Are We Yet Sick of New Technologies? The Unequal Health Effects of Workplace Digitalization*

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Abstract

This study quantifies the relationship between workplace digitalization, characterized by the increasing use of frontier technologies, and workers' health outcomes using novel and representative German linked employer-employee data. Analyzing changes in individual-level technology use between 2011 and 2019, we find that digitalization induces similar shifts toward more complex and service-oriented tasks for all workers but exacerbates health disparities between cognitive and manual workers. Unlike mature, computer-based technologies, recent frontier technologies significantly degrade manual workers' subjective health and increase sick leave, while leaving cognitive workers unaffected. Our findings suggest that these negative effects are mitigated in firms that provide training and support to help workers adjust to technological changes.

Keywords: health, inequality, technology, automation, tasks, capital-labor substitution
JEL: I14, J21, J23, J24, O33

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1 Introduction

Technological change impacts workers in many ways: By displacing and reallocating people across jobs (Graetz and Michaels, 2018; Bárány and Siegel, 2020; Dauth et al., 2021), inducing economic inequality (Acemoglu and Restrepo, 2022; Autor and Dorn, 2013), and transforming tasks performed by workers within jobs and occupations (Spitz-Oener, 2006; Acemoglu and Restrepo, 2019). While the consequences of technological change on wages and employment are typically at the forefront of interest, much less is known about how it affects workers' health.

Theories from fields such as organizational science and psychology have long emphasized that increasing workplace technology dependency may negatively influence workers' psychological and physical health by triggering "technostress" (Brod, 1984; Tarafdar et al., 2015).[1] On the other hand, modern digital technologies and automation hold the potential to relieve workers from physically demanding tasks, enabling them to engage in healthier activities on the job. Yet, there is a clear lack of evidence on the health effects of introducing frontier technologies, such as AI, in the workplace for a representative sample of workers across all sectors and occupational groups.

In this paper, we use a novel data set, which, for the first time, allows us to link digitalization in the workplace between 2011 and 2019 to individual health outcomes. Notably, our measure of workplace digitalization reflects the actual adoption of the full spectrum of frontier technologies and is thus not limited to a particular type of technology. Further, it allows us to distinguish the use of modern smart technologies from more commonly used computer-based technologies. Our analysis is based on linked employer-employee data that combine social security records of firms and employees with separate firm and employee surveys that collect workplace information about the changing use of different types of digital technologies and tasks performed. In order to find the effect of digitalization on health, we use a first-difference model relating individual-level changes in technology use at the workplace to individual health outcomes. Although experimental data would be preferable to gauge the causal effect of workplace digitalization on health, experimental data is typically limited to a single firm context and a specific type of technology, thereby limiting the external validity of the estimated effects. In comparison, our approach comes with the merit of drawing a representative picture for the first time of how digitalization, i.e.

[1]For example, the survey by Tarafdar et al. (2015) describes technostress as a "situation of stress experienced by the individual because of an inability to adapt to the introduction of new technology in a healthy manner". A related but distinct aspect is that exposure to technology might also increase job insecurity (see for example Dengler and Gundert (2021)). However, our evidence suggests that the health effects we estimate are not explained by increased job insecurity and are more likely to reflect technostress due to having to learn new technologies and having to switch to new tasks.

modern technologies, affects workers in Germany. By exploiting the rich information of the linked employer-employee dataset, we are able to control for major confounders, including firm and workplace characteristics, such as initial tasks performed, and worker controls, such as past health and earnings, technological comprehension, and personality traits. This allows us to compare health outcomes of very similar individuals in formerly similar firms and jobs that differ in the speed of frontier technology adoption in the workplace.

We start by documenting how the most recent wave of progress in digital technologies has changed workplaces between 2011 and 2019. In this, our dataset allows us to examine both changes in tools used and in tasks performed. We find that digitalization is most strongly linked to the increasing use of artificial intelligence, big data, and the Internet of Things. We further observe that the increasing use of these technologies is leading workers to turn to less repetitive and more social, mathematical, and programming-related tasks, which are also perceived as involving more performance and time pressure.[2]

Motivated by psychological literature, which emphasizes that increasing complexity at work particularly overwhelms those workers who are not used to complex tasks (Bakker and Demerouti, 2007; Schaufeli and Bakker, 2004), we hypothesize that digitalization is most stressful for low-skilled workers with primarily non-cognitive tasks, resulting in negative health outcomes. To test this hypothesis, we use individual-level data on over a dozen tasks performed at work to classify workers according to their initial task profile. To reduce the dimensionality, we perform a principal component analysis (PCA) which shows that most initial variation in task profiles is captured by one single component. This component is positively correlated with office-related, complex, and cognitive tasks and allows for a split of the sample into “manual” and "cognitive" workers. Moreover, this sample split not only reflects tasks, similar to the pioneering classification by Autor et al. (2003), but also correlates strongly with education.

For the average worker we find economically and statistically insignificant health effects of workplace digitalization. Yet, this masks substantial effect heterogeneity between worker groups. For manual workers, a one-standard deviation increase in digitalization corresponds to a decline of approximately 0.22 Likert points in self-reported health over the eight-year period from 2011 to 2019. For a manual worker that experiences digitalization at the average rate in our sample, this implies an annual decline of around 0.01 Likert points in perceived health. Considering that

[2]This distinguishes modern digitalization from computerization, which primarily leads to an increased frequency of information and communication tools (ICT) use such as general and specialized software, while leaving the complexity of the task profile unaffected.

one year of aging corresponds to a 0.0363 Likert-point reduction in perceived health, this health effect of digitalization experienced per year is equivalent to around three months of aging.

This reduction in perceived health comes not only with consequences for workers but also for firms, given that reduced worker happiness has previously been shown to impair labor productivity (Bellet et al., 2024). Using sick days at work as a more objective measure of health, the same picture emerges: While cognitive workers are not affected, manual workers experience 0.3325 more sick days per year as a result of the digitalization they experience on average in the workplace. Over the period of 8 years, this sums up to 2.66 days for the average manual worker, an economically substantial effect given that manual workers have, on average, 13.5 sick days per year. Overall, our results suggest that for manual workers, the additional technostress caused by digitalization in the workplace outweighs any potential positive effects, for instance from relieving them from repetitive tasks. These findings are robust to the inclusion of a rich set of individual, firm, and workplace-related controls, as well as occupation and industry fixed effects.

We further show that differential health outcomes are not driven by a different treatment intensity or content. Both the type of technologies adopted in workplaces exposed to digitalization and the resulting shifts in tasks are quite similar across both worker groups. Moreover, we do not observe manual workers receiving monetary compensation for their deteriorated health, as both employment and earnings effects are small and statistically indistinguishable from zero. Hence, workplace digitalization increases health disparities between both worker groups. Since the group of manual (and mostly low-skilled) workers already report poorer health from the start, digitalization thus also magnifies the already well-documented health disparities between educational groups (see e.g. Meara et al. (2008); Currie (2009)) or groups of different social class (see, for example, the landmark studies by Marmot et al. (1984) and Marmot et al. (1991)).

Consistent with interpreting the negative health effects among manual workers as a result of increased technostress, we also provide tentative evidence that manual workers in firms with a more supportive firm culture and more IT-related training suffer less from workplace digitalization. This suggests that firm policies to assist workers in coping with technology shocks may be an effective means to prevent negative health outcomes and the accompanying productivity losses.

Our paper relates to the literature on the interplay between technological change and individuals' health. One strand of the literature looks at how automation directly affects workers' health by altering tasks performed. Gihleb et al. (2022) and Gunadi and Ryu (2021) find that robot exposure correlates with fewer repetitive tasks and injuries, emphasizing a positive effect of automation on low-skilled workers. We expand the focus and consider the entire spectrum of frontier technologies, some of which aim at automating tasks while others aim at augmenting tasks. In fact, we show that for both manual and cognitive workers overall, digitalization is shifting jobs toward more complex and less automatable tasks and that this, in contrast to pure automation technologies, has negative health consequences for manual workers. Another strand of literature looks at how potential automation affects workers' health by inducing mental strain (Blasco et al., 2024; Lordan and Stringer, 2022; Abeliansky et al., 2024). In contrast to those papers, we use actual individual-level changes in the use of technologies at the workplace and link them to the well-being of workers. Additionally, we can show how reduced subjective health translates into increasing sickness absence, thereby also imposing costs on employers.

This paper also relates to the literature on how changing economic circumstances affect workers' health (Sullivan and Wachter, 2009; Pierce and Schott, 2020; Case and Deaton, 2021). Different from this literature, we do *not* focus on workers who experience prolonged periods of non-employment or sharply reduced wages, allowing us to isolate the effect of changing tasks at the workplace on health. Given we do not detect significant effects of digitalization on earnings and employment, the estimated health consequences are plausibly driven by changing workplace environments and job tasks and not changing economic circumstances. This highlights that modern technological change induces a new dimension of inequality widening the health gap across education groups (Meara et al., 2008; Currie, 2009). Further, our results imply that the group of low-skilled workers is especially vulnerable as also less drastic shocks than exposure to job loss strongly affect their welfare.

Hernnäs (2023) focuses on occupational decline, capturing slower-moving deterioration in labor market prospects (Edin et al., 2023), and shows that gradual economic shocks also carry significant negative health effects, especially on initially lower-paid workers. Lastly, our findings on how changing workplaces affect health also complement the expanding body of literature highlighting the significance of non-medical elements in contributing to health inequalities (Case and Deaton, 2021; Finkelstein et al., 2021, 2024).

The remainder of our paper is organized as follows. Section 2 presents our data. Section 3 discusses our empirical strategy. Section 4 documents what kind of technologies and tools have entered the workplace in the period under consideration and how they changed task profiles. Section 5 presents the results for health inequalities as well as potential mechanisms at work. Section 6 concludes.

2 Data and Descriptive Statistics

2.1 Data

Our analysis is based on the Digital Transformation of Work dataset (henceforth: DiWaBe, "Digitaler Wandel der Beschäftigung"). It is a linked employer-employee dataset that combines administrative information about firms[3] and employees from social security records with a separate firm[4] and employee survey[5] that collect information about the adoption of digital technologies at the firm and worker level.

The firm survey was conducted in 2016 among a representative sample of 2,032 German establishments.[6] The survey's purpose was to collect firm level information on the use of digital technologies both in 2016 and, retrospectively, in 2011. In order to complement this dataset with more detailed information on the use of digital technologies at the workplace, a linked employee survey was conducted in 2019[7], sampled from all 266,000 regular workers[8] employed in any of the surveyed firms on June 30th, 2011 or 2016, and aged between 16 and 65 years in 2016. This workforce is representative of the German workforce in 2011 and 2016. Since the sample was stratified, we use sampling weights for all subsequent analyses. See Appendix B.2 for details on the stratified sampling and the weights.

The purpose of the employee survey was to collect worker level information on the use of (digital) work equipment at the workplace. Importantly, respondents were also asked to retrospectively assess their use of work equipment in 2011 in the same way.[9] By comparing the use of work equipment in 2011 and 2019, we are able to construct a measure of *computerization* and *digitalization*. With the term *computerization* we refer to a change in the use of already

[3]To be precise, the dataset includes establishments rather than firms, but we use the term "firms" for simplicity.

[4]The firm survey without additional administrative information is called "IAB-ZEW-Labor Market 4.0-Establishment Survey (BIZA)" (`DOI:10.5164/IAB.FDZD.2107.de.v1`), which is available at the Research Data Centre (FDZ) of the German Federal Employment Agency. For a data report of the firm survey, see Lehmer et al. (2021)

[5]The DiWaBe employee survey without administrative data (`DOI:10.5164/IAB.DIWABE_W01.de.en.v1`) is available at the Research Data Centre (FDZ) of the German Federal Employment Agency. For a data report, see Müller et al. (2023).

[6]It is a stratified random sample of all German establishments with at least one employee subject to social security contributions.

[7]See Appendix B.1 for details on the survey and non-response.

[8]The sample thus excludes civil servants, workers in minor jobs, interns, working students, and persons in vocational training.

[9]An extensive pretest was conducted to examine how to best help respondents to recall 2011. As a result of this pretest, respondents were first asked to recall either a personal event in 2011, the nuclear catastrophe in Fukushima in early 2011 or the soccer World Championship in 2010 before being asked to recall their work situation during that time. With this approach, the majority of respondents was able to recall their work situation at that time. Note that a remaining measurement error for the retrospective information is unproblematic as long as the recall error is unrelated to workplace digitalization. At most, such random noise would attenuate our results.

mature computer-based tools, while *digitalization* relates to frontier technologies of the latest technology wave such as artificial intelligence (see Section 2.3 for details).

In addition, the survey also collects information on the respondents' typical workplace tasks, job requirements, and health status for both 2019 and 2011. This allows us to examine how changes in these dimensions relate to computerization and digitalization. Furthermore, the dataset includes valuable additional information on working conditions, workplace organization, and training, as well as background characteristics such as migration status, household structure, income, a self-assessment of someone's technical affinity, self-efficacy, and personality traits ("Big Five"). Finally, the data was merged with administrative information from the social security records of each sampled worker. This includes, among others, longitudinal information on workers' employment status, earnings, occupation and industry.[10]

2.2 Sample of Analysis

For the subsequent analysis we mainly use the employee survey and impose a number of sample restrictions on the DiWaBe sample of 7,698 respondents. As we want to find out how employees are affected by digitalization induced by their firm, we confine the sample to respondents who are least likely to have consciously selected into a firm due to digitalization and who cannot decide for themselves on the use of digital devices. We, therefore, keep only observations from employees in regular employment and those who were already employed in one of the surveyed firms in 2011.[11] Additionally, we restrict the sample to individuals aged between 20 and 55 in 2011 to ensure that the results are not biased by (early) retirement. Further, as we use a rich set of administrative information as controls, we lose all respondents who did not give consent to linking their responses to administrative records. Lastly, all individuals with missing information in any of the outcomes or treatment variables are dropped, which leaves us with a final sample size of 3,235 individuals. This sample is representative of the German workforce employed in 2011, as Table 17 in Appendix B.3 shows.

[10]These records were merged from the Integrated Employment Biographies (IEB) of the Institute for Employment Research (IAB). The precise citation of the data is: IAB Integrierte Erwerbsbiografien (IEB) V16.00.01-202012, Nürnberg 2021.

[11]We thus drop 2,625 workers who entered a surveyed firm between 2011 and 2016.

2.3 Treatment Definition and Key Outcome Measures

Measuring Digitalization at the Workplace Our main interest lies in the health effects of the increasing use of *advanced* digital technologies at the workplace, a process that we will refer to as *digitalization* in the rest of the paper. The detailed information on the use of technologies in the survey allows us to differentiate between a change in the use of these "smart" tools and computer-based *mature* digital technologies. We refer to the latter as *computerization*.

To be more precise, survey respondents were asked to assess their use of work equipment both contemporaneously for 2019 and retrospectively for 2011. In particular, they were first asked to assess whether and how often they use (or used) information and communication equipment (ICT) or machines/tools. For both types of work equipment, workers were then asked to assess to what extent these tools are (or were) computer-assisted (5-point Likert scale).[12] To separate more mature from advanced digital technologies, all respondents with at least a minimum use of computer-assisted tools were asked to what extent the tools used at their workplace could also be considered "smart" (5-point Likert scale).[13] For this, respondents were told that "smart" tools are *"computer-assisted tools that connect different parts of the company or production process by automatically forwarding or receiving information in order to control or optimize processes and procedures"*.[14]

As we are interested in whether individuals' health is impaired by an increase in the *complexity* of digital tools rather than a sole increase in the *frequency*, we measure workplace digitalization as the degree to which someone's most frequently used workplace equipment has become "smarter" between 2011 and 2019. To be precise, digitalization is calculated as the average change in the use of smart ICT and smart machines, weighted by the initial importance of ICT relative to machines w_i^{2011}:[15]

$$\Delta Digi_i = w_i^{2011} * \Delta ICT_i + (1 - w_i^{2011}) * \Delta Machines_i \tag{1}$$

[12]The exact wording for 2019 was: *"To what extent is the work equipment that you use computer-assisted? By "computer-assisted" we mean work equipment that processes data or is equipped with a computer."*. All 5-point Likert scales are measured from 0 to 4, whereby 0 indicates low and 4 high levels of agreement.

[13]For respondents who indicated that they would not use any computer-assisted tools, we impute a zero usage for the use of "smart" tools.

[14]To ease the respondents' understanding, the survey provides examples for "computer-assisted" and "smart" tools. For tools and machines, the examples were digital measuring or diagnostic devices, CNC machines, robots, and 3D printers. For ICT, examples were digital fax, copy or telephone devices, desktop PCs, laptops, and smartphones.

[15]We measure the initial relative importance of ICT as the relative frequency of ICT use relative to machine use in 2011, i.e. $w_i^{2011} = f_{ICT,i}^{2011}/(f_{ICT,i}^{2011} + f_{Machines,i}^{2011})$.

This reflects the intuition that an individual mostly working with machines experiences machine-related technological change more strongly compared to ICT-related technological change. Analogously, we calculate a measure of computerization at the workplace, $\Delta Comp_i$, as the change in computer-assisted tools with respect to ICT and machines/tools, again weighted by the initial relative frequency of ICT use, w_i^{2011}. Compared to previous studies that focused only on a specific type of technology (e.g. robots), these general measures have the advantage that they are applicable to workers independent of their industry or occupation. Further, we are able to disentangle the impact of adopting modern technologies from the impact of adopting mature technologies at the workplace. In Section 3, we show that this distinction is important as computerization and digitalization are associated with very different changes in terms of tools used and tasks performed. However, while digitalization and computerization vary independently, it has to be borne in mind that the structure of the survey means that we cannot always cleanly separate them. For example, for a worker that starts from a situation with no computer-assisted tools, the subsequent adoption of a smart tool will be counted as both digitalization and computerization. As a consequence, we might assign some of the consequences of digitalization to computerization. Given this inaccuracy in measurement, we find the stark effect differences between digitalization and computerization that we find below even more remarkable.

Outcome Variables: Health Measures. Our key interest is to assess the impact of digitalization on health outcomes. In order to be able to depict a holistic picture and to allow for better comparability with other studies, we use both objective and subjective health measures. As a subjective measure, we use the difference between individuals' own assessment of health in 2019 and 2011 (surveyed in each year on a 10-point Likert scale). Additionally, we use the number of sickness absence days in the 12 months preceding the interview in 2019 as an objective measure of health.[16]

2.4 Initial Task Heterogeneity

As discussed in the introduction, we hypothesize that workers in previously more manual and less complex jobs are more vulnerable to the increasing task complexity and cognitive requirements

[16]Note that absence days are affected not only by health but also by institutional conditions such as paid sick leave regulations (Maclean et al., 2020; Callison and Pesko, 2022). Germany has one of the most generous universal sick leave systems, with a legally mandated minimal sick leave entitlement of six weeks per year. Hence, differences in sick leave that are related to workplace digitalization are likely to reflect health shifts rather than any institutional differences.

induced by digitalization. In order to test this hypothesis, we first aim to classify workplaces into meaningful subgroups using the survey information on 13 different tasks performed at the workplace in 2011[17]. A common dimension reduction method in the social sciences is the so-called principal component analysis (PCA) (see Acemoglu et al. (2014) and Sánchez De La Sierra (2020) for recent examples). It is a data-driven approach that essentially summarizes associations between multiple variables using a smaller number of "variables", called principal components, which capture most of the variation between the original variables. As we aim to identify meaningful groups of employees based on the similarity of their initial workplaces, this method is particularly well suited.

The results of the PCA suggest that a single principal component, which reflects 29.21% of the total variation of the original 13 variables, is a useful way to distinguish types of workers in a parsimonious yet meaningful way. This component relates positively to typical office tasks like long periods of sitting, frequent writing, use of software and ICT, and negatively to manual tasks that come with physical exertion and machine use, see Appendix B.4 for details.

Figure 1 shows that the PCA score relates well to occupation-level task shares commonly used in the literature[18]: It correlates strongly and positively with analytical non-routine and routine cognitive tasks, but negatively with manual tasks. Moreover, Figure 1 also shows that skill requirements[19] increase with the PCA score. Overall, our PCA component thus seems to summarize important multi-dimensional workplace differences in only one dimension.

Yet, as we want to investigate whether digitalization adversely affects workers in more manual and less complex workplaces, which are based on the lower end of the PCA score distribution, compared to workers in already more complex workplaces, we need to find a suitable cutoff between those two worker types. Here, we make use of the classification of occupations based on their main task share according to Autor et al. (2003) (henceforth, ALM).[20]

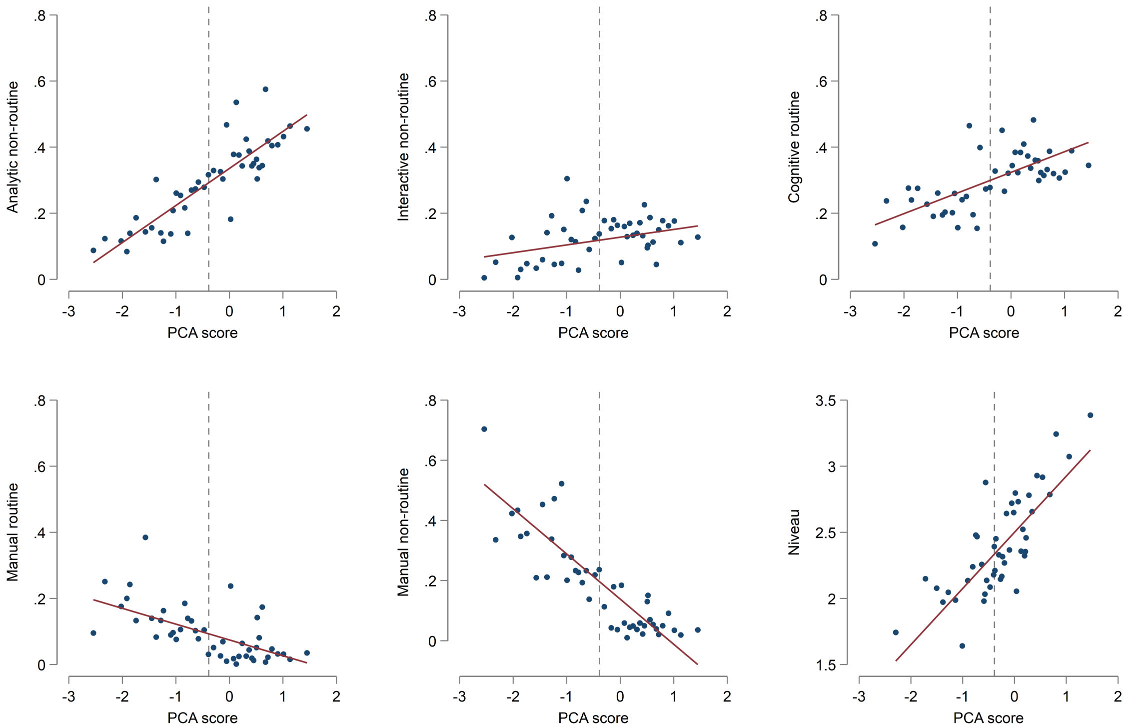
[17]These tasks include, among others, the frequency and degree of cognitive and physical tasks, but also of work pressure and independence. A full list and description of the variables can be found in Appendix B.4.

[18]For this we merge in information on the occupation-level task shares from Dengler and Gundert (2021).

[19]The skill requirements are indicated by the fifth digit of the German occupation code and refer to the skill level that the employer considers necessary for the job. It distinguishes helpers from skilled workers, specialists, and experts.

[20]Occupations are classified as either analytic non-routine, interactive non-routine, cognitive routine, manual routine, or manual non-routine if the respective task share exceeds the other task shares.

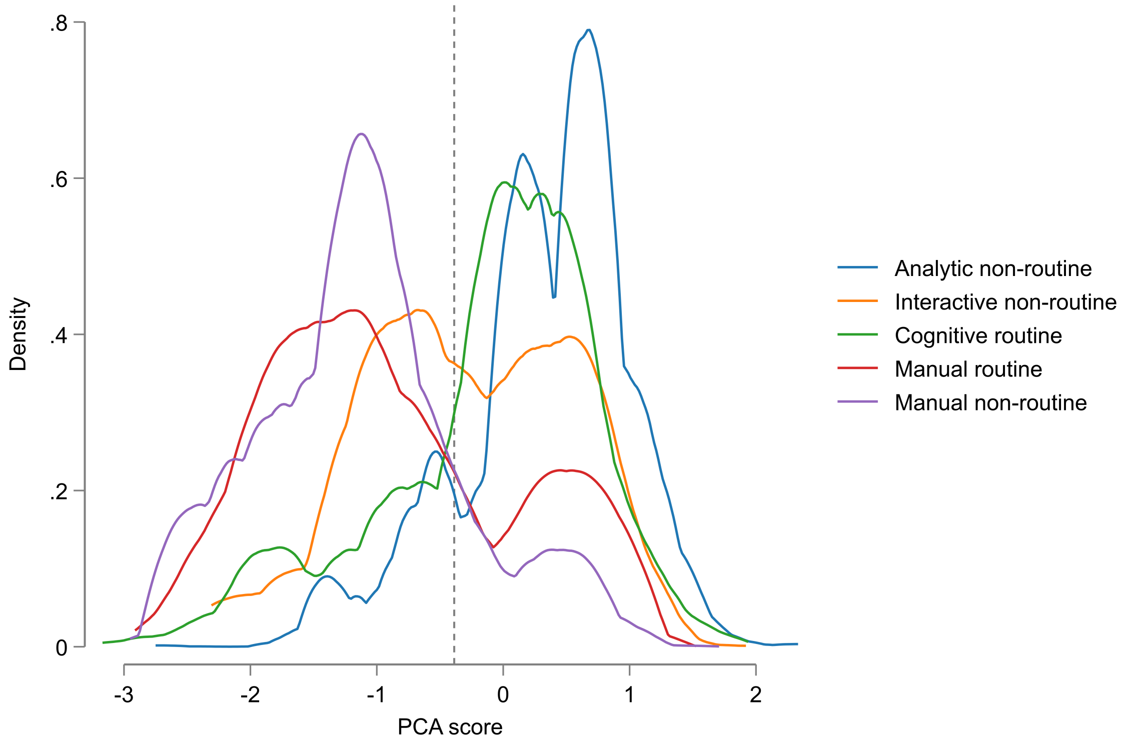
Figure 1: Comparison between ALM task categories, skill requirements, and PCA score



Notes: These graphs show the correlation between the PCA score and occupation-level task shares as well as the occupational skill requirement (denoted "niveau"). The PCA score is obtained from a principal component analysis using respondents' information on tasks performed at their workplace in 2011 and reflects the frequency of typical office tasks (for details, see Appendix B.4). Occupation-level task shares are obtained from the BiBB/BAuA Employee Survey 2012 and divided into analytic non-routine (ANR), interactive non-routine (INR), cognitive routine (CR), manual routine (MR), and manual non-routine (MNR) tasks. These tasks are mutually exclusive and sum up to 1 for each 2-digit occupation. The occupational skill requirement is indicated by the fifth digit of individuals' KldB occupation code in 2011. It ranges from 1 to 4, with 1 being unskilled and 4 highly complex tasks. Observations are weighted using post-stratified sampling weights, further explained in Appendix B.2.

Figure 2 shows that the lowest tertile of the PCA score distribution (the area below the vertical line) contains mostly workers in manual occupations, whereas the upper two tertiles consist of merely cognitive or analytical occupations. This classification allows us to test whether "manual workers" (lowest tertile) face a more severe health burden through the increasing complexity induced by new digital technologies than "cognitive workers" (upper tertiles).

Figure 2: Kernel-density plot of the PCA score across occupation main groups



Notes: This graph displays the kernel-density plot of the PCA core separately for each occupation main group. The PCA score is obtained from a principal component analysis using respondents' information on tasks performed at their workplace in 2011 and reflects the frequency of typical office tasks (for details, see Appendix B.4). Individuals are categorized into occupation main groups based on the most common type of tasks performed in their occupation in 2012. Occupation-level task shares are obtained from the BiBB/BAuA Employee Survey 2012 and divided into analytic non-routine (ANR), interactive non-routine (INR), cognitive routine (CR), manual routine (MR), and manual non-routine (MNR) tasks. These tasks are mutually exclusive and sum up to 1 for each 2-digit occupation. Observations are weighted using post-stratified sampling weights, further explained in Appendix B.2.

2.5 Descriptive Statistics

Table 7 in Appendix A provides summary statistics for the individual-level controls of both worker groups. On average, manual workers turn out to be younger, more likely to be male and migrants, and have much less education than cognitive workers.[21] Manual workers also report different personality traits, e.g., a lower level of extraversion, less technological comprehension, slightly lower subjective health, and, unsurprisingly, lower labor income.

Manual and cognitive workers do not seem to work in different firms in terms of their size, but of their structure: Manual workers are more often in manufacturing firms with a high share of

[21] Although the skill level is strongly related to the worker group, the use of our task-based approach of classifying workers is preferable to a skill-based classification as a high fraction of workers hold a vocational degree although their workplaces differ substantially. In addition to this omitted heterogeneity for individuals with vocational education, a feature of the German vocational system is that only very few employees have no degree at all. Still, we use a skill-based classification in a sensitivity analysis.

blue-collar workers and a low share of highly skilled individuals. Further, their firms mainly use analog tools, whereas cognitive workers' firms are mostly equipped with computerized tools (see Table 8 in Appendix A for details).

Finally, Table 9 in Appendix A provides summary statistics for our treatment and outcome variables. On average, workers report an increase in workplace digitalization by 0.48 points (from an initial level of 1.15). For comparison, the initial level of computerization in 2011 at the average workplace was 2.14 and increased only by 0.18 points between 2011 and 2019. Hence, on average, there is a strong trend towards digitalizing workplaces in Germany. However, in relative terms, manual workers experience digitalization more rapidly. Given their initially low level of 0.61 points, they experience an increase of around 65%, while cognitive workers "only" see an increase of around 35% on average. Further, manual workers face both an increase in computerization and digitalization, whereas cognitive workers' workplaces seem to be already computerized.

When it comes to health outcomes, the average worker reports 9.8 days of sick leave in 2019 and a decline in subjective health by 0.36 points (from initially 7.86 points in 2011) reflecting - among other factors - aging.[22] However, one can observe stark differences between worker types: Manual workers report more than twice as many days of sick leave than cognitive workers and both a lower initial level as well as a much stronger decline in subjective health. As shown, our worker type classification maps differences in education levels well, meaning that this health difference is in line with other studies that observe disparities in health outcomes between education groups (e.g., Meara et al. (2008); Currie (2009)). Whether the stronger health decline for manual and, thus, low-skilled workers is partly due to modern technological change and thus digitalization accelerates existing health gaps is the focus of the subsequent analysis.

3 Digitalization at the Workplace

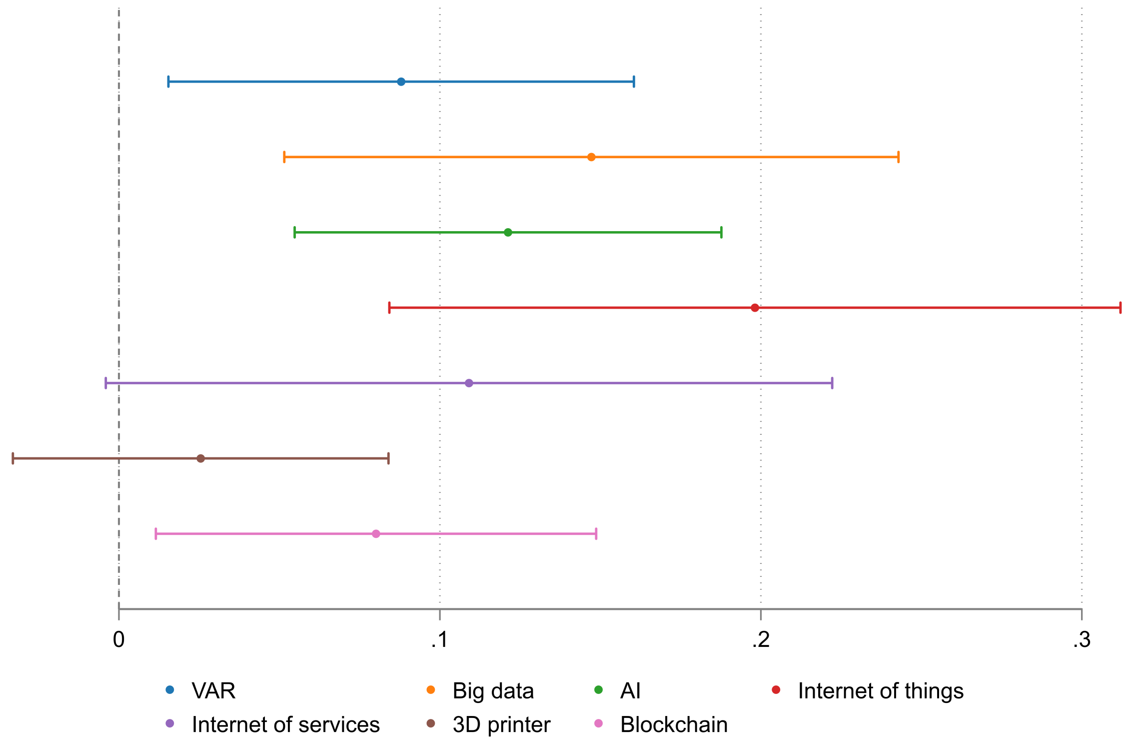
Before examining the health effects of digitalization, we first aim to get a better picture of what workplace digitalization (compared to computerization) actually entails in terms of the adoption of new technologies and related task shifts. Describing these processes using workers' own assessment is interesting in itself, as only a few studies are able to describe changes at

[22]On average, employees in Germany had 10.9 sick days in 2019. This difference can be explained by the sampling exclusion of older employees, which is why our sample is also 4 years younger than the population of employees in Germany.

the workplace level for the same workers across time and not rely on higher aggregates or use repeated cross-sectional information.

Adoption of Advanced Technologies. We first show what our digitalization measure actually captures in terms of tools and technologies used. For this, we calculate the change in the frequency with which respondents report using specific digital tools (asked in 2011 and 2019 on a 5-point Likert scale).We regress this difference on our measure of digitalization while controlling for initial workplace and firm characteristics, as well as occupation-level fixed effects.

Figure 3: Digitalization and change in tools used

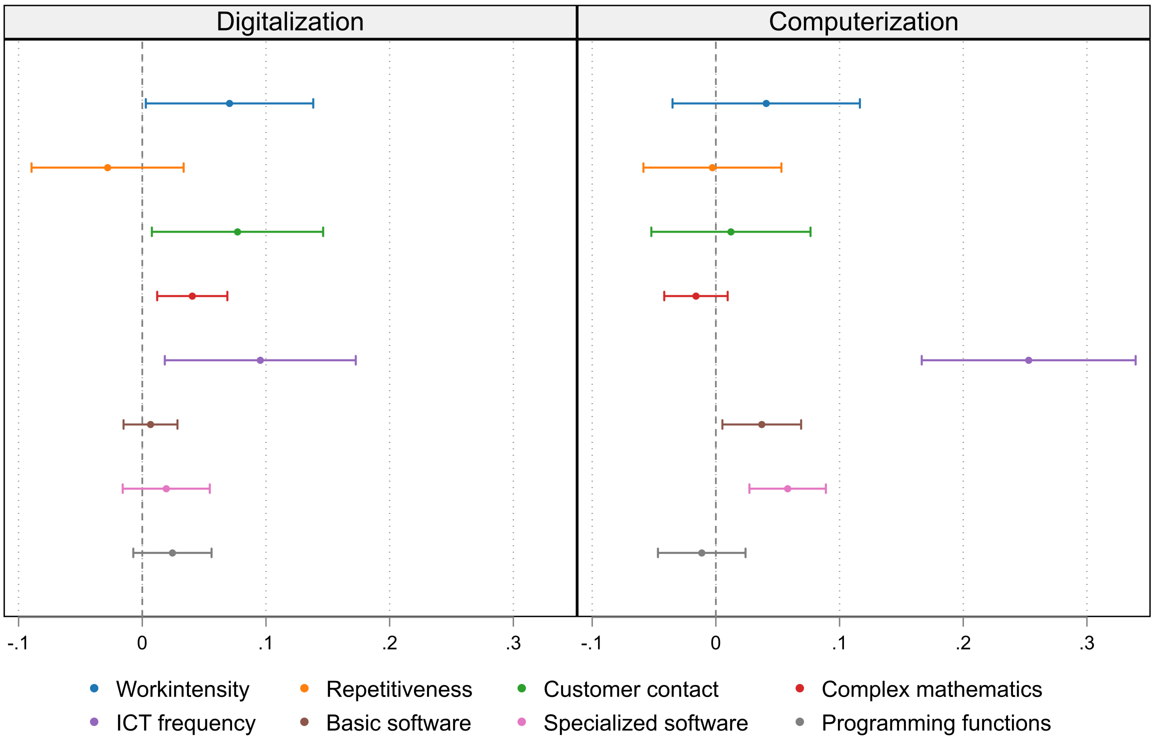


Notes: This figure displays the coefficients of separate regression of a change in the use of a specific digital tool used on digitalization. "VAR" refers to virtual and augmented reality, "AI" to artificial intelligence. The frequency of tool use is measured on a 5-point Likert scale in 2011 and 2019 and the change is calculated as the difference. Digitalization refers to a change in the use of modern digital work equipment, like smart devices. The construction of the treatment variable is explained in Section 2.3. In all regressions, we control for initial workplace and firm characteristics (as in Equation 2), as well as 2-digit occupation fixed effects. Observations are weighted using trimmed post-stratified sampling weights, further explained in Appendix B.2. Whiskers display 95%-confidence intervals obtained from robust standard errors clustered at the firm level.

Figure 3 shows that workers who report more workplace digitalization are also significantly more likely to report an increase in the use of modern technologies, such as the Internet of Things, big data, artificial intelligence, blockchain technology, and virtual augmented reality. This confirms the plausibility of our measure: Workplace digitalization seems to capture the adoption of advanced technologies that are associated with the most recent wave of technology.

Task Shifts. In the next step, we test how digitalization and computerization affect tasks performed at work. The adoption of new tools and technologies likely results in a new task mix, either through the creation or substitution of tasks formerly performed by labor. In fact, we think that the digitalization-accompanying change in tasks performed may be one major reason why new technologies affect health outcomes. We examine how task shifts relate to technological change by regressing the change in the frequency of performing a specific task on both digitalization and computerization along with the same controls as before.

Figure 4: Digitalization and task change



Notes: This figure displays the coefficients of separate regression of a change in the performance of tasks on digitalization and computerization. In both 2019 and 2011, respondents were asked to rate (on a 5-point Likert scale) how often they (i) work under deadline or performance pressure, (ii) perform repeating identical work processes, (iii) deal with people who are not colleagues, (iv) how complex their mathematical tasks are (No calculation requirements, simple calculations, fraction/percent calculations or similar complex, area/volume calculations or similar complex, higher mathematics) and (v) how often they use ICT. Further, they were asked if they use (vi) standard software (e.g., Microsoft Office), (vii) job-specific software, or (viii) programming functions. The change is calculated as the simple difference between respondents' assessments in 2019 and 2011. Digitalization (computerization) refers to a change in the use of modern (mature) digital work equipment, like smart (computer-based) devices. The construction of the treatment variables is explained in Section 2.3. In all regressions, we control for initial workplace and firm characteristics (as in Equation 2), as well as 2-digit occupation fixed effects. Observations are weighted using trimmed post-stratified sampling weights, further explained in Appendix B.2. Whiskers display 95%-confidence intervals obtained from robust standard errors clustered at the firm level.

Figure 4 shows the results for those tasks for which we expect a transformation due to digitalization. It becomes evident that digitalization and computerization change workplaces in fundamentally different ways leading to different implications for workers' health. While computerization is associated with a stark increase in the usage of ICT, basic software, and specialized software, digitalization shifts workplaces towards more complex tasks. It is associated with a higher frequency of customer contact, increased importance of higher mathematics (e.g. regression analyses), ICT use, and programming (but not standard software). Especially the increasing use of advanced programming functions connects well to the increasing use of AI and Big Data depicted in Figure 3. Moreover, and importantly for our analysis of its health effects, respondents report a higher deadline and performance pressure, i.e., work intensity, related to digitalization. This again contrasts with computerization, which has a statistically insignificant relationship with work intensity.

Taken together, our examination of tasks and tools suggests that digitalization increases complexity by requiring workers to perform cognitively more demanding *analytical tasks* and to work with increasingly complex, partially autonomous processes and tools, such as artificial intelligence. By contrast, computerization reflects solely an increasing use of standard and rather independent software programs to perform more *cognitive-routine tasks.*

Treatment Heterogeneity. As we aim to shed light on how digitalization impacts workers differently depending on their initial workplace, i.e., what they were used to, our treatment measure has to be comparable across worker types. We can directly test if digitalization comes with the same task shifts and reflects the same technologies for both manual and cognitive workers by adding an interaction between digitalization and an indicator that equals one if a respondent belongs to the group of cognitive workers.

Figure 5 in Appendix A shows that the difference in the adoption of specific tools for both worker groups turns out to be close to zero and insignificant. Hence, on average, both manual and cognitive workers who experience workplace digitalization are exposed to the increased use of very similar types of technologies. The same holds true for the task shifts (see Figure 6 in Appendix A). For both groups, digitalization similarly increases work intensity, customer contact, and the usage of complex mathematics, specialized software, and programming functions. Only the coefficient on ICT frequency is significantly lower among cognitive workers, likely reflecting a reversion to the mean.

We conclude that digitalization changes workplaces rather homogeneously. Thus, any heterogeneity in the health effects of digitalization therefore likely captures differences in workers' ability to cope with new technologies rather than differences in what workers have to adjust to in terms of new technologies and tasks.[23]

4 Estimation Strategy

Technology adoption at the workplace is an endogenous choice that results from decisions by firms and workers. Although the ultimate decision about whether or not to adopt new technologies rests with the firm, individuals consciously choose their profession, industry, firm, and even their workplace within a firm, taking aspects such as technological change and health into account. Moreover, there may be confounding occupational trends, such as trade shocks, that may affect both technology adoption and workplace organization as well as health outcomes. For all these reasons, the identification of the causal effect of technology adoption on worker health is extremely demanding. Although we cannot make use of any quasi-experimental variation, our rich dataset allows for addressing many potential confounders such that we expect the remaining biases to be small.

Main Analysis. More specifically, our estimation equation for individual i in establishment j, occupation o, and industry sector s takes the form

$$Y_i = \alpha + \beta \Delta Dig_i + \gamma \Delta Comp_i + \xi X_{i,j(i)} + \rho_{o(i)} + \zeta_{s(i)} + \eta F_{j(i)} + \epsilon_i \tag{2}$$

where ΔDig_i measures workplace digitalization and $\Delta Comp_i$ controls for changes in already mature computerized technologies between 2011 and 2019. Our main interest lies in β, i.e. the coefficient of the effect of digitalization on health. We use two measures of health as outcome variables Y_i: For sick leave days, we only have cross-sectional data for 2019. For subjective health, on the other hand, we observe the change between 2011 and 2019. By using this difference, we can eliminate any time-invariant, individual-specific effects that also affect health. To facilitate interpretation, we standardize ΔDig_i and $\Delta Comp_i$ to have a mean of zero and standard deviation of one, so that effect sizes can be interpreted per standard deviation change in these variables.

[23]We also tested whether digitalization increases perceived job insecurity among the two worker groups. Appendix Table 15 shows that perceived risks of job loss and related concerns do neither increase for manual nor cognitive workers if their workplaces are exposed to digitalization.

We cluster robust standard errors at the firm level, as workplaces within the same firm are unlikely to be independent.

Unobserved confounders that affect both the use of technology as well as health pose a threat to identification. For instance, if the likelihood of modern machines being adopted relates to other individual, workplace and firm differences that also affect someone's health trajectory, not controlling for them yields biased estimates. In order to account for such confounders, we control for a rich set of individual, workplace, and firm characteristics $X_{i,j(i)}$ that are either time-constant or reflect initial characteristics in 2011. At the individual level, these do not only include typical demographics such as age, education, gender, migration background, and log mean daily earnings between 2009 and 2011 as an indicator of initial productivity. In addition, we also capture individual characteristics that are often unobserved and likely confounders, such as the Big Five personality traits and technological comprehension. Moreover, we condition on subjective health in 2011. In addition, we control for initial workplace characteristics, i.e. the frequency of tasks performed in 2011 (see Appendix Table 19 for the full list), as well as firm size and the share of blue-collar workers as baseline firm characteristics. A detailed list and description of all control variables included can be found in Tables 7 and 8 in Appendix A.

This means that we identify our coefficient of interest by comparing individuals who have similar demographics, skills, and personality traits, have very similar initial workplaces in similar firms, show a similar initial affinity for technical innovations, and report similar initial health, but differ in workplace digitalization. In our first-differenced specification for subjective health, controlling for levels of these variables is equivalent to allowing them to have a time-varying effect on health.

In our baseline specification, we further include 2-digit occupation fixed effects ρ_o to additionally control for common trends influencing both the adoption of technologies and health. Among many other things, such as occupation-specific changes in working conditions and regulations, these will also control for the automation risk associated with the individual's initial occupation, as this can affect the individual's physical or mental health (see, for example, Patel et al. (2018)). In an extended version, we add 1-digit industry fixed effects ζ_s to also control for sector-specific trends. Finally, in the most demanding specification, we add additional firm-level controls $F_{j(i)}$ reflecting the structure of the firm in terms of skill, age, organization, and initial technology level. We believe that these variables map the ability of firms to provide resources and aid to workers in dealing with technological change (see *Additional firm controls* in Table 8 in Appendix A).

Compared to previous studies, we are thus able to control for important confounders both at the firm, occupation, industry, and worker level.

Another threat to identification is reverse causality, for instance, if firms allocate digital tools to workers with worsening health, or if firms with a more or less healthy workforce are more prone to adopt digital technologies. However, we think this is unlikely. Firstly, conditional on occupation fixed effects, we find that the adoption of digital production technology is uncorrelated with the 2011 level of self-reported health. Secondly, our results are also robust to controlling for the average health change of all other workers at a given firm.[24]

Heterogeneity Analysis. In order to test the hypothesis that workers in initially more manual jobs suffer more from workplace digitalization as they are less used to complex digital environments, we allow for treatment heterogeneity and adapt our estimation equation as follows:

$$Y_i = \alpha + \beta_t\Big(\Delta Dig_i \times I(t)\Big) + \gamma\Delta Comp_i + \xi X_{i,j(i)} + \rho_{o(i)} + \zeta_{s(i)} + \eta F_{j(i)} + \epsilon_i \tag{3}$$

with $t = \{manual, cognitive\}$. $I(t)$ equals one if an individual i belongs to the respective group of manual or cognitive workers that we defined in section 2.4.[25]

Channels, Compensating Differentials, and Moderating Factors. If there is a health effect of digitalization, better understanding its causes, as well as factors that may compensate for it or moderate its impact, is highly relevant from a policy and welfare perspective. We therefore first investigate the channels through which digitalization impacts health. In particular, health effects might stem from the task shifts induced by technological change, but they might also be driven by specific types of tools adopted at these workplaces. Secondly, we also aim to examine whether digitalization affects perceived job risks and job satisfaction. Thirdly, we examine whether negative health effects are compensated for by higher earnings or better employment prospects. Finally, we shed light on the factors that may help to cushion the impact of digitalization on health such as training or a supportive firm culture.

[24] Results available upon request.

[25] This equation is equivalent to using a difference-in-difference framework and displaying the relative effect difference between the two groups combined with the effect for a reference group. However, as we are interested in displaying the absolute effect for each group separately, we use the interaction of digitalization with both mutually exclusive groups. As we control for each workplace characteristic in 2011 separately, the inclusion of a worker-type fixed effect is not necessary and does not affect the results.

5 The Health Effects of Modern Technology

5.1 Main Results

Table 1 displays the main results of our analysis. *Panel A* shows overall effects for all workers where columns 1-3 use the change in self-reported health as an outcome, followed by the number of sick leave days in columns 4-6. For each outcome, we start with a specification that includes our baseline control variables and occupation fixed effects. We then subsequently augment the specification first by 1-digit industry fixed effects and finally a detailed set of firm-level controls as described in Section 4.

All three specifications show the same result regarding the coefficient of workplace digitalization: While the point estimates indicate a slight worsening in subjective health and a slight increase in sick leave, coefficients are usually not significantly different from zero and also not economically large. An increase in digitalization of one standard deviation over the course of 8 years, which corresponds to 1.13 points, decreases self-reported health by around 0.03 points, or 1.5% of a standard deviation. For example, given that one year of aging relates to a reduction of subjective health in 2019 by around 0.036 Likert points, the average health consequences of digitalization appear negligible.[26]

We next explore the heterogeneity between worker types in *Panel B*. As expected, we do not find any health effects for cognitive workers. Manual workers, on the other hand, experience a stark decline in subjective health of around 0.22 points per standard deviation increase in the use of modern technologies. To put into perspective: On average, manual workers experience an increase in digitalization of 0.4 over eight years, which corresponds to 35% of the standard deviation (see Table 9 in Appendix A). Thus, scaling the effect by what the average worker experiences *per year*, we find that a manual worker that experiences digitalization at the average rate in our sample would experience an annual decline of around 0.01 Likert points - the equivalent of aging a quarter of a year.

[26]This coefficient of aging results from a bivariate regression of subjective health in 2019 on age.

Table 1: Health effects

	Change of subjective health			Sickness absence days		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Overall						
Digitalization	-0.031	-0.033	-0.029	1.385	1.385	1.333
	(0.066)	(0.065)	(0.066)	(1.101)	(1.100)	(1.085)
Computerization	-0.097	-0.092	-0.099	0.874	0.862	0.930
	(0.062)	(0.061)	(0.061)	(1.071)	(1.067)	(1.093)
R-squared	0.44	0.44	0.46	0.14	0.14	0.14
Panel B: By workplace type						
Digitalization (Manual)	-0.237**	-0.239**	-0.220*	7.680**	7.684**	7.567**
	(0.105)	(0.106)	(0.119)	(3.240)	(3.234)	(3.241)
Digitalization (Cognitive)	0.070	0.069	0.065	-1.216	-1.234	-1.229
	(0.076)	(0.073)	(0.071)	(0.855)	(0.851)	(0.868)
Computerization	-0.079	-0.075	-0.083	0.253	0.235	0.303
	(0.060)	(0.059)	(0.059)	(0.948)	(0.948)	(0.975)
Further controls	Occupation	Industry	Firm	Occupation	Industry	Firm
R-squared	0.44	0.45	0.46	0.15	0.15	0.16
N	3235	3235	3235	3049	3049	3049

Notes: This table reports the effect of technological change on a change in individuals' subjective health between 2019 and 2011 (columns (1) – (3)) and the number of sickness absence days in 2019 (columns (4) – (6)). Subjective health is measured in each year on a 10-point Likert scale. Digitalization (computerization) refers to a change in the use of modern (mature) digital work equipment, like smart devices (computers). The construction of the treatment variables is explained in Section 2.3. Panel A shows the overall effect of digitalization and computerization. In Panel B, an interaction between an indicator for the worker type and digitalization is added to the measure of digitalization as shown in Equation 3. Based on initial workplace in 2011 and using a PCA in order to reduce dimensions, respondents were divided into two main worker types: manual and cognitive workers. Details on this classification can be found in Section 2.4. The sample consists of respondents from the DiWaBe employee survey conducted in 2019, linked to IAB administrative records and a firm survey. It consists of individuals in regular employment in one of the surveyed firms in 2011, aged 20-55 in 2011, giving consent to linking with administrative records, and having non-missing responses in treatment and outcome variables. To ensure that results are representative for the German workforce, we use post-stratified trimmed survey weights (see Appendix B.2 for details). In columns (1) and (4), we control for individual- and baseline firm-level controls as well as 2-digit occupation fixed effects. In columns (2) and (5) we add one-digit industry fixed effects. In columns (3) and (6) we further add controls reflecting the firm structure (see Section 4 for details). Robust standard errors clustered at the firm level appear in parentheses.

Similarly, manual workers report, on average, 7.6 more days of sick leave in 2019 due to one standard deviation higher digitalization. Again, relating it to the degree of digitalization experienced by the average manual worker per year, we find that sick days increase by 0.3325 days. This is not only a statistically but also economically significant effect given that, on average, one sick day at work translates into direct wage costs of 123 euros and an estimated 209 euros due to the loss of labor productivity (BAuA, 2021). With a back-of-the-envelope calculation, we can benchmark aggregate health costs. This yields a number of 905 million euros per year.[27] These results are robust to the inclusion of industry fixed effects or controlling for additional firm-level controls reflecting the initial organizational structure of the firm, indicating that not larger trends but the change at the individual workplace is the key driver behind the effects.

5.2 Robustness

As our summary statistics have shown, computerization is still a quantitatively important aspect of technological change at the workplace for manual workers. Although we have always controlled for workplace computerization, we did not allow for any related heterogeneity between manual and cognitive workers so far. However, to see whether the negative health effect of digitalization is indeed due to manual workers being burdened by the increasing complexity of tasks and tools at their workplace which they are not used to, the increasing use of more common computer-based tools should not have any negative effect for them. This can be seen as a type of placebo test.

Table 10 in Appendix A shows that our results remain unchanged when we allow the coefficient of computerization to vary across manual and cognitive workers. Moreover, our "placebo test" seems to hold as computerization itself does not come with similar heterogeneous effects on worker groups as digitalization. This indicates that manual workers are really affected by the increasing complexity of workplaces through advanced technologies and not overwhelmed by the quantity of any technology usage per se. We also do not find any evidence that the heterogeneous health effect might be driven by how workplace digitalization affects perceived job insecurity or job satisfaction (see Appendix Table 15). Taken together, this suggests that the health effects we estimate likely reflect technostress due to having to learn new technologies and having to switch to new tasks.

Our sample consists of workers who experience a change in workplace digitalization while staying with the same employer ("stayers") and workers who experience such changes after changing employers ("leavers"). Moreover, some of those who report workplace digitalization may have experienced this due to changing occupations while others experience digitalization

[27] This number is derived from the economic costs per worker (0.3325 days x 332 euros per day) multiplied by the number of manual workers (one-third of 24.6 million employees in Germany, i.e. 8.2 million workers).

while staying in the same occupation. In order to examine whether our results are driven by occupation or job movers, Table 6 in Appendix A includes dummies for whether workers have changed jobs, firms, or both between 2011 and 2019 and indicates that results remain essentially unchanged compared to the baseline.

So far, we examined the effect heterogeneity between manual and cognitive workers, whereby this distinction resulted from a principal component analysis (PCA, see Appendix B.4 for details) based on the task structure in the initial workplace. Yet, as shown before, this task-based classification is strongly linked to formal education. Only one out of 10 manual workers has a college degree, compared to 40% of all cognitive workers. On the other hand, 7% of the manual workers have no vocational degree, while this share among cognitive workers is only 1%.

Table 2: Health effects by education group

	Change of subjective health			Sickness absence days		
	(1)	(2)	(3)	(4)	(5)	(6)
Digitalization (Unqualified)	-0.402*	-0.419*	-0.408*	14.075**	14.092**	14.218**
	(0.226)	(0.222)	(0.218)	(5.579)	(5.574)	(5.551)
Digitalization (Qualified)	-0.089	-0.094	-0.077	0.865	0.886	0.828
	(0.090)	(0.090)	(0.092)	(1.902)	(1.928)	(1.899)
Digitalization (College)	0.092	0.095	0.087	-0.533	-0.500	-0.612
	(0.085)	(0.080)	(0.080)	(0.913)	(0.934)	(0.963)
Computerization	-0.081	-0.077	-0.085	0.451	0.423	0.521
	(0.062)	(0.061)	(0.061)	(1.125)	(1.126)	(1.141)
Further controls	Occupation	Industry	Firm	Occupation	Industry	Firm
R-squared	0.44	0.45	0.47	0.15	0.15	0.16
N	3235	3235	3235	3049	3049	3049

Notes: This table reports the effect of technological change on a change in individuals' subjective health between 2019 and 2011 (columns (1) – (3)) and the number of sickness absence days in 2019 (columns (4) – (6)). Subjective health is measured in each year on a 10-point Likert scale. Digitalization (computerization) refers to a change in the use of modern (mature) digital work equipment, like smart devices (computers). The construction of the treatment variables is explained in Section 2.3. For each skill level an interaction between an indicator for being in the respective education group and digitalization is added to the measure of digitalization, analogue to the interaction with worker types in Equation 3. (Un-)Qualified refers to individuals with(out) vocational degree that have not obtained a bachelor's or master's degree. College refers to individuals with at least a bachelor's degree. The sample consists of respondents from the DiWaBe employee survey conducted in 2019, linked to IAB administrative records and a firm survey. It consists of individuals in regular employment in one of the surveyed firms in 2011, aged 20-55 in 2011, giving consent to linking with administrative records, and having non-missing responses in treatment and outcome variables. To ensure that results are representative for the German workforce, we use post-stratified trimmed survey weights (see Appendix B.2 for details). In columns (1) and (4), we control for individual- and baseline firm-level controls as well as 2-digit occupation fixed effects. In columns (2) and (5) we add one-digit industry fixed effects. In columns (3) and (6) we further add controls reflecting the firm structure (see Section 4 for details). Robust standard errors clustered at the firm level appear in parentheses.

In Table 2, we therefore examine the effect heterogeneity based on individuals' formal education and find the expected pattern: Workplace digitalization has sizeable negative effects on self-reported health changes and sick leave for the least educated workers while leaving more educated workers unaffected. Hence, the unequal impact of digitalization on workers' health can be seen from both a task and a skill perspective: The health burden stemming from modern technological change comes most strongly for workers with a low level of education in formerly more analogue workplaces. We see this as a first hint that formal education and training might play a role in mitigating these adverse effects.

5.3 Channels and Compensating Differentials

As shown in Goh et al. (2016), workers' health can be impaired by technology in various ways, for instance, by increasing job insecurity or changes in working hours. As shown in Section 3, digitalization is associated with the adoption of new tools and a reconfiguration of tasks, which points to an increase in the complexity of workplaces. If this increased complexity and the associated increase in time and performance pressure were the sole reason for the negative health effects of digitalization for manual workers, we would expect the latter to disappear once we control for changes in the tasks performed and the tools used as the workplace.[28] Indeed, as Table 13 in Appendix A shows, the effect on subjective health becomes smaller and insignificant, although not zero, when controlling for task changes. For sick days, the effect size remains largely unaffected, suggesting that manual workers' reporting of illness and their actual perceived change in health are influenced by either other digitalization accompanying factors or, more directly, through technostress. To see if the health effects are driven by the *increasing complexity* and not the *higher frequency* of tools used, we control for the change in ICT and machine use in Table 14 in Appendix A. Coefficients for both subjective and objective health outcomes remain similar, thus strengthening our interpretation that modern technological change impairs health through technostress.

As shown, for example, by Abeliansky et al. (2024), technological change can affect workers' mental health through the fear of worsening employment prospects, especially for those in routine occupations. To investigate if digitalization impairs manual workers rather indirectly through the fear of replacement than directly through actual changes at the workplace, we use workers'

[28]Note that by adding these changes as controls, we also take account of differences in the task and tool changes between manual and cognitive workers, albeit Section 3 suggested these differences to be small and insignificant.

perception of their job being at risk as alternative outcome variables. However, we find that digitalization does not affect workers' job satisfaction, their perception of their workplace being at risk, or being actually worried about losing their job (see Table 15 in Appendix A). It also seems that there is little reason for this concern as Table 16 in Appendix A shows that neither manual nor cognitive workers report a reduction in real or contracted working hours related to digitalization.

Administrative data confirm the results from the survey, as for both groups, there is no digitalization-induced change in employment and earnings prospects.[29] Table 5 in Appendix A examines whether digitalization is associated with a change in the log of the total number of days employed and the log of the cumulative labor earnings between 2012 and 2019. However, there appears to be no link between these two outcomes and workplace-level digitalization. This is true for both the average worker (Panel A) and for each worker type (Panel B). While this suggests that neither concerns nor worsening economic circumstances are responsible for the health effects, it also implies that manual workers are not being compensated for the adverse health effects they experience.

5.4 Moderating Factors

Whether and how the introduction of new technologies in the workplace affects workers' health likely depends on existing organizational structures, corporate culture, and working conditions.[30] Therefore, we further investigate whether adequate training, the presence of works councils, and support from supervisors can mitigate the negative health effects of digitalization for those being affected, i.e. manual workers.

First, we explore the role of training. If individuals feel exposed to digitalization because they lack the necessary skills to meet changing demands, (adequate) training might reduce such feelings and help workers adjust to changing skill needs. Hence, we run an augmented version of Equation 2 that additionally includes an interaction term of digitalization with a dummy for whether the worker participated in any training over the last 12 months in 2019. Due to the absence of health effects for cognitive workers, we focus on manual workers in this analysis.

Table 3 contains the results. Strikingly, we find that the negative effect of workplace digital-

[29] This is different from other forms of technological change, such as robotization, which have been found to impact workers in economic terms, but also organizational structures of the firm (Dixon et al., 2021).

[30] Beyond the firm level, Lauterbach et al. (2023) provide cross-country evidence that labor market policies like unemployment benefits might mitigate perceived technostress.

ization on their health is entirely driven by workers who did not participate in training. Training participation completely offsets (and in some specifications even slightly overcompensates) the adverse health effects of technology adoption for manual workers. This especially holds in the specifications where we control for the detailed structure of the firm. Thus, two similar workers who have similar individual and workplace characteristics and work in a comparable firm in terms of their organizational structure and level of technology face very different health outcomes from digitalization depending on whether they participate in training or not.

Table 3: Manual workers' health effects by individual-level training uptake

	Change of subjective health			Sickness absence days		
	(1)	(2)	(3)	(4)	(5)	(6)
Digitalization	-0.212	-0.206	-0.252*	10.462***	11.017***	11.492***
	(0.138)	(0.139)	(0.137)	(3.849)	(3.622)	(3.657)
Yes × Digitalization	0.263	0.234	0.387**	-7.558*	-8.052**	-10.783**
	(0.191)	(0.187)	(0.179)	(4.134)	(3.998)	(4.338)
Computerization	-0.139	-0.137	-0.151	0.171	-0.068	0.152
	(0.108)	(0.110)	(0.107)	(2.610)	(2.615)	(2.599)
Further controls	Occupation	Industry	Firm	Occupation	Industry	Firm
R-squared	0.57	0.58	0.61	0.34	0.35	0.39
N	1009	1009	1009	936	936	936

Notes: This table reports the effect of technological change on a change in individuals' subjective health between 2019 and 2011 (columns (1) – (3)) and the number of sickness absence days in 2019 (columns (4) – (6)). Subjective health is measured in each year on a 10-point Likert scale. Digitalization (computerization) refers to a change in the use of modern (mature) digital work equipment, like smart devices (computers). The construction of the treatment variables is explained in Section 2.3. The sample consists of respondents from the DiWaBe employee survey conducted in 2019, linked to IAB administrative records and a firm survey. It consists of individuals in regular employment in one of the surveyed firms in 2011, aged 20-55 in 2011, giving consent to linking with administrative records, and having non-missing responses in treatment and outcome variables. To ensure that results are representative for the German workforce, we use post-stratified trimmed survey weights (see Appendix B.2 for details). Additionally, we restrict the sample to manual workers as only they appear to be negatively affected by technological change. Details on this classification can be found in Section 2.4. In columns (1) and (4), we control for individual- and baseline firm-level controls as well as 2-digit occupation fixed effects. In columns (2) and (5) we add one-digit industry fixed effects. In columns (3) and (6) we further add controls reflecting the firm structure (see Section 4 for details). Throughout all specifications, we interact our measure of digitalization with an indicator of whether a manual worker participated in any training during the last 12 months prior to the interview. Robust standard errors clustered at the firm level appear in parentheses.

A caveat to these results is that training participation could be endogenous to worker health. If workers who suffer more from digitalization participate less in training, we have a reverse causality issue. In Table 4, we therefore use firm-provided training rather than individual take-up as a moderating factor.[31]

Table 4: Health effects by firm-level training provision

	Change of subjective health			Sickness absence days		
	(1)	(2)	(3)	(4)	(5)	(6)
Digitalization	-0.485**	-0.452**	-0.448**	7.553	7.496	7.508
	(0.192)	(0.184)	(0.187)	(6.219)	(6.235)	(6.046)
Digitalization × ICT skills	0.131**	0.129**	0.144**	-1.021	-1.036	-1.051
	(0.059)	(0.058)	(0.057)	(1.570)	(1.574)	(1.575)
Digitalization × Soft skills	-0.027	-0.030	-0.035	-0.373	-0.359	-0.335
	(0.056)	(0.054)	(0.055)	(0.832)	(0.863)	(0.826)
Digitalization × Upskilling	0.074*	0.066	0.050	-1.232	-1.175	-1.173
	(0.042)	(0.041)	(0.040)	(1.004)	(1.046)	(1.022)
Computerization	-0.071	-0.069	-0.077	0.913	0.856	0.886
	(0.070)	(0.070)	(0.069)	(1.024)	(1.014)	(1.018)
Further controls	Occupation	Industry	Firm	Occupation	Industry	Firm
R-squared	0.47	0.48	0.49	0.14	0.14	0.14
N	2617	2617	2617	2472	2472	2472

Notes: This table reports the effect of technological change on a change in individuals' subjective health between 2019 and 2011 (columns (1) – (3)) and the number of sickness absence days in 2019 (columns (4) – (6)). Subjective health is measured in each year on a 10-point Likert scale. Digitalization (computerization) refers to a change in the use of modern (mature) digital work equipment, like smart devices (computers). The construction of the treatment variables is explained in Section 2.3. The sample consists of respondents from the DiWaBe employee survey conducted in 2019, linked to IAB administrative records and a firm survey. It consists of individuals in regular employment in one of the surveyed firms in 2011, aged 20-55 in 2011, giving consent to linking with administrative records, and having non-missing responses in treatment and outcome variables. To ensure that results are representative for the German workforce, we use post-stratified trimmed survey weights (see Appendix B.2 for details). In columns (1) and (4), we control for individual- and baseline firm-level controls as well as 2-digit occupation fixed effects. In columns (2) and (5) we add one-digit industry fixed effects. In columns (3) and (6) we further add controls reflecting the firm structure (see Section 4 for details). Throughout all specifications, we interact our measure of digialization with firms' own assessment of whether or not (i) they increasingly train employees in the use of the latest ICT technologies, (ii) they increasingly train more interdisciplinary "soft" skills relative to job-specific skills and (iii) offer employees the opportunity to gain higher qualifications on the job. All assessments are on a 5-point Likert scale, asked in 2016 and relative to 2011. Robust standard errors clustered at the firm level appear in parentheses.

Specifically, firms were asked in 2016 whether (i) they increasingly train employees in the use of the latest ICT technologies, (ii) they increasingly train more interdisciplinary "soft" skills relative to job-specific skills and (iii) offer employees the opportunity to gain higher qualification in the last five years (on a 5-point Likert scale). If individuals' health is impaired by digitalization

[31]In this setting, we use the entire sample as due to missing information on training in the firm survey, the sub-sample of manual workers becomes very small.

through the higher complexity of tasks and digital tools used, we expect a strong positive moderating role of technology-related training. A more general "upskilling" and soft skill training, on the other hand, could provide important resources for workers in order to deal with increasing job demands, but we do not expect them to play a similar role for shielding workers' health from technostress. In line with this argumentation, we find that both types of general training have no counteracting effect, while, by contrast, employees in firms with extensive digital training experience less of a decline in their subjective health related to digitalization than those in firms without such training efforts. Although the attenuating effect of firm-level training is less strong than in the case of individual take-up, it suggests that the positive effect of training is not solely driven by the endogenous sorting of workers into training.

In addition to training, a supportive and employee-oriented firm culture might help employees deal with digitalization. Hence, we examine whether the presence of a works council or the perceived support from superiors mitigates the negative health effects of digitalization for manual workers. While the presence of a works council does not seem to have any moderating effect on the health effect of digitalization, we find some evidence that workers are less likely to experience increasing sickness days if they feel supported by their superiors (see Tables 12 and 11 in Appendix A). For subjective health, we also find the expected positive signs, but the effect remains insignificant. This might be indicative that a supportive firm culture can help workers to better adjust to workplace changes, albeit we caution against drawing too strong policy conclusions from these results given the potentially endogenous perception of a supportive work environment by employees.

6 Conclusion

To the best of our knowledge, this paper is the first to estimate the health effects of frontier technologies from the latest wave of technological advances on a representative sample of workers. Utilizing a novel linked employer-employee dataset from Germany, we capture the increasing prevalence of technologies such as the Internet of Things, AI, Big Data, and the Internet of Services at individual workplaces.

Our findings indicate that the rise of these modern technologies, which we refer to as digitalization, is associated with increased work complexity, heightened time and performance pressure, and more service-oriented tasks. While the health of workers initially engaged in cognitive tasks remains unaffected by these changes, the health of manual workers significantly deteriorates as a result of workplace digitalization. Notably, manual workers already reported poorer health prior to the introduction of new technologies, suggesting that digitalization exacerbates existing health disparities between manual and cognitive workers. Given that manual workers typically have lower education levels than cognitive workers, this trend also amplifies the well-documented health gaps across different education groups.

Our paper thus introduces another dimension of inequality to the well-documented widening of wage and income disparities caused by automation technologies (Acemoglu and Restrepo, 2022). Since health is a key determinant of employment and income prospects (Currie and Madrian, 1999; García-Gómez, 2011), our findings have significant implications for perpetuating inequality dynamics. On a positive note, our research highlights the importance of the firm context, providing tentative evidence that a supportive corporate culture and targeted training measures can help workers cope with technological disruptions. However, further research is necessary to determine how re-skilling initiatives can effectively prevent technology shocks from translating into health shocks for the most vulnerable workers.

References

Abeliansky, A. L., Beulmann, M., and Prettner, K. (2024). Are they coming for us? Industrial robots and the mental health of workers. *Research Policy*, 53(3):104956.

Acemoglu, D., Reed, T., and Robinson, J. A. (2014). Chiefs: Economic Development and Elite Control of Civil Society in Sierra Leone. *Journal of Political Economy*, 122(2):319–368.

Acemoglu, D. and Restrepo, P. (2019). Automation and New Tasks: How Technology Displaces and Reinstates Labor. *Journal of Economic Perspectives*, 33(2):3–30.

Acemoglu, D. and Restrepo, P. (2022). Tasks, Automation, and the Rise in U.S. Wage Inequality. *Econometrica*, 90(5):1973–2016.

Arntz, M., Dengler, K., Dorau, R., Gregory, T., Hartwig, M., Helmrich, R., Lehmer, F., Matthes, B., Tisch, A., Wischniewski, S., and Zierahn, U. (2020). Digitalisierung und Wandel der Beschäftigung (DIWABE): Eine Datengrundlage für die interdisziplinäre Sozialpolitikforschung. ZEW Dokumentation 20-02, ZEW - Leibniz-Zentrum für Europäische Wirtschaftsforschung, Mannheim.

Autor, D. H. and Dorn, D. (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review*, 103(5):1553–1597.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics*, 118(4):1279–1333.

Bakker, A. B. and Demerouti, E. (2007). The Job Demands-Resources model: State of the art. *Journal of Managerial Psychology*, 22(3):309–328.

Bárány, Z. L. and Siegel, C. (2020). Biased technological change and employment reallocation. *Labour Economics*, 67:101930.

BAuA (2021). Volkswirtschaftliche Kosten durch Arbeitsunfähigkeit 2019.

Bellet, C. S., De Neve, J.-E., and Ward, G. (2024). Does Employee Happiness have an Impact on Productivity? *Management Science*, 70(3):1656–1679.

Blasco, S., Rochut, J., and Rouland, B. (2024). Displaced or depressed? Working in automatable jobs and mental health. *Industrial Relations: A Journal of Economy and Society*, page irel.12356.

Brod, C. (1984). *Technostress: The Human Cost of the Computer Revolution.* Addison-Wesley, Reading, Mass.

Callison, K. and Pesko, M. F. (2022). The effect of paid sick leave mandates on coverage, work absences, and presenteeism. *Journal of Human Resources*, 57(4):1178–1208.

Case, A. and Deaton, A. (2021). Life expectancy in adulthood is falling for those without a BA degree, but as educational gaps have widened, racial gaps have narrowed. *Proceedings of the National Academy of Sciences*, 118(11):e2024777118.

Currie, J. (2009). Healthy, Wealthy, and Wise: Socioeconomic Status, Poor Health in Childhood, and Human Capital Development. *Journal of Economic Literature*, 47(1):87–122.

Currie, J. and Madrian, B. C. (1999). Health, health insurance and the labor market. *Handbook of Eabor Lconomics*, 3:3309–3416.

Dauth, W., Findeisen, S., Suedekum, J., and Woessner, N. (2021). The Adjustment of Labor Markets to Robots. *Journal of the European Economic Association*, 19(6):3104–3153.

Dengler, K. and Gundert, S. (2021). Digital transformation and subjective job insecurity in Germany. *European Sociological Review*, 37(5):799–817.

Dixon, J., Hong, B., and Wu, L. (2021). The Robot Revolution: Managerial and Employment Consequences for Firms. *Management Science*, 67(9):5586–5605.

Edin, P.-A., Evans, T., Graetz, G., Hernnäs, S., and Michaels, G. (2023). Individual Consequences of Occupational Decline. *The Economic Journal*, 133(654):2178–2209.

Finkelstein, A., Gentzkow, M., and Williams, H. (2021). Place-Based Drivers of Mortality: Evidence from Migration. *American Economic Review*, 111(8):2697–2735.

Finkelstein, A., Schilbach, M. J. N. F., and Zhang, J. (2024). Lives vs. Livelihoods: The impact of the great recession on mortality and welfare. Technical report, National Bureau of Economic Research, Inc.

García-Gómez, P. (2011). Institutions, health shocks and labour market outcomes across Europe. *Journal of Health Economics*, 30(1):200–213.

Gihleb, R., Giuntella, O., Stella, L., and Wang, T. (2022). Industrial robots, Workers' safety, and health. *Labour Economics*, 78:102205.

Goh, J., Pfeffer, J., and Zenios, S. A. (2016). The Relationship Between Workplace Stressors and Mortality and Health Costs in the United States. *Management Science*, 62(2):608–628.

Graetz, G. and Michaels, G. (2018). Robots at Work. *The Review of Economics and Statistics*, 100(5):753–768.

Gunadi, C. and Ryu, H. (2021). Does the rise of robotic technology make people healthier? *Health Economics*, 30(9):2047–2062.

Hernnäs, S. (2023). Mortality, morbidity, and occupational decline. Technical report, IFAU-Institute for Evaluation of Labour Market and Education Policy.

Lauterbach, S., A., Tober, T., Kunze, F., and Busemeyer, M. R. (2023). Can welfare states buffer technostress? Income and technostress in the context of various OECD countries. *PLOS ONE*, 18(12):e0295229.

Lehmer, F., Müller, C., Arntz, M., Gregory, T., Hanebrink, A., Janssen, S., Matthes, B., and Zierahn, U. (2021). IAB-ZEW-Labor Market 4.0-Establishment Survey (BIZA)Betriebsbefragung IAB-ZEW-Arbeitswelt 4.0 (BIZA).

Lordan, G. and Stringer, E.-J. (2022). People versus machines: The impact of being in an automatable job on Australian worker's mental health and life satisfaction. *Economics & Human Biology*, 46:101144.

Maclean, J. C., Pichler, S., and Ziebarth, N. R. (2020). Mandated sick pay: Coverage, utilization, and welfare effects. Technical report, National Bureau of Economic Research.

Marmot, M., Shipley, M., and Rose, G. (1984). Inequalities in Death—Secific Explanations of a General Pattern? *The Lancet*, 323(8384):1003–1006.

Marmot, M., Stansfeld, S., Patel, C., North, F., Head, J., White, I., Brunner, E., Feeney, A., Marmot, M., and Smith, G. (1991). Health inequalities among British civil servants: The Whitehall II study. *The Lancet*, 337(8754):1387–1393.

Meara, E. R., Richards, S., and Cutler, D. M. (2008). The Gap Gets Bigger: Changes In Mortality And Life Expectancy, By Education, 1981–2000. *Health Affairs*, 27(2):350–360.

Müller, C., Ungerer, K., and Müller, J. (2023). DiWaBe-Beschäftigtenbefragung. *FDZ-Datenreport*.

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

Pierce, J. R. and Schott, P. K. (2020). Trade Liberalization and Mortality: Evidence from US Counties. *American Economic Review: Insights*, 2(1):47–63.

Sánchez De La Sierra, R. (2020). On the Origins of the State: Stationary Bandits and Taxation in Eastern Congo. *Journal of Political Economy*, 128(1):32–74.

Schaufeli, W. B. and Bakker, A. B. (2004). Job demands, job resources, and their relationship with burnout and engagement: A multi-sample study. *Journal of Organizational Behavior*, 25(3):293–315.

Spitz-Oener, A. (2006). Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure. *Journal of Labor Economics*, 24(2):235–270.

Sullivan, D. and Wachter, T. V. (2009). Job Displacement and Mortality: An Analysis Using Administrative Data [*]. *Quarterly Journal of Economics*, 124(3):1265–1306.

Tarafdar, M., Pullins, E. B., and Ragu-Nathan, T. S. (2015). Technostress: Negative effect on performance and possible mitigations. *Information Systems Journal*, 25(2):103–132.

A Appendix: Additional Tables and Figures

Table 5: Economic effects

	Log days employed			Log labor earnings		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Overall						
Digitalization	0.000	0.002	0.001	0.000	0.004	0.004
	(0.008)	(0.008)	(0.008)	(0.013)	(0.013)	(0.013)
Computerization	0.015^{**}	0.015^{**}	0.016^{**}	0.040^{***}	0.039^{***}	0.043^{***}
	(0.007)	(0.007)	(0.007)	(0.013)	(0.013)	(0.013)
R-squared	0.27	0.27	0.28	0.65	0.66	0.66
Panel B: By workplace type						
Digitalization (Manual)	0.013	0.014	0.015	0.015	0.015	0.019
	(0.011)	(0.011)	(0.012)	(0.020)	(0.020)	(0.021)
Digitalization (Cognitive)	-0.005	-0.004	-0.004	-0.007	-0.002	-0.003
	(0.010)	(0.010)	(0.010)	(0.016)	(0.016)	(0.015)
Computerization	0.014^{*}	0.013^{*}	0.015^{**}	0.039^{***}	0.038^{***}	0.042^{***}
	(0.007)	(0.007)	(0.007)	(0.013)	(0.013)	(0.013)
Further controls	Occupation	Industry	Firm	Occupation	Industry	Firm
R-squared	0.27	0.28	0.28	0.65	0.66	0.67
N	3167	3167	3167	3167	3167	3167

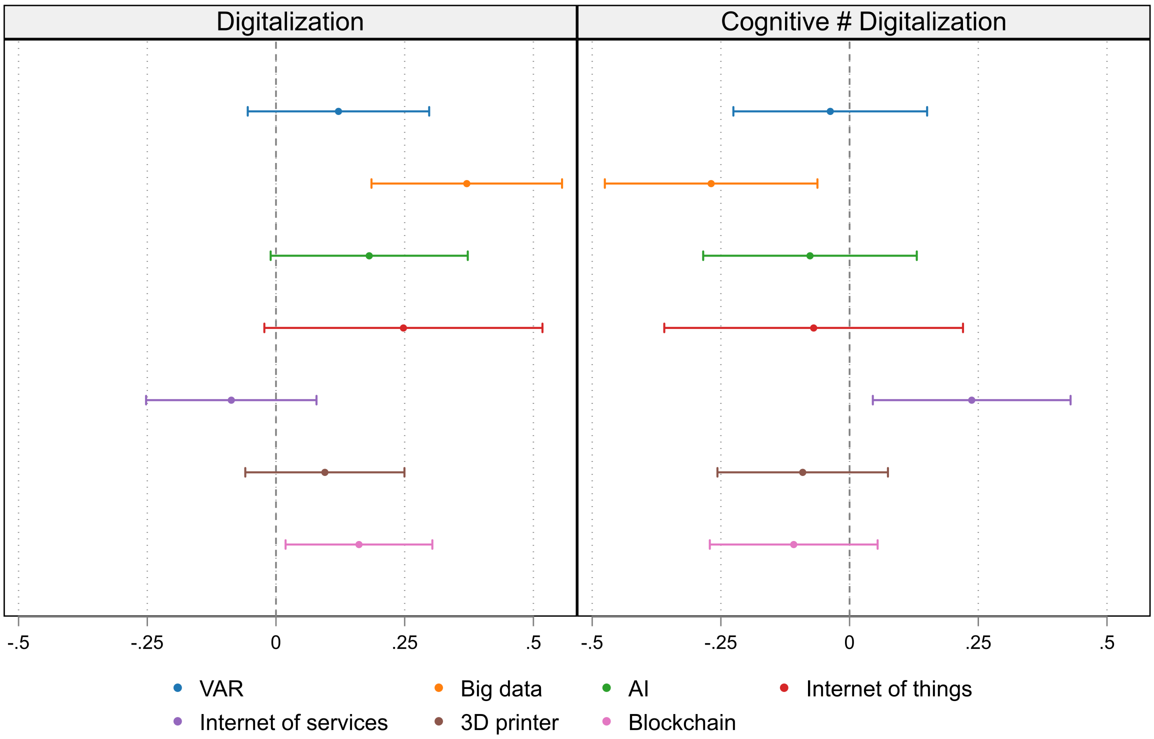
Notes: This table reports the effect of technological change on the log total numbers of days employed (columns (1) – (3)) and the log cumulative earnings between 2012 and 2019 (columns (4) – (6)). Digitalization (computerization) refers to a change in the use of modern (mature) digital work equipment, like smart devices (computers). The construction of the treatment variables is explained in Section 2.3. Panel A shows the overall effect of digitalization and computerization. In Panel B, an interaction between an indicator for the worker type and digitalization is added to the measure of digitalization as shown in Equation 3. Based on initial workplace in 2011 and using a PCA in order to reduce dimensions, respondents were divided into two main worker types: manual and cognitive workers. Details on this classification can be found in Section 2.4. The sample consists of respondents from the DiWaBe employee survey conducted in 2019, linked to IAB administrative records and a firm survey. It consists of individuals in regular employment in one of the surveyed firms in 2011, aged 20-55 in 2011, giving consent to linking with administrative records, and having non-missing responses in treatment and outcome variables. To ensure that results are representative for the German workforce, we use post-stratified trimmed survey weights (see Appendix B.2 for details). In columns (1) and (4), we control for individual- and baseline firm-level controls as well as 2-digit occupation fixed effects. In columns (2) and (5) we add one-digit industry fixed effects. In columns (3) and (6) we further add controls reflecting the firm structure (see Section 4 for details). Robust standard errors clustered at the firm level appear in parentheses.

Table 6: Health effects after controlling for occupation and firm switching

	Change of subjective health			Sickness absence days		
	(1)	(2)	(3)	(4)	(5)	(6)
Digitalization (Manual)	-0.238**	-0.242**	-0.222*	7.689**	7.684**	7.572**
	(0.103)	(0.103)	(0.116)	(3.190)	(3.187)	(3.201)
Digitalization (Cognitive)	0.064	0.063	0.059	-1.327	-1.326	-1.319
	(0.075)	(0.072)	(0.070)	(0.871)	(0.867)	(0.883)
Computerization	-0.075	-0.071	-0.079	0.326	0.300	0.346
	(0.060)	(0.059)	(0.059)	(0.960)	(0.960)	(0.982)
Further controls	Occupation	Industry	Firm	Occupation	Industry	Firm
R-squared	0.45	0.45	0.47	0.16	0.16	0.16
N	3235	3235	3235	3049	3049	3049

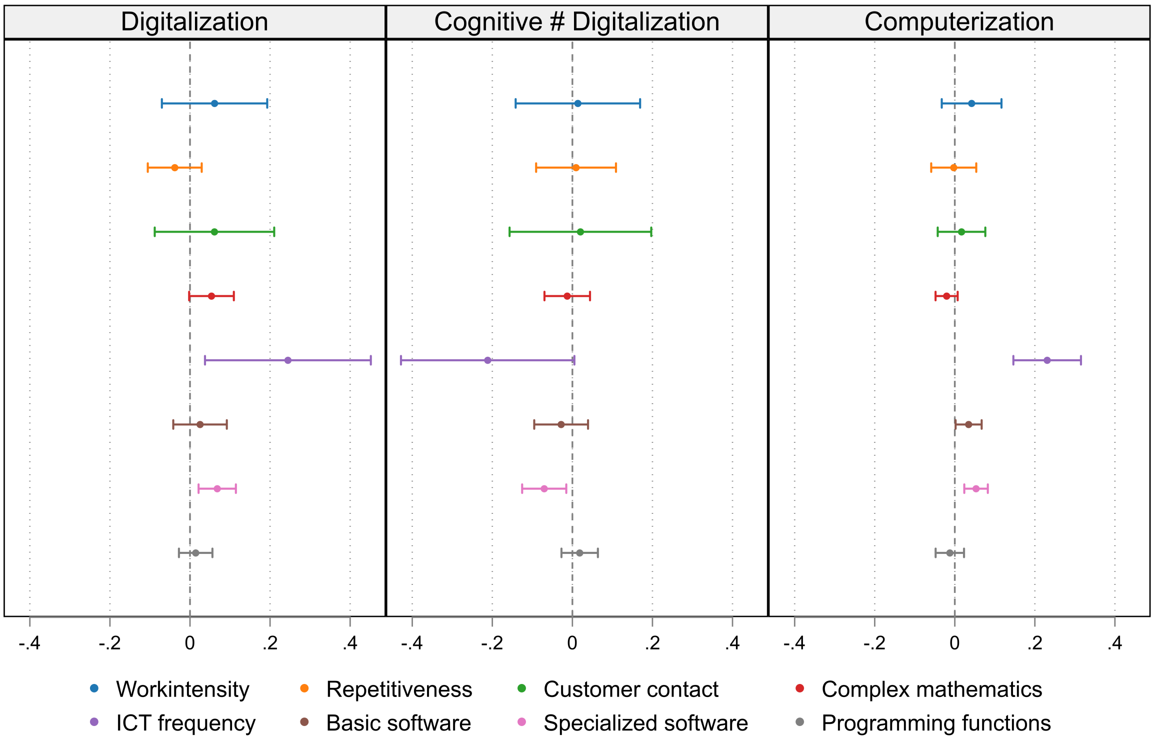
Notes: This table reports the effect of technological change on a change in individuals' subjective health between 2019 and 2011 (columns (1) – (3)) and the number of sickness absence days in 2019 (columns (4) – (6)). Subjective health is measured in each year on a 10-point Likert scale. Digitalization (computerization) refers to a change in the use of modern (mature) digital work equipment, like smart devices (computers). The construction of the treatment variables is explained in Section 2.3. Based on initial workplace in 2011 and using a PCA in order to reduce dimensions, respondents were divided into two main worker types: manual and cognitive workers. For each worker type an interaction between an indicator for the type and digitalization is added to the measure of digitalization as shown in Equation 3. Details on this classification can be found in Section 2.4. The sample consists of respondents from the DiWaBe employee survey conducted in 2019, linked to IAB administrative records and a firm survey. It consists of individuals in regular employment in one of the surveyed firms in 2011, aged 20-55 in 2011, giving consent to linking with administrative records, and having non-missing responses in treatment and outcome variables. To ensure that results are representative for the German workforce, we use post-stratified trimmed survey weights (see Appendix B.2 for details). In columns (1) and (4), we control for individual- and baseline firm-level controls as well as 2-digit occupation fixed effects. In columns (2) and (5) we add one-digit industry fixed effects. In columns (3) and (6) we further add controls reflecting the firm structure (see Section 4 for details). Additionally, we include a dummy for whether respondents switched firms, occupations, or both. Robust standard errors clustered at the firm level appear in parentheses.

Figure 5: Digitalization and change in tools used by PCA score



Notes: This figure displays the coefficients of separate regression of a change in the use of a specific digital tool used on digitalization, overall and interacted with a dummy variable that equals one if a person belongs to the group of cognitive workers. "VAR" refers to virtual and augmented reality, "AI" to artificial intelligence. The frequency of tool use is measured on a 5-point Likert scale in 2011 and 2019 and the change is calculated as the difference. Digitalization refers to a change in the use of modern digital work equipment, like smart devices. The construction of the treatment variable is explained in Section 2.3. Cognitive workers are defined as those in the upper two tertiles of the PCA score distribution as described in 2.4. In all regressions, we control for initial workplace and firm characteristics (as in Equation 2), as well as 2-digit occupation fixed effects. Observations are weighted using trimmed post-stratified sampling weights, further explained in Appendix B.2. Whiskers display 95%-confidence intervals obtained from robust standard errors clustered at the firm level.

Figure 6: Digitalization and task change by PCA score



Notes: This figure displays the coefficients of separate regression of a change in the performance of tasks on digitalization, overall and interacted with a dummy variable that equals one if a person belongs to the group of cognitive workers. In both 2019 and 2011, respondents were asked to rate (on a 5-point Likert scale) how often they (i) work under deadline or performance pressure, (ii) perform repeating identical work processes, (iii) deal with people who are not colleagues, (iv) how complex their mathematical tasks are (No calculation requirements, simple calculations, fraction/percent calculations or similar complex, area/volume calculations or similar complex, higher mathematics) and (v) how often they use ICT. Further they were asked if they use (vi) standard software (e.g. Microsoft Office), (vii) job-specific software, or (viii) programming functions. The change is calculated as the simple difference between respondents' assessment in 2019 and 2011. Digitalization refers to a change in the use of modern digital work equipment, like smart devices. The construction of the treatment variable is explained in Section 2.3. Cognitive workers are defined as those in the upper two tertiles of the PCA score distribution as described in 2.4. In all regressions, we control for initial workplace and firm characteristics (as in Equation 2), as well as 2-digit occupation fixed effects. Observations are weighted using trimmed post-stratified sampling weights, further explained in Appendix B.2. Whiskers display 95%-confidence intervals obtained from robust standard errors clustered at the firm level.

Table 7: Summary statistics: Individual-level controls

	Manual	Cognitive	Total
Age (in 2011)	38.80	41.15	40.08
	(9.89)	(8.67)	(9.32)
Female	0.32	0.51	0.42
	(0.47)	(0.50)	(0.49)
Migrant	0.10	0.06	0.08
	(0.30)	(0.23)	(0.27)
No vocational degree	0.07	0.01	0.04
	(0.26)	(0.11)	(0.19)
Vocational degree	0.83	0.59	0.70
	(0.38)	(0.49)	(0.46)
College degree	0.10	0.40	0.26
	(0.30)	(0.49)	(0.44)
Extraversion	2.79	3.10	2.96
	(0.93)	(0.91)	(0.93)
Agreeableness	2.05	2.16	2.11
	(0.93)	(0.69)	(0.81)
Conscientiousness	2.20	2.24	2.23
	(0.61)	(0.51)	(0.56)
Emotional Stability (Low Neuroticism)	3.15	3.04	3.09
	(0.83)	(0.78)	(0.80)
Openness to Experiences	2.99	3.07	3.03
	(0.89)	(0.93)	(0.91)
Technocomprehension 2011	2.45	2.71	2.59
	(1.45)	(1.01)	(1.24)
PCA score	-1.27	0.40	-0.37
	(0.59)	(0.43)	(0.98)
Subjective health 2011	7.80	7.92	7.86
	(1.78)	(1.72)	(1.75)
Log mean daily earnings 2009-2011	4.22	4.58	4.42
	(0.44)	(0.52)	(0.52)

Notes: This table contains the mean and standard deviations (in parentheses) of all individual-level variables, which are used as controls in the baseline version of Equation 2 and 3 separately displayed for the group of manual workers, cognitive workers, and over the whole sample. Observations are weighted using trimmed post-stratified sampling weights, further explained in Appendix B.2. The Big Five personality traits (extraversion, agreeableness, conscientiousness, emotional stability, and openness to experiences) are calculated as simple mean based on the 10-item inventory and 5-point Likert scales (from 0 to 4). The PCA score captures the degree to which workplaces contain typical office tasks in 2011 and its calculation is described in Appendix B.4.

Table 8: Summary statistics: Firm-level controls

	Manual	Cognitive	Total
Baseline firm controls			
Firm size <50	0.46	0.44	0.45
	(0.50)	(0.50)	(0.50)
Firm size 50-199	0.23	0.24	0.24
	(0.42)	(0.42)	(0.42)
Firm size >=200	0.31	0.33	0.32
	(0.46)	(0.47)	(0.47)
Share of blue-collar workers 2011	0.38	0.17	0.27
	(0.34)	(0.25)	(0.31)
Additional firm controls			
Manufacturing establishment	0.33	0.21	0.27
	(0.47)	(0.41)	(0.44)
Public entity	0.08	0.12	0.10
	(0.27)	(0.33)	(0.30)
Trainee program	0.64	0.78	0.72
	(0.48)	(0.41)	(0.45)
Age structure (share above 55)	0.11	0.13	0.12
	(0.09)	(0.11)	(0.10)
Skill structure (share high-qualified)	0.11	0.27	0.20
	(0.14)	(0.24)	(0.22)
Firm-level share 2011: Analogue	54.29	42.14	47.60
	(26.28)	(22.94)	(25.23)
Firm-level share 2011: Computerized	33.89	48.79	42.06
	(24.76)	(24.28)	(25.59)
Firm-level share 2011: Digitalized	5.73	6.41	6.10
	(14.47)	(12.68)	(13.52)

Notes: This table contains the mean and standard deviations (in parentheses) of all firm-level variables, which are used as controls in either the baseline or an advanced version of Equation 2 and 3 separately displayed for the group of manual workers, cognitive workers, and over the whole sample. Observations are weighted using trimmed post-stratified sampling weights, further explained in Appendix B.2. Shares of technologies are based on the assessment of firms to which degree their office tools/machines are analogue/manually operated, IT-based/indirectly operated, or IT-integrated/operate autonomously (from 0 to 100). Similar to the worker level, these shares are weighted between machines and ICT by the share of blue-collar workers in 2011.

Table 9: Summary statistics: Outcome and treatment variables

	Manual	Cognitive	Total
Outcome variables			
Subjective health change	-0.46	-0.29	-0.36
	(2.11)	(1.83)	(1.96)
Days sick at work 2019	13.52	6.83	9.84
	(29.63)	(20.94)	(25.43)
Log total days employed 2012-2019	7.81	7.88	7.85
	(0.42)	(0.26)	(0.35)
Log total labor earnings 2012-2019	12.20	12.61	12.43
	(0.65)	(0.57)	(0.64)
Technological change			
Computerization	0.36	0.04	0.18
	(1.15)	(1.01)	(1.09)
Digitalization	0.40	0.56	0.48
	(1.13)	(1.12)	(1.13)
Baseline technology			
Computerization 2011	1.16	2.96	2.14
	(1.20)	(0.92)	(1.39)
Digitalization 2011	0.61	1.60	1.15
	(0.98)	(1.29)	(1.26)
Time share 2011: Computerized	14.90	40.56	28.94
	(20.46)	(28.32)	(28.13)
Time share 2011: Digitalized	8.10	25.72	17.74
	(16.55)	(29.91)	(26.27)

Notes: This table contains the mean and standard deviations (in parentheses) of all outcome and treatment variables, which are used in the empirical analysis, separately displayed for the group of manual workers, cognitive workers, and over the whole sample. Additional variable on the use of technology in 2011, which are not used in the analysis, are displayed at the bottom. As for technological change, digitalization/computerization is calculated as the weighted mean of the degree to which ICT and machines are smart/computer-based. Note that while we use a standardized measure of digitalization and computerization in the analysis, with a mean of 0 and a standard deviation of 1, here we display unstandardized values. Time shares refer to workers' assessment of their "working time spent using non-computerized, computerized or intelligently connected work equipment" (0-100). Observations are weighted using trimmed post-stratified sampling weights, further explained in Appendix B.2.

Table 10: Controlling for group-specific computerization

	Change of subjective health			Sickness absence days		
	(1)	(2)	(3)	(4)	(5)	(6)
Digitalization (Manual)	-0.195	-0.201	-0.176	7.797**	7.838**	7.652**
	(0.120)	(0.122)	(0.139)	(3.550)	(3.538)	(3.538)
Digitalization (Cognitive)	0.062	0.062	0.057	-1.269	-1.294	-1.272
	(0.075)	(0.073)	(0.070)	(0.828)	(0.820)	(0.836)
Computerization (Manual)	-0.151	-0.142	-0.158	0.045	-0.036	0.154
	(0.116)	(0.117)	(0.125)	(2.399)	(2.438)	(2.435)
Computerization (Cognitive)	-0.053	-0.050	-0.054	0.429	0.441	0.448
	(0.067)	(0.065)	(0.063)	(0.720)	(0.738)	(0.767)
Further controls	Occupation	Industry	Firm	Occupation	Industry	Firm
R-squared	0.44	0.45	0.46	0.15	0.15	0.16
N	3235	3235	3235	3049	3049	3049

Notes: This table reports the effect of technological change on a change in individuals' subjective health between 2019 and 2011 (columns (1) – (3)) and the number of sickness absence days in 2019 (columns (4) – (6)). Subjective health is measured in each year on a 10-point Likert scale. Digitalization (computerization) refers to a change in the use of modern (mature) digital work equipment, like smart devices (computers). The construction of the treatment variables is explained in Section 2.3. Based on initial workplace in 2011 and using a PCA in order to reduce dimensions, respondents were divided into two main worker types: manual and cognitive workers. For each worker type an interaction between an indicator for the type and digitalization is added to the measure of digitalization as shown in Equation 3. In this table, this is done analogously for computerization. Details on this classification can be found in Section 2.4. The sample consists of respondents from the DiWaBe employee survey conducted in 2019, linked to IAB administrative records and a firm survey. It consists of individuals in regular employment in one of the surveyed firms in 2011, aged 20-55 in 2011, giving consent to linking with administrative records, and having non-missing responses in treatment and outcome variables. To ensure that results are representative for the German workforce, we use post-stratified trimmed survey weights (see Appendix B.2 for details). In columns (1) and (4), we control for individual- and baseline firm-level controls as well as 2-digit occupation fixed effects. In columns (2) and (5) we add one-digit industry fixed effects. In columns (3) and (6) we further add controls reflecting the firm structure (see Section 4 for details). Robust standard errors clustered at the firm level appear in parentheses.

Table 11: Effect moderation: Support by superior

	Change of subjective health			Sickness absence days		
	(1)	(2)	(3)	(4)	(5)	(6)
Digitalization	-0.330*	-0.348*	-0.262	13.072***	13.726***	12.796***
	(0.183)	(0.189)	(0.195)	(3.318)	(3.339)	(3.248)
Yes × Digitalization	0.223	0.227	0.105	-7.499*	-7.794*	-7.674*
	(0.202)	(0.203)	(0.208)	(4.459)	(4.224)	(4.337)
Computerization	-0.076	-0.067	-0.111	-0.311	-0.675	-0.108
	(0.106)	(0.108)	(0.107)	(2.475)	(2.560)	(2.570)
Further controls	Occupation	Industry	Firm	Occupation	Industry	Firm
R-squared	0.60	0.60	0.64	0.34	0.35	0.39
N	993	993	993	921	921	921

Notes: This table reports the effect of technological change on a change in individuals' subjective health between 2019 and 2011 (columns (1) – (3)) and the number of sickness absence days in 2019 (columns (4) – (6)). Subjective health is measured in each year on a 10-point Likert scale. Digitalization (computerization) refers to a change in the use of modern (mature) digital work equipment, like smart devices (computers). The construction of the treatment variables is explained in Section 2.3. Digitalization is further interacted with an indicator that equals one if an individual reported feeling supported by their superior in 2019. The sample consists of respondents from the DiWaBe employee survey conducted in 2019, linked to IAB administrative records and a firm survey. It consists of individuals in regular employment in one of the surveyed firms in 2011, aged 20-55 in 2011, giving consent to linking with administrative records, and having non-missing responses in treatment and outcome variables. To ensure that results are representative for the German workforce, we use post-stratified trimmed survey weights (see Appendix B.2 for details). In this table, we further restrict our sample to workers classified as manual workers based on the 2011 workplace. Details on this classification can be found in Section 2.4. In columns (1) and (4), we control for individual- and baseline firm-level controls as well as 2-digit occupation fixed effects. In columns (2) and (5) we add one-digit industry fixed effects. In columns (3) and (6) we further add controls reflecting the firm structure (see Section 4 for details). Robust standard errors clustered at the firm level appear in parentheses.

Table 12: Effect moderation: Firm has a works council

	Change of subjective health			Sickness absence days		
	(1)	(2)	(3)	(4)	(5)	(6)
Digitalization	-0.013	0.008	0.039	16.118*	16.698*	15.894
	(0.222)	(0.233)	(0.224)	(9.598)	(10.041)	(10.028)
Yes × Digitalization	-0.148	-0.178	-0.214	-9.212	-9.539	-9.512
	(0.210)	(0.218)	(0.213)	(9.597)	(10.130)	(10.207)
Computerization	-0.150	-0.149	-0.156	0.260	0.148	0.575
	(0.112)	(0.112)	(0.111)	(2.739)	(2.812)	(2.698)
Further controls	Occupation	Industry	Firm	Occupation	Industry	Firm
R-squared	0.58	0.58	0.61	0.34	0.36	0.39
N	992	992	992	919	919	919

Notes: This table reports the effect of technological change on a change in individuals' subjective health between 2019 and 2011 (columns (1) – (3)) and the number of sickness absence days in 2019 (columns (4) – (6)). Subjective health is measured in each year on a 10-point Likert scale. Digitalization (computerization) refers to a change in the use of modern (mature) digital work equipment, like smart devices (computers). The construction of the treatment variables is explained in Section 2.3. Digitalization is further interacted with an indicator that equals one if a firm has a works council established. The sample consists of respondents from the DiWaBe employee survey conducted in 2019, linked to IAB administrative records and a firm survey. It consists of individuals in regular employment in one of the surveyed firms in 2011, aged 20-55 in 2011, giving consent to linking with administrative records, and having non-missing responses in treatment and outcome variables. To ensure that results are representative for the German workforce, we use post-stratified trimmed survey weights (see Appendix B.2 for details). In this table, we further restrict our sample to workers classified as manual workers based on the 2011 workplace. Details on this classification can be found in Section 2.4. In columns (1) and (4), we control for individual- and baseline firm-level controls as well as 2-digit occupation fixed effects. In columns (2) and (5) we add one-digit industry fixed effects. In columns (3) and (6) we further add controls reflecting the firm structure (see Section 4 for details). Robust standard errors clustered at the firm level appear in parentheses.

Table 13: Health effects conditional on task changes

	Change of subjective health			Sickness absence days		
	(1)	(2)	(3)	(4)	(5)	(6)
Digitalization (Manual)	-0.152	-0.162	-0.144	7.878**	8.169**	8.153**
	(0.127)	(0.122)	(0.130)	(3.325)	(3.334)	(3.299)
Digitalization (Cognitive)	0.046	0.058	0.064	-0.779	-0.731	-0.598
	(0.079)	(0.076)	(0.076)	(1.116)	(1.109)	(1.145)
Computerization	-0.117*	-0.115*	-0.134**	0.989	0.869	1.075
	(0.068)	(0.066)	(0.066)	(1.103)	(1.077)	(1.117)
Further controls	Occupation	Industry	Firm	Occupation	Industry	Firm
R-squared	0.48	0.49	0.50	0.25	0.25	0.26
N	2659	2659	2659	2520	2520	2520

Notes: This table reports the effect of technological change on a change in individuals' subjective health between 2019 and 2011 (columns (1) – (3)) and the number of sickness absence days in 2019 (columns (4) – (6)). Subjective health is measured in each year on a 10-point Likert scale. Digitalization (computerization) refers to a change in the use of modern (mature) digital work equipment, like smart devices (computers). The construction of the treatment variables is explained in Section 2.3. Based on initial workplace in 2011 and using a PCA in order to reduce dimensions, respondents were divided into two main worker types: manual and cognitive workers. For each worker type an interaction between an indicator for the type and digitalization is added to the measure of digitalization as shown in Equation 3. Details on this classification can be found in Section 2.4. The sample consists of respondents from the DiWaBe employee survey conducted in 2019, linked to IAB administrative records and a firm survey. It consists of individuals in regular employment in one of the surveyed firms in 2011, aged 20-55 in 2011, giving consent to linking with administrative records, and having non-missing responses in treatment and outcome variables. To ensure that results are representative for the German workforce, we use post-stratified trimmed survey weights (see Appendix B.2 for details). In columns (1) and (4), we control for individual- and baseline firm-level controls as well as 2-digit occupation fixed effects. In columns (2) and (5) we add one-digit industry fixed effects. In columns (3) and (6) we further add controls reflecting the firm structure (see Section 4 for details). Additionally, we control for task changes between 2019 and 2011 (for a detailed overview, see the notes of Figure 4). Robust standard errors clustered at the firm level appear in parentheses.

Table 14: Health effects conditional on change in frequency of ICT and machine use

	Change of subjective health			Sickness absence days		
	(1)	(2)	(3)	(4)	(5)	(6)
Digitalization (Manual)	-0.223**	-0.224**	-0.204*	7.774**	7.762**	7.677**
	(0.102)	(0.103)	(0.116)	(3.333)	(3.318)	(3.326)
Digitalization (Cognitive)	0.073	0.072	0.068	-1.152	-1.165	-1.155
	(0.076)	(0.073)	(0.071)	(0.842)	(0.835)	(0.849)
Computerization	-0.071	-0.064	-0.072	0.214	0.187	0.267
	(0.061)	(0.060)	(0.061)	(1.069)	(1.073)	(1.107)
Further controls	Occupation	Industry	Firm	Occupation	Industry	Firm
R-squared	0.44	0.45	0.46	0.15	0.15	0.16
N	3235	3235	3235	3049	3049	3049

Notes: This table reports the effect of technological change on a change in individuals' subjective health between 2019 and 2011 (columns (1) – (3)) and the number of sickness absence days in 2019 (columns (4) – (6)). Subjective health is measured in each year on a 10-point Likert scale. Digitalization (computerization) refers to a change in the use of modern (mature) digital work equipment, like smart devices (computers). The construction of the treatment variables is explained in Section 2.3. Based on initial workplace in 2011 and using a PCA in order to reduce dimensions, respondents were divided into two main worker types: manual and cognitive workers. For each worker type an interaction between an indicator for the type and digitalization is added to the measure of digitalization as shown in Equation 3. Details on this classification can be found in Section 2.4. The sample consists of respondents from the DiWaBe employee survey conducted in 2019, linked to IAB administrative records and a firm survey. It consists of individuals in regular employment in one of the surveyed firms in 2011, aged 20-55 in 2011, giving consent to linking with administrative records, and having non-missing responses in treatment and outcome variables. To ensure that results are representative for the German workforce, we use post-stratified trimmed survey weights (see Appendix B.2 for details). In columns (1) and (4), we control for individual- and baseline firm-level controls as well as 2-digit occupation fixed effects. In columns (2) and (5) we add one-digit industry fixed effects. In columns (3) and (6) we further add controls reflecting the firm structure (see Section 4 for details). Additionally, we control for the change in the frequency of ICT and machine use (asked in both 2019 and 2011 on a 5-point Likert scale) Robust standard errors clustered at the firm level appear in parentheses.

Table 15: Worries about job

	Job satisfaction		Job in danger		Job sorrow	
	(1)	(2)	(3)	(4)	(5)	(6)
Digitalization (Manual)	0.087	0.093	-0.023	-0.022	-0.013	-0.019
	(0.108)	(0.122)	(0.021)	(0.022)	(0.027)	(0.029)
Digitalization (Cognitive)	0.069	0.045	-0.006	-0.003	-0.015	-0.012
	(0.077)	(0.071)	(0.013)	(0.013)	(0.015)	(0.014)
Computerization	-0.163***	-0.156***	-0.009	-0.009	0.013	0.012
	(0.061)	(0.060)	(0.009)	(0.010)	(0.012)	(0.012)
Further controls	Occupation	Industry	Occupation	Industry	Occupation	Industry
R-squared	0.21	0.23	0.19	0.24	0.24	0.27
N	3234	3234	3215	3215	2993	2993

Notes: This table reports the effect of technological change on job satisfaction (columns (1) – (2)), workers' assessment of the likelihood their job being at risk (columns (3) – (4)), and the degree to which workers have actual sorrows about losing their job (columns (5) – (6)). Job satisfaction is measured in 2019 on a 10-point Likert scale. The other variables are measured on a 5-point Likert scale. Digitalization (computerization) refers to a change in the use of modern (mature) digital work equipment, like smart devices (computers). The construction of the treatment variables is explained in Section 2.3. Based on initial workplace in 2011 and using a PCA in order to reduce dimensions, respondents were divided into two main worker types: manual and cognitive workers. For each worker type an interaction between an indicator for the type and digitalization is added to the measure of digitalization as shown in Equation 3. Details on this classification can be found in Section 2.4. The sample consists of respondents from the DiWaBe employee survey conducted in 2019, linked to IAB administrative records and a firm survey. It consists of individuals in regular employment in one of the surveyed firms in 2011, aged 20-55 in 2011, giving consent to linking with administrative records, and having non-missing responses in treatment and outcome variables. To ensure that results are representative for the German workforce, we use post-stratified trimmed survey weights (see Appendix B.2 for details). In columns (1), (3), and (5), we control for individual- and baseline firm-level controls as well as 2-digit occupation fixed effects. In columns (2), (4), and (6) we add one-digit industry fixed effects. Robust standard errors clustered at the firm level appear in parentheses.

Table 16: Working time

	Change of real workingtime			Change of contracted workingtime		
	(1)	(2)	(3)	(4)	(5)	(6)
Digitalization (Manual)	0.023	0.084	0.022	0.080	0.096	0.053
	(0.488)	(0.481)	(0.483)	(0.294)	(0.295)	(0.294)
Digitalization (Cognitive)	0.291	0.458	0.529*	0.688**	0.738**	0.754**
	(0.322)	(0.317)	(0.311)	(0.303)	(0.303)	(0.293)
Computerization	0.367	0.311	0.223	0.069	0.058	0.033
	(0.258)	(0.266)	(0.251)	(0.190)	(0.192)	(0.187)
Further controls	Occupation	Industry	Firm	Occupation	Industry	Firm
R-squared	0.18	0.22	0.24	0.18	0.19	0.20
N	3133	3133	3133	3195	3195	3195

Notes: This table reports the effect of technological change on the change in hours actually worked per week (columns (1) – (3)) and contracted weekly working hours (columns (4) – (6)) based on the difference between workers' self-assessment in 2019 and 2011. Digitalization (computerization) refers to a change in the use of modern (mature) digital work equipment, like smart devices (computers). The construction of the treatment variables is explained in Section 2.3. Based on initial workplace in 2011 and using a PCA in order to reduce dimensions, respondents were divided into two main worker types: manual and cognitive workers. For each worker type an interaction between an indicator for the type and digitalization is added to the measure of digitalization as shown in Equation 3. Details on this classification can be found in Section 2.4. The sample consists of respondents from the DiWaBe employee survey conducted in 2019, linked to IAB administrative records and a firm survey. It consists of individuals in regular employment in one of the surveyed firms in 2011, aged 20-55 in 2011, giving consent to linking with administrative records, and having non-missing responses in treatment and outcome variables. To ensure that results are representative for the German workforce, we use post-stratified trimmed survey weights (see Appendix B.2 for details). In columns (1) and (4), we control for individual- and baseline firm-level controls as well as 2-digit occupation fixed effects. In columns (2) and (5) we add one-digit industry fixed effects. In columns (3) and (6) we further add controls reflecting the firm structure (see Section 4 for details). Robust standard errors clustered at the firm level appear in parentheses.

B Appendix: Data

B.1 DiWaBe: Survey participation and non-response

The CATI interviews for the DiWaBe employee survey were conducted by the survey provider *Umfragezentrum Bonn GmbH* between July and November 2019. All workers drawn from the sample population received a written invitation for the survey before being called. 16.4 percent of all invited workers participated in the survey, resulting in 7,900 interviews. On average, an interview lasted 37.5 minutes. Non-participation was typically due to general refusal of interviews, especially on the phone, as well as due to time restrictions. However, the topic of the survey was largely irrelevant to non-participation, which gives confidence that non-response was not influenced by awareness of or interest in the topic. Still, non-response was systematically lower among workers with a tertiary degree, and we take account of this in the sampling weights, see Appendix B.2.

B.2 DiWaBe: Sampling and Weights

Our analysis is based on individuals who took part in the DiWaBe employee survey. As these respondents were in turn selected on the basis of a firm survey, weighting is essential to ensure the representativeness of the final sample and by that ensure that our descriptive statistics and treatment effects are also representative. The details of sampling and weighting are described in the following.

Firstly, the firms were selected from the potential group of participants in the "IAB-ZEW Arbeitswelt 4.0" firm survey, stratified into 40 cells by region, firm size class and sector. From these 2,032 firms, all employees subject to social insurance contributions aged 16 to 65 who had an employment spell in 2011, 2016 or both were drawn. The gross sample of 266,000 employees was further divided into three groups: Stayers, Leavers and Entrants. For each group, the employees were in turn divided into a total of 81 stratification cells based on the following stratification characteristics: company size class (small/medium/large), education (low/medium/high) and age (young/medium/old).

As the drawing design of the gross sample without weighting is not representative of all dependent employees in Germany, design weights were created. The basis for calculating the design weights of a respondent is the inclusion probability of their firm within the 40 strata of the firm survey. The inclusion probability of a firm from a specific stratum is calculated as the ratio of the number of surveyed firms to the total number of firms in the population in the same stratum. As the final net sample for the employee survey is again a stratified simple random sample from the firms, which were again drawn stratified, both draws must be taken into account simultaneously. The probability of inclusion was estimated for each employee from a specific stratum of the employee sample in a specific establishment on the basis of the total number of employees and the number of employees in the respective stratum. The design weights of an employee from a particular stratum were calculated as the inverse of the estimated inclusion probability of this stratum. This value therefore reflects the probability of an employee from a specific stratum and a specific establishment being included in the sample.

In order to adjust the distribution of the stratum variables of the employee sample to the distribution in the population of all employees in Germany and to compensate for the non-response that occurred, an additional post-stratification was carried out. For this purpose, the number of employees in each stratum of the population was divided by the number of employees in the same stratum of the net sample, i.e. the persons ultimately surveyed. These post-stratified design weights are used for all descriptive statistics. For the causal analysis, however, we use a trimmed version. Trimming the weights at the 99th percentile makes the analysis less susceptible to outliers and represents a compromise between outlier sensitivity and bias due to weight adjustment. Details on the stratified sampling of respondents, the calculation of the weights and their effect can be found in Chapter 2.5 in Arntz et al. (2020).

B.3 DiWaBe: Representativeness

Table 17 compares major characteristics of the unweighted and weighted sample of analysis with the corresponding population characteristics. The population refers to the entire German workforce employed in 2011 for whom the sample restrictions discussed in Section 2 apply. As can be seen, especially the weighted sample matches the overall population quite well, but we have a slight over-representation of college graduates and an under-representation of older workers. The under-sampling of older workers is due to the fact that for our analysis, we include only workers aged between 20 and 55 in 2011 to ensure that the health effects are not contaminated by (early) retirement.

Table 17: Representativeness of the final sample

	Population	Weighted	Unweighted
Education			
No vocational degree	0.09	0.04	0.02
Vocational degree	0.74	0.70	0.48
College degree	0.17	0.26	0.49
Age			
Age <35	0.29	0.32	0.35
Age 35-49	0.45	0.50	0.42
Age >=50	0.26	0.17	0.23
Firm size			
Firm size <50	0.44	0.45	0.16
Firm size 50-199	0.24	0.23	0.34
Firm size >=200	0.32	0.32	0.50
Location			
East Germany	0.19	0.19	0.47
Sector			
Secondary sector, non knowledge-intensive	0.20	0.29	0.16
Secondary sector, knowledge-intensive	0.10	0.09	0.22
Tertiary sector, non knowledge-intensive	0.48	0.39	0.17
Tertiary sector, knowledge-intensive	0.18	0.18	0.25
ICT sector	0.03	0.05	0.21
Female			
Female	0.45	0.42	0.37
Observations	24.6M	3235	3235

Notes: This table shows key characteristics for the population and the final sample, both unweighted and weighted. The population is defined as all persons in Germany who were in regular employment subject to social security contributions on June 30, 2011 without special characteristics, i.e. no civil servants or trainees. In addition, only individuals aged between 16 and 65 or who were not yet over 60 in 2011 are included. The final sample used in our analysis includes people who were working in one of the surveyed firms in 2011 and who otherwise have the same characteristics, with the exception that they are not older than 55 in 2011. In addition, individuals are excluded who have missing information for outcome and treatment variables and have not agreed to the linking of the survey data with administrative IAB data. The weights used are post-stratified design weights as described in Appendix B.2.

B.4 Principal Component Analysis

As already described in Section 2, a Principal Component Analysis (PCA) is a data-driven statistical method that aims to reduce the dimensionality and thus the complexity of (large) data sets while retaining as much of the original variance as possible. This is achieved by recognizing correlations and patterns between the variables and combining them into a small number of new variables. These represent uncorrelated linear combinations of the original numerous correlated variables and are referred to as principal components. They are evaluated in terms of their variance or eigenvalue, i.e. the amount of variation captured in the data, and arranged in descending order. The first principal component therefore has the highest eigenvalue/variance, i.e. it summarizes the most significant characteristics of the data. The order of the principal components is important because the subsequent principal components must be uncorrelated with the previous principal components. This means that the second principal component therefore summarizes the second most variance *under the condition* that it is orthogonal to the first principal component.

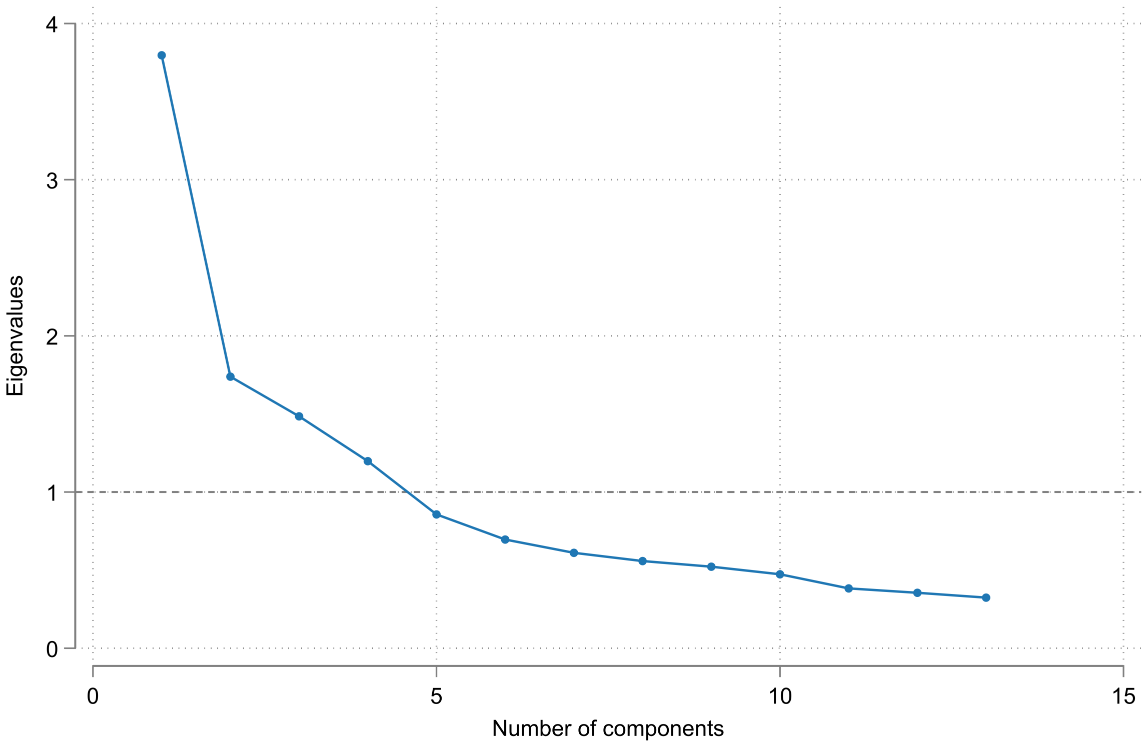
In our case, we want to reduce the number of task dimensions and thus capture groups of employees with similar workplaces and illustrate them more easily. For this purpose, we use 13 variables that describe the workplace of all respondents in 2011 (listed in Table 19).[32] Figure 7 shows that these 13 task dimensions can be characterized well with a single component that represents 29.21% of the total variation. As the sharp drop in eigenvalues between components 1 and 2 indicates that the first component captures the largest share of variance in the data and that additional components explain little additional variability, we chose only one component to be retained.

Table 18 shows the loadings, the share of unexplained variation, and the Kaiser-Meyer-Olkin (KMO) measure of our retained single principal component.The KMO measure reflects the suitability of the data for the PCA based on the proportion of common variance among variables and is provided for each variable and overall. It ranges from 0 (bad) to 1 (good); thus, as all variables separately, as well as in sum, have a high value, we can conclude that the data is well-suited. Especially typical office activities like writing, sitting, and the usage of ICT, software, and mathematics have high loadings, i.e., a strong association with the princpial component. Workplaces with high loadings are also less repetitive and require less physical exertion, but

[32]In order to provide the most comprehensive picture possible of workplace characteristics, all 6,923 respondents who were employed in 2011 and had no missings in any of the 13 task dimensions form the basis for the PCA.

are more independent. Based on individuals' workplaces, we assign each worker a *PCA score* (standardized to have mean 0 and a variance of 1) reflecting their degree of office-like tasks performed in 2011.

Figure 7: Scree plot



Notes: This figure shows the eigenvalues of each principal component on the y-axis and the corresponding component number on the x-axis resulting from the Principal Component Analysis (PCA) described in Appendix B.4. The eigenvalues represent the amount of variance captured by each component relative to the original variables. This means that principal components with eigenvalues below one, indicated by the horizontal line, explain less variance than the original variable and should be left out ("Kaiser criterion"). The steep decline at the beginning indicates that the first component explains a substantial amount of variance, while the gradual leveling off suggests that subsequent components contribute less.

Table 18: Loadings of the first principal component

	Loadings	Unexplained	KMO
Writing 2011	**0.342**	0.555	0.901
Math 2011	**0.255**	0.754	0.781
Software 2011	**0.382**	0.447	0.848
Repetitive tasks 2011	-0.218	0.819	0.847
Unpredictable tasks 2011	0.151	0.913	0.691
Physical exertion 2011	**-0.379**	0.455	0.808
Sitting 2011	**0.376**	0.464	0.890
Customer contact 2011	0.149	0.915	0.691
ICT 2011: Frequency	**0.385**	0.438	0.881
Machines 2011: Frequency	**-0.256**	0.751	0.735
Workintensity 2011	0.090	0.969	0.662
Task-independence 2011	**0.222**	0.813	0.646
Time-independence 2011	0.154	0.911	0.565
Observations:	6923	Overall KMO:	0.787

Notes: This table presents the loadings, the share of unexplained variation, and the KMO measure for all 13 variables considered in the PCA. Loadings can be interpreted as correlations between the original variables and the component, with a higher absolute value indicating a stronger relationship. The Kaiser-Meyer-Olkin (KMO) measure is provided for each variable, indicating their adequacy for the PCA, with the cumulative KMO measure displayed at the bottom. KMO values range from 0 to 1, with values below 0.5 considered unacceptable, between 0.5 and 0.7 mediocre, between 0.7 and 0.8 good, between 0.8 and 0.9 great, and above 0.9 superb.

Table 19: Workplace Characteristics in 2011

Variable	Description
Work pressure 2011	Rating on 5-point scale of statement "How often do you have to work under sever deadline or performance pressure?"
Self-determination 2011	Rating on 5-point scale of statement "How often can you arrange tasks yourself?"
Self-scheduling 2011	Rating on 5-point scale of statement "How often can you determine your own work pace?"
Repetitiveness 2011	Rating on 5-point scale of statement "How often do you perform repeating identical work processes?"
Unpredictability 2011	Rating on 5-point scale of statement "How often do situations arise that need an individual response?"
Physical exertion 2011	Rating on 5-point scale of statement "How often does your work involve great physical exertion?"
Sitting 2011	Rating on 5-point scale of statement "How often do you work sitting continuously for at least one hour?"
Customer contact 2011	Rating on 5-point scale of statement "How often do you deal with people who are not your colleagues?"
Writing complexity 2011	5 categories: No writing requirements, smaller texts, at least 1-page texts, at least 5-page texts, at least 25-page texts
Math complexity 2011	5 categories: No math, simple calculations, fraction/percent (or similar complex), area calculations (or similar compl.), higher math
Software use 2011	5 categories: No software, specific or standard software, specific and standard software, advanced programming functions, self-programming
ICT frequency 2011	Rating on 5-point scale of statement "How often do you use information and communication technologies?"
Machine frequency 2011	Rating on 5-point scale of statement "How often do you use machines?"

Notes: This table displays the names and a detailed description of all variables considered in the PCA. The 5-point Likert scale ranges from 0 (do not agree/not at all) to 4 (strongly agree/always). For writing and math complexity, as well as software use, respondents were subsequently asked whether their workplace requires them to do certain tasks/work with a certain type of software programs (yes/no). Respondents are then categorized into five categories based on the highest requirement level they report.