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IMPACT OF ARTIFICIAL INTELLIGENCE ON WORKFORCE DEVELOPMENT: ADAPTING SKILLS, TRAINING MODELS, AND EMPLOYEE WELL-BEING FOR THE FUTURE OF WORK

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Abstract
This study uses longitudinal survey data from Germany (2000-2020) to investigate the link between artificial intelligence (AI) and workers' mental health and well-being. To compare AI-exposed and non-exposed workers, we develop a measure of individual exposure to AI technology based on the occupation in which people in our sample were initially engaged. We also investigate an event study design and a difference-in-differences technique. There is no proof of distinct pre-trends in workers' well-being and worries about their financial fate before the widespread availability of AI. However, since 2015, as AI has become more widely used in German businesses, we have seen that workers exposed to AI are less content with their lives and careers and more worried about their financial status and job security. However, there is little proof that AI significantly affects employees' mental health, anxiety, or sadness.

INTRODUCTION

The global adoption of artificial intelligence (AI) by companies has seen a remarkable surge in recent years. The emergence of generative AI has further amplified public interest, highlighting the potential of this technology to fundamentally reshape daily life, cognitive processes, and professional activities (The Economist, 2023). Investment in AI is growing at a high rate, with about half of all companies reporting the use of AI technologies in at least one business area as of 2022. The global AI market is projected to grow at a rate exceeding 37% between 2023 and 2030 [1] [2].

AI holds the promise of transformative impacts on economic growth, healthcare, safety, and transportation, while also potentially lowering the costs and barriers associated with information access, education, and training. Similar to past technological shifts, AI can contribute to reducing work-related risks. While recent research has started to investigate the effects of AI on labor market outcomes and

productivity, a significant gap remains in understanding its influence on workers' well-being and mental health using longitudinal data. This paper tries to fill this research gap, drawing on a comprehensive study from Germany in order to explore the relationship between the exposure of AI and workforce development with regards to well-being, skill adaptation, and the future of work [3] [4].
A fundamental difference exists between AI and earlier automation technologies, such as industrial robots. Whereas robotics relies on physical manipulation, AI is focused on computer-based learning [5]. This makes it possible for AI to automate non-routine tasks. As a result, a new group of relatively highly-educated workers may be in danger of becoming automated. Concerns have been raised that AI could exacerbate the erosion of the middle class by reducing opportunities for secure, well-paying jobs that do not demand advanced qualifications. The distributional consequences of this technology depend crucially on which specific tasks are automated and which groups of workers perform them, with mid-skilled occupations likely to be the most negatively affected [6] [7].
There are differing opinions among employees on AI. While some polls, like recent Pew research conducted in the US, show that workers in more exposed industries do not feel endangered, others show rising worldwide anxiety about AI's influence on labor market prospects. AI may supplement humans and increase production, but it can potentially completely replace human labor [8]. This implies that the balance between complementarity and substitutability will determine the overall impact on labor market results. Additionally, AI can affect workers' perceptions of their own value and job happiness by altering the nature of their labor [9].
This study [10] uses longitudinal data from Germany to estimate the impact of workplace AI adoption on workers' well-being, their concerns about the economic future, and their mental health. These are important results for helping design workforce development policies, including any initiatives for skill adaptation and training in the light of an ongoing AI revolution [11].

2. Institutional Background: The German Context

When examining the effects of AI on employment, Germany offers an interesting case study. Only recently has the application of AI in the German economy advanced. Gathmann and Grimm (2022) claim that from 2015, the number of patent applications for AI technology started to rise significantly, reaching a higher peak in 2017 and 2018. A consistent longitudinal perspective on this adoption is offered by data from the ZEW-Leibniz Centre for European Economic Research innovation survey [12].
Before 2010, AI was not widely used, and adoption rates were quite low until 2016. But during the past few years, these rates have significantly increased. Prior to 2016, just 2% of German businesses used AI; by 2019, that number had risen to 6%, and by 2021, it had reached 10%. Different sectors have different rates of AI adoption. Finance (24%) and information technology (21%) were the top adopters in 2019, followed by skilled services (18%) like law, architecture, consulting, and research. On the other hand, transportation (5.3%), various business services (2.3%), and mining (1.6%) had the lowest adoption rates. Individual-level data on AI exposure reflects these industry disparities [13].
Alongside this growing acceptance, the government made large investments. The German Federal Government announced its Artificial Intelligence Strategy in 2018 and committed to spending about 5 billion euros on AI research by 2025. Establishing 12 centers for AI technology development and more than 100 departmental seats for AI researchers at German universities is one of the initiative's main objectives. Additionally, the government's EXIST project seeks to distribute about 2 billion euros to both new and established AI start-up businesses. Germany provides a great framework for examining how increased exposure to AI affects worker wellbeing because of these factors [14].

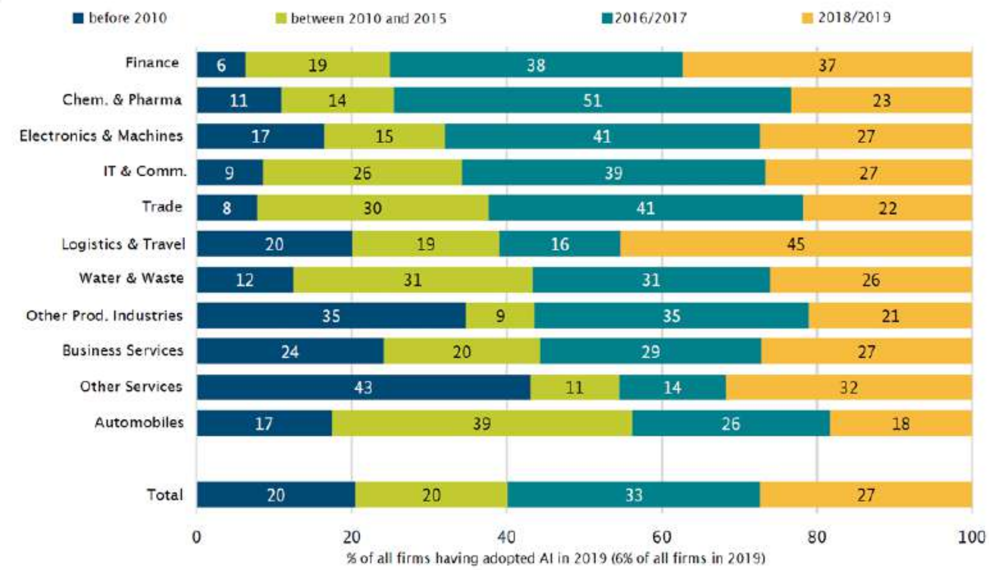

Figure 1: Share of firms among AI adopters in 2019 from the point of first use. Source: Rammer et al. (2020)

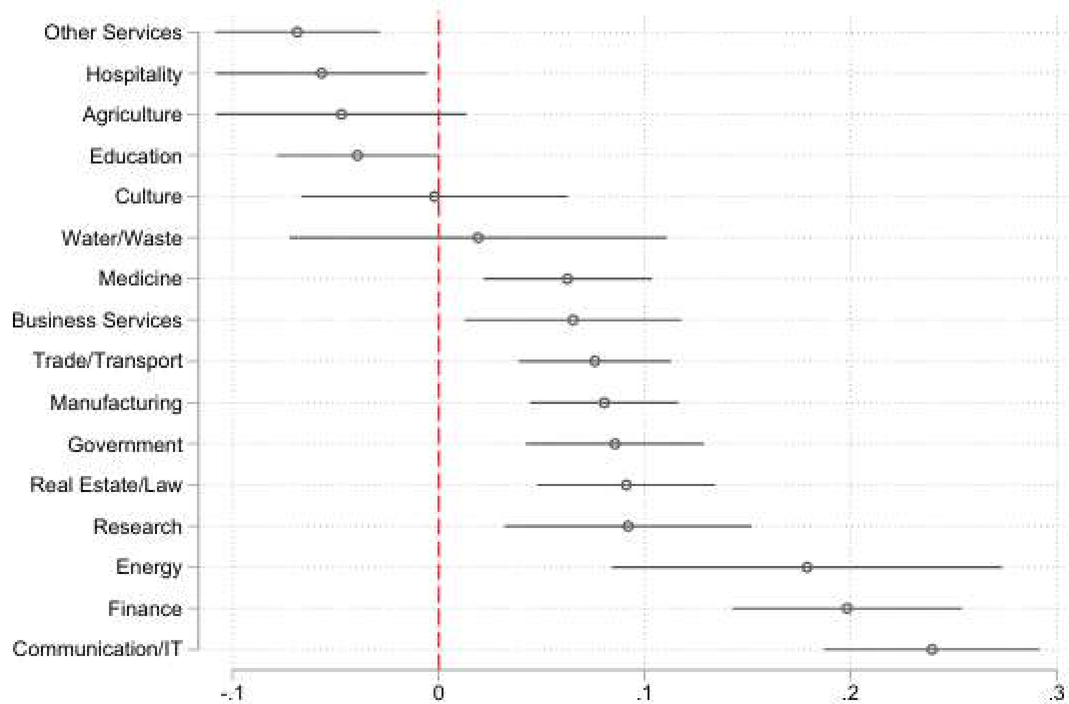

Figure 2: AI Exposure by Industry based on Probit Predictions

3. Data and Measurement

The German Socio-Economic Panel (SOEP), a representative longitudinal data set that has polled German homes and people since 1984, is the source of the data used in this research. The SOEP is especially well-suited for this investigation due to a number of special features [15].

It contains comprehensive details about the characteristics of jobs and, correspondingly, employment histories, including long-running series of four-digit International Standard Classification of

Occupation - ISCO - codes. This makes it possible to construct a pre-specified measure of AI exposure based on job classification [11] .

Second, a wide range of self-reported well-being indicators are included in the sample. An 11-point Likert scale, ranging from 0 (extremely unsatisfied) to 10 (very satisfied), is used to evaluate life satisfaction and job satisfaction, which are the primary outcome variables of this analysis. Additionally, a scale ranging from "not concerned at all" to "very concerned" is used to question respondents about domain-specific issues, such as concerns regarding their own financial condition and job security. The Mental Component Score (MCS) from the SF-12 questionnaire, doctor-diagnosed depression (a binary variable), and the frequency of sensations of anxiety (on a 5-point scale) are among the other measures of mental well-being included in the SOEP [16] [17].

Third, and most critically, the 2020 wave of the SOEP introduced a new module designed to measure individual-level exposure to AI in the workplace. Employed respondents were asked about their exposure to and frequency of interaction with various digital systems across five areas: 1) natural language processing; 2) image and video processing; 3) text processing; 4) information processing and evaluation; and 5) knowledge gathering. The use-frequency categories were "several times a day," "daily," "weekly," "less often," and "never." A key advantage of this questionnaire is that it indirectly asks workers about their use of AI technologies, thereby minimizing potential measurement errors stemming from their familiarity with the term "AI." [18] [19].

This data is used to create a broad indicator of AI exposure at the person level. If an individual works with any of these digital technologies at least once a week, they are deemed exposed. Next, each two-digit ISCO occupation's average level of exposure is calculated. A dummy variable that indicates whether an employee works in a field with a high level of AI exposure serves as the primary explanatory variable [20].

The analytic sample is limited to those who joined the workforce before 2000, far before AI became popular in Germany, so order to allay worries that the growing significance of AI may affect workers' self-selection into particular professions. The working sample focuses on employees between the ages of 25 and 65 and covers survey years 2000 to 2020. About 166,000 person-year observations from roughly 16,000 people make up the final longitudinal sample [21].

Table 1: Descriptive Statistics

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

Notes: Data are drawn from the SOEP for individuals aged 25-65 years (2000-2020).

4. Empirical Strategy

Two distinct empirical methods are used to investigate the connection between worker outcomes and AI exposure: A difference-in-differences (DiD) design and an event study [22].

The event study approach estimates the following equation:

$$Y_{ijst} = \sum_{t=2000, t\neq 2009}^{2020} * \gamma_t P_t + \sum_{t=2000, t\neq 2009}^{2020} * \delta_t P_t \times AI\text{-}exposed_{ijst} + \alpha X_{ijst} + \theta_i + \lambda_{st} + \epsilon_{ijst}$$

where Y_{ijst} represents the outcome variable for individual i in occupation j, state s, and year t. P_t is a set of calendar year dummies, with 2009 as the reference period. $AI\text{-}exposed_{ijst}$ is a dummy variable indicating high exposure to AI in the worker's initial occupation. The coefficients of interest, δ_t, capture the average difference in outcomes between AI-exposed and non-exposed workers over time. The model includes worker-level covariates (X_{ijst}), individual fixed effects (θ_i), and federal state × year fixed effects (λ_{st}).

The DiD approach estimates the following model:

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

Here, $Post_t$ is a dummy variable equal to one for the years after 2015, the period when AI adoption markedly increased in Germany. The key coefficient, β, captures the difference in outcomes for AI-exposed workers after 2015, relative to non-exposed workers. This specification also includes survey year fixed effects (τ_t) [23].

The identification strategy relies on the assumption of parallel trends in outcomes between the two groups before the widespread rollout of AI. The analysis supports this assumption by showing no significant pre-trend differences before 2015. The use of individual fixed effects helps account for time-invariant confounding factors, and the focus on initial occupations for workers entering the labor market before 2000 further alleviates concerns about selection bias [24].

5. Results: The Impact of AI on Well-being and Concerns

5.1 Trends and Event Study Analysis

After 2015, there was a significant difference between those who were exposed to AI and those who were not, according to visual evidence of well-being trends. Prior to this time, there was no indication that the two groups' levels of life satisfaction, work satisfaction, or economic worries differed significantly. However, compared to their non-exposed peers, AI-exposed professionals exhibit noticeably poorer life and career satisfaction starting in 2015 and grow more worried about their own financial condition and job security.

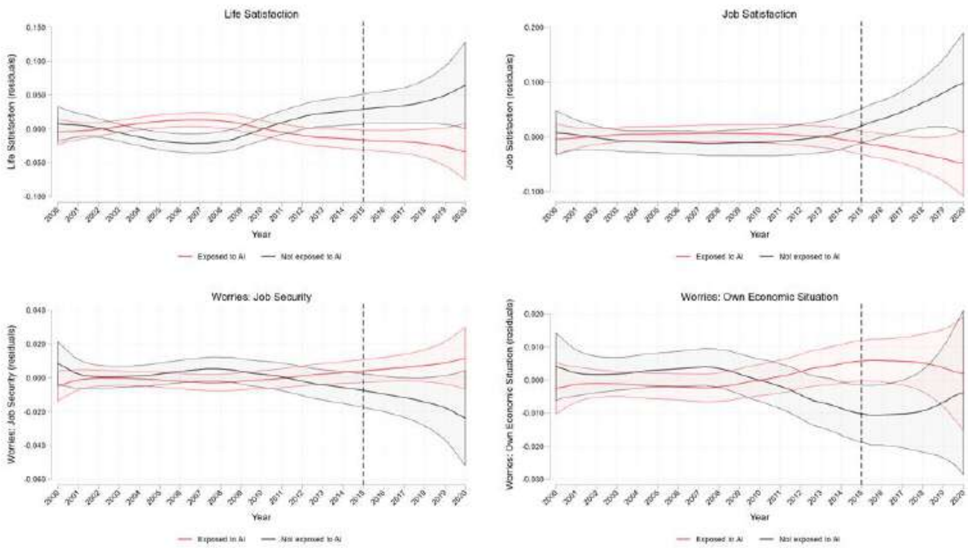

Figure 3: AI Exposure by Occupation based on Probit Predictions

The event study analysis formalizes these trends. For life satisfaction, job satisfaction, and economic concerns, the coefficients show a flat pre-trend from 2000 to 2009, with estimates statistically insignificant and close to zero. No significant effects are observed during the early adoption phase (2010-2014). However, beginning in 2015, a clear decline in satisfaction measures and an increase in concern measures emerge for AI-exposed workers relative to the control group.

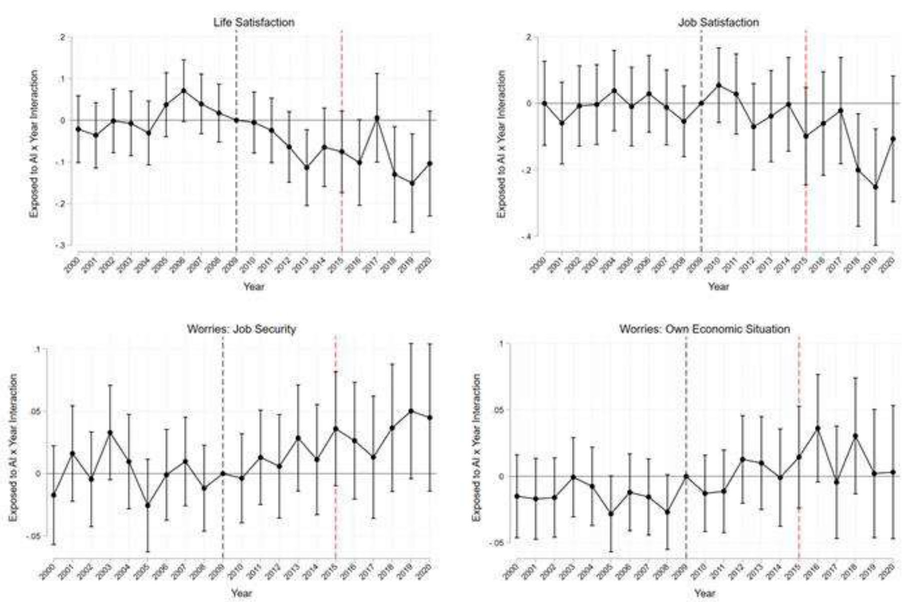

Figure 4: Exposure to AI and Workers' Well-being, 2000-2020 – Event Study Analysis.

In contrast, the event study analysis for mental health outcomes Mental Component Score (MCS), anxiety, and depression shows no significant differences between AI-exposed and non-exposed workers at any point during the study period. coefficients are small, statistically insignificant, and consistently close to zero.

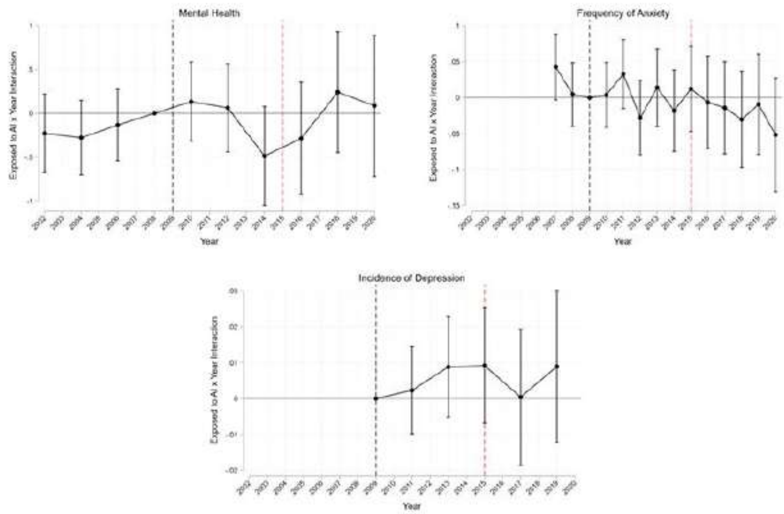

Figure 5: Exposure to AI and Workers' Mental Health Outcomes, 2000-2020 – Event Study Analysis

5.2 Difference-in-Differences Estimates

The DiD analysis quantifies the overall effect of AI exposure since 2015. The results, presented in Table 2, indicate that AI-exposed workers report statistically significant lower levels of life satisfaction and job satisfaction compared to non-exposed workers.

Table 2: Effects of Exposure to AI on Workers' Well-being – DiD Estimates

Dep. var.:	**(1) Life satisfaction**	**(2) Job satisfaction**	**(3) Worries: job security**	**(4) Worries: economic situation**
Exposed to AI * 2015-2020	-0.073** (0.031)	-0.105** (0.045)	0.028** (0.014)	0.024** (0.012)
Mean of dep. var.	6.895	6.885	1.663	1.971
Std. dev. of dep. var.	1.739	2.076	0.700	0.689
Observations	165,776	130,655	127,044	165,487

*Notes: Standard errors clustered at the individual level in parentheses.
**Significant at 5%.

The effect on life satisfaction corresponds to a decrease of approximately 0.04 standard deviations. To contextualize this magnitude, in the sample, this estimate is comparable to about 16% of the positive effect of having a college degree on life satisfaction, or roughly 13% of the negative effect of being unemployed. The decline in job satisfaction is approximately 0.05 standard deviations, equivalent to about one-third of the positive effect of a college degree on job satisfaction or 5% of the negative effect of unemployment.

Furthermore, AI-exposed workers show a significant increase in concerns about job security and their personal economic situation. Reassuringly, the hypothesis that the pre-trend coefficients (2000-2014) sum to zero cannot be rejected for any of these outcomes, supporting the validity of the research design.

Table 3: Effects of Exposure to AI on Workers' Mental Health Outcomes – DiD Estimates

Dep. var.:	(1) Mental health	(2) Anxiety	(3) Depression
Exposed to AI * 2015-2020	0.104 (0.231)	-0.018 (0.017)	0.003 (0.006)
Mean of dep. var.	49.53	1.982	0.0828
Std. dev. of dep. var.	9.867	0.978	0.276
Observations	69,206	77,467	30,018

As shown in Table 3, the analysis finds no evidence of a significant impact of AI exposure on any of the mental health metrics. The estimated coefficients are negligible and statistically insignificant, and the pre-trends are flat. This suggests that, at least in this early transitional phase, AI exposure affects subjective well-being and economic anxieties but has not yet translated into clinically measurable mental health deficits.

6. Heterogeneity and Robustness

The findings are robust to a series of sensitivity checks, including using the initial state of residence, excluding individuals who moved, using alternative sample restrictions (e.g., entering the labor market before 2005), and employing different definitions for the outcome variables (e.g., binary satisfaction and concern measures). The core results remain consistent across these alternative specifications.

Heterogeneity analyses reveal important variations in the effects across different worker subgroups:

- **Gender:** The negative effects on life and job satisfaction are similar for men and women. However, the increase in concerns about job security and personal economic situation is significantly larger and more pronounced among male workers.
- **Education:** The adverse effects on life and job satisfaction are primarily driven by medium-skilled workers (those with a high school diploma). This aligns with previous evidence indicating that middle-skill tasks are most exposed to the displacement effects of AI (Brekelmans and Petropoulos, 2020). The effects on low-skilled and high-skilled workers are generally smaller and statistically insignificant.
- **Region:** The negative impact on job satisfaction and the increase in economic concerns are larger for workers in East Germany compared to those in West Germany.

These heterogeneous effects underline that the influence of AI does not bear evenly on the workforce. In particular, medium-skilled workers seem to be the most vulnerable in this technological transition since it reduces both their current well-being related to the job they perform and increases their anxiety about their future economic prospects.

7. Discussion: Implications for Workforce Development

Results from this study have important implications for workforce development strategies in the age of AI. The findings indicate that, since the significant increase in AI adoption post-2015, workers in highly exposed occupations have experienced a decline in life and job satisfaction, with greater concerns about their job security and economic future. Crucially, these effects are concentrated among medium-skilled workers.

This creates a paradox: whereas existing studies have shown little to no negative effect of AI on objective labor market outcomes such as employment and wages at the aggregate level, this research demonstrates a clear negative subjective influence on worker well-being. Therefore, it indicates that even though workers may not lose their jobs immediately, their perception is that there is a threat to economic prospects and job stability during this transition phase, which is negative and influencing satisfaction.

For policymakers and business leaders, this underlines the urgent need to rethink the architecture of workforce development systems. Preventing unemployment is not enough; the focus needs to be on protecting worker well-being and enabling confident adaptation.

1. Adapting Skills and Training Models: The fact that negative effects are concentrated among medium-skilled workers points to a critical target for reskilling and upskilling efforts. Training models need to change in order to arm this portion of the workforce with skills that will complement, rather than be substituted by, AI. This goes through and beyond the encouragement of advanced digital literacy, critical thinking, problem-solving, and socio-emotional skills which AI cannot easily substitute for. Effective retraining programs are key in softening the negative consequences of automation impacts on worker welfare.

2. Supporting Employee Well-Being: This increase in economic anxieties, even without a corresponding decline in mental health, indicates a state of precariousness that could have longer-term consequences. Labor policies should protect vulnerable workers during technological transitions. Such policies could include social safety nets to catch dislocated workers; counseling and support services to manage transition-related stress; and ensuring deployment of AI in workplaces is done with employees, so that feelings of dignity and control are preserved.

3. The Role of Institutions: The German context, with its historical strength of unions and extensive employment protection legislation, may have played a role in mitigating more severe negative outcomes, as has been observed with the introduction of industrial robots. This emphasizes once again the importance of strong institutions and proactive policies in framing the future of work. Policies aimed at fostering innovation need to be balanced with those that protect employee dignity and ensure shared benefits of AI.

8. Conclusion and Limitations

This study provides among the first longitudinal evidence on the relationship between artificial intelligence and workers' well-being. The analysis demonstrates that the increasing adoption of AI in German workplaces since 2015 is associated with a relative decline in the life and job satisfaction of exposed workers and an increase in their concerns about job security and their personal economic situation. These effects are most pronounced among medium-skilled workers, a group identified as being particularly exposed to the displacement potential of AI. Notably, no significant effects were found on various metrics of mental health, such as depression and anxiety.

The study has several limitations. First, the measure of AI exposure is based on self-reported data. Second, as the AI revolution is still in its early phases, it may be premature to draw definitive conclusions about its long-term impact on workers. Third, due to the identification strategy focusing on workers who entered the labor market before 2000, the results primarily capture the effects on middle-aged and older workers and may not be generalizable to younger cohorts.

Despite these limitations, the findings represent important first steps. They suggest that the process of structural adjustment because of the AI transition is already producing significant objective and subjective effects on the well-being of workers, in ways that decouple perceived economic risks and measured economic experience. Understanding such heterogeneous effects is important for the formulation of appropriate labor market policies and regulations. Protecting vulnerable workers, constructing successful retraining packages, and helping workers adapt to technological change all have critical roles to play in shaping the future of work in a way that advances innovation while protecting worker well-being and dignity.

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