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Impact of Artificial Intelligence on the Mental Health of AI-using Workers

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Research Article

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Abstract

Artificial Intelligence has been reshaping the world of work over the past decade. Many studies have been conducted to assess its direct impact on labour employment, wages, and other economic indicators. However, what stands in the way is how workers perceive this technological innovation, which affects their mental health, which, in turn, is the key determinant of their productivity and job performance. This paper focuses on the mental health of workers engaged with AI, using OECD survey data from the finance and manufacturing sectors across seven countries (Austria, Canada, France, Germany, Ireland, the United Kingdom, and the United States). Five latent constructs are derived from survey responses using exploratory factor analysis, representing dimensions of AI-at-work experience: anxiety, decision support, organizational trust, workplace impact, and life satisfaction and one binary measure of wage expectations. Then these constructs are entered into an ordered logistic regression with self-reported mental health outcomes as the dependent variable, categorised into three categories—Improved, Neutral, and Worsened (N = 1,190) —controlling for demographic characteristics—gender, age, education, country, and sector. AI Workplace Impact emerges as the strongest predictor of mental health outcomes. The factor AI Anxiety loses its statistical significance once other constructs are taken into account. Among demographic controls, only the 35–49 age band reaches significance. These findings suggest the AI's impact on mental health depends less on exposure to technology itself and more on how it is introduced by their organization and on their psychological preparedness, rather than by who the worker is in demographic terms.

1. Introduction

Imagine a worker arriving at work one morning to find that a task which once took two hours can now be completed in a few minutes with the help of an AI system. For the firm, it might seem like a no-brainer: productivity increases, expenses decrease, and employees have time for more involved jobs. The same change, however, can trigger a different set of questions for the worker: Will my skills still be needed? Can I expect my salary to be adjusted? Will I have to work quicker? Besides, what about me at the end of the day? Will I still have a job in this evolving work world? Here are some of the basic economic questions associated with technological advancement. In the history of automation, economists have argued that new technologies either replace workers or augment workers' skills, leading to new opportunities to increase productivity [2, 3]. This debate has been fueled by the artificial intelligence wave of technological change, which has moved beyond simple, manual tasks targeted by previous waves of automation [9] into more sophisticated, knowledge-rich work [7].

The significance of the current wave is that its impacts extend beyond what is traditionally measured in the labour market, including employment, wages, and productivity. The impacts of AI on jobs are likely to vary significantly from one worker to another, even when two people are using the same technology, because it affects their work differently in terms of decision-making, job security, and relationships with the employer. This is reflected directly in the OECD survey used in this study: nearly one in five finance and manufacturing workers expressed great concern about becoming redundant due to AI; close to two-thirds indicated that AI has made their jobs more enjoyable [17]. The economic consequences of AI, in other words, are not experienced solely through whether a job disappears or a wage changes; they are also experienced through how workers perceive and adapt to the transformation of their work.

This raises an important, and comparatively less explored, dimension of technological change: the well-being of the worker. If employment, income, job security and the organization of work are central to economic well-being, then changes in these dimensions may also shape workers' psychological experiences. The question, therefore, is

not simply whether artificial intelligence is good or bad for workers, but which aspects of AI-driven workplace transformation determine whether they experience the transition as an opportunity or as a threat.

Mental Health conditions are already among the leading causes of lost productivity and reduced quality of life in the workplace [27]. AI is being adopted faster than the research community can keep pace. Early evidence, reviewed in full in section 2, is genuinely mixed: some large studies find AI improves workers' psychological well-being, others find it erodes it, and many find that it depends on the worker, the workplace, and the purpose for which AI is used. The word "depends" is where this paper's contribution begins. Rather than asking whether AI is good or bad for mental health in general, this paper asks a more specific and more useful question — what factors are influencing the psychological wellbeing of the workers by taking into account their perceptions on various aspects — how decisions get made, how much a worker trusts their employer to use the technology responsibly, whether they feel secure about the wages after the wave of artificial intelligence and others. This paper investigates which of these actually predicts workers' mental health, once the others are accounted for.

To answer that question, this paper draws on survey data collected by the OECD from the workers in the finance and manufacturing sectors across seven countries — Austria, Canada, France, Germany, Ireland, the United Kingdom, and the United States — and combines two analytical steps. First, we conduct an exploratory factor analysis. This helps us take many survey questions and reduce them to a few ideas that really mean something. These ideas include how anxious people are about Artificial Intelligence, how much they trust their company to use AI, how Artificial Intelligence helps with decisions at work, how it affects the workplace in general, and how scared people are that it will cause them to lose wages. Second, these constructs, along with life satisfaction and standard demographic controls, are entered into an ordered logistic regression to predict self-reported change in mental health since the arrival of AI. This allows six competing explanations of AI's psychological effects to be tested against one another within a single model, using a genuinely international sample.

1.1 Research Objectives

This paper is guided by the following objectives:

1. 1. To identify the distinct psychological and organizational dimensions of workers' AI-at-work experience through factor analysis.
2. 2. To test which of these dimensions — alongside demographic and structural factors — significantly predict self-reported change in worker mental health.

The paper proceeds as follows. Section 2 of the paper reviews the literature; Section 3 sets out the analytical strategy employed in this paper; Section 4 details the procedure for construct validation and the reliability statistics; Section 5 of the paper reports descriptive statistics, the pairwise correlations among the explanatory variables, and a multicollinearity check; Section 6 presents the results from the ordered logistic regressions as well as the average marginal effects; and Section 7 concludes with limitations and future scope of the research.

2. Literature Review

Artificial Intelligence is changing the way people work. It is affecting how employees do their jobs, make decisions and deal with the system at work. It has the potential to make work more efficient. A few studies suggest that AI can make people happier by reducing workload and improving the work environment [25, 28, 17]. Other studies suggested that AI could cause stress, anxiety, and worries about job security [29, 12, 6]. The relationship between

AI and psychological well-being is complicated. Most of the studies we have are from a single country and focus on specific job roles, which limits our understanding of how psychological and organizational factors affect mental health outcomes [23, 6]. Furthermore, little attention has been given to examining these factors simultaneously in a common analytical framework using cross-country analysis. This section examines what the evidence actually shows, moving from the economy as a whole to the individual worker, and concludes with the gap this paper seeks to fill.

2.1 The Emergence of AI and Automation

Economists have studied automation and jobs for years, long before “AI and mental health” came into the research field. An estimated 47% of US jobs were at high risk of automation, particularly lower-paid, lower-education jobs in transportation, logistics, and administrative support [9]. Separate empirical work tracing local labour-market exposure to industrial robots found broadly similar displacement effects [1]. Others push back by claiming that technology might substitute for some tasks but also complement them and raise demand and therefore pay for those jobs, so it has not led to mass unemployment but to “job polarisation”, which means wage gains concentrated at the top and bottom of the skill distribution, with the middle squeezed [3]. Both sides can be true at once by introducing the displacement effect—automation displaces some jobs—and the reinstatement effect, which creates others [2]. Whether the workers end up better or worse off depends on which effect overpowers.

Generative AI looks different from earlier automation. AI models like ChatGPT could affect a larger share of tasks across all jobs, including higher-paid, higher-skilled ones, rather than just the routine jobs identified in earlier automation studies [7, 9]. Customer support workers who used an AI assistant found that productivity rose 15% on average [4]. However, this average masks enormous heterogeneity, with the largest gains among newer, less experienced workers, who improved both speed and work quality [4]. That finding — AI as a leveller closes the gap between novice and expert rather than uniformly lifting everyone — is a strikingly different situation. It is consistent with evidence that AI is benefiting the mental health of Chinese manufacturing workers, particularly among the low-skilled [25], and it provides a concrete mechanism for why self-efficacy in AI learning matters so much psychologically [15]. These findings suggested that workers who gain the most from AI are likely those whose confidence in using it has the most room to grow.

The OECD’s own evidence, using the same survey from which this paper's data is drawn, found a mixed picture as well [17]. 27% of jobs are in occupations at high risk of automation, once all automation technologies are counted, and about 1 in 5 finance and manufacturing workers were very worried about losing their jobs to AI, yet almost two-thirds said AI had made their work more enjoyable, as those workers got free from dangerous or tedious work, giving them the time for more complex work which needed human attention. This uncertainty about AI's economic effects — helpful for some, harmful for others — is the backdrop against which the more psychologically focused studies reviewed next are set.

2.2 Algorithmic management

There have been very few studies that focus on algorithmic management software, which is used to schedule, monitor, reward, and assign tasks. In a study of gig workers, this algorithmic oversight was not found to be uniform; it was reported as both a positive challenge (beneficial technical support, making workers more efficient) and a hindrance (persistent surveillance, inducing stress), and it also resulted in negative behaviours in the workplace [29]. This separation of AI to assist workers from AI to monitor workers is what makes the differentiation between AI that supports the worker and AI that watches the worker.

2.3 Double-sided stories of AI and Mental Health

There is no clear answer from the studies on whether “AI is good” or “AI is bad”. A comprehensive literature review comes back with a genuinely two-sided picture: AI helps, through early detection of fatigue and stress, workload automation, and personalised wellness support — and AI harms, through job displacement, surveillance-related stress, algorithmic bias, loss of human connection, technostress, and lack of inclusivity [6]. Crucially, they also flagged what the field was missing: almost no one had studied the organizational conditions — culture, digital literacy, ethical oversight — that might tip a given workplace toward one outcome or the other [6]. A separate study reviewed 92 studies and found that the field has grown rapidly since 2020, yet still lacks a consensus [23].

By contrast, Chinese data from the Federation of Robotics matched industrial-robot counts to individual mental health scores from the China Family Panel Studies [28]. Their claim from the study, reinforced by an instrumental-variables strategy designed to rule out causality, was ambiguous: more robots (also termed industrial AI) were associated with better mental health across all six well-being measures used [28]. A similar claim using data from the 2018 China Labour Force Dynamics Survey found that AI adoption reduced manufacturing workers' depression scores by 1.643 points on average [25]. However, studies from South Korea went in the opposite direction. Three survey waves completed by 416 working professionals suggest that the adoption of AI in the workplace does not have a statistically significant impact on employee burnout [15]. Another examined the impact of the adoption of Organizational AI on employee depression using a three-wave survey of 381 South Korean employees, finding that ethical leadership mitigates these negative effects and highlighting the importance of organizational support [16]. Another study surveyed 349 Chinese manufacturing employees about their “STARA awareness” — their perceived threat from smart technology, AI, robotics, and algorithms — found that the more threatened employees felt, the worse their work affective well-being became [12].

2.4 The real cause

At this point, things begin to get more interesting. A framework weaves the various studies together: none of them argued that AI was the most important variable in itself; all of them concluded that the effects of AI permeated other domains. Kim and Lee (2024) were perhaps the first to really consider this, and they compared two models [15]. In one model, AI adoption predicted burnout, whereas in the other, the prediction was driven only by job stress [15]. Kim, Kim and Lee (2025) found the same pattern through psychological safety [16]. Jin, Jiang, and Liao (2024) again found that job stress served as an intervening effect between STARA awareness and mental well-being. They found that AI threatens other job-related factors: skills, job security, and income, on which employees depend [12]. Thus, it is such factors that cause stress in reality rather than the AI itself. Even the two “positive” China studies fit this pattern: Wei and Li (2022) found the work environment, not overtime, explained the benefit [25], and Yang, Liu, Gai and He (2022) traced their result to higher wages and shorter hours [28]. The lesson is the same as that shown by this paper's own results: AI Anxiety loses its effect once Organizational Trust and AI Workplace Impact are added to the model (Section 6). AI's effect on mental health depends on what stands between the technology and the worker.

2.5 Detangling the affected workers’ characteristics

No story really ends in a way where everything is resolved, and neither does this one. The effects of AI are more concentrated, with a greater impact on the mental health of older and low-skilled workers (born before 1980). For younger and more skilled workers, no benefits were observed [25]. The authors state that AI was introduced to relieve low-skilled older workers of dangerous, dull, and repetitive tasks [25]. When this is compared with the study

currently being analysed, they seem to contradict each other. The earlier study identifies significant demographic interactions, whereas the present analysis finds only that the main effects of demographics reach significance. A main effect, rather than an interaction, suggests that this study's demographic heterogeneity does not run as deep as that captured previously.

2.6 The research gaps

Put the pieces of this literature side by side, and three gaps stand out, each one a thread the present study picks up. First, primary studies are set in a single country — particularly in China and South Korea — and both reviews explicitly call for evidence that travels further; the present study answers that call directly, drawing on OECD survey data spanning seven countries and two sectors. Second, every primary study builds its case around a single mediator and, at most, a single moderator, tested in isolation. This paper instead puts six substantive constructs — AI Anxiety, AI Decision Support, Organizational Trust, AI Workplace Impact, AI Wage Fear, and Life Satisfaction — into the same model at once, trading the ability to trace one clean causal chain for the ability to see which constructs still matter once the others are accounted for, which is exactly how it catches AI Anxiety's effect being absorbed by Organizational Trust and AI Workplace Impact. Third, and perhaps most tellingly, none of the five primary studies places a direct measure of trust in the employer's governance of AI at the centre of its model, even though two of them — psychological safety and ethical leadership — are visibly circling the same idea from different angles. The Organizational Trust construct, and its place as the second-strongest predictor in the main results (Section 6), steps into that gap — and makes the case that trust deserves a central seat at the table in future research on AI and worker mental health, not a supporting role.

3. Analytical Strategy

The process of empirical analysis is done in two stages. Firstly, the Likert-scale data is reduced to a smaller set of latent constructs using Exploratory Factor Analysis (EFA) [8]. Then, internal consistency was assessed using Cronbach's alpha [24], and sampling adequacy was assessed using the Kaiser-Meyer-Olkin (KMO) statistic [14]. Second, the resulting factor indices showing a small score of single item indicators created using factor analysis with a binary variable created outside the factor analysis model (to be discussed in Section 4) are then put together into an Ordered Logistic Regression (ologit) [18, 19] predicting workers' self-reported assessment in their mental health and well-being after AI adoption, which is measured on a five-point ordinal scale starting from "Improved it a lot" to "Worsened it a lot" is converted into three category outcome — Improved, Neutral, and Worsened for simplification. Complete analyses were performed in Stata using a worker-level sample drawn from two major sectors, Finance & Insurance and Manufacturing, across seven OECD member countries [17]. Pairwise correlations and variance inflation factors (VIFs) among the explanatory variables are also examined as multicollinearity diagnostics (Section 5).

Mathematically, following the specification in Long and Freese [18], the ordered logistic regression model can be expressed as:

$$\log\left[\frac{P\left(MH_i \leq j\right)}{P\left(MH_i > j\right)}\right] = \alpha_j - \beta' Z_i, \qquad j = 1,2 \qquad (1)$$

Where MH_i is the ordered mental-health outcome (1 = Improved, 2 = Neutral, 3 = Worsened) for worker *i;* α_j are the threshold (cut-point) parameters separating the three categories. Z_i is the vector of explanatory variables and controls, comprising the six core constructs- AI Anxiety, AI Decision Support, Organizational Trust, AI Workplace

Impact, AI Wage Fear, and Life Satisfaction — together with the demographic and structural controls (gender, age, education, country, and sector). A positive coefficient in this specification indicates that higher values of the associated variables are less likely to fall into a better (low-numbered) category, as higher values of that variable push people towards worse mental health outcomes. If it's negative, higher values push people toward better outcomes.

The dependent variable, the self-reported mental health impact, is available only for respondents who were active AI users at work, which limits the analytical sample compared to the full survey; additionally, deletion of non-responsive entries further reduces the sample size to 1,190 observations in the preferred specification. Section 6 presents the regression results.

4. Construct Validation: Factor Analysis and Reliability

Principal factor extraction with varimax rotation yielded five latent constructs from the underlying Likert-scale responses, retaining factors with eigenvalues greater than 1 (the Kaiser criterion [13, 14]), thereby reflecting a strongly dominant structure. Item wording was in the opposite direction of the construct and was reverse-coded (Higher values represent a more positive attitude after reversal). All retained items loaded above the conventional threshold of 0.5 [11], well within the range considered practically significant for a sample of this size. The psychometric properties of each construct are summarised in Table 1.

Table 1
Summary of Factor Analysis and Reliability Statistics

Construct	Items[#]	α	KMO	Eigenvalue	Loadings range
AI Anxiety (attitudes toward AI + fear of job loss)	5	0.902	0.831	3.053	0.733–0.803
AI Decision Support (AI-assisted decision-making)	3	0.720	0.681	1.215	0.630–0.647
Organizational Trust (trust in employer's use of AI)	5	0.844	0.861	2.552	0.671–0.769
AI Workplace Impact (performance, enjoyment, health, fairness)	4	0.788	0.763	1.868	0.609–0.723
Life Satisfaction (job, health, financial situation)	3	0.741	0.689	1.301	0.651–0.666

#See Appendix A for all variable constructs (items included in each construct)

Reliability, measured by the Cronbach's alpha statistic, was good to excellent for AI Anxiety and Organizational Trust ($\alpha > 0.8$), meeting "good" threshold [10]; moderate for AI Workplace Impact and AI Decision Support and Life Satisfaction ($0.70 < \alpha < 0.80$) [22]. KMO statistics are greater than 0.60 (the conventional threshold) across all latent groups, supporting the accuracy of the item correlations used for factor construction. Another variable was kept outside the factor analysis: AI Wage fear, a dummy variable coded as 1 for respondents who reported expectation of a decrease in Wages as a result of AI in the workplace and 0 for those who showed positive expectations or no impact on the wages (respondents who answered "don't know" were treated as missing).

5. Descriptive Overview

The dependent variable will capture each respondent's evaluation of AI's impact on their mental health and well-being in the workplace. Of those in the study who use AI and responded to its direct impact on their mental wellbeing, 481 (22.9%) say that AI has helped them to improve their mental wellbeing significantly, 754 (35.9%) a little, 615 (29.3%) have seen no impact, 195 (9.3%) a little negative, and 57 (2.7%) worsened a lot. Thus, the majority of workers who use AI (58.8%) reported a positive impact on their mental health, while under 12% reported a negative impact. The two “improved” categories are taken together, and the two “worsened” categories are also clubbed for the multivariate model because they are likely to be the same.

For descriptive purposes only, the original outcome is broken down into five categories in Table 3; the regression results for the collapsed three-category outcome are presented in Tables 4 and 5. This distribution is broken down by the sample's major demographic and structural attributes, as shown in Table 3. This cross-tabulation is descriptive and is a helpful background for the following regression results.

5.1 Correlation Analysis and Multicollinearity Check

Table 2 presents the pairwise Pearson correlations among the six main explanatory variables. The correlations are generally low to moderate, indicating that the constructs are related but capture distinct dimensions of workers’ experiences with AI. The strongest association is between AI Decision Support and Organizational Trust (r = 0.517), followed by AI Decision Support and AI Workplace Impact (r = 0.479), Organizational Trust and Life Satisfaction (r = 0.437), and Organizational Trust and AI Workplace Impact (r = 0.430). AI Wage Fear is negatively correlated with AI Decision Support, Organizational Trust, AI Workplace Impact and Life Satisfaction (r ranging from − 0.225 to − 0.329). AI Anxiety, in contrast, is almost uncorrelated with AI Decision Support (r = 0.032) and Organizational Trust (r = − 0.014), neither of which is statistically significant, and its correlations with the remaining variables do not exceed 0.340. The largest absolute pairwise correlation is 0.517, which does not suggest any exceptionally high association among the explanatory variables.

Table 2
Pairwise Correlations Among the Main Explanatory Variables

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
(1) AI Anxiety	1.000					
(2) AI Decision Support	0.032	1.000				
(3) Organizational Trust	−0.014	0.517***	1.000			
(4) AI Workplace Impact	0.340***	0.479***	0.430***	1.000		
(5) AI Wage Fear	0.137***	−0.225***	−0.329***	−0.228***	1.000	
(6) Life Satisfaction	0.091***	0.401***	0.437***	0.386***	−0.267***	1.000
*Note: Entries are Pearson pairwise correlation coefficients. *** p < 0.01*						

Variance inflation factors (VIFs) were also calculated as a diagnostic for multicollinearity among the six main explanatory variables. The VIF values range from 1.19 to 1.74, with a mean VIF of 1.48, well below the commonly used cutoffs of 5 and 10 [11]. Multicollinearity is therefore unlikely to be a concern in the preferred specification, and the regression results in Section 6, including the loss of statistical significance of AI Anxiety, are unlikely to be artefacts of overlap among the explanatory constructs.

5.2 Country AI-Preparedness Context

The seven countries in the sample vary in how prepared they are for AI adoption at the national level. Using the IMF's AI Preparedness Index (AIPI) — a composite 0–1 measure spanning digital infrastructure, human capital, technological innovation, and regulatory frameworks across 174 economies [5] — the United States ranks highest in the sample (3rd globally, AIPI = 0.77), followed by Germany (9th, 0.75), the United Kingdom (13th, 0.73), Austria (17th, 0.72), Canada (18th, 0.71), France (22nd, 0.70), and Ireland (23rd, 0.69). All seven fall within the top quartile of the 174 economies the index covers, so the sample represents relatively AI-ready contexts rather than the full global range of AI preparedness — a point worth bearing in mind when judging how far the findings generalise to lower-preparedness economies (see Section 7). Within this narrow band, country does not emerge as a significant predictor of workers' mental health once the Organizational and psychological constructs are included in the model (Section 6), suggesting that, at least among economies that are well-prepared for AI, differences in national digital readiness matter less for worker wellbeing than how AI is implemented inside the workplace.

Table 3
Self-Reported Mental Health Impact of AI, by Respondent and Job Characteristics

Category	Sub-category	Improved a lot	Improved a little	Neutral	Worsened a little	Worsened a lot	Total N
Gender	Male	26.2%	36.7%	26.6%	8.2%	2.3%	**1,323**
	Female	17.2%	34.5%	33.9%	11.1%	3.2%	**772**
Age	16–24	22.4%	35.9%	26.3%	11.4%	3.9%	**281**
	25–34	23.9%	36.6%	26.4%	10.3%	2.8%	**632**
	35–49	24.4%	36.3%	29.6%	7.6%	2.1%	**922**
	50–64	14.9%	32.7%	38.3%	10.9%	3.2%	**248**
	65 and above	26.3%	31.6%	31.6%	5.3%	5.3%	**19**
Education	Graduate	25.9%	37.3%	26.5%	8.2%	2.2%	**1455**
	Not graduate	15.8%	33.0%	36.0%	11.5%	3.8%	**628**
Sector	Finance and Insurance	24.5%	34.6%	28.7%	9.1%	3.1%	**1,207**
	Manufacturing	20.7%	37.5%	30.1%	9.5%	2.2%	**895**
Country	Austria	17.1%	36.9%	28.8%	14.9%	2.3%	**222**
	Canada	22.8%	39.1%	28.3%	7.7%	2.2%	**325**
	Germany	15.9%	33.6%	38.3%	10.5%	1.7%	**295**
	Ireland	27.2%	35.7%	25.9%	9.4%	1.8%	**224**
	UK	21.7%	38.1%	29.1%	8.4%	2.7%	**299**
	USA	34.9%	32.6%	21.9%	7.6%	3.1%	**393**
	France	17.2%	36.0%	33.4%	8.7%	4.7%	**344**
Role in the Organization	Manager	30.1%	36.6%	25.0%	7.3%	1.1%	**725**
	Professional	22.1%	34.8%	31.3%	8.3%	3.5%	**457**
	Technician/associate professional	19.4%	41.7%	28.5%	7.9%	2.5%	**242**
	Clerical support worker	13.2%	33.5%	34.6%	14.0%	4.8%	**272**
	Service and sales worker	16.7%	31.6%	33.3%	13.2%	5.3%	**114**
	Craft and related trades worker	32.4%	24.3%	27.0%	13.5%	2.7%	**37**
	Plant/machine operator and assembler	15.9%	35.4%	36.6%	9.8%	2.4%	**164**

Category	Sub-category	Improved a lot	Improved a little	Neutral	Worsened a little	Worsened a lot	Total N
	Elementary occupation	14.5%	14.5%	29.1%	12.7%	1.8%	**55**
	Other	27.3%	63.6%	9.1%	0.0%	0.0%	**11**
Size of the company	Up to 19	25.6%	41.9%	18.6%	10.5%	3.5%	**86**
	20–49	20.8%	41.7%	23.6%	11.1%	2.8%	**144**
	50–99	28.5%	40.9%	17.8%	10.3%	2.5%	**242**
	100–249	26.3%	38.1%	23.6%	9.7%	2.4%	**331**
	250–499	31.5%	36.4%	19.3%	9.5%	3.4%	**327**
	500 and above	17.5%	32.4%	38.9%	8.6%	2.6%	**945**
Type of employment contract	Permanent	19.5%	35.4%	32.8%	9.6%	2.8%	**1,233**
	Temporary	18.9%	42.6%	20.5%	14.8%	3.3%	**122**
Employment type	Full time	23.6%	35.7%	29.2%	9.0%	2.5%	**1,928**
	Part time	14.1%	38.2%	30.0%	12.9%	4.7%	**170**
Salary type	Hourly wages	31.8%	33.4%	22.4%	8.9%	3.5%	**371**
	Salaried	26.5%	37.6%	27.7%	6.4%	1.7%	**343**

Cell entries are row percentages (summing to 100% across the five outcome categories within each row, subject to rounding). For the Elementary Occupation subgroup, the underlying category counts sum to slightly less than the reported total N; this reflects a small number of "don't know"/missing responses within that subgroup that are not attributable to any specific outcome category and are therefore excluded from the percentage base elsewhere in the table.

None of the structural or demographic categories is quite as different from the sample overall as any other (the share reporting a worsened outcome, a sum of the two "worsened" columns, ranges from about 10% to 15% across all structural and demographic categories, with a few small exceptions, such as clerical support workers at 18.8%, and workers on temporary contracts at 18.0%). This relative lack of difference across demographies foreshadows the regression results in Section 4, which indicate that the demography controls do not emerge as significant once the Organizational and psychological controls are taken into account, except for the significant mid-career (35–49) age effect.

AI Wage Fear was built upon an independent question asking respondents if they believe AI will increase, decrease or have no effect on wages in their sector in the next decade. Of the 4,371 who provided a substantive answer, 2,158 (49.4%) believed that AI will lead to a decrease in wages, while 2,213 (50.6%) believed there will be no impact or increase in wages, and the 963 "do not know" responses were treated as missing.

6. Main Findings: Ordered Logistic Regression

The preferred specification regresses the three-category mental health outcome on the six substantive constructs of theoretical interest — AI Anxiety, AI Decision Support, Organizational Trust, AI Workplace Impact, AI Wage Fear, and Life Satisfaction, while controlling for demographic and structural characteristics (gender, age category, education, country, and sector). The model was estimated using 1,190 observations and explained a reasonable proportion of the variation in mental health outcomes, with a Pseudo R^2 of 0.265 —a value between 0.20 and 0.40, which is regarded as indicating an excellent fit for a discrete-choice model of this kind [20, 21]. Pseudo-R^2 measures are constructed differently from OLS R^2, and are typically much lower, so they should not be interpreted the same way. Table 4 shows the full specifications of the results.

Table 4
Ordered Logistic Regression of Self-Reported Mental Health Impact

Variable	Coef.	Odds-ratio	z	p-value
1. Core Explanatory Variables				
AI Anxiety	0.061	1.063	0.62	0.537
AI Decision Support	−0.210*	0.811	−1.91	0.056
Organizational Trust	−0.351***	0.704	−3.04	0.002
AI Workplace Impact	−1.468***	0.230	−11.98	0.000
AI Wage Fear (= 1)	0.603***	1.827	3.64	0.000
Life Satisfaction	−0.397***	0.672	−3.45	0.001
2. Control Variables				
Gender (Male = ref.)				
Female	-0.086	0.917	0.53	0.599
Age (16–24 years = ref.)				
25–34 years	−0.339	0.712	−1.45	0.148
35–49 years	−0.567**	0.567	−2.47	0.013
50–64 years	−0.248	0.780	−0.85	0.397
Age 65 years and above	0.332	1.393	0.45	0.653
Education (University degree = ref.)				
No university degree	−0.107	0.899	-0.59	0.558
Country (Austria = ref.)				
Canada	−0.385	0.680	−1.32	0.186
Germany	-0.200	0.818	-0.71	0.479
Ireland	−0.005	0.994	−0.02	0.986
United Kingdom	−0.420	0.657	−1.34	0.179
United States	−0.415	0.660	−1.40	0.161
France	-0.191	0.826	-0.68	0.498
Sector (Finance & Insurance = ref.)				
Manufacturing	−0.092	0.911	−0.57	0.571

****p < 0.01, **p < 0.05, *p < 0.10. Threshold parameters: α_1 = 0.220 (SE = 0.306), α_2 = 2.010 (SE = 0.316).*

Four constructs are statistically significant predictors of self-reported mental health change at conventional levels: Organizational Trust, AI Workplace Impact, and Life Satisfaction are all negatively associated with the odds of

reporting a worse mental health outcome, while AI Wage Fear is positively associated with worsened mental health. AI Decision Support narrowly misses the conventional 5% threshold. In contrast, AI Anxiety is not significant once Organizational Trust and AI Workplace Impact are included in the same model, suggesting that generalised anxiety operates indirectly through workplace experiences rather than independently. The diagnostics in Section 5 indicate that this is unlikely to reflect multicollinearity: AI Anxiety has a VIF of 1.19 (Section 5.1) and is correlated with the other constructs by no more than 0.340 in absolute value (Table 2). As none of the demographic or structural controls — gender, age, education, country, or sector showed significance (except only one age category 35–49), this pattern is central to the substantive argument of the paper that the mental health consequences of AI exposure appear to be shaped by how AI is Organizationally implemented and psychologically experienced (trust in the employer, perceived fairness and support, wage security, general life satisfaction) rather than by who the worker is in demographic terms.

6.1: Average Marginal Effects

As the coefficients of the ordered logit model are not directly interpretable as changes in probability, we use average marginal effects (AMEs) [26] for the probability of each of the three categories. Table 5 represents these effects for the core explanatory predictors.

Each AME represents the average change in the predicted probability of a given outcome associated with a one-unit increase in the explanatory variable, holding other covariates at their observed values, following the marginal effects approach of Williams [26]; because the three probabilities for any worker must sum to one, the AMEs reported in each row of Table 5 necessarily sum to approximately zero.

Table 5
Average Marginal Effects (dy/dx for all categories)

Variable	Positive	Neutral	Negative	p-value
AI Anxiety	−0.0079	0.0039	0.0039	0.530
AI Decision Support	0.0272	-0.0136	-0.0136	0.055
Organizational Trust	0.0455	-0.0227	-0.0228	0.002
AI Workplace Impact	0.1902	-0.0950	−0.0952	0.000
AI Wage Fear (= 1)	-0.0817	0.0417	0.0400	0.000
Life Satisfaction	0.0514	-0.0256	−0.0257	0.000

AI Workplace Impact is found to be the strongest correlate of positive mental health outcome in the model by a considerable margin, followed by Organizational Trust. Figures 1–5 plot the predicted probability across the observed range of each predictor, constructed from the Stata margins output.

In all the Figs. 1–4, the horizontal axis does not show the original Likert response values, ranging from “worsened it a lot” to “Improved it a lot”. Instead, it shows the value created by the factor analysis construct, ranging from − 2 to + 2. It shows the standardised factor scores with a mean of 0 and a standard deviation of 1. The lower extreme value, -2, represents a very low perception among workers in a particular category, whereas + 2 represents a higher perception. Consequently, values around 0 indicate the average, while negative values are below the average and positive values are above it. Therefore, the figures represent the predicted probability of three constructed

outcomes: Positive, Neutral and Negative in mental health changes as respondents move from relatively low to relatively high levels of each latent construct

In all the figures above (1–4), AI Workplace Impact has shown the largest marginal effect. A one-unit increase raises the probability of a Positive mental health outcome by approximately 19 percentage points (Table 5) while reducing the probabilities of Neutral and negative outcomes by about 9.5 percentage points each. Figure 1 shows that the workers with unfavourable perceptions (extreme negative values on the x-axis) of AI's workplace impact are most likely to report negative mental health effects. As workers' perceptions tend to shift towards positive values on the x-axis, negative and neutral outcomes are declining sharply, while positive mental health responses are increasing. It tells us that as workers' perceptions of their workplace improve, their responses to positive mental health also improve. These findings suggest that workers' mental health experiences are driven primarily by their workplace rather than by AI itself. Figure 5 shows the binary outcome of AI Wage Fear on the x-axis, with a rise in the probability of negative mental health among workers who believe a decrease in wages is an implication of AI (= 1). On the other hand, there is a decline in the positive probability for workers who believe (= 1) that AI intervention will decrease their wages.

7. Concluding Remark and Future Scope

This paper set out to answer a specific question: among the many ways AI changes a job, which factors actually predict a worker's mental health? As seen in data from OECD surveys of 1,190 workers across seven countries, the analysis shows that AI Workplace Impact and Organizational Trust are the strongest predictors, followed by AI Wage Fear, AI Decision Support, and Life Satisfaction. Generalised AI Anxiety, by comparison, does not explain any of these more specific constructs, and none of the demographic controls (gender, age, education, country, and sector) are significant (with the exception of one age category). The key takeaway is that the impact of AI on workers' mental health is not just about the technology but how it is used in the Organization and the psychological impact it has on the individual.

This has a very real consequence that needs to be made clear. Efforts to safeguard workplace mental health during the implementation of AI are more likely to succeed if they target Organizational practices rather than demographic subgroups (such as women or individuals with disabilities): transparency in governance, worker consultation, and clear evidence of fairness in how decisions are made with AI. While employers have no control over the people they hire, they can modify the way they integrate AI into their teams, and the findings in this paper indicate that the choice is more important.

There are definite limitations to the study. Its data is cross-sectional, so the relationships found are associations, not causal effects. A worker who already believes that they have high levels of trust in their employer may be more likely to report high levels of mental health than another worker, without that trust causing the mental health. The findings cannot be interpreted as generalisable to other sectors or applied to the labour markets of lower and middle-income countries, as they only include two sectors (finance and manufacturing) within seven high-income countries. Lastly, the analysis examines only main effects, and it does not assess whether the protective factors identified elsewhere in the literature (e.g., self-efficacy in AI learning, psychological resilience, and ethical leadership) moderate the relationships identified here.

These limits should be tackled on a case-by-case basis in future studies. Real causal claims would be possible with longitudinal or panel data, data that follows the same workers before and after the adoption of AI. Extending the survey to other sectors and to labour markets outside the OECD would test how far these findings generalise.

Testing interaction effects between the demographic variables and the core constructs would clarify whether the heterogeneity Wei and Li (2022) found in Chinese manufacturing — larger AI benefits for low-skilled and older workers — also holds in this seven-country sample, which the main effects tested here cannot rule out. Moreover, directly measuring self-efficacy in AI learning, psychological resilience, and Organizational ethical leadership alongside Organizational Trust would show whether trust is doing the same protective work these other constructs do in the wider literature, or something distinct. As AI's presence in the workplace continues to grow, closing these gaps will matter more and more for both researchers and the Organizations trying to introduce AI responsibly.

It is not a matter of good or bad regarding the use of AI for the individual behind the screen, but rather whether the Organization in which that individual works has earned their trust and enabled them to have a genuine say in its use. For researchers, that reimagining represents a real research opportunity; for employers and policymakers struggling to adapt to the introduction of AI today, it offers a useful reminder that the mental health impact of AI is not inherent in the technology but in the decisions surrounding its adoption.

Declarations

Competing Interests:

The author declares no competing interests.

Ethics, Consent to Participate and Consent to Publish Declaration

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Author Contribution

The concept was proposed by Dr Namrata Gulati. The paper was written by Versha Agarwal. Data analysis was done by Versha Agarwal. The final manuscript was read by Versha Agarwal.

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Data Availability

The data analysed in this study are drawn from the OECD AI Surveys of Workers. This microdata is not publicly available. Access requires an accreditation application through the OECD’s survey project and is restricted to non-commercial research use in accordance with their Terms of Use.

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Figures

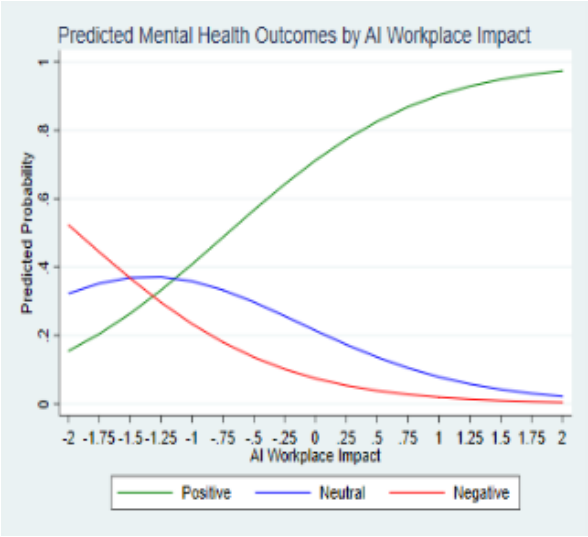


Figure 1

Predicted probability of mental health outcomes, by AI Workplace Impact.

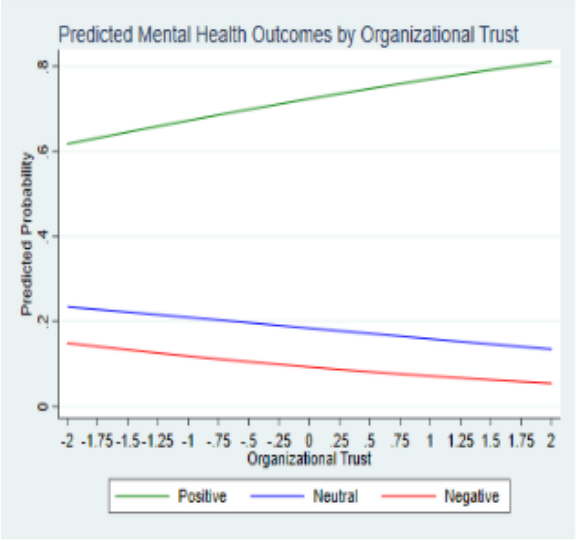


Figure 2

Predicted probability of mental health outcomes, by Organizational Trust.

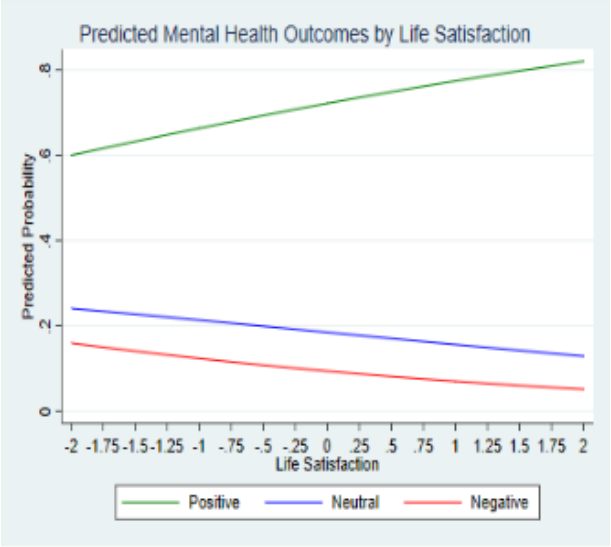


Figure 3

Predicted probability of mental health outcomes by Life Satisfaction.

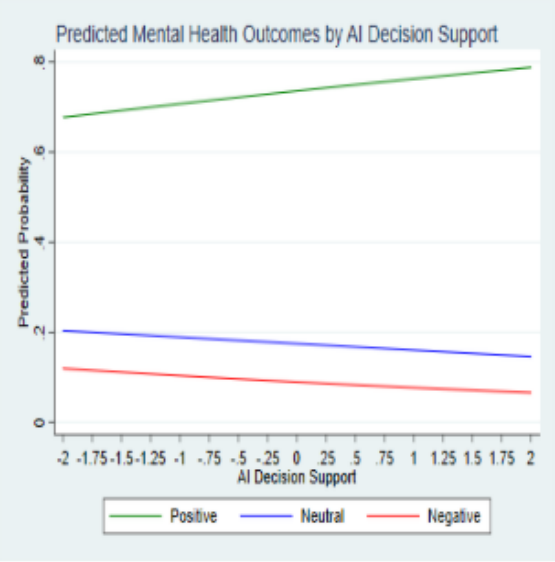


Figure 4

Predicted probability of mental health outcomes, by AI Decision Support.

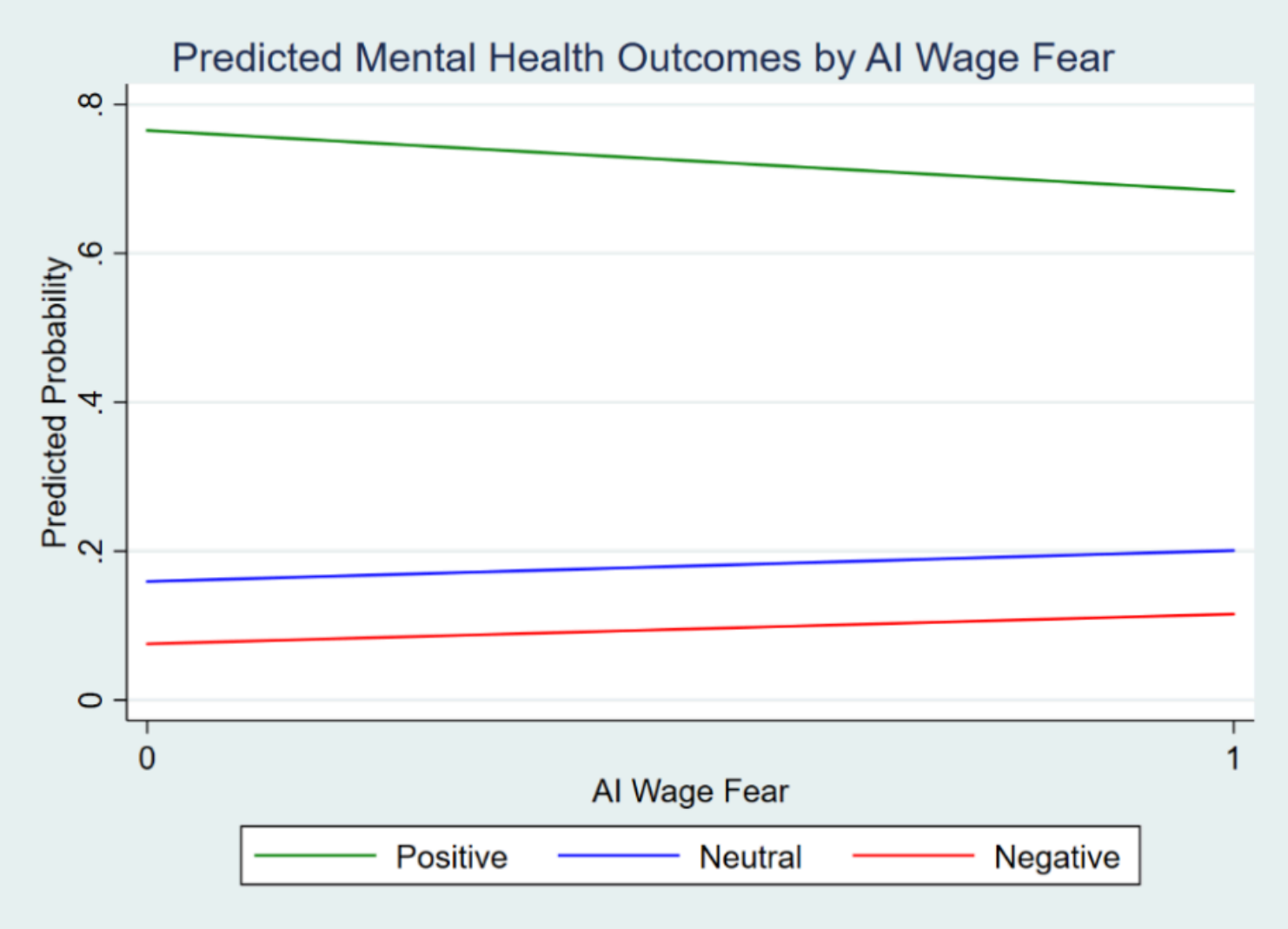


Figure 5

Predicted probability of mental health outcomes, by AI Wage Fear.

Supplementary Files

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- AppendixA.docx