaction and sickness absence stratified by occupational characteristics

Finally, no statistically significant effect of high risk of automation on healthcare use is found in the considered occupational groups. As in the previous section, our findings suffer from a statistical power issue, while indicating the presence of some minor heterogeneity in the effects.

4.4. Sensitivity analysis: alternative thresholds

Our analysis is based on the high automation risk measure (*Risk70*), which arises from the share of routine tasks in the occupation, and equals one if this value is above 70%, and zero otherwise (the standard threshold used in the previous literature). In order to test whether our estimates are sensitive to the downward shift of this threshold, we construct alternative risk measures and re-estimate our main models (see Table 2).

Table 2 – Estimated coefficients for alternative risk measures (pooled sample)

	SRH	Anxiety	Health satisfaction	Healthcare use	Sickness absence
Risk measure (share of routine tasks)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Risk70 (>70%) - baseline	-0.022**	0.013	-0.049*	-0.002	0.049***
	(0.011)	(0.012)	(0.025)	(0.006)	(0.007)
Risk_SD (>67.4%)	-0.019*	0.012	-0.046*	0.001	0.042***
	(0.010)	(0.011)	(0.024)	(0.006)	(0.006)
Risk_Q4 (>62.2%)	-0.017*	0.025**	-0.046**	0.003	0.039***
	(0.009)	(0.010)	(0.021)	(0.005)	(0.006)
Risk50 (>50%)	-0.008	0.019**	-0.036*	-0.007	0.022***
	(0.008)	(0.009)	(0.018)	(0.005)	(0.005)
Risk_MD (>40.2%)	-0.006	0.020**	-0.026	-0.003	0.007
	(0.008)	(0.009)	(0.019)	(0.005)	(0.005)
Number of observations	58,196	58,196	58,196	58,196	58,196
Number of individuals	18,283	18,283	18,283	18,283	18,283

*Note. *p-value<0.10, **p-value<0.05, ***p-value<0.01*

All models include controls for age, squared age, gender, marital status, educational attainment, income, migration background, and region of settlement. Robust standard errors are clustered at an individual level.

Risk_SD equals one if the percentage of routine tasks in the occupation exceeds the value of a sample mean plus one standard deviation, and zero otherwise (the threshold is set up at 67.4% of routine tasks in the occupation). *Risk_Q4* equals one if the percentage of routine tasks in the occupation exceeds the last 25% of the sample distribution, and zero otherwise (62.2% of routine tasks). *Risk50* equals one if the percentage of routine tasks in the occupation exceeds 50, and equals zero otherwise. Finally, *Risk_MD* equals one if the percentage of routine tasks in the occupation exceeds the sample median, and zero otherwise (40.2% of routine tasks).

As shown in Table 2, we observe a decline in the magnitude of effects for most health-related outcomes (exceptions are anxiety and healthcare use), while moving from the highest threshold (more than 70% of routine tasks) to the lowest threshold (more than 40%), which indicates the presence of a dose-response relationship. Nevertheless, our estimates for SRH, health satisfaction, and sickness absence with alternative risk measures are largely consistent with the main findings. Since the results for healthcare use are not statistically significant and remain relatively unchanged over alternative risk measures, we may conclude that high automation risk is associated with mild physical and mental health issues that can be treated without visiting a doctor. Finally, the direction of the effect for anxiety remains consistent over all thresholds; however, a statistically significant relationship is only observed in the range between the median value and 62.2% of routine tasks in the occupation. We conclude that this might be a power issue, since a downward shift of the threshold leads to an increase in the sample size of the high risk group.

4.5. Further robustness checks

We conduct a set of robustness checks to test whether our baseline estimates are consistent across various model specifications. We estimate fixed effects (FE) and population-averaged (PA) linear regressions, along with panel probit for our binary health outcomes, and G2SLS random effects IV regressions (see Table S4 in the supplementary materials). Overall, our estimates remain relatively consistent over various model specifications. The population-averaged estimator provides almost identical results to those of the RE specification. The estimates from the FE specification show the same direction of the effect, but the coefficients are no longer statistically significant due to the limited within variation in our main explanatory variable (as discussed earlier). After adjusting for potential endogeneity, we end up with estimates of the same direction and comparable magnitude for most of our health-related outcomes (except SRH and healthcare use), which are, however, no longer statistically significant (except sickness absence).

5. Discussion

5.1 Main findings

This study investigates the impact of exposure to a high automation risk at work on the subjective and objective health outcomes of workers in Germany. Our findings suggest that employment in highly automatable occupations is negatively associated with self-reported health and health satisfaction, and is positively related to sickness absence and, depending on how the risk of automation is measured, to anxiety. No effect is observed for healthcare use. Moreover, we find that the impact of high automation risk slightly varies by several demographic and occupational characteristics. Finally, we show that the way automation risk is measured may affect the magnitude somewhat, and, in some cases, the significance of the observed effects. However, the overall impact of the measurement approach on the conclusions is moderate. We also estimate several alternative model specifications as robustness checks, with the findings remaining largely consistent with our main results.

Our findings suggest that workers employed in occupations with a high risk of automation are 0.022 points (on the scale from one to five) and 0.049 points (on the scale from zero to 10) worse off in terms of SRH and health satisfaction, respectively (consistent with earlier evidence for the US from Nazareno and Schiff (2021) and Liu (2023), who also considered automation risk defined at the occupational level). However, the magnitude of our estimates is rather moderate, being slightly lower in absolute terms than the impact of employment status and job insecurity on health satisfaction and self-reported health (measured on the same scales as our health outcomes) in Germany (Otterbach and Sousa-Poza, 2016; Kühn et al., 2019).

Our findings also reveal a small positive relationship between high automation risk and anxiety, which is consistent with Abeliansky et al. (2024), albeit with some variation depending on the specific measurement used. Finally, we observe a positive association of high automation risk with sickness absence, while no effect is found for healthcare use. The latter finding is perhaps not overly surprising, given that German workers are able to stay home for up to three days without going to a doctor and requesting official sick leave. Overall, our results provide evidence that in the German context, high automation risk contributes to minor physical and mental health issues, rather than to serious disorders, since the healthcare use variable remains unaffected. For instance, mild psychological distress caused by automation risk might be related to the feeling of job insecurity (Caroli and Godard, 2016; Patel et al., 2018; Lordan and Stringer, 2022; Giuntella et al., 2023), in particular to the fear of job loss and the fear of occupational or qualification change (Blasco et al., 2022), which might, in turn, induce absenteeism.

We have also conducted a heterogeneity analysis with respect to several demographic and occupational characteristics, reflecting the nature of German society and the German labor market, which have previously been overlooked in the literature. Our findings show that no group differs significantly from the pooled result, and that no subgroup comparison (e.g., men vs. women or east vs. west) yields a statistically significant difference, as the confidence intervals overlap. Moreover, in contrast to the pooled sample, most confidence intervals include zero (except sickness absence). Overall, this provides evidence that our heterogeneity analysis has little statistical power. There are, however, some groups that stick out a bit, indicating some minor differences in effects. In particular, the health of workers employed in smaller companies and in sectors that are not automation-prone tends to be more vulnerable to the impact of automation risk. At first glance, this observation seems to be counterintuitive, since it is often assumed that workers employed in large companies and in highly automatable sectors (like manufacturing) perceive and face the threats of ongoing technological advancement much faster than their counterparts working in less automation-prone settings (Zhao et al., 2022; Abeliansky et al., 2024). Our contradictory evidence might be explained through the prism of adaptation, suggesting that workers who deal with a highly automatable environment on a regular basis are less likely to treat it as a shock, and, consequently, to experience negative health outcomes in response to it (Lordan and Stringer, 2022).

Finally, our results suggest that once the share of routine tasks in the occupation declines, the detrimental impact of automation risk on most of our health measures becomes less pronounced in terms of magnitude (evidence for a dose-response relationship). However, the opposite pattern is observed for anxiety, indicating a power issue in our estimates for this health outcome.

5.2 Methodological considerations

Our analysis faces some challenges. To begin with, our main explanatory variable, high risk of automation, is quite limited in terms of within variation, which does not allow us to address unobserved heterogeneity through the fixed effects models. Moreover, it relies on a country-specific distribution of tasks within occupations. While this reflects the labor market conditions in

Germany, it might not directly translate to the conditions in other countries. In addition, since our sample size is relatively small, we have struggled with some power issues, in particular at the stage of heterogeneity analysis. Finally, our estimates may suffer from an intent-to-treat issue, which seems to arise in studies that deal with objective proxies for automation risk measured at the individual level. This problem might occur if individuals who are at the real risk of being displaced are completely ignorant of it, while individuals who are employed in relatively "safe" occupations are, by contrast, overly stressed about the threat of technological unemployment. This issue tends to bias estimates toward zero. Nevertheless, given this bias, our study, along with earlier literature, still finds some reasonable effects.

6. Outlook

Our analysis can be extended in several ways. Some research is needed on the transmission mechanisms that underlie the relationship between automation risk and the health outcomes of workers. From a methodological point of view, it would be useful to compare various objective measures of automation risk and to check whether our estimates are sensitive to such a change. Finally, we do not address the issue of reverse causality (the methodological question of whether automation risk affects the health of workers or whether workers with a certain health status are selected into occupations with a certain degree of risk) in our analysis, since doing so would be beyond the scope of this study. Nevertheless, this research question should not be overlooked in future investigations.

This study may also provide some useful insights for policymakers. Our results promote the development and the introduction of professional training programs on digital literacy targeted at the general workforce, with a particular focus on the groups who are more vulnerable to the impact of automation risk. Such programs may help to reduce the levels of psychological tension and distress related to dealing with new technologies, and nudge workers to treat them as a complement, rather than as an enemy, in the fight for better employment opportunities.

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Conflict of interests

We have no conflict of interests to declare.

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Data availability

The Occupational Panel for Germany is openly available, while the SOEP data cannot be openly shared with the public. However, we provide estimation codes for STATA (version 18), which are available at: https://osf.io/kv684/?view_only=7436b515d32849a7998770a03281d2db.

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Table S1 – 20 most frequent occupations with high automation risk in Germany (2013-2018)

KldB10 code (5 digits)	Occupation	Professional class (skill level)
25102	Occupations in machine-building and -operating (without specialization)	Skilled tasks
26212	Electricians in construction	Skilled tasks
72112	Bankers	Skilled tasks
51311	Occupations in warehousing and logistics	Unskilled/semi-skilled tasks
25122	Machine and plant operators	Skilled tasks
24412	Occupations in metal constructing	Skilled tasks
72213	Occupations in accounting	Complex tasks
24232	Occupations in metalworking: cutting	Skilled tasks
72302	Occupations in tax consultancy	Skilled tasks
29201	Occupations in the production of foodstuffs (without specialization)	Unskilled/semi-skilled tasks
41312	Occupations in chemical and pharmaceutical engineering	Skilled tasks
25212	Technical occupations in the automotive industries	Skilled tasks
52531	Operators of cranes, lifts, and related lifting devices	Unskilled/semi-skilled tasks
25101	Occupations in machine-building and -operating (without specialization)	Unskilled/semi-skilled tasks
24201	Occupations in metalworking (without specialization)	Unskilled/semi-skilled tasks
25132	Technical service staff in maintenance and repair	Skilled tasks
41322	Chemical technical laboratory occupations	Skilled tasks
24422	Occupations in welding and joining	Skilled tasks
27312	Technical occupations in quality control	Skilled tasks
26312	Occupations in information and telecommunication technology	Skilled tasks

Table S2 – Descriptive statistics (pooled sample)

Variable	Full sample (58,196 observations, 18,283 individuals) Definition	Mean	SD
Dependent variables:			
SRH	5 categories sorted from 1 "bad" to 5 "very good"	3.586	0.843
Anxiety	5 categories sorted from 1 "very rarely" to 5 "very often"	1.823	0.897
Health satisfaction	11 categories sorted from 0 "completely dissatisfied" to 10 "completely satisfied"	7.105	1.894
Healthcare use	Has visited a doctor in the last 3 months=1, otherwise=0	0.649	0.477
Sickness absence	Has taken days off work due to own illness in the last year=1, otherwise=0	0.627	0.484
Socio-economic characteristics:			
Age	Number of full years [range of 18-65 years old]	43.754	10.350
Gender	Male=0, Female=1	0.507	0.500
Marital status	Married/cohabiting=0, otherwise=1	0.376	0.484
Educational attainment dummies:			
Low education	1-2 levels of isced97=1, otherwise=0	0.070	0.255
Medium education	3-4 levels of isced97=1, otherwise=0	0.605	0.489
High education	5-6 levels of isced97=1, otherwise=0	0.325	0.468
Income (ln)	Natural log of net household income adjusted for CPI and the household size	3.121	0.411
Migrant	No or indirect migration background=0, Direct migration background=1	0.193	0.394
Region	West Germany=0, East Germany=1	0.215	0.411
Occupational characteristics:			
Type of employment	Full-time job=0, Part-time job=1	0.296	0.457
Company size dummies:			
Small and medium companies	Headcount less than 200 employees=1, otherwise=0	0.494	0.500
Large companies	Headcount of 200-2000 employees=1, otherwise=0	0.234	0.423
Very large companies	Headcount of more than 2000 employees=1, otherwise=0	0.272	0.445
Automation-prone sectors	Agriculture, energy, mining, manufacturing, bank and insurance=1, otherwise=0	0.326	0.469
Professional class dummies:			
Low-skilled	Unskilled/semi-skilled tasks=1, otherwise=0	0.105	0.306
Medium-skilled	Specialist tasks=1, otherwise=0	0.546	0.498
High-skilled	Complex and highly complex tasks=1, otherwise=0	0.349	0.477
Main explanatory variable:			
High automation risk	More than 70% of routine tasks in the occupation=1, otherwise=0	0.158	0.365

Table S3 – Descriptive statistics (by groups of automation risk)

Variable	Low risk (Mean) n=48,999	High risk (Mean) n=9,197	Difference (t-test)
Dependent variables:			
SRH	3.588	3.578	
Anxiety	1.838	1.740	***
Health satisfaction	7.101	7.127	
Healthcare use	0.655	0.615	***
Sickness absence	0.621	0.655	***
Socioeconomic characteristics:			
Age	43.819	43.404	***
Gender	0.550	0.275	***
Marital status	0.382	0.343	***
Educational attainment dummies:			
Low education	0.065	0.099	***
Medium education	0.576	0.758	***
High education	0.359	0.143	***
Income (ln)	3.133	3.062	***
Migrant	0.177	0.274	***
Region	0.216	0.206	**
Occupational characteristics:			
Type of employment	0.325	0.144	***
Company size dummies:			
Small and medium companies	0.498	0.468	***
Large companies	0.228	0.266	***
Very large companies	0.274	0.266	
Automation-prone sectors	0.246	0.754	***
Professional class dummies:			
Low-skilled	0.087	0.198	***
Medium-skilled	0.517	0.700	***
High-skilled	0.395	0.102	***

Note. *p-value<0.10, **p-value<0.05, ***p-value<0.01

Table S4 – Estimated coefficients for alternative model specifications (pooled sample)

	SRH	Anxiety	Health satisfaction	Healthcare use	Sickness absence
Model	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
RE (baseline)	-0.022**	0.013	-0.049*	-0.002	0.049***
	(0.011)	(0.012)	(0.025)	(0.006)	(0.007)
FE	-0.013	0.024	-0.016	-0.009	0.010
	(0.015)	(0.018)	(0.035)	(0.010)	(0.011)
PA	-0.021*	0.011	-0.046*	-0.002	0.049***
	(0.011)	(0.012)	(0.025)	(0.006)	(0.007)
RE probit (marginal effects)				-0.001	0.049***
				(0.006)	(0.07)
RE (risk70$_{t-1}$)				-0.002	0.048***
				(0.008)	(0.008)
G2SLS RE (2nd stage)	0.014	0.041	-0.018	0.017	0.071***
	(0.049)	(0.049)	(0.111)	(0.023)	(0.026)

*Note. *p-value<0.10, **p-value<0.05, ***p-value<0.01*

All models include controls for age, squared age, gender, marital status, educational attainment, income, migration background, and region of settlement. Robust standard errors are clustered at an individual level.

Number of observations (individuals) for the models with one-year lagged risk measure risk70$_{t-1}$ accounts for 37,574 (13,135).

Table S5 – Distribution of the share of the German population employed in highly automatable occupations over years and sectors (instrument statistics)

year	Sector1	Sector2	Sector3	Sector4	Sector5	Sector6	Sector7	Sector8	Sector9	Sector10
2013	0.001	0.012	0.034	0.655	0.033	0.058	0.018	0.001	0.179	0.010
2014	0.001	0.012	0.033	0.654	0.032	0.057	0.018	0.001	0.182	0.010
2015	0.001	0.012	0.033	0.654	0.032	0.055	0.018	0.002	0.184	0.009
2016	0.001	0.010	0.024	0.579	0.033	0.071	0.038	0.016	0.220	0.009
2017	0.001	0.009	0.023	0.579	0.034	0.071	0.039	0.016	0.219	0.009
2018	0.001	0.009	0.024	0.582	0.033	0.071	0.039	0.016	0.217	0.008

Note.
Sector1 – agriculture, sector2 – energy, sector3 – mining, sector4 – manufacture, sector5 – construction, sector6 – trade, sector7 – transport, sector8 - bank, insurance, sector9 – services, sector10 - other