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The Hidden Costs of Technological Change: Investigating Pathways Through Which Highly Automatable Jobs Undermine Workers' Health in Germany

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Abstract

The ongoing economic transformation driven by automation has significant social implications, particularly for the health and well-being of workers who face the risk of job displacement and the pressure to acquire new skills and qualifications. However, the specific pathways through which exposure to automation risk affects health outcomes remain poorly understood, and the relative contribution of each potential mechanism is still unclear. In this study, we examine the nature of the relationship between high workplace exposure to automation risk and a range of subjective health outcomes – including self-reported health, anxiety, and both physical and mental component summary scores from the SF-12 Health Survey – among workers in Germany. Using data from the German Socio-Economic Panel (SOEP) linked with administrative records from the Occupational Panel for Germany (2014–2022), we apply the Karlson-Holm-Breen (KHB) mediation analysis method to assess whether broader indicators of economic uncertainty, alongside automation-specific factors, mediate the relationship between high automation risk and workers' health. Our results indicate that the negative impact of high automation risk on health in Germany primarily operates through indirect pathways (related to mediators) for both genders, with the exception of physical health among male workers, where a direct negative effect is also evident. Economic concerns – particularly job insecurity and worries about one's future financial situation – emerge as more significant mediators than automation-specific factors. Overall, our findings suggest that the mechanisms linking high automation risk to health are gender- and context-sensitive, and are shaped by broader economic conditions and workplace environments.

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

Key words: automation risk, routine tasks, health, Germany, mediation analysis, KHB method

1. Introduction

Automation is fundamentally transforming national economic systems, driving changes in productivity (Graetz and Michaels, 2018; Kromann et al., 2020), wage distributions (Vannutelli et al., 2022; Martins-Neto et al., 2024), and the occupational composition of labor markets (Balsmeier and Woerter, 2019), thereby placing some workers at risk of displacement and creating a critical need for the acquisition of new skills and knowledge (Dengler et al., 2014; Frey and Osborne, 2017). These economic disruptions are deeply interwoven with social and health consequences, as anticipated reskilling, wage suppression, job insecurity, and even job loss often translate into heightened stress and the deterioration of both mental and physical health (Kim and von dem Knesebeck, 2016; Kim et al., 2020; Tsai et al., 2024; Mikucka et al., 2025).

Recent studies on the social costs of technological change primarily focus on linking exposure to automation in the workplace with workers' mental health and well-being outcomes, while largely overlooking the underlying pathways through which this relationship is transmitted. For instance, a small number of studies suggest that the impact of automation on health is mediated by job insecurity, observing that workers who are more exposed to automation tend to experience greater job insecurity, which in turn contributes to poorer health outcomes (Patel et al., 2018; Cheng et al., 2020; Abeliansky et al., 2024). However, these studies often lack a precise decomposition of the estimated total effects, as they fail to clearly distinguish between the proportion directly attributable to automation and the proportion operating through specific mediating channels. Moreover, although some of these studies consider multiple mediators, they typically assess the significance of each pathway separately (Nazareno and Schiff, 2021; Yang et al., 2022).

In addition, previous research on the overall impact of automation on health shows considerable variation in the measures of automation used, which may contribute to inconsistent findings. Specifically, U.S. studies predominantly use occupation-level exposure to automation, and consistently report adverse effects on workers' mental health and well-being (Patel et al., 2018; Nazareno and Schiff, 2021). The European evidence relies on a sector-level measure of automation, with findings suggesting either no effect (Gihleb et al., 2022; Giuntella et al., 2023) or a negative effect on mental health (Blasco et al., 2022; Abeliansky et al., 2024). In contrast, the evidence from China, based on a sector-level measure, indicates a positive association between automation exposure and workers’ mental health outcomes (Yang et al., 2022).

This study contributes to the growing body of literature on the health outcomes of automation by examining the relationship between high exposure to automation risk in the workplace and various health outcomes (self-reported health, anxiety, and the physical and mental component summary scores from the SF-12 Health Survey), and how this relationship is mediated by economic uncertainty in general as well as by more specific concerns related to automation. We conduct a gender-specific mediation analysis using the Karlson-Holm-Breen (KHB) method on longitudinal survey data from the German Socio-Economic Panel (SOEP), combined with country-specific occupation-level estimates of automation risk from the Occupational Panel for Germany (2014-2022).

Germany is a particularly relevant case for investigation for several reasons. First, with 415 industrial robots per 10,000 employees in 2022 – well above the EU average of 208 units – Germany is a leading adopter of automation in Europe (Müller, 2023). Second, its economy is heavily anchored in the industrial sector, which has long been dominated by routine-intensive occupations that are particularly vulnerable to the impact of automation. These two factors suggest that the effects of automation, and particularly the risk of job displacement, are likely to be more pronounced in Germany than in other European countries. Third, recent research on the mental health outcomes of automation in Germany presents conflicting findings, with some studies reporting significant negative effects (Abeliansky et al., 2024), and others showing no clear association (Gihleb et al., 2022; Giuntella et al., 2023).

This study adds valuable insights to the existing literature in several ways. First, we examine multiple pathways through which automation risk may affect workers' health simultaneously, and quantify the contribution of each pathway once mediation is confirmed – an approach that has not yet been explored in the existing literature. Second, we utilize a task-based measure of automation risk, proxied by the share of routine tasks in an occupation, as proposed by Dengler et al. (2014) for the German labor market. To the best of our knowledge, up-to-date evidence for Germany primarily relies on either sectoral or subjective measures of automation exposure in the workplace. Third, we conduct our analysis separately for men and women, accounting for the gender-segregated nature of the German labor market, whereas previous studies have drawn conclusions based on pooled sample estimates. Finally, we evaluate the robustness of our baseline findings by examining their consistency under different economic conditions and sample selection criteria.

2. Background

2.1. Automation and health outcomes

Automation is a multidimensional concept encompassing various types of technologies, and can therefore be assessed from multiple perspectives. Literature addressing the actual level of automation typically relies on implementation metrics (such as intensity, adoption, or investment rates) related to information and communication technologies and software, industrial robots, machine-based digital systems, and artificial intelligence (Filippi et al., 2023). Such approaches typically consider automation and its effects through macro- and meso-level lenses, focusing on sectoral or firm dynamics. An alternative approach adopts a more abstract and forward-looking concept of exposure to automation, defined at the micro level (individual or occupational). This perspective focuses on the distribution of tasks within occupations and is often framed in terms such as automation probability, substitution potential, or automation risk, with each representing the extent to which a given occupation may be susceptible to displacement in the future (Dengler et al., 2014; Arntz et al., 2016; Frey and Osborne, 2017).

The growing literature linking automation with the health and well-being outcomes of workers primarily relies on three well-established objective measures: robot intensity, computerization probabilities, and routine task intensity. A few studies, however, diverge from this approach by focusing on workers' self-reported exposure to automation in the workplace. In general, regardless of the automation measure used, most existing studies – with a few limited exceptions – find either negative or insignificant effects, while offering little insight into the potential mechanisms underlying the observed relationship.

For instance, studies built on the sectoral measure of robot intensity, derived from robotics market data from the International Federation of Robotics (IFR), have yielded mixed evidence. On the one hand, increased adoption of industrial robots has been linked to higher all-cause mortality among middle-aged individuals and young women in the U.S. (O'Brien et al., 2022), an increase in drug- and alcohol-related mortality across the U.S. population, and mental health deterioration (Gihleb et al., 2022). On the other hand, increased robot adoption has been associated with a decline in reports of poor health among low-skilled workers, reduced work disability, and fewer cases of job exit due to health reasons in the U.S. (Gunadi and Ryu, 2021), as well as a decline in work-related injuries in the U.S. and in all-cause disability in Germany (Gihleb et al., 2022).

Additionally, higher robot intensity has been associated with a moderate decline in workers' mental health in Germany (Abeliansky et al., 2024); however, no significant effects on psychological burden or life satisfaction have been found (Gihleb et al., 2022). In contrast, evidence from China indicates that increased robot adoption is linked to improved mental health outcomes among workers (Yang et al., 2022).

A few studies utilizing respondents' subjective assessments of current exposure to automation in the workplace report a positive association with major depressive episodes and generalized anxiety disorder in France (Blasco et al., 2022), and a decline in life satisfaction – but no significant effects on overall mental health, anxiety, or depression – in Germany (Giuntella et al., 2023).

Studies dealing with automation potential and drawing on the computerization probabilities developed by Frey and Osborne (2017) for U.S. occupations consistently find a negative association between automation and general, physical, and mental health outcomes (Patel et al., 2018; Nazareno and Schiff, 2021; Liu, 2023). This measure represents the likelihood of job displacement due to new technologies over the next two decades based on expert estimates supported by advanced computational algorithms. Non-U.S. studies relying on the Frey and Osborne (2017) estimates show that a higher computerization probability in an occupation is positively associated with the risk of work-related injuries and disease prevalence in Taiwan (Cheng et al., 2020), and is negatively related to life satisfaction among middle-aged workers in the UK (Zheng et al., 2024).

To the best of our knowledge, the only health-related study that employs routine task intensity (the proportion of routine manual and routine cognitive tasks within an occupation) as a measure of automation potential finds a negative association with physical health and bodily pain, a positive association with vitality and satisfaction with free time, and no significant effect on overall mental health or life satisfaction among workers in Australia (Lordan and Stringer, 2022).

Overall, much of the existing evidence – particularly studies using computerization probabilities and robot intensity measures – originates from the U.S. labor market, where findings consistently suggest that both current and anticipated automation negatively impact workers' physical and mental health. In contrast, the robot intensity measure is more commonly applied in European contexts, where results are far more heterogeneous. While some studies report protective effects of automation on health, such findings are relatively rare, are often country-specific, and are

typically confined to certain population subgroups. Finally, the routine task intensity measure is notably underused, despite its theoretical relevance for assessing susceptibility to displacement.

2.2. Underlying mechanisms linking automation and health outcomes

Automation may affect health through multiple channels. On the one hand, its potential to substitute human labor can worsen workers' health outcomes by leading to job loss, occupational shifts, and the need for reskilling. It can also heighten concerns about future technological unemployment, rising demands for skills and qualifications, job insecurity, economic instability, and reduced long-term employability. On the other hand, automation's potential to complement human labor by replacing physically demanding, hazardous, or routine-intensive tasks may have a positive impact on workers' health.

Several studies mentioned in the section above attempt to shed light on the underlying mechanisms driving the relationship between automation and workers' health. For instance, evidence from the U.S. studies is mixed, with Patel et al. (2018) showing that perceived declines in job security tend to mediate the relationship between increased automation potential and workers' adverse health outcomes. In contrast, Nazareno and Schiff (2021) find no support for the hypothesis that this relationship is significantly mediated by job context (e.g., workplace safety, socialization and management, and career advancement and benefits), job content (e.g., task type, autonomy, and workload), or job security.

Evidence from the Asia-Pacific region suggests that job insecurity is a plausible channel through which high automation potential negatively affects the health of workers in Taiwan (Cheng et al., 2020). In contrast, research from China shows that increased wages and reduced working hours serve as pathways through which exposure to automation in the workplace exerts a protective effect on workers' mental health (Yang et al., 2022). Finally, Lordan and Stringer (2022) provide evidence for Australia that high automation potential is negatively associated with workers' physical health, which may in turn have a detrimental impact on their mental health outcomes.

Evidence from Europe indicates that the mental health of French workers in automatable jobs is primarily undermined by perceived job insecurity, manifested as fears of job loss, occupational or qualification displacement, and pressure to accept an undesirable job in the future (Blasco et al., 2022). Abeliansky et al. (2024) examine whether automation (measured by sectoral robot

intensity) is linked to workers' mental health in Germany through various potential pathways, including worries about one's economic situation, job security, satisfaction with income and work, sense of achievement, time pressure, working hours, vitality, and physical health. Among these, only worries about job security and sense of achievement are found to significantly mediate this relationship. Finally, although Giuntella et al. (2023), using a subjective measure of exposure to AI at work, find no significant association between AI exposure and mental health outcomes in Germany, they do report that it is significantly related to increased worries about job insecurity and concerns about one's economic situation.

Overall, the studies mentioned above either focus on a single potential pathway linking automation to workers' health outcomes or examine multiple pathways separately by regressing each mediator on the selected automation measure. Such approaches can only suggest possible mediation effects, while lacking the capacity to fully decompose the total estimated effect into direct (attributable to the main explanatory variable) and indirect (transmitted through specific mediators) components. Additionally, they cannot quantify the individual contribution of each mediator to the relationship of interest.

2.3. Research aims

Our study has three aims. First, we perform an explicit gender-specific mediation analysis using the Karlson-Holm-Breen (KHB) method to test both the direct and the indirect effects of automation on workers' health outcomes in Germany. We employ the routine task intensity measure of automation exposure – an approach largely overlooked in previous research – and examine its impact on various physical and mental health outcomes, comparing estimates for male and female subsamples, given the pronounced gender segregation in the German labor market. Building on findings from the European context, we incorporate both broad mediators, such as concerns about job insecurity and one's future financial situation, and more specific automation-related indicators, including worries about coping with technological change, the risk of occupational obsolescence, and anticipated changes in health risks, work productivity, and qualification demands. Second, we further decompose the estimated effects on composite health outcomes – specifically, the physical and mental component summary scores from the SF-12 health survey – into their underlying domains: physical functioning, role physical, bodily pain, and general health (for physical health score); and vitality, social functioning, role emotional, and

mental health (for mental health score). This approach allows us to identify the specific health components most affected by automation exposure. In addition, domain-level decomposition enables us to detect hidden patterns and assess the consistency and plausibility of the observed effects. While aggregated summary scores may mask important variation across domains, breaking them down reduces the likelihood that the results are driven by noise or measurement bias within composite measures. Third, we conduct several robustness and sensitivity checks by applying specific sample selection criteria and estimating alternative model specifications to ensure the reliability of our baseline findings.

3. Data and methods

3.1. Sample

Our analysis draws on two data sources, with the primary dataset being the German Socio-Economic Panel (SOEP), version SOEP-Core v39. The SOEP is a nationally representative longitudinal survey conducted by the German Institute for Economic Research (DIW Berlin), covering both individual- and household-level data. It provides extensive information on a wide range of topics, including demographic and socioeconomic characteristics, employment trajectories, health, and the overall well-being of the German population (Goebel et al., 2019). The Occupational Panel for Germany, developed by the Institute for Employment Research (IAB), serves as the source of our main explanatory variable, high automation risk. This dataset includes detailed administrative records on the demographic and employment structure of the German workforce at the occupational level, along with a task-content decomposition for each occupation (Grienberger et al., 2022).

We merge these two data sources using occupational codes from the German Classification of Occupations 2010 (KldB 2010) in combination with the survey year. The occupational code variable is defined at the 3+5-digit level, with the three-digit level grouping occupations based on similar skills, abilities, and knowledge requirements (e.g., electricians in construction, machine and plant operators), and the fifth digit distinguishing occupations according to the complexity of work tasks (e.g., unskilled or semi-skilled, specialist, complex, and highly complex). This classification scheme corresponds to the occupational structure used in the Occupational Panel. Our resulting dataset contains individual-level records combined with yearly information on the proportion of routine tasks associated with each occupation.

In our analysis, we focus exclusively on individuals who are currently employed, excluding respondents on maternity leave, students, and retirees. Additionally, we omit occupational groups with distinct characteristics and labor market regulations, such as civil servants, members of the armed forces, individuals in irregular marginal employment, the self-employed, and disabled individuals. Our final sample includes 9,808 regularly employed men and 10,125 regularly employed women aged 18 to 65. This yields a total of 43,536 observations with no missing values in the variables of interest, collected biennially over the 2014–2022 period. Descriptive statistics of the full sample are provided in Table S1 of the supplementary materials.

3.2 Key independent variable: high automation risk

We derive our main explanatory variable, high automation risk, from the Occupational Panel, which employs the routine-task intensity approach to assess the susceptibility of occupations to automation (the so-called substitution potential proxied by the proportion of routine tasks in an occupation). The substitution potential estimates were initially computed in 2013, and have since been updated every three years. In the Occupational Panel for Germany, occupations with more than 70% routine tasks (both manual and cognitive) are classified as highly exposed to displacement (Grienberger et al., 2022). This 70% threshold is based on earlier implementations in studies by Arntz et al. (2016) for OECD countries and Frey and Osborne (2017) for the U.S. Accordingly, our key explanatory variable is coded as one if the proportion of routine tasks in an occupation exceeds this established threshold, and as zero otherwise.

As shown in Table S1, the share of highly automatable occupations is 25.8% and 14.6% in the male and female subsample, respectively. Moreover, the most frequent occupations exposed to high automation risk are overrepresented in the middle-skilled segment of the workforce, and are primarily concentrated in industrial sectors for men and in service sectors for women, reflecting persistent patterns of labor market polarization and gender segregation in Germany (see Table S2 in the supplementary materials).

3.3. Dependent variables: health outcomes

We use a set of subjective health outcomes as dependent variables, including self-reported health (SRH), self-reported anxiety, and the Physical Component Summary (PCS) and Mental Component Summary (MCS) scores from the SF-12 Health Survey (Ware et al., 1996). SRH is

based on the question “How would you describe your current health?” and is measured on a five-point categorical scale ranging from 1 (bad) to 5 (very good). This is widely recognized as a valid and reliable indicator of general health status (Bombak, 2013). Self-reported anxiety captures how often respondents have felt worried during the past four weeks and is likewise measured on a five-point scale ranging from 1 (very often) to 5 (very rarely).

The SF-12 Health Survey questionnaire, along with the standardized PCS and MCS scores, have been administered in the SOEP on a biennial basis since 2002. The summary scores are calculated by applying weighted scoring algorithms to responses across eight health domains (Andersen et al., 2007). The PCS primarily reflects physical functioning, role physical, bodily pain, and general health, while the MCS captures vitality, social functioning, role emotional, and mental health.

In our sample, respondents of both genders are most likely to rate their SRH as “good.” With regard to anxiety, most men (women) in the sample report experiencing it “very rarely” (“rarely”) in the past month. As shown in Table S1, the PCS and MCS scores, along with their respective health domains, mainly display means and standard deviations close to 50 and 10, respectively, consistent with the norm-based scoring values established for a reference population.

3.4 Mediators

Consistent with previous literature (Patel et al., 2018; Lordan and Stringer, 2022; Abeliansky et al., 2024), we include self-reported concerns about job insecurity and one’s future financial situation as mediating variables in our baseline analysis. We dichotomize the original SOEP categorical variables such that each takes the value of one if the respondent reports being slightly or very concerned, and the value of zero otherwise. As shown in Table S1 in the supplementary materials, 39.6% of men and 35.5% of women in our sample are concerned about job insecurity, while worries about one’s future financial situation are even more prevalent, affecting 60.3% of men and 65.8% of women.

Along with general measures of job insecurity and concerns about one’s future financial situation, we also consider more automation-related stressors, although these are available in the SOEP only for the year 2020. Specifically, respondents are asked to evaluate their ability to cope with technological change and the fear that their occupation may become obsolete. Similar to the general set of mediators, we dichotomize these categorical variables so that each takes the value

of zero if the respondent is not concerned at all, and the value of one otherwise (see Table S3 in the supplementary materials for descriptive statistics).

Finally, the SOEP also captures respondents' expectations about labor market changes related to technological advancements, including changes in health risks, work productivity, and demand for qualifications. However, these questions are only available for the years 2016 and 2018, and are only posed to individuals who reported dealing with new tools or technologies at work in previous periods. We create binary indicators for each original expectation variable, coding it as one if the respondent anticipates an increase in the respective indicator, and as zero otherwise (descriptive statistics for this restricted subsample are provided in Table S4 in the supplementary materials).

3.5 Control variables

Our baseline models include a standard set of socioeconomic and work-related control variables, including age, age squared, marital status (married/cohabiting vs. otherwise), educational level (low (categories 1-2 of ISCED-97), medium (categories 3-4 of ISCED-97), and high (categories 5-6 of ISCED-97)), natural log of the yearly net household income in thousands of euros adjusted for the consumer price index and household size (Modified OECD Equivalence Scale), migration background (no migration background vs. otherwise), region of residence (western vs. eastern Germany), type of employment (full-time vs. part-time job), company size with respect to headcount (small (less than 100 people), medium (100-199), large (200-2000), very large (more than 2000)), and sector of employment (commercial services, primary sector, manufacturing and construction, trade, and public services). Additionally, we include year dummies in our baseline models, as our analysis covers the years of the COVID-19 pandemic lockdown (see Table S1 in the supplementary materials for a detailed overview of the control variables).

3.6. Estimation strategy

We apply the Karlson-Holm-Breen (KHB) method to decompose the total effect of high automation risk on our subjective health outcomes into a direct effect – attributable solely to our main explanatory variable – and an indirect effect, operating through selected mechanisms that we treat as mediators (Karlson et al., 2012). The KHB method has notable advantages over other mediation techniques, such as Baron and Kenny's (1986) approach. It enables the decomposition of the indirect effect across multiple mediators, clearly quantifying each mediator's individual

contribution and its statistical significance. Additionally, the KHB method effectively corrects for rescaling bias – an issue that arises from simply comparing coefficients between models with and without mediators. While this approach works adequately in linear models, it tends to produce inaccurate estimates in nonlinear contexts.

We employ the *khb* command developed by Kohler et al. (2011), available in Stata (version 18), and estimate linear model specifications, while also treating our categorical dependent variables (SRH and anxiety) as cardinal. This approach is justified by previous methodological research demonstrating similar results between linear and ordered latent response model estimates (Dudel et al., 2016; Ferrer-i-Carbonell and Frijters, 2004). Nevertheless, we estimate non-linear ordinal response models as a robustness check, while also conducting further sensitivity analyses, which are summarized in Table S5 of the supplementary materials and discussed in Section 4.5.

4. Results

4.1. Baseline results

Table 1 summarizes the effect of high automation risk on a range of subjective health outcomes for men and women, capturing both direct effects and indirect pathways through two key mediators: concerns about one's future financial situation and concerns about job insecurity. The total effect reflects the overall association between high automation risk and each health outcome. The direct effect isolates the portion of this relationship that remains after accounting for the mediating role of financial concerns and job insecurity. The indirect effect captures the extent to which the overall effect operates through these mediators. When the indirect effect is statistically significant, it is further decomposed to show the individual contributions of each mediator.

In the male subsample, high automation risk is associated with a decline in PCS (-0.370 points), driven primarily by a substantial direct negative effect (-0.313 points). Additionally, both mediators, concerns about one's financial situation and job insecurity, contribute approximately equally to the remaining indirect effect (-0.057 points). In contrast, for women, the total and direct effects of high automation risk on PCS are positive but not statistically significant, while a significant negative indirect effect (-0.054 points) emerges through increased job insecurity. Notably, the observed effect sizes are rather moderate; for instance, actual job loss in Germany

has been associated with a decline of approximately 2.2 points in the PCS score compared to remaining employed (Unger et al., 2018).

High automation risk also appears to negatively affect MCS through both mediators in the male subsample, with job insecurity (-0.077 points) contributing slightly more than financial concerns (-0.052 points). In the female subsample, the negative indirect effect operates exclusively through job insecurity (-0.066 points). However, the total and direct effects of high automation risk on MCS remain positive but statistically insignificant for both men and women. Put plainly, the magnitude of the estimated effects on MCS is relatively modest. For instance, in Germany, unemployment has been associated with a 3.7-point decline in MCS compared to employment, with the income pathway accounting for 0.715 points of this effect (Neubert et al., 2019).

Table 1 – Summary of estimates: mediation analysis (KHB method)

	PCS		MCS		SRH		Anxiety	
	Men	Women	Men	Women	Men	Women	Men	Women
	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Total effect	-0.370**	0.225	0.143	0.180	-0.028*	0.003	0.008	0.008
	(0.153)	(0.189)	(0.168)	(0.222)	(0.016)	(0.020)	(0.016)	(0.022)
Direct effect	-0.313**	0.279	0.273	0.286	-0.019	0.010	0.022	0.019
	(0.152)	(0.189)	(0.168)	(0.222)	(0.016)	(0.020)	(0.016)	(0.022)
Indirect effect (IE)	-0.057***	-0.054**	-0.129***	-0.106**	-0.008***	-0.007*	-0.014***	-0.012**
	(0.019)	(0.027)	(0.038)	(0.048)	(0.003)	(0.004)	(0.004)	(0.005)
Decomposition of IE:								
Financial concerns	-0.028**	-0.025	-0.052**	-0.040	-0.004**	-0.003	-0.005*	-0.004
	(0.014)	(0.021)	(0.026)	(0.033)	(0.002)	(0.003)	(0.003)	(0.004)
Job insecurity	-0.029***	-0.029***	-0.077***	-0.066***	-0.004***	-0.003***	-0.009***	-0.007**
	(0.009)	(0.011)	(0.019)	(0.024)	(0.001)	(0.001)	(0.002)	(0.003)
Observations	21,443	22,093	21,443	22,093	21,443	22,093	21,443	22,093
Individuals	9,808	10,125	9,808	10,125	9,808	10,125	9,808	10,125

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

All models include controls for age, squared age, marital status, educational attainment, income, migration background, region of settlement, company size, industrial sector, and survey year.

Robust standard errors are clustered at an individual level.

Furthermore, among male respondents, high automation risk shows a negative total effect on SRH (-0.028 points), primarily driven by an indirect pathway. The overall indirect effect (-0.008 points) is evenly split between job insecurity and financial concerns (-0.004 points each). The direct effect is also negative but not statistically significant. In the female subsample, the negative impact of

high automation risk on SRH emerges solely through increased job insecurity (-0.003 points), while both the total and direct effects remain positive but statistically insignificant. Finally, consistent with the results for MCS, high automation risk exhibits positive – though statistically insignificant – total and direct effects on anxiety for both men and women. The main significant source of increased anxiety comes through the pathway of increased job insecurity, accounting for -0.009 points in men and -0.007 points in women. Previous research suggests that lower job security is associated with a 0.059-point decline in self-reported health among German workers (Otterbach and Sousa-Poza, 2016). Thus, our findings indicate that high automation risk may have only a relatively minor effect on self-rated health and anxiety in the German context.

Overall, our baseline results provide evidence that high automation risk does not directly contribute to the considered subjective health measures (except for PCS in the male subsample). However, the consistently significant (but relatively modest in magnitude) indirect effects across all outcomes and gender groups indicate that its impact on workers' health operates primarily through the selected mediators. While both job insecurity and financial concerns serve as important pathways linking high automation risk to health outcomes among male workers, job insecurity is the only mediator that significantly influences women's health across all examined outcomes.

4.2. Decomposing the effects on PCS and MCS scores by SF-12 health domains

To gain a more detailed understanding of the total, direct, and indirect effects (through job insecurity and financial concerns) of high automation risk on PCS and MCS scores presented in Table 1, we additionally conduct gender-specific analyses across four physical domains (physical functioning (PF), role physical (RP), bodily pain (BP), and general health (GH)) and four mental domains (vitality (VT), social functioning (SF), role emotional (REM), and mental health (MHE)), corresponding to the PCS and MCS components, respectively.

As shown in Table 2, in the male subsample, significant negative total and direct effects of high automation risk are observed for the role physical and vitality domains. A significant negative total effect is also found for general health (aligning with our earlier findings for SRH), though the related direct effect is no longer statistically significant. Interestingly, the total and direct effects for role emotional and mental health are positive, with statistical significance being reached only for mental health, probably reflecting the presence of potential coping mechanisms, selection patterns, or unobserved protective factors in certain occupations. Despite these variations, the

indirect effects, which capture the influence of job insecurity and financial concerns, remain consistently negative and statistically significant across all health domains. The largest effects are observed for bodily pain (-0.097 points) and role physical (-0.087 points) within the physical health component, and for mental health (-0.136 points) and role emotional (-0.122 points) within the mental health component.

Table 2 – Summary of estimates: decomposition by health domains (KHB method)

	PCS domains				MCS domains			
	PF	RP	BP	GH	VT	SF	REM	MHE
	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Men								
Total effect	-0.132	-0.350**	-0.155	-0.286*	-0.426**	-0.133	0.120	0.350*
	(0.149)	(0.159)	(0.179)	(0.167)	(0.177)	(0.157)	(0.153)	(0.180)
Direct effect	-0.062	-0.263*	-0.058	-0.202	-0.352**	-0.034	0.242	0.487***
	(0.148)	(0.159)	(0.179)	(0.167)	(0.177)	(0.157)	(0.153)	(0.180)
Indirect effect	-0.071***	-0.087***	-0.097***	-0.084***	-0.074***	-0.099***	-0.122***	-0.136***
	(0.022)	(0.026)	(0.030)	(0.029)	(0.025)	(0.030)	(0.034)	(0.042)
Observations	21,443	21,443	21,443	21,443	21,443	21,443	21,443	21,443
Individuals	9,808	9,808	9,808	9,808	9,808	9,808	9,808	9,808
Women								
Total effect	0.257	0.157	0.595***	0.035	-0.405*	0.437**	0.128	0.438**
	(0.187)	(0.202)	(0.212)	(0.206)	(0.216)	(0.215)	(0.209)	(0.218)
Direct effect	0.324*	0.235	0.675***	0.107	-0.339	0.535**	0.226	0.541**
	(0.187)	(0.202)	(0.212)	(0.206)	(0.216)	(0.215)	(0.209)	(0.218)
Indirect effect	-0.066**	-0.078**	-0.080**	-0.071*	-0.066**	-0.098**	-0.098**	-0.104**
	(0.032)	(0.036)	(0.038)	(0.037)	(0.033)	(0.043)	(0.043)	(0.050)
Observations	22,093	22,093	22,093	22,093	22,093	22,093	22,093	22,093
Individuals	10,125	10,125	10,125	10,125	10,125	10,125	10,125	10,125

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

All models include controls for age, squared age, marital status, educational attainment, income, migration background, region of settlement, company size, industrial sector, and survey year.

Robust standard errors are clustered at an individual level.

In contrast, women employed in highly automatable occupations tend to report better outcomes in several health domains. Both the total and direct effects are positive and statistically significant for bodily pain, social functioning, and mental health, while physical functioning shows a significantly positive direct effect only. Across all physical and mental health domains, the only negative association is observed for vitality, where the total effect is statistically significant, but

the direct effect is not. Finally, similar to among men, among women significant negative indirect effects are observed across all PCS and MCS domains, with the largest magnitudes being found for social functioning and role emotional (both coefficients are -0.098 points) and mental health (-0.104 points).

Thus, our results provide evidence that high automation risk may be silently undermining workers' health via mechanisms like job insecurity and financial concerns. Additionally, we observe pronounced gender differences in the effects, underscoring the importance of stratifying the analysis by gender. These differences likely reflect the unequal distribution of physical and psychosocial stressors across sectors, as men and women in highly automatable occupations may experience distinct exposures and vulnerabilities, adopt different coping mechanisms, and follow different patterns of occupational selection. Overall, our decomposition across the four physical and four mental SF-12 health domains yields results that are largely consistent with the broader estimates for the PCS and MCS scores. Importantly, it highlights specific health components impacted by automation risk, both directly and indirectly through the selected mediators.

4.3. Automation-related mediators: the 2020 subsample

Table 3 reports the results of a mediation analysis incorporating two additional automation-related mediators, concerns about one's ability to cope with technological change and concerns about one's occupational obsolescence, both of which are available only in the year 2020. These mediators are conceptually linked to job insecurity, as they reflect specific dimensions of it, and are moderately correlated with it (correlation coefficients range from 0.2 to 0.4, depending on gender). As such, they are expected to partially mediate the relationship previously attributed solely to job insecurity. We first estimated model specifications for the 2020 subsample using two basic mediators, job insecurity and financial concerns, and then estimated a model that included the two additional mediators while excluding job insecurity. However, the results closely mirrored those presented in Table 3. Given the similarities, we opted to retain all four mediators in the final analysis.

As shown in Table 3, high automation risk has a significant and negative effect, both direct and indirect, on physical health outcomes (PCS and SRH) in the male subsample (mainly consistent with our baseline findings). However, for these outcomes, financial concerns emerge as the primary mediating channel. In contrast, for mental health outcomes (MCS and anxiety), the

negative impact of high automation risk operates entirely through indirect pathways, with financial concerns again playing the dominant role, followed by job insecurity. Notably, the other automation-related mediators, concerns about coping with technological change and occupational obsolescence, do not significantly mediate the relationship in the male subsample. None of the total, direct, or indirect effects of high automation risk on the examined health outcomes is statistically significant in the female subsample.

Table 3 – Summary of estimates: special case of the year 2020 (KHB method)

	PCS		MCS		SRH		Anxiety	
	Men	Women	Men	Women	Men	Women	Men	Women
	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Total effect	-0.680**	0.505	-0.388	0.212	-0.062**	0.008	-0.049	0.025
	(0.273)	(0.310)	(0.303)	(0.364)	(0.029)	(0.033)	(0.031)	(0.039)
Direct effect	-0.584**	0.501	-0.163	0.190	-0.048*	0.008	-0.027	0.023
	(0.273)	(0.310)	(0.303)	(0.364)	(0.029)	(0.033)	(0.031)	(0.039)
Indirect effect (IE)	-0.096**	0.003	-0.225***	0.022	-0.014**	0.000	-0.023***	0.002
	(0.043)	(0.049)	(0.086)	(0.096)	(0.005)	(0.006)	(0.008)	(0.011)
Decomposition of IE:								
Financial concerns	-0.053**		-0.084**		-0.009**		-0.011**	
	(0.025)		(0.038)		(0.004)		(0.005)	
Job insecurity	0.002		-0.055**		-0.001		-0.005**	
	(0.012)		(0.025)		(0.002)		(0.002)	
Coping with	-0.021		-0.039		-0.002		-0.003	
technological change	(0.019)		(0.034)		(0.002)		(0.002)	
Occupation may	-0.024		-0.048		-0.002		-0.004	
become obsolete	(0.018)		(0.032)		(0.002)		(0.003)	
Observations	4,423	4,640	4,423	4,640	4,423	4,640	4,423	4,640

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

All models include controls for age, squared age, marital status, educational attainment, income, migration background, region of settlement, company size, and industrial sector.

Robust standard errors are clustered at an individual level.

Although our findings from the year 2020 enrich the baseline narrative and provide additional evidence that men's physical health components are more sensitive to both the direct impact of high automation risk and the indirect effects operating through the selected pathways, we refrain from making generalizations due to the very specific characteristics of the period under analysis. The year 2020, marked by the COVID-19 pandemic lockdown, was characterized by a widespread deterioration in general and mental health (Knolle et al., 2021; Zrnić Novaković et al., 2025) and

significant changes in working conditions, such as shifts to remote work, reduced hours, and temporary unpaid leave, as well as heightened job precariousness and financial strain (Eurofound, 2021). These trends are partially reflected in our findings, particularly among male respondents.

4.4. Special case: the restricted subsample of 2016-2018

Table 4 summarizes the estimates for a restricted subsample of respondents who had previously experienced changes in tools and technologies at work and were subsequently asked about their expectations regarding health risks, work productivity, and the demand for qualifications in the future. We treat these expectation variables as additional pathways linking high automation risk to health outcomes and incorporate them into our models.

Table 4 – Summary of estimates: restricted subsample of 2016-2018 (KHB method)

	PCS		MCS		SRH		Anxiety	
	Men	Women	Men	Women	Men	Women	Men	Women
	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Total effect	-0.033	0.815	0.505	0.295	0.022	0.029	-0.006	0.020
	(0.418)	(0.546)	(0.460)	(0.630)	(0.045)	(0.058)	(0.044)	(0.062)
Direct effect	0.051	0.854	0.874	0.418	0.036	0.036	0.025	0.029
	(0.419)	(0.547)	(0.462)	(0.630)	(0.045)	(0.058)	(0.044)	(0.062)
Indirect effect (IE)	-0.084	-0.038	-0.370**	-0.124	-0.015	-0.007	-0.030***	-0.009
	(0.064)	(0.079)	(0.143)	(0.175)	(0.010)	(0.014)	(0.011)	(0.015)
Decomposition of IE:								
Financial concerns			-0.250***				-0.016***	
			(0.096)				(0.006)	
Job insecurity			-0.089*				-0.013**	
			(0.046)				(0.006)	
Health risks			-0.006				-0.000	
			(0.062)				(0.004)	
Work productivity			0.040				0.001	
			(0.035)				(0.001)	
Demand for qualifications			-0.066				-0.002	
			(0.041)				(0.003)	
Observations	2,138	1,828	2,138	1,828	2,138	1,828	2,138	1,828

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

All models include controls for age, squared age, marital status, educational attainment, income, migration background, region of settlement, company size, and industrial sector, and survey year.

Robust standard errors are clustered at an individual level.

Overall, we find no robust evidence of a direct relationship between high automation risk and the examined health outcomes for either gender. However, the analysis reveals significant indirect effects for men, particularly in relation to mental health outcomes, with financial concerns and job insecurity emerging as key mediating mechanisms. Additional pathways related to respondents' expectations remain negligible and statistically insignificant across all model specifications and for both genders. For women, none of the effects reach statistical significance, indicating no evidence of either a direct relationship or mediation in this group. Nevertheless, these findings should be interpreted with caution due to the high selectivity of the analyzed subsamples and the limited statistical power associated with the relatively small subsample sizes.

4.5. Further robustness checks

We also perform several robustness checks to assess the validity of our baseline results, while keeping the set of mediators, job insecurity and financial concerns, unchanged. The estimated coefficients are summarized in Table S5 of the supplementary materials. First, we exclude observations from the year 2020, as this period was marked by an external shock that significantly affected both national labor markets and population health. Second, we restrict the sample to relatively healthy respondents by omitting individuals with both PCS and MCS scores below 30, as such values indicate serious physical and mental health conditions comparable to disability. Finally, we estimate ordered logit models for SRH and anxiety to appropriately account for the ordinal nature of these health outcomes (however, we report only the estimated coefficients, as the average partial effects cannot be computed for indirect pathways in non-linear settings).

As shown in Table S5, across all model specifications, the indirect effects of high automation risk on health outcomes, mediated by financial concerns and job insecurity, are consistently negative and statistically significant for both men and women (in line with our baseline findings). In contrast, the total and direct effects are often statistically insignificant (with a few exceptions), which indicates that the adverse health impact of working in a highly automatable job mainly operates through increased economic uncertainty, rather than through direct exposure to automation risk alone.

5. Discussion

5.1 Main findings

This study investigates the nature of the relationship between exposure to automation risk in the workplace and the physical and mental health outcomes of workers in Germany. Using the Karlson-Holm-Breen (KHB) mediation analysis method, we show that, in the German context, high automation risk tends to negatively affect workers' health primarily through indirect pathways – specifically, via economic uncertainty channels – rather than through direct effects (with a few exceptions). However, the contributions of these channels vary by gender: among male respondents, concerns about job insecurity and one's future financial situation are weighted almost equally, whereas for female respondents, only job insecurity appears to play a significant role.

Overall, our findings show that high automation risk is associated with a 0.370-point decrease in the PCS score (on a 0-100 scale) among male respondents, with -0.313 points being attributable to the direct effect. It is also linked to a 0.028-point decline in SRH (on a 1-5 scale). In contrast, the estimated total effects for female workers are positive, though considerably smaller and not statistically significant. These results align broadly with previous studies using occupation-level measures of automation exposure, which report negative impacts of automation risk on workers' physical and general health (Patel et al., 2018; Nazareno and Schiff, 2021; Liu, 2023).

However, the total effect sizes we estimate are relatively modest – several times smaller than those reported in studies examining the impact of job insecurity or job loss on similar health outcomes in Germany (Otterbach and Sousa-Poza, 2016; Unger et al., 2018). Consistent with Gihleb et al. (2022) and Giuntella et al. (2023), we also find no significant association – neither total nor direct – between high automation risk and MCS scores or self-reported anxiety for either gender. Nonetheless, the indirect effects of automation risk, operating through channels such as job insecurity and financial concerns, are consistently negative and statistically significant across all health outcomes and both gender groups (reinforced by several robustness and sensitivity checks).

Since composite summary scores can mask important variation, potentially obscuring significant associations between automation exposure and specific physical and mental health domains, we provide further decomposition by these outcomes. Among men, high automation risk is associated with negative total and direct effects on the role physical and vitality domains, as well as a negative

total effect on general health (consistent with our findings for SRH). This is not overly surprising, given that highly automatable jobs in the male segment of the labor market are primarily concentrated in heavy industrial sectors and are often characterized by physically demanding tasks and hazardous working conditions (Lordan and Stringer, 2022). In contrast, the observed positive total and direct effects on the mental health domain may indicate that such jobs are linked to lower levels of psychosocial stress. Alternatively, these results may reflect certain selection patterns – that is, individuals with greater mental resilience may be more likely to self-select into occupations with higher exposure to automation risk.

Among women, the negative indirect effects of high automation risk on health – transmitted through perceived job insecurity – appear to be offset by positive direct effects, which in most cases exceed the total effects. This pattern is particularly evident in the domains of physical functioning, bodily pain, social functioning, and mental health. Vitality is the only domain in which a negative total effect of high automation risk is observed. Possible explanations for these patterns may lie in the job context and content of highly automatable occupations within the female segment of the labor market, which warrant closer examination in future research. Overall, the decomposition by physical and mental health domains closely mirrors our baseline results while offering deeper insights into the specific sources of the effects observed in the composite indices.

Finally, our analysis finds no significant evidence that the relationship between high automation risk and workers' health outcomes in Germany is mediated by specific automation-related factors, such as one's ability to cope with technological change, fear of occupational obsolescence, or expectations regarding changes in health risks, qualification demands, or work productivity. This finding contrasts with the results reported by Blasco et al. (2022) for France. However, the significant transmission mechanisms we do identify, namely job insecurity and financial concerns, are consistent with earlier findings reported by Giuntella et al. (2023) and Abeliansky et al. (2024) for Germany. However, it is worth noting that the pathways through which high automation risk affects workers' health tend to be highly gender- and context-dependent, shaped by shifts in the economic environment and working conditions. Consequently, these factors should be carefully considered in future investigations.

5.2 Methodological considerations

Our analysis faces several challenges. First, our main explanatory variable, high automation risk, is derived from a country-specific distribution of tasks within occupations. While it effectively captures the particular characteristics of the German labor market, its external validity for cross-country comparisons remains limited. Second, our analysis relies on self-reported health measures, which are subject to reporting heterogeneity bias. This bias arises in self-assessed ordinal outcomes, as individuals may interpret and use response scales differently, placing thresholds between adjacent categories inconsistently (King and Wand, 2007). Finally, our estimates may be subject to an intent-to-treat bias, which is common in studies that use objective, individual-level proxies for automation exposure. This issue occurs because workers whose jobs are genuinely at risk of automation may not recognize that risk, while other workers who are in relatively secure jobs may nonetheless experience elevated stress due to fears of technological unemployment. Such misclassification typically biases the results toward zero. Nevertheless, consistent with prior studies, we still observe meaningful effects.

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/274ba/overview?view_only=138d4ad8998e4148a0371cc813853acf.

References

Abeliansky, A. L., Beulmann, M., & Prettner, K. (2024). Are they coming for us? Industrial robots and the mental health of workers. Research Policy, 53(3), 104956. https://doi.org/10.1016/j.respol.2024.104956.

Andersen, H. H., Mühlbacher, A., Nübling, M., Schupp, J., & Wagner, G. G. (2007). Computation of standard values for physical and mental health scale scores using the SOEP version of SF-12v2. Journal of Contextual Economics – Schmollers Jahrbuch, 127(1), 171–182. https://elibrary.duncker-humblot.com.

Arntz, M., Gregory, T., & Zierahn, U. (2016). The risk of automation for jobs in OECD countries: A comparative analysis (OECD Social, Employment and Migration Working Papers No. 189). OECD Publishing. https://doi.org/10.1787/5jlz9h56dvq7-en.

Balsmeier, B., & Woerter, M. (2019). Is this time different? How digitalization influences job creation and destruction. Research Policy, 48(8), 103765. https://doi.org/10.1016/j.respol.2019.03.010.

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. Journal of Personality and Social Psychology, 51(6), 1173–1182. https://doi.org/10.1037/0022-3514.51.6.1173.

Blasco, S., Rochut, J., & Rouland, B. (2022). Displaced or depressed? The effect of working in automatable jobs on mental health (IZA Discussion Paper No. 15434). IZA Institute of Labor Economics. https://www.iza.org/publications/dp/15434/displaced-or-depressed-the-effect-of-working-in-automatable-jobs-on-mental-health.

Bombak, A. E. (2013). Self-rated health and public health: A critical perspective. Frontiers in Public Health, 1, 15. https://doi.org/10.3389/fpubh.2013.00015.

Cheng, W., Pien, L., & Cheng, Y. (2021). Occupation-level automation probability is associated with psychosocial work conditions and workers' health: A multilevel study. American Journal of Industrial Medicine, 64(2), 108–117. https://doi.org/10.1002/ajim.23210.

Dengler, K., Matthes, B., & Paulus, W. (2014). Occupational tasks in the German labour market: An alternative measurement on the basis of an expert database (FDZ-Methodenreport).

Dudel, C., Ott, N., & Werding, M. (2016). Maintaining one's living standard at old age: What does that mean? Empirical Economics. Advance online publication. https://doi.org/10.1007/s00181-015-1042-8.

Eurofound. (2021). Living, working and COVID-19 (Update April 2021): Mental health and trust decline across EU as pandemic enters another year. Publications Office of the European Union. https://data.europa.eu/doi/10.2806/16362.

Ferrer-i-Carbonell, A., & Frijters, P. (2004). How important is methodology for the estimates of the determinants of happiness? The Economic Journal, 114(497), 641–659. https://doi.org/10.1111/j.1468-0297.2004.00235.x.

Filippi, E., Bannò, M., & Trento, S. (2023). Automation technologies and their impact on employment: A review, synthesis and future research agenda. Technological Forecasting and Social Change, 191, 122448. https://doi.org/10.1016/j.techfore.2023.122448

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? Technological Forecasting and Social Change, 114, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019.

Gihleb, R., Giuntella, O., Stella, L., & Wang, T. (2022). Industrial robots, workers' safety, and health. Labour Economics, 78, 102205. https://doi.org/10.1016/j.labeco.2022.102205.

Giuntella, O., Koenig, J., & Stella, L. (2023). Artificial intelligence and workers' well-being (IZA Discussion Paper No. 16485). IZA Institute of Labor Economics. https://www.iza.org/publications/dp/16485/artificial-intelligence-and-workers-well-being.

Graetz, G., & Michaels, G. (2018). Robots at work. The Review of Economics and Statistics, 100(5), 753–768. https://doi.org/10.1162/rest_a_00754.

Goebel, J., Grabka, M. M., Liebig, S., Kroh, M., Richter, D., Schröder, C., & Schupp, J. (2019). The German Socio-Economic Panel (SOEP). Jahrbücher für Nationalökonomie und Statistik, 239(2), 345–360. https://doi.org/10.1515/jbnst-2018-0022.

Grienberger, K., Janser, M., & Lehmer, F. (2023). The Occupational Panel for Germany. Jahrbücher für Nationalökonomie und Statistik, 243(6), 711–724. https://doi.org/10.1515/jbnst-2022-0053.

Gunadi, C., & Ryu, H. (2021). Does the rise of robotic technology make people healthier? Health Economics, 30(9), 2047–2062. https://doi.org/10.1002/hec.4361.

Karlson, K. B., Holm, A., & Breen, R. (2012). Comparing regression coefficients between same-sample nested models using logit and probit: A new method. Sociological Methodology, 42(1), 286–313. https://doi.org/10.1177/0081175012444861.

Kim, H. D., Park, S. G., Won, Y., Ju, H., Jang, S. W., Choi, G., Jang, H. S., Kim, H. C., & Leem, J. H. (2020). Longitudinal associations between occupational stress and depressive symptoms. Annals of Occupational and Environmental Medicine, 32, e13. https://doi.org/10.35371/aoem.2020.32.e13.

Kim, T. J., & von dem Knesebeck, O. (2016). Perceived job insecurity, unemployment and depressive symptoms: A systematic review and meta-analysis of prospective observational studies. International Archives of Occupational and Environmental Health, 89(4), 561-573. https://doi.org/10.1007/s00420-015-1107-1.

King, G., & Wand, J. (2007). Comparing incomparable survey responses: New tools for anchoring vignettes. Political Analysis, 15(1), 46–66. https://doi.org/10.1093/pan/mpl011.

Knolle, F., Ronan, L., & Murray, G. K. (2021). The impact of the COVID-19 pandemic on mental health in the general population: A comparison between Germany and the UK. BMC Psychology, 9(1), 60. https://doi.org/10.1186/s40359-021-00565-y.

Kohler, U., Karlson, K. B., & Holm, A. (2011). Comparing coefficients of nested nonlinear probability models. Stata Journal, 11(3), 420–438.

Kromann, L., Malchow-Møller, N., Skaksen, J. R., & Sørensen, A. (2020). Automation and productivity: A cross-country, cross-industry comparison. Industrial and Corporate Change, 29(2), 265–287. https://doi.org/10.1093/icc/dtz039.

Liu, L. (2023). Job quality and automation: Do more automatable occupations have less job satisfaction and health? Journal of Industrial Relations, 65(1), 72–87. https://doi.org/10.1177/00221856221129639.

Lordan, G., & Stringer, E.-J. (2022). People versus machines: The impact of being in an automatable job on Australian workers' mental health and life satisfaction. Economics and Human Biology, 46, 101144. https://doi.org/10.1016/j.ehb.2022.101144.

Martins-Neto, A., Mathew, N., Mohnen, P., & Treibich, T. (2024). Is there job polarization in developing economies? A review and outlook. World Bank Research Observer, 39(2), 259–288. https://doi.org/10.1093/wbro/lkad008.

Mikucka, M., Arránz Becker, O., & Worl, C. (2025). Short- and long-term health effects of job insecurity: Fixed effects panel analysis of German data. Scandinavian Journal of Work, Environment & Health, 51(2), 68-76. https://doi.org/10.5271/sjweh.4206.

Müller, C. (2023). World Robotics 2023 – Industrial robots. IFR Statistical Department, VDMA Services GmbH.

Nazareno, L., & Schiff, D. S. (2021). The impact of automation and artificial intelligence on worker well-being. Technology in Society, 67, 101679. https://doi.org/10.1016/j.techsoc.2021.101679.

Neubert, M., Süssenbach, P., Rief, W., & Euteneuer, F. (2019). Unemployment and mental health in the German population: The role of subjective social status. Psychology Research and Behavior Management, 12, Article 557-564. https://doi.org/10.2147/PRBM.S207971.

O'Brien, R., Bair, E. F., & Venkataramani, A. S. (2022). Death by robots? Automation and working-age mortality in the United States. Demography, 59(2), 607–628. https://doi.org/10.1215/00703370-9774819.

Patel, P. C., Devaraj, S., Hicks, M. J., & Wornell, E. J. (2018). County-level job automation risk and health: Evidence from the United States. Social Science & Medicine, 202, 54–60. https://doi.org/10.1016/j.socscimed.2018.02.025.

Tsai, Y.-Y., Huang, P.-C., & Yang, T.-T. (2024). Long-term effects of job displacement on earnings and mental health: Evidence from population-wide administrative data. Economics Letters, 238, 111688. https://doi.org/10.1016/j.econlet.2024.111688.

Unger, S., Tisch, A., & Tophoven, S. (2018). Age and gender differences in the impact of labour-market transitions on subjective health in Germany. Scandinavian Journal of Public Health, 46(19_suppl), 49–64. https://doi.org/10.1177/1403494817738430.

Vannutelli, S., Scicchitano, S., & Biagetti, M. (2022). Routine-biased technological change and wage inequality: Do workers' perceptions matter? Eurasian Business Review, 12(3), 409–450. https://doi.org/10.1007/s40821-022-00222-3.

Ware, J. E., Kosinski, M., & Keller, S. D. (1996). A 12-item short-form health survey: Construction of scales and preliminary tests of reliability and validity. Medical Care, 34(3), 220–233. https://doi.org/10.1097/00005650-199603000-00003.

Yang, S., Liu, K., Gai, J., & He, X. (2022). Transformation to industrial artificial intelligence and workers' mental health: Evidence from China. Frontiers in Public Health, 10, 881827. https://doi.org/10.3389/fpubh.2022.881827.

Zheng, J., Rohenkohl, B., Barahona, M., & Clarke, J. M. (2024). Automation risk and subjective wellbeing in the UK. Preprint. https://doi.org/10.1101/2024.01.18.24301484.

Zrnić Novaković, I., Ajduković, D., Ajduković, M., Kenntemich, L., Lotzin, A., Schäfer, I., Anastassiou-Hadjicharalambous, X., Evgeniou, E., Borges, C., Figueiredo-Braga, M., Russo, M., & Lueger-Schuster, B. (2025). Mental health during and after the COVID-19 pandemic – A longitudinal study over 42 months in five European countries. European Journal of Psychotraumatology, 16(1), 2488700. https://doi.org/10.1080/20008066.2025.2488700.

Table S1 – Descriptive statistics stratified by gender (full sample)

Variable	Definition	Men (n=21,443 obs.)		Women (n=22,093 obs.)		
		Mean	SD	Mean	SD	t-test
SRH	5 categories sorted from 1 “bad” to 5 “very good”	3.670	0.837	3.547	0.876	***
Anxiety	5 categories sorted from 1 “very often” to 5 “very rarely”	4.284	0.860	3.920	1.001	***
PCS	Physical Component Summary score	52.717	7.746	51.649	8.395	***
MCS	Mental Component Summary score	51.873	8.667	49.900	9.547	***
PF	Physical functioning domain	53.311	7.421	51.732	8.149	***
RP	Role physical domain	53.241	8.143	51.495	8.983	***
BP	Bodily pain domain	51.737	8.916	50.539	9.524	***
GH	General health domain	52.569	8.688	51.294	9.090	***
VT	Vitality domain	50.824	8.958	49.765	9.270	***
SF	Social functioning domain	52.410	8.376	50.565	9.731	***
REM	Role emotional domain	53.141	8.122	51.464	9.129	***
MHE	Mental health domain	51.796	8.979	49.596	9.228	***
High automation risk	More than 70% of routine tasks in the occupation=1, otherwise=0	0.258	0.438	0.146	0.353	***
Age	Age (number of full years)	43.475	10.914	44.031	10.752	***
Marital status	Married/cohabiting=0, otherwise=1	0.351	0.477	0.448	0.497	***
Educational dummies:						
Low education	1-2 levels of ISCED-97=1, otherwise=0	0.077	0.267	0.062	0.241	***
Medium education	3-4 levels of ISCED-97=1, otherwise=0	0.539	0.499	0.608	0.488	***
High education	5-6 levels of ISCED-97=1, otherwise=0	0.384	0.486	0.330	0.470	***
Income	Net household income adjusted for CPI and the household size	27.617	13.348	26.972	12.449	***
Migrant	Migration background=1, otherwise=0	0.303	0.460	0.264	0.441	***
Region	West Germany=0, East Germany=1	0.227	0.419	0.244	0.430	***
Type of employment	Full-time job=0, part-time job=1	0.065	0.246	0.512	0.500	***
Company size dummies:						
Small company	Headcount less than 100 employees=1, otherwise=0	0.358	0.479	0.407	0.491	***
Medium company	Headcount of 100-199 employees=1, otherwise=0	0.093	0.290	0.094	0.292	
Large company	Headcount of 200-2000 employees=1, otherwise=0	0.242	0.428	0.237	0.425	
Very large company	Headcount of more than 2000 employees=1, otherwise=0	0.307	0.461	0.262	0.439	***
Sectoral dummies:						
Sector_1	Commercial services=1, otherwise=0	0.292	0.455	0.302	0.459	**
Sector_2	Primary sector=1, otherwise=0	0.037	0.189	0.015	0.123	***
Sector_3	Manufacturing and construction=1, otherwise=0	0.439	0.496	0.148	0.355	***
Sector_4	Trade=1, otherwise=0	0.084	0.278	0.135	0.341	***
Sector_5	Public services=1, otherwise=0	0.148	0.355	0.400	0.490	***
Future financial situation	Concerned =1, otherwise=0	0.603	0.489	0.658	0.474	***
Job insecurity	Concerned =1, otherwise=0	0.396	0.489	0.355	0.479	***

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

Table S2 – Most frequent highly automatable occupations (full sample)

KldB10 code (5 digits)	Title	Professional class (task complexity)
	Men	
25102	Occupations in machine-building and -operating (without specialization)	skilled tasks
26212	Electricians in construction	skilled tasks
51311	Occupations in warehousing and logistics	unskilled/semiskilled tasks
25122	Machine and plant operators	skilled tasks
24412	Occupations in metal constructing	skilled tasks
25212	Technical occupations in the automotive industries	skilled tasks
24232	Occupations in metalworking: cutting	skilled tasks
72112	Bankers	skilled tasks
25132	Technical service staff in maintenance and repair	skilled tasks
52531	Operators of cranes, lifts and related lifting devices	unskilled/semiskilled tasks
41312	Occupations in chemical and pharmaceutical engineering	skilled tasks
27312	Technical occupations in quality control	skilled tasks
24422	Occupations in welding and joining	skilled tasks
	Women	
71402	Office clerks and secretaries (without specialization)	skilled
72213	Occupations in accounting	complex tasks
72112	Bankers	skilled tasks
72302	Occupations in tax consultancy	skilled tasks
51311	Occupations in warehousing and logistics	unskilled/semiskilled
41322	Chemical technical laboratory occupations	skilled tasks

Table S3 – Descriptive statistics stratified by gender (year 2020)

Variable	Definition	Men (n=4,423 obs.)		Women (n=4,640 obs.)		
		Mean	SD	Mean	SD	t-test
SRH	5 categories sorted from 1 “bad” to 5 “very good”	3.732	0.855	3.569	0.879	***
Anxiety	5 categories sorted from 1 “very often” to 5 “very rarely”	4.201	0.889	3.778	1.044	***
PCS	Physical Component Summary score	52.860	7.870	51.683	8.488	***
MCS	Mental Component Summary score	51.491	8.691	49.572	9.514	***
High automation risk	More than 70% of routine tasks in the occupation=1, otherwise=0	0.275	0.447	0.205	0.404	***
Age	Age (number of full years)	44.230	11.376	44.959	11.059	***
Marital status	Married/cohabiting=0, otherwise=1	0.382	0.486	0.447	0.497	***
Educational dummies:						
Low education	1-2 levels of ISCED-97=1, otherwise=0	0.081	0.272	0.064	0.244	***
Medium education	3-4 levels of ISCED-97=1, otherwise=0	0.526	0.499	0.602	0.490	***
High education	5-6 levels of ISCED-97=1, otherwise=0	0.394	0.489	0.334	0.472	***
Income	Net household income adjusted for CPI and the household size	29.890	15.343	28.851	13.375	***
Migrant	Migration background=1, otherwise=0	0.289	0.454	0.259	0.438	***
Region	West Germany=0, East Germany=1	0.245	0.430	0.247	0.432	
Type of employment	Full-time job=0, part-time job=1	0.073	0.261	0.513	0.500	***
Company size dummies:						
Small company	Headcount less than 100 employees=1, otherwise=0	0.349	0.477	0.392	0.488	***
Medium company	Headcount of 100-199 employees=1, otherwise=0	0.090	0.286	0.090	0.286	
Large company	Headcount of 200-2000 employees=1, otherwise=0	0.238	0.426	0.245	0.430	
Very large company	Headcount of more than 2000 employees=1, otherwise=0	0.323	0.468	0.272	0.445	***
Sectoral dummies:						
Sector_1	Commercial services=1, otherwise=0	0.332	0.471	0.353	0.478	**
Sector_2	Primary sector=1, otherwise=0	0.033	0.179	0.015	0.121	***
Sector_3	Manufacturing and construction=1, otherwise=0	0.406	0.491	0.138	0.345	***
Sector_4	Trade=1, otherwise=0	0.090	0.287	0.127	0.332	***
Sector_5	Public services=1, otherwise=0	0.139	0.346	0.367	0.482	***
Future financial situation	Concerned =1, otherwise=0	0.583	0.493	0.627	0.484	***
Job insecurity	Concerned =1, otherwise=0	0.366	0.482	0.325	0.468	***
Coping with technological change	Concerned =1, otherwise=0	0.271	0.445	0.350	0.477	***
Occupation may become obsolete	Concerned =1, otherwise=0	0.236	0.425	0.270	0.444	***

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

Table S4 – Descriptive statistics stratified by gender (restricted sample)

Variable	Definition	Men (n=2,138 obs.)		Women (n=1,828 obs.)		
		Mean	SD	Mean	SD	t-test
SRH	5 categories sorted from 1 “bad” to 5 “very good”	3.627	0.828	3.560	0.868	**
Anxiety	5 categories sorted from 1 “very often” to 5 “very rarely”	4.336	0.810	4.011	0.923	***
PCS	Physical Component Summary score	52.411	7.524	51.344	8.309	***
MCS	Mental Component Summary score	52.150	8.528	50.462	9.378	***
High automation risk	More than 70% of routine tasks in the occupation=1, otherwise=0	0.284	0.451	0.168	0.374	***
Age	Age (number of full years)	42.928	10.572	43.821	10.445	***
Marital status	Married/cohabiting=0, otherwise=1	0.345	0.476	0.445	0.497	***
Educational dummies:		2.340	0.586	2.293	0.534	***
Low education	1-2 levels of ISCED-97=1, otherwise=0	0.059	0.236	0.039	0.193	***
Medium education	3-4 levels of ISCED-97=1, otherwise=0	0.541	0.498	0.630	0.483	***
High education	5-6 levels of ISCED-97=1, otherwise=0	0.399	0.490	0.332	0.471	***
Income	Net household income adjusted for CPI and the household size	28.692	11.704	28.476	11.644	
Migrant	Migration background=1, otherwise=0	0.259	0.438	0.207	0.406	***
Region	West Germany=0, East Germany=1	0.205	0.404	0.238	0.426	**
Type of employment	Full-time job=0, part-time job=1	0.046	0.209	0.476	0.500	***
Company size dummies:		2.745	1.216	2.595	1.238	***
Small company	Headcount less than 100 employees=1, otherwise=0	0.269	0.444	0.320	0.467	***
Medium company	Headcount of 100-199 employees=1, otherwise=0	0.090	0.287	0.090	0.287	
Large company	Headcount of 200-2000 employees=1, otherwise=0	0.266	0.442	0.265	0.441	
Very large company	Headcount of more than 2000 employees=1, otherwise=0	0.374	0.484	0.325	0.468	***
Sectoral dummies:		2.761	1.308	3.315	1.651	***
Sector_1	Commercial services=1, otherwise=0	0.277	0.448	0.284	0.451	
Sector_2	Primary sector=1, otherwise=0	0.031	0.173	0.016	0.125	***
Sector_3	Manufacturing and construction=1, otherwise=0	0.484	0.500	0.185	0.388	***
Sector_4	Trade=1, otherwise=0	0.068	0.252	0.130	0.336	***
Sector_5	Public services=1, otherwise=0	0.139	0.346	0.385	0.487	***
Future financial situation	Concerned =1, otherwise=0	0.558	0.497	0.615	0.487	***
Job insecurity	Concerned =1, otherwise=0	0.354	0.478	0.310	0.463	***
Change in health risks	Expected increase=1, otherwise=0	0.100	0.300	0.114	0.318	
Change in work productivity	Expected increase=1, otherwise=0	0.524	0.500	0.454	0.498	***
Change in demand for qualifications	Expected increase=1, otherwise=0	0.527	0.499	0.452	0.498	***

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

Table S5 – Estimated coefficients for alternative model specifications (KHB method)

	PCS		MCS		SRH		Anxiety	
	Men	Women	Men	Women	Men	Women	Men	Women
	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Without Y2020:								
Total effect	-0.277*	0.140	0.274	0.208	-0.017	0.004	0.022	0.004
	(0.165)	(0.212)	(0.183)	(0.251)	(0.017)	(0.023)	(0.017)	(0.025)
Direct effect	-0.225	0.210	0.387**	0.339	-0.009	0.013	0.035**	0.018
	(0.165)	(0.212)	(0.183)	(0.251)	(0.017)	(0.023)	(0.017)	(0.025)
Indirect effect	-0.052**	-0.070**	-0.113***	-0.131**	-0.007**	-0.009**	-0.013***	-0.014**
	(0.021)	(0.031)	(0.041)	(0.055)	(0.003)	(0.004)	(0.004)	(0.006)
PCS>30 & MCS>30:								
Total effect	-0.453***	0.170	0.147	0.142	-0.030*	-0.003	0.005	0.013
	(0.143)	(0.177)	(0.152)	(0.195)	(0.016)	(0.019)	(0.016)	(0.022)
Direct effect	-0.398***	0.237	0.258*	0.256	-0.022	0.005	0.018	0.026
	(0.144)	(0.177)	(0.152)	(0.195)	(0.016)	(0.019)	(0.016)	(0.022)
Indirect effect	-0.054***	-0.067**	-0.111***	-0.114***	-0.007***	-0.008**	-0.013***	-0.014***
	(0.018)	(0.027)	(0.033)	(0.041)	(0.003)	(0.003)	(0.004)	(0.005)
Ordered logit model:								
Total effect					-0.060	0.009	-0.004	0.020
					(0.038)	(0.044)	(0.038)	(0.042)
Direct effect					-0.040	0.024	0.027	0.042
					(0.038)	(0.044)	(0.038)	(0.042)
Indirect effect					-0.019***	-0.015*	-0.031***	-0.022**
					(0.007)	(0.008)	(0.009)	(0.010)

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

All models include controls for age, squared age, marital status, educational attainment, income, migration background, region of settlement, company size, industrial sector, and survey year.

Robust standard errors are clustered at an individual level.