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【要旨】

This study investigates the causal impact of subjective AI-induced job replacement anxiety on work motivation, turnover intentions, and mental well-being among Japanese workers. Integrating task-based theory, efficiency wage theory, and health capital models, we formalize the fear of future replacement as a microeconomic friction. To address endogeneity, we employ a simultaneous ordered probit framework using the ILO's Global Index of Occupational Exposure and Japan's Automation Risk Index as instrumental variables. Results reveal that AI anxiety significantly erodes work engagement and meaningfulness. Critically, AI anxiety heightens turnover intentions for the full sample, strictly aligning with theoretical predictions. However, we identify a non-monotonic generational pattern: middle-aged workers exhibit a defensive "lock-in" effect, whereas younger and older cohorts show increased mobility. Furthermore, mental health deterioration is concentrated among younger and self-employed individuals. These anticipatory psychological frictions distort labor incentives long before actual displacement, highlighting the need for human-centered AI policies.

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Abstract

This study investigates the causal impact of subjective AI-induced job replacement anxiety on work motivation, turnover intentions, and mental well-being among Japanese workers. Integrating task-based theory, efficiency wage theory, and health capital models, we formalize the fear of future replacement as a microeconomic friction. To address endogeneity, we employ a simultaneous ordered probit framework using the ILO's Global Index of Occupational Exposure and Japan's Automation Risk Index as instrumental variables. Results reveal that AI anxiety significantly erodes work engagement and meaningfulness. Critically, AI anxiety heightens turnover intentions for the full sample, strictly aligning with theoretical predictions. However, we identify a non-monotonic generational pattern: middle-aged workers exhibit a defensive "lock-in" effect, whereas younger and older cohorts show increased mobility. Furthermore, mental health deterioration is concentrated among younger and self-employed individuals. These anticipatory psychological frictions distort labor incentives long before actual displacement, highlighting the need for human-centered AI policies.

Keywords: Generative AI, Work Motivation, Turnover Intention, Mental Well-being, Japan

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1. Introduction

The rapid advancement of artificial intelligence (AI), particularly generative AI (GenAI), represents one of the most transformative shifts in the modern labor market, prompting intense debate among economists and policymakers. To understand how technology reshapes labor demand, the foundational task-based approach—pioneered by Autor et al. (2003)—established that jobs should be viewed as a bundle of tasks rather than indivisible units. This framework clarified that while technology substitutes for workers in routine tasks governed by explicit rules, it often complements those performing non-routine cognitive tasks. Acemoglu and Restrepo (2018, 2019) further refined this by formulating the displacement effect, where automation directly replaces human labor in specific task domains, and the reinstatement effect, where new, more complex tasks are created in which humans maintain a comparative advantage. While these models provide a robust macroeconomic lens for analyzing realized job loss and wage fluctuations, they typically focus on ex-post outcomes.

A significant research gap remains: the micro-level anticipatory impact of technology. the majority of the existing economic literature focuses on ex-post outcomes, such as actual job loss or wage fluctuations at the industry or aggregate level. Recently, micro-level evidence has begun to highlight the positive potential of AI deployment. Noy and Zhang (2023) demonstrated through a randomized trial that ChatGPT reduced writing time by 40% while raising quality by 18%, primarily benefiting lower-skilled workers and reducing productivity gaps. Similarly, Brynjolfsson et al. (2025) reported that the actual deployment of GenAI enhances worker productivity and improves well-being and retention in customer support roles. Conversely, the micro-level anticipatory mechanisms through which “subjective AI anxiety”—the fear held by workers who have not yet been displaced—impacts current labor incentives and mental well-being remain insufficiently understood. Evaluating how this fear of the future transforms current labor supply behavior and human capital accumulation is essential for understanding labor market sustainability in the AI era.

Recent empirical evidence on previous waves of automation provides a foundation for this inquiry. Abeliansky et al. (2024) find that increased exposure to industrial robots significantly deteriorates the mental health of workers, a process primarily mediated by heightened worries about job security. Similarly, Blasco et al. (2025) demonstrate that French workers in automatable occupations are more likely to report severe mental disorders, identifying the fear of unwanted job mobility as a key psychological channel. Regarding GenAI specifically, Gmyrek et al. (2025) report that workers in highly exposed clerical and cognitive roles are already cognizant of these threats, exhibiting noticeably higher levels of subjective concern compared to those in manual roles. These psychological pressures are increasingly linked to adverse labor behaviors such as "quiet quitting"—a form of psychological withdrawal where workers reduce their effort to the bare minimum—and increased turnover intentions (Gupta and Banerjee, 2026; Sayem et al., 2026; Uygungil-Erdogan et al., 2025).

To formalize these observations, this paper presents a new micro-incentive framework that integrates task-based theory with the efficiency wage theory (the no-shirking model) of Shapiro and Stiglitz (1984). In our model, a rise in the objective risk of technological displacement is defined for the individual worker as a discontinuous upward shock to the exogenous separation rate. As suggested by the Shapiro-Stiglitz framework, an increase in the exogenous separation rate significantly reduces the expected present value of future economic rents obtained by remaining at a current job. Unless firms compensate for this risk with a wage premium, the worker's no-shirking condition (NSC) collapses. Consequently, workers rationally lower their effort levels (work motivation) and increase their search for external options. In our study, the latter is dealt as turnover intention and quiet quitting. Furthermore, using the framework of Grossman (1972), we model this persistent uncertainty as a negative shock that depletes health capital (mental health).

Methodologically, the primary identification challenge is the endogeneity of subjective AI job replacement anxiety. To address this, we follow a burgeoning literature that utilizes objective, job-based exposure indicators as an exogenous source of variation (Abeliansky et al., 2024; Babina et al., 2024; Massenkoff and McCrory, 2026). We employ the Global Index of Occupational Exposure to Generative AI (GIOE in short) developed by Gmyrek et al. (2025) for the International Labour Organization (ILO) as an excluded exogenous variable. This index is an objective technical scoring based on the multimodal capabilities of GenAI, independent of individual psychological traits. As demonstrated by the survey results of Gmyrek et al. (2025), workers in high-exposure roles—particularly clerical support workers—report significantly higher levels of subjective concern regarding future replacement, thereby ensuring the relevance of the excluded exogenous variable.

This study makes two primary contributions. First, it formalizes the fear of technological unemployment as a friction that disrupts the dynamic incentive structure of the labor market. Second, it provides a rigorous causal identification of the link between AI anxiety and work motivation, and mental health. Our findings highlight the profound psychological frictions caused by technological progress and offer vital implications for corporate retention and labor market policy.

The rest of this paper is organized as follows. In the next section, we develop a theoretical model that yields testable hypotheses for empirical analysis. Section 3 explores the data. Section 4 shows the empirical models and the estimation results. In Section 5, we discuss the obtained results as well as the policy implications. Section 6 presents the conclusions.

2. Theoretical model

We show a model that formalizes how the anxiety of AI job replacement acts as a microeconomic friction that reduces work motivation and increases turnover intentions and quiet quitting, drawing on the macroeconomic task-based approach of Acemoglu and Restrepo (2018, 2019) and the efficiency wage theory of Shapiro and Stiglitz (1984). We also show how the anxiety of AI job replacement acts in reducing mental well-being using the health capital framework of Grossman (1972).

Formulation of the objective AI exposure index (z_i)

Following Acemoglu and Restrepo (2018, 2019), the production process is defined as a set of tasks. Concretely, the aggregate output Y is a combination of tasks j distributed over a unit interval $[N-1, N]$. Then, there exists a technical threshold I such that tasks $j \leq I$ can be performed by capital (AI), while tasks $j > I$ must be performed by labor. This I is so to speak automation threshold.

Each individual worker i is assigned to a specific set of tasks $\tau_i \subset [N-1, N]$ corresponding to their job. This is the idea that jobs are viewed as a bundle of tasks (Autor et al., 2003). We define the objective job exposure to AI (z_i) as the extent to which the macro-level automation threshold I penetrates the tasks assigned to worker i. Hence, z_i represents the proportion of tasks in τ_i that are technologically replaceable:

$$z_i(I) = \frac{Measure(\{j \in \tau_i | j < I\})}{Measure(\tau_i)}$$

Since we consider a simple static model and we use a cross-section dataset in the following sections, I is fixed and we can safely express $z_i(I)$ as z_i.[1] Note that $z_i \in [0.1]$. This z_i serves as an exogenous source of variation (excluded exogenous variable) in the later section since it

[1] We can extend the model in a dynamics way by assuming I can change over time.

is determined by technical capabilities independent of individual psychological traits.

The extended efficiency wage model

We incorporate this macro displacement risk, z_i, into the Shapiro and Stiglitz (1984) no-shirking framework to observe individual behavioral changes. Instantaneous utility of worker i is

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$$U_i = w_i - e_i,$$

where w_i is the wage and e_i is the effort level. The worker chooses between providing effort ($e_i > 0$) or shirking ($e_i = o$). The key in this model is to redefine the exogenous separation rate (λ). In the standard model, workers lose jobs only due to external factors (b). In our model, worker i perceives a subjective probability of displacement π_i, which is a strictly increasing function of their objective exposure z_i ($\pi_i'(z_i)$>0). Hence, effective separation rate, λ_i, of worker i is defined as:

$$\lambda_i(z_i) = b + \pi_i(z_i).$$

Building on the efficiency wage model of Shapiro and Stiglitz (1984), we define the expected lifetime utility for worker i:

Non-shirker ($V_{N,i}$): $rV_{N,i} = w_i - e_i + \lambda_i(z_i)\big(V_U - V_{N,i}\big)$, and

Shirker ($V_{S,i}$): $rV_{S,i} = w_i + \{\lambda_i(z_i) + q\}\big(V_U - V_{S,i}\big)$, where V_U is the value of being unemployed.

To induce worker i to provide effort, the condition $V_{N,i} \geq V_{S,i}$ must hold. Solving for the boundary condition ($V_{N,i} = V_{S,i}$) allows us to derive the no-shirking condition (NSC):

$$w_i \geq rV_U + \frac{e_i(r + b + \pi_i(z_i) + q)}{q}$$

The derived condition illustrates how AI job replacement anxiety acts as a friction in the labor market.

(A) Effort depletion (lower work motivation and/or quiet quitting): Since the right-hand side of NSC is an increasing function of π_i, the NSC collapses ($V_{N,i} < V_{S,i}$) if wages are sticky and do not provide a risk premium. leading the worker to rationally reduce effort to the bare minimum ($e_i \to 0$). This could be interpreted as lower work motivation and/or quiet quitting.

(B) Turnover Intention: The rise in π_i reduces the expected present value of staying at the current job ($V_{N,i}$), increasing the relative attractiveness of external options and thereby heightening turnover intentions.

Impact on mental well-being: the health capital model

Finally, we integrate the Grossman (1972) health capital model to describe the impact on mental well-being. Let mental health be defined as health capital (H_i). Then, the change in H_i from time t to $t + 1$ can be expressed as:

$$H_{it+1} - H_{it} = I_{it+1} - \delta_H(\pi_i(z_i))H_{it}$$

where I_i is the new investment on mental health capital and δ_H is the depreciation rate of mental health capital. Subjective replacement anxiety π_i acts as a persistent stressor that increases the depreciation rate of mental health capital. Hence, $\delta_H(\cdot)$ is an increase function of $\pi_i(z_i)$. Consequently, higher exposure z_i leads to a rapid decline in mental health stock H_i, providing the theoretical link for our empirical findings that AI anxiety deteriorates worker's mental well-being.

We test these theoretical predictions using Japanese microdata, as detailed in the subsequent sections.

3. Data

We utilized data from the sixth wave of the Japan COVID-19 pandemic and the Society Internet Survey (JACSIS). The JACSIS is a population-based, online questionnaire survey that recruits participants from a panel maintained by Rakuten Insight, Inc., which comprises approximately 2.2 million individuals aged 15 or above. While the detailed study design of the previous five waves has been documented elsewhere[2], this study specifically focuses on the sixth wave, administered between December 2025 and February 2026. For this wave, a follow-up survey was conducted from December 22, 2025, to February 22, 2026, targeting 24,626 individuals who had participated in prior waves and consented to further contact. Of these, 16,518 individuals provided valid responses and consent (a response rate of 67.1%). Concurrently, a new supplementary survey using the same questionnaire was administered from January 19 to February 22, 2026, targeting panellists aged 16–79, which yielded an additional 13,828 respondents. Combining the follow-up and supplementary samples, our final

[2] The detailed information on JACSIS is available on its website: https://jacsis-study.jp/

dataset consists of 27,630 respondents.

Of the six JACSIS waves conducted to date, the sixth wave is the first to incorporate a comprehensive set of questions regarding AI, which motivates its selection for this study. Because detailed AI-related questions were addressed only to individuals with prior AI experience due to the survey's skip logic, we exclude those who had never used AI. In our dataset, approximately half of the respondents (51.1%, or 14,121 individuals) fall into this category. Furthermore, since our research primarily focuses on AI-related employment issues, we restrict the analysis sample to individuals who were currently employed and had used AI for personal use, business use, or both. Finally, we exclude employed individuals whose job type was classified as “other.” Consequently, the final sample size for our main analysis is 9,117.

3.1. Outcome variables

We utilize six outcome variables as proxies for labor motivation and mental well-being, whose definitions and descriptive distributions are summarized in Table 1.

The first outcome variable, work engagement, is constructed from responses to the following three items: (a) “I feel energized when I'm working,” (b) “I take pride in my work,” and (c) “My job is a good fit for me.” For each statement, respondents select from four options: 1 (strongly agree), 2 (agree), 3 (disagree), or 4 (strongly disagree). These responses are reverse-coded so that higher values indicate stronger agreement and then aggregated, yielding a composite index ranging from 3 to 12. A higher score thus reflects a higher level of work engagement.

The second variable is job satisfaction. While the options were originally coded from 1 for “strongly agree” to 4 for “strongly disagree,” these scores are reverse-coded for the empirical analysis so that a higher value reflects greater satisfaction.

The third variable is work meaningfulness. As with job satisfaction, the responses were originally coded from 1 for "strongly agree" to 4 for "strongly disagree," and are reverse-coded for the empirical analysis. While job satisfaction captures how content employees are with their overall work environment, work meaningfulness reflects their intrinsic motivation and the perceived value of their tasks.

The fourth outcome variable, turnover intention, is based on the statement, "I want to quit my current job." Response options originally ranged from 1 (strongly agree) to 4 (strongly disagree). These scores are reverse-coded for the analysis so that higher values indicate a stronger desire to leave one's current job.

The fifth variable measures "quiet quitting," defined not as formal resignation, but as the practice of fulfilling the exact duties outlined in one's job description while deliberately withholding discretionary, uncompensated effort—essentially rejecting the expectation to go above and beyond. This variable is constructed from the responses to five statements: (a) doing only the bare minimum required for the job, (b) delegating tasks within one's own work that colleagues could handle, (c) taking as many breaks as possible, (d) refraining from expressing opinions to avoid additional workload, and (e) refraining from sharing suggestions regarding tasks due to the belief that working conditions will remain unchanged. Each item is rated on a five-point scale, from 1 (Strongly disagree) to 5 (Strongly agree), and summed to yield a composite score ranging from 5 to 25, where higher scores reflect a stronger propensity. For our empirical analysis, we discretize this score into three distinct, ordered categories to capture the varying intensity of this behavior: 1 for scores 5–15 (low), 2 for 16–20 (moderate), and 3 for 21–25 (high).

Finally, the sixth outcome variable is psychological distress, measured using the 6-item Kessler Psychological Distress Scale (K6) (Kessler et al., 2002, 2003). The K6 is a widely validated screening tool that assesses the frequency of non-specific psychological distress over the past 30 days. The total score ranges from 0 to 24, where higher values reflect more severe psychological distress and a greater probability of serious mental illness. Following Kessler et al. (2003) and Prochaska et al. (2012), we classify the cumulative scores into three distinct ordered categories: 1 for scores 0–4 (low or no distress), 2 for scores 5–12 (moderate distress), and 3 for scores 13–24 (severe distress).

3.2. Variables of interest

The main variable of interest in this study is AI job replacement anxiety. It is based on the statement "I am anxious that my job might be replaced by AI", with seven response options: 1: Strongly disagree, 2: Disagree, 3: Somewhat disagree, 4: Neither agree nor disagree, 5: Somewhat agree, 6: Agree, 7: Strongly agree. That is, the higher the value is, the more strongly the individual experiences anxiety about their job being replaced by AI. We use this (seven-point Likert scale) variable as a set of seven dummy variables or as it is (i.e., quasi-continuous variable). The descriptive statistics of this variable is shown in Table 2.

3.3. Excluded exogenous variable (Instrumental variable)

As discussed in detail below, our primary variable of interest—AI job replacement anxiety—is a subjective measure and thus highly susceptible to endogeneity bias. To address this endogeneity issue, we introduce an excluded exogenous variable that satisfies the exclusion restriction; that is, it is included in the first-stage equation for AI anxiety but excluded from the main outcome equations. This variable functions as an instrumental variable (IV) in a conventional linear simultaneous equations model.

As our excluded exogenous variable, we utilize the Global Index of Occupational Exposure to Generative AI (GIOE), developed by Gmyrek et al. (2025) for the International Labour Organization (ILO). The GIOE is a refined metric designed to assess the potential of

Generative AI to automate or augment job tasks. Adopting a task-based approach, the index estimates the technical automation potential of individual occupational tasks by integrating human judgment—gathered from large-scale worker surveys and international expert panels—with scalable Large Language Model (LLM) predictions. By mapping these scores to the ISCO-08 international classification system, the index provides a standardized framework for estimating the employment share exposed to GenAI, taking a value between 0 (not automatable with current GenAI technology) and 1 (fully automatable). Importantly, these scores reflect "technical exposure" (feasibility) rather than the "actual employment impact," as actual adoption may be constrained by infrastructure, implementation costs, social acceptance, and regulatory frameworks.

The JACSIS dataset provides information on 20 industry categories and 9 job types for each employed individual, yielding 180 distinct industry-occupation cells. Since this level of aggregation does not always allow for an exact one-to-one match with the 4-digit ISCO-08 codes, we manually map each cell to the closest 4-digit ISCO-08 occupation on a case-by-case basis.

The descriptive statistics for this variable are presented in Table 2, and further methodological details are available in Appendix 1.

3.4. Control variables

We control for a variety of individual-level factors, including both AI-related variables and conventional controls.

For AI-related control variables at the individual level, we include anxiety of being left behind by advances in AI technology and pricing plans for AI used at work. Anxiety of being left behind by advances in AI technology is the response to the following statement: I am anxious that I might not be able to keep up with the rapid advancement of AI technology", with seven response options: 1: Strongly disagree, 2: Disagree, 3: Somewhat disagree, 4: Neither agree nor disagree, 5: Somewhat agree, 6: Agree, 7: Strongly agree. Pricing plans for AI used at work is one of the following three options: 1: no use of AI at work, 2: free plan, or 3: paid plan.

As a set of individual-level conventional control variables, we include age, gender dummy (=1 if female, 0 otherwise), academic attainment, household income, company size (number of employees), employment type, average daily working hours when working on-site, frequency of work from home, and prefecture dummies.[3]

Educational attainment is originally measured using 11 categories: junior high school, private high school, national or public high school, vocational school, junior college or national college of technology, private university, national university, public university, graduate school, and others. For our analysis, we reclassify these into five consolidated categories: (1) high school graduate or less (covering junior high school, private high school, and national or public high school), (2) vocational school or junior college (covering vocational school and junior college or national college of technology), (3) university graduate or above (covering private, national, and public universities, and graduate school), and (4) others.

Annual household income is originally measured using 20 categories ranging from zero to 20 million Japanese yen (JPY) or more, in addition to "I don't want to answer" and "I don't know." For our analysis, we consolidate these into six distinct categories: (1) less than JPY 4 million, (2) JPY 4 million to less than JPY 8 million, (3) JPY 8 million to less than JPY 14 million, (4) JPY 14 million or more, (5) "I don't want to answer," and (6) "I don't know."

Company size (number of employees) is originally measured using 10 categories ranging from 1 to 1,000 or more employees, in addition to "I don't know." For our analysis,

[3] Japan is divided into 47 prefectures, which are like states or provinces.

we consolidate these into five distinct categories: (1) less than 30 employees, (2) 30 to less than 100 employees, (3) 100 to less than 1,000 employees, (4) 1,000 employees or more, and (5) "I don't know."

Employment type is originally measured using 12 categories: corporate executives, regular employees in managerial positions, regular employees in non-managerial positions, the self-employed, freelancers, unpaid family workers, temporary agency (dispatched) workers, fixed-term contract or re-employed staff, part-time and casual workers, gig or platform workers, home-based pieceworkers, and working students. For our analysis, we consolidate these into three distinct categories: (1) regular employment, (2) non-regular employment, and (3) self-employment.

Average daily working hours when working on-site is originally measured using 16 categories ranging from zero to 12 hours or more, in addition to "I don't know." For our analysis, we consolidate these into four distinct categories: (1) less than 5 hours, (2) 5 hours to less than 9 hours, (3) 9 hours or more, and (4) "I don't know.

Finally, we create a dummy variable indicating whether an individual worked from home at least once during the past month, taking the value of 2 if yes and 1 otherwise.

Table 2 reports the summary statistics for the full set of control variables.

4. Empirical model and results

4.1 Empirical model

To rigorously evaluate the causal impact of subjective AI-induced job anxiety on labor outcomes (such as work motivation and mental well-being), we must address the inherent endogeneity of our primary regressor. Unobserved individual traits (e.g., innate pessimism, unobserved workplace stressors, or personality traits) could simultaneously drive both the subjective perception of job insecurity and psychological outcomes. This unobserved confounding, along with potential reverse causality, leads to biased and inconsistent estimates under standalone Ordered Probit models.

To overcome this identification challenge, we employ a simultaneous estimation of the outcome and endogenous covariate equations using Full-Information Maximum Likelihood (FIML). We apply an ordered probit specification to both equations. The outcome equation is formulated via a latent variable approach:

$$Y_{ip}^{*} = \delta_0 + \delta_1 Job\_replacement\_anxiety_{ip} + control_{ip}' \delta_2 + \theta_p + \epsilon_{ip}, \quad (1)$$

where Y_{ip}^{*} is the unobserved latent level of the outcome for individual i in prefecture p. $Job\_replacement\_anxiety_{ip}$ denotes the endogenous discrete measure of subjective AI-induced job anxiety. $control_{ip}$ is a vector of individual-level control variables. The observed ordinal outcome Y_{ip} is mapped through a series of threshold parameters (cutpoints) κ :

$$Y_{ip} = j \ if \ \kappa_{j-1} < Y_{ip}^{*} < \kappa_j \ (j = 1, \dots J; J \leq 10). \quad (2)$$

Because the endogenous regressor $Job\_replacement\_anxiety_{ip}$ is inherently discrete and ordinal (e.g., a measured on a Likert scale), modeling it as a standard linear function is econometrically inappropriate and may yield biased estimates. Thus, we specify an ordered probit model for the endogenous covariate equation within the simultaneous estimation framework:

$$Job\_replacement\_anxiety_{ip}^{*} = \pi_0 + \pi_1 GIOE_{ip} + \pi_2 control_{ip}' + \vartheta_p + \rho_{ip}, \quad (3)$$

$$Job\_replacement\_anxiety_{ip} = m \quad if \quad \tau_{m-1} < Job\_replacement\_anxiety^{*}_{ip} \leq \tau_m$$

$$(m = 1, \ldots 7)$$

where $Job\_replacement\_anxiety^{*}_{ip}$ is the latent propensity of experiencing AI-induced job anxiety, and τ represents the threshold parameters.

Crucially, $GIOE_{ip}$ serves as our excluded exogenous variable: the Global Index of Occupational Exposure to Generative AI developed by Gmyrek et al. (2025) for the ILO. This index captures the objective, task-level vulnerability of an individual's occupation to Generative AI capabilities and is strictly excluded from the primary outcome equations.

It is worth noting that while the non-linear functional form of the simultaneous ordered probit framework theoretically allows for mathematical identification even without an instrument (Wilde, 2000), relying solely on such distributional assumptions is notoriously fragile and widely criticized in empirical economics. By explicitly incorporating $GIOE_{ip}$ as a strictly excluded exogenous variable, our identification strategy does not rely on the joint normality assumption for identification. Instead, it leverages genuine, external variation in occupational technology exposure, thereby ensuring that the estimated causal impact (δ_1) is robustly and credibly identified rather than being an artifact of functional form assumptions.

For this excluded exogenous variable to be valid in our econometric model, it must satisfy two standard conditions: relevance and the exclusion restriction. The first condition requires that the GIOE be strongly correlated with workers' subjective anxiety regarding AI job replacement. In this regard, the GIOE by Gmyrek et al. (2025) provides an objective, technical scoring of the extent to which occupational tasks can be automated or transformed by current GenAI technologies.

As noted by Gmyrek et al. (2025), the rapid advancement of GenAI has been accompanied by substantial media attention and growing societal apprehension regarding the potential for technology to automate knowledge work. Their survey results indicate that workers in occupations with high technical exposure—particularly those in clerical support roles—tend to report higher levels of subjective concern regarding the likelihood of their jobs being replaced by AI. This suggests that workers are cognizant of the technical substitutability of their roles, whether through direct observation of AI's capabilities in daily tasks or through external signals such as media reports and organizational policies. Therefore, a higher objective exposure score (i.e., the GIOE) is theoretically and empirically expected to significantly increase a worker's subjective job replacement anxiety.

The second and most critical condition is the exclusion restriction. That is, the GIOE must not directly affect the outcome variables (motivation and mental well-being) except through the channel of AI job replacement anxiety. We support the validity of this identification assumption through the following three arguments.

First, the GIOE is a measure of technical potential calculated exogenously based on macro-level task classifications and the technical capabilities of AI. It is entirely independent of an individual worker's current psychological state, health, or the specific performance of their firm.

Second, we consider whether AI exposure might affect well-being through direct channels other than anxiety, such as reducing workload through actual AI implementation. While research by Brynjolfsson et al. (2025) suggests that the actual deployment of AI can positively impact worker well-being by improving customer sentiment and operational efficiency, our excluded exogenous variable captures "unimplemented technical exposure" (potential) rather than the specific implementation status or changes in the work environment at an individual firm. Thus, it is conceptually distinct from the direct effects associated with the actual use of the technology.

Third, to address concerns that inherent occupational characteristics might act as confounders, this study strictly controls for educational attainment and employment statuses (regular employment, non-regular employment, and self-employment). As Gmyrek et al. (2025) and Brynjolfsson et al. (2025) demonstrate, GenAI exposure is concentrated in cognitive and knowledge-intensive occupations that typically require higher levels of formal education. Because educational attainment and socioeconomic status are powerful predictors of baseline mental well-being and job motivation, failing to control for them could bias our estimates. By simultaneously controlling for education and these employment statuses, the variation in our excluded exogenous variable isolates the impact of task-level technological exposure among workers who share equivalent educational backgrounds and economic protections. Although data constraints prevent the direct inclusion of broad occupational fixed effects, these combined covariates serve as robust proxies for the heterogeneity in socioeconomic status and work environments across different roles. Consequently, we believe our model sufficiently mitigates omitted variable bias and satisfies the exclusion restriction.

The simultaneous equation system is jointly identified under the assumption that the error term from the outcome equation (ϵ_{ip}) and the error term from the endogenous covariate equation (ρ_{ip}) follow a bivariate normal distribution with a mean vector of zero. Because the outcome equation models an unobserved latent variable (Y_{ip}^*), the scale of the parameters cannot be identified separately from the variance of the error term. To secure identification, we impose the standard normalization restriction by fixing the variance of the error term in the outcome equation to unity ($\sigma_\epsilon^2 = 1$). Consequently, the joint error structure is defined as:

$$\begin{pmatrix} \epsilon_{ip} \\ \rho_{ip} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \Sigma_1\right], \quad \Sigma_1 = \begin{pmatrix} 1 & \eta_{\epsilon\rho}\sigma_\rho \\ \eta_{\epsilon\rho}\sigma_\rho & \sigma_\rho^2 \end{pmatrix}$$

where σ_ρ^2 represents the variance of the error term of the endogenous covariate equation. The pivotal parameter for diagnosing endogeneity is $\eta_{\epsilon\rho}$, which measures the correlation between the unobserved determinants of AI-induced job anxiety and the outcomes. If $\eta_{\epsilon\rho}$ is statistically significant ($\eta_{\epsilon\rho} \neq 0$), it empirically confirms the presence of endogeneity, demonstrating that the simultaneous equation system is methodologically necessary to eliminate endogeneity bias and deliver consistent estimates of δ_1. Conversely, if we fail to reject the null hypothesis of zero correlation, it implies that unobserved confounders do not severely distort standard estimations in our specific sample. Even in the absence of a significant correlation, we retain the simultaneous equation system as our preferred specification. By utilizing the excluded exogenous variable ($GIOE_{ip}$), the model effectively purges any latent confounding mechanisms and identifies the causal effect (δ_1) solely through the exogenous variation in technological exposure. Therefore, the simultaneous equation system serves as a powerful conservative approach and a rigorous robustness check, ensuring that the estimated causal effects are robust to unobserved individual or occupational characteristics.

Finally, to account for potential within-prefecture correlation, standard errors are clustered at the prefecture level.

4.2 Results

4.2.1. Main results

Table 3 reports the main results. Each column corresponds to each of the six outcome variables. Panel A shows the results of the outcome equations, whereas Panel B shows those of the endogenous covariate equation.

In Panel B, the excluded exogenous variable (i.e., GIOE) is positive and statistically significant at 1% level in all columns, suggesting our excluded exogenous variable is strongly associated with subjective AI job replacement anxiety. That is, the more individuals' jobs are technically automatable by GenAI, the more intense the AI job replacement anxiety they experience.

Panel A presents the impact of AI job replacement anxiety on labor motivation and turnover intention. In Column (1), the coefficients for AI anxiety are uniformly negative relative to the base category (“1: Strongly disagree”) and grow in absolute magnitude as anxiety intensifies, with all estimates being statistically significant at the 1% level. This confirms that heightened AI job replacement anxiety severely dampens work engagement, strictly aligning with the theoretical predictions in Section 2. Regarding job satisfaction in Column (2), while the coefficients display a similar negative and monotonic pattern relative to the base category, they lack statistical significance. For work meaningfulness in Column (3), the estimates closely mirror the pattern and strong statistical significance observed in Column (1). Specifically, a stronger fear of AI job replacement significantly reduces perceived work meaningfulness, again corroborating the predictions of our theoretical framework.

In Column (4), the coefficient on AI job replacement anxiety is significantly positive at the 1% level, indicating that stronger displacement fears actually increase turnover intention, which is consistent with our initial theoretical prediction. In contrast, Column (5) shows no statistically significant effect of AI job replacement anxiety on "quiet quitting" (the intentional withdrawal of discretionary effort), which contradicts our initial theoretical prediction that the collapse of the No-Shirking Condition (NSC) would lead to effort depletion. This unexpected result can be explained by the unique institutional context of the Japanese labor market and the threat-rigidity mechanism.

Recent evidence by Kambayashi and Kato (2026) demonstrates the remarkable resilience of Japan's long-term employment system, even in the face of major systemic shocks. Within this rigid structure, workers who perceive a severe technological threat may find themselves essentially frozen due to the high costs of external mobility and the loss of firm-specific human capital. In such a high-stakes environment, engaging in quiet quitting becomes a highly irrational and risky strategy. Reducing effort would signal expendability, making the worker a primary candidate for actual AI replacement or internal restructuring. As supported by the literature on job insecurity and work effort (Brockner et al., 1992; Sverke et al., 2002), workers lacking viable outside options often adopt a job preservation strategy. Rather than withdrawing effort, they may maintain or even intensify their performance to signal their irreplaceability to the employer. Therefore, our statistically insignificant result on quiet quitting suggests that Japanese workers, driven by survival motives, actively refrain from withdrawal behaviors that could further jeopardize their standing in an already uncertain, AI-exposed environment.

Finally, mental health, as measured by the K6 scale, is not significantly affected by AI job replacement anxiety in the full sample. However, as demonstrated below, we identify heterogeneous impacts of AI job replacement anxiety on mental health across different groups.

The correlations between the stochastic disturbances of the outcome and the endogenous covariate equations in some Columns are worth investing. The error term correlation in Column (1) is positive and statistically significant at 1% level, indicating that unobserved factors increasing AI anxiety are positively associated with determinants of work engagement. In organizational psychology, this paradox aligns with the challenge-hindrance stressor framework (Cavanaugh et al., 2000). For highly engaged and career-conscious employees, rapid GenAI advancement is cognitively appraised as a “challenge stressor” rather than a purely destructive threat. Consequently, their heightened awareness of technological disruption induces higher subjective anxiety, which coexists with—and potentially fuels—a deeper dedication to showcasing unique human capabilities that AI cannot easily replicate.

In Columns (3), the error term correlation is positive and statistically significant at the

1% level. This apparent paradox aligns with Conservation of Resources theory (Hobfoll, 1989). Employees who view their work as a "calling" (Wrzesniewski et al., 1997) possess a profound psychological attachment to their professional identity. Because these highly engaged workers have more to lose, they become more acutely anxious about GenAI devaluing their skills compared to disengaged workers.

In Columns (4), the error term correlation is negative and statistically significant. This indicates that unobserved individual characteristics increasing the latent propensity to experience AI-induced job anxiety are negatively associated with the unobserved determinants of intention to leave the current organization. This finding can be rigorously interpreted as a “lock-in effect” driven by risk aversion under technological uncertainty. Workers who acutely perceive that their tasks are vulnerable to AI substitution face heightened perceived uncertainty regarding their external market value. Anticipating that switching employers will not necessarily shield them from the overarching macroeconomic shock of GenAI, these individuals exhibit a strong preference for the status quo. Consequently, those who are unobservably more anxious about AI choose to imbed themselves deeper within their current organization—where they have already accumulated firm-specific human capital and psychological safety—rather than risking friction in the external labor market.

Taken together, these findings demonstrate that subjective AI job replacement anxiety exerts a profound impact on multiple dimensions of worker outcomes, ranging from work engagement and perceived meaningfulness to turnover intention. Crucially, our empirical framework reveals a consistent methodological and psychological pattern across these diverse specifications. The significant error term correlations indicate that standard baseline models systematically confound the true impact of AI anxiety with unobserved selection mechanisms.

Our models successfully partialed out these complex psychological confounders. Once the inherent resilience, dedication, and risk-aversion of the workers are controlled for, the unconfounded causal estimates (δ_1) paint a stark and consistent empirical reality: independent of unobserved individual traits, unmanaged AI-induced anxiety fundamentally erodes intrinsic motivation, diminishes the sense of occupational meaning, and increase turnover intention.

4.2.2. Robustness checks

Alternative excluded exogenous variable

In the main analyses, we use the Global Index of Occupational Exposure to Generative AI (Gmyrek et al., 2025) as the excluded exogenous variable. Another viable candidate is the Automation Risk Index (ARI), developed by Fukao et al. (2025a, 2025b), which provides a novel dataset to quantify the exposure of Japanese occupations and industries to AI- and robotics-driven automation. Building upon the foundational methodologies of Frey and Osborne (2017) and Paolillo et al. (2022), the ARI integrates two primary data sources: the Occupation Information Database (JobTag-OID), compiled by the Japan Institute for Labour Policy and Training (JILPT), and a custom-designed expert survey conducted in 2024 by the Research Institute of Economy, Trade and Industry (RIETI) in collaboration with the Nomura Research Institute (NRI). This survey utilized a panel of 13 experts in Japan to assess the technological substitutability of human competencies across approximately 500 occupations.

Methodologically, the ARI assesses 53 distinct indicators, including 39 skills, 5 abilities (such as finger dexterity and ingenuity), and 9 job adaptability attributes (including teamwork and face-to-face communication), all of which are utilized to model the probability of task substitution through a logistic function. A distinguishing feature of this index is its inclusion of temporal projections across three distinct timeframes—the present (2024), 2030, and 2040—to capture both current and anticipated technological impacts. Furthermore, the expert evaluations were grounded in rigorous economic viability assumptions, requiring that the technology be implementable by a medium-sized enterprise within one year and yield cost savings relative to human labor.

The resulting index provides granular data for 487 occupations and is subsequently aggregated to the industry level using a 100-industry classification system based on the Japan Industry and Productivity (JIP) Database. The ARI is particularly well-suited for our study because it is constructed using Japan-specific data, ensuring high compatibility with our individual-level Japanese survey. Although the ARI captures automation risks driven by both robotics and AI, we employ it as an alternative excluded exogenous variable to verify the robustness of our primary findings.[4]

Descriptive statistics for this variable are presented in Table 2, and further methodological details are provided in Appendix 1.

Table 4 presents the estimation results using the ARI as the excluded exogenous variable. The structure of this table is identical to that of Table 3, with the ARI replacing the GIOE. We obtain highly consistent—and in some cases, stronger—results when employing the ARI. Subjective AI job replacement anxiety continues to exert a profound impact on work engagement, perceived meaningfulness, and turnover intention. Under the ARI specification, AI job replacement anxiety significantly affects both job satisfaction and mental health (Columns (2) and (6), respectively), though some coefficients in Column (2) are not statistically significant. In Column (6), the coefficients increase monotonically in absolute value with anxiety intensity, and all are statistically significant at the 1% level.

Ultimately, these findings confirm that our baseline results are robust to the selection of an alternative, country-specific excluded exogenous variable.

[4] It is worth noting that while the ARI is a skill- and ability-based index, the GIOE is explicitly task-based. Consequently, whereas the latter aligns directly with our theoretical model, the former does not strictly fit this framework. Here, we utilize the ARI as an alternative excluded exogenous variable to test robustness, rather than as a measure perfectly aligned with our core theoretical model.

Alternative empirical specifications: linear two-stage least squares (2SLS)

Although our main specification using a simultaneous ordered probit model is well-suited to the characteristics of our data, we also estimate the model using standard linear two-stage least squares (2SLS) as a robustness check. In this approach, we treat both the outcome variables and the endogenous variable (AI job replacement anxiety) as quasi-continuous. Furthermore, we utilize the raw quiet quitting scores (ranging from 5 to 25) and K6 scores (ranging from 0 to 24) to prevent any loss of information associated with recategorization. The Global Index of Occupational Exposure to Generative AI serves as the instrumental variable (IV).

Table 5 reports the 2SLS estimation results. The first-stage F-statistic (58.79) confirms that our instrumental variable is strongly correlated with workers' subjective anxiety regarding AI job replacement. Furthermore, as discussed in Subsection 4.1, it is highly plausible that our IV (GIOE) affects the outcome variables exclusively through the channel of AI job replacement anxiety, thereby satisfying the exclusion restriction.

The second-stage results are qualitatively similar to our main findings, although the coefficient on AI job replacement anxiety for turnover intention is not statistically significant. Conversely, the coefficients for job satisfaction and quiet quitting are statistically significant at the 1% level. Overall, these findings corroborate that AI job replacement anxiety exerts a profound impact on work engagement, job satisfaction, perceived meaningfulness, and quiet quitting.[5]

4.2.3. Heterogeneity analysis: age, education, and employment status

To examine potential heterogeneous effects, we conduct a series of subsample analyses,

[5] In Appendix 2, we present the 2SLS results using the ARI as the IV. This specification yields sharper estimates and confirms that AI job replacement anxiety significantly affects work engagement, job satisfaction, perceived meaningfulness, turnover intention, quiet quitting, and the K6 score, all in line with our theoretical predictions.

partitioning the full sample along three dimensions: age, educational attainment, and employment status. For brevity, we report the results exclusively for work engagement, work meaningfulness, turnover intention, and mental health (K6). The estimates for job satisfaction and quiet quitting are omitted as they generally lack statistical significance; furthermore, where the results for job satisfaction do achieve significance, they qualitatively mirror the patterns observed for work meaningfulness.

Tables 6, 7, and 8 present the results of these heterogeneity analyses. Across all specifications, we find that more intense AI job replacement anxiety generally leads to lower work engagement and reduced work meaningfulness. The sole exception is the work engagement of self-employed individuals in Column (3) of Table 8, where stronger AI job replacement anxiety is associated with higher work engagement. This positive association is plausible, as disengaging from one's own business when facing heightened threat from AI replacement would be counterproductive and economically disadvantageous.

In Table 6, our analysis identifies a distinct U-shaped pattern: AI anxiety heightens turnover intentions for younger (<35) and older (>56) workers but suppresses them for the middle-aged cohort (36–55). This suggests that middle-aged workers, who form the core of Japan’s resilient long-term employment system, react via threat-rigidity. Possessing high firm-specific capital but facing systemic uncertainty, they opt for a defensive "lock-in" strategy to leverage internal organizational buffers. In contrast, younger workers face a longer career horizon with lower switching costs, prompting them to pivot toward AI-complementary roles or industries. For older workers, the high cost of adapting to disruptive technology near retirement likely triggers an early-exit motive, consistent with the horizon effect. Ultimately, these results indicate that AI displacement fear causes behavioral paralysis among those most embedded in traditional employment structures, while inducing labor mobility at both ends of the age spectrum.

Crucially, the K6 results show that AI anxiety deteriorates mental health exclusively among younger workers (aged 35 and under). Given their extensive remaining career horizons, this vulnerability aligns with literature showing that career uncertainty severely threatens early-career workers' expected lifetime returns on human capital (Sverke et al., 2002). Furthermore, as Brougham and Haar (2018) note, technological disruption induces severe anxiety and lower well-being among those facing skill obsolescence at the inception of their careers. Unlike older cohorts, younger workers face prolonged exposure to AI-driven labor market volatility, compounding their psychological distress.

The subsample analysis presented in Table 7 reveals that heightened anxiety increases turnover intentions among workers with a high school education or less, as well as those with a university degree or higher. Although not all coefficients are statistically significant, a similar pattern is observed for vocational school or college graduates. Regarding mental health, we find suggestive evidence that intensified anxiety may precipitate a deterioration in mental well-being among workers with a university degree or higher. Although these coefficients increase monotonically with the level of AI replacement anxiety, most remain statistically insignificant. Given the substantial human capital investments inherent in higher education, these workers likely perceive GenAI as a profound threat to their professional identity and expected lifetime earnings, thereby triggering adverse psychological responses.

Table 8 reveals that regular and non-regular workers exhibit higher turnover intention as their AI job replacement anxiety intensifies, consistent with the baseline findings for the full sample although the pattern is weak in statistical sense for non-regular workers.

Notably, self-employed individuals exhibit a unique paradox: intensified AI anxiety suppresses their turnover intentions while simultaneously deteriorating their mental health. This suggests that this group is caught in a structural trap where, unlike organizational employees, they face prohibitive barriers to career transition, such as the difficulty of objectively signaling their human capital to the external market and the high switching costs of specialized business investments. Faced with AI as a systemic, market-wide shock, they likely experience a defensive "lock-in" effect driven by threat-rigidity. The lack of viable safe havens in the external labor market leads to behavioral paralysis, forcing these individuals to remain in increasingly precarious positions. Consequently, AI-induced displacement fear functions as a chronic psychological friction that accelerates the depreciation of health capital.

5. Discussion

Our empirical results demonstrate that heightened AI-induced job displacement anxiety significantly erodes work engagement and the perceived meaningfulness of work among Japanese employees. These findings provide robust support for our integrated micro-incentive framework. In the extended Shapiro and Stiglitz (1984) framework, an increase in the objective risk of technological displacement acts as a discontinuous upward shock to the effective separation rate. As the effective separation rate rises, the expected present value of future economic rents from remaining in the current position diminishes. Consequently, the No-Shirking Condition (NSC) collapses unless firms provide a risk premium to compensate for the increased probability of job loss. Workers thus rationally reduce their effort level, manifesting as the observed depletion in work motivation and engagement.

Furthermore, the finding that AI job replacement anxiety significantly heightens turnover intention is strictly aligned with our initial theoretical predictions. According to the efficiency wage model, the decline in the present value of future utility from the current job reduces the opportunity cost of job loss. As the relative attractiveness of staying in the current firm diminishes, workers rationally increase their search for external options to secure their career horizons. These results suggest that the "fear" of replacement itself acts as a powerful labor market friction, distorting both effort incentives and labor mobility long before actual displacement occurs.

Our findings reveal that displacement fears prompt a strategic pivot among younger workers and an anticipatory exit among those nearing retirement, while the middle-aged cohort exhibits a defensive “lock-in” effect. Consequently, the impact of AI replacement anxiety is highly heterogeneous across generations. This non-monotonic pattern suggests that the structural rigidity of Japan's long-term employment system acts as a stabilizing anchor for prime-age employees, who leverage organizational seniority and firm-specific capital to weather technological shocks. In contrast, the ends of the age spectrum respond with heightened external mobility, driven by either the necessity for long-term career realignment among the young or the prohibitive adaptation costs associated with the horizon effect as retirement approaches.

Our analysis reveals that the impacts of AI-induced job displacement anxiety on mental health are highly heterogeneous. Specifically, such anxiety significantly deteriorates the mental well-being of younger and self-employed workers. These findings can be interpreted through the lenses of a longer career horizon for the young and the limited certifiability of professional history for the self-employed.

Furthermore, the results for self-employed individuals suggest the need for a theoretical framework distinct from our integrated micro-incentive model. This group exhibits a unique paradox: as AI job replacement anxiety intensifies, they report heightened work engagement and suppressed turnover intentions despite their worsening mental health. These responses diverge from our standard theoretical predictions, identifying a compelling avenue for future research.

6. Conclusion

This study investigates the causal impact of subjective AI-induced job replacement anxiety on work motivation, turnover intentions, and mental well-being among Japanese workers. By integrating the macroeconomic, task-based framework of Acemoglu and Restrepo (2018, 2019) with the micro-level efficiency wage theory of Shapiro and Stiglitz (1984) and the health capital model of Grossman (1972), we provide a novel theoretical synthesis explaining how the anticipation of technological disruption reshapes labor supply behavior and human capital. To address the inherent endogeneity of psychological perceptions, we employ the ILO's Global Index of Occupational Exposure to Generative AI (Gmyrek et al., 2025) and the Automation Risk Index (Fukao et al., 2025) as excluded exogenous variables, thereby isolating objective technological shocks from unobserved individual traits.

Our empirical analysis yielded three primary findings. First, heightened AI anxiety significantly erodes intrinsic motivation, manifesting as reduced work engagement and a diminished sense of meaningfulness. This confirms that the perceived risk of future replacement acts as a discontinuous shock to the effective separation rate, thereby disrupting the No-Shirking Condition and weakening the dynamic incentive structure of employment relationships. Second, we find that AI job replacement anxiety significantly heightens turnover intention for the full sample, strictly aligning with theoretical predictions that technological displacement risk reduces the expected present value of current employment. However, this impact exhibits a distinct non-monotonic pattern across generations: while anxiety prompts a strategic pivot among younger workers and an anticipatory exit among those nearing retirement, the middle-aged cohort exhibits a defensive "lock-in" effect, leveraging firm-specific capital and organizational seniority as a buffer. Third, the impacts of AI anxiety on mental health are highly heterogeneous, as psychological distress from anticipated job replacement specifically deteriorates the well-being of younger and self-employed workers.

In conclusion, this study illuminates a critical, yet frequently overlooked, dimension of the technological transition: the profound behavioral and psychological frictions that precede actual labor displacement. Our results demonstrate that the proliferation of generative AI reshapes the fundamentally precarious nature of human and health capital well before automation is fully realized. Managing these psychological distortions is therefore paramount to ensuring that technological progress drives sustainable economic growth rather than the depletion of workplace motivation. Future research must expand upon these insights, turning its attention to how these anticipatory behavioral shifts—such as defensive organizational attachment and heightened psychological distress—alter the long-term dynamics of aggregate productivity and lifetime human capital accumulation.

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Table 1: Variable Definitions and Descriptive Statistics of Dependent Variables

Variable	Description	Index	(%)
Work engagement	Sum of reverse-coded scores (1–4 scale) from three items regarding energy, pride, and job-fit. The composite index ranges from 3 to 12; higher scores indicate stronger work engagement.	3	4.75
		4	3.28
		5	5.54
		6	13.28
		7	14.97
		8	17.09
		9	23.8
		10	7.16
		11	5.05
		12	5.08
Job satisfaction	Reverse-coded 4-point Likert scale score for job satisfaction (range: 1–4; higher values indicate greater satisfaction)	1	7.11
		2	25.21
		3	54.34
		4	13.35
Work meaningfulness	Reverse-coded score of a single item on work meaningfulness, originally measured on a 1–4 scale (1: strongly agree, 4: strongly disagree). Measures intrinsic motivation and perceived task value.	1	10.37
		2	25.79
		3	47.75
		4	16.1
Turnover intention	Reverse-coded score of a single item on turnover intention, based on the statement 'I want to quit my current job' (originally measured on a 1–4 scale; higher values indicate a stronger desire to leave).	1	32.72
		2	33.82
		3	23.87
		4	9.6
Quiet quitting	An ordinal index (1–4) capturing 'quiet quitting' (withholding discretionary effort). Constructed by summing five 5-point Likert items regarding behavioral withdrawal (raw score range: 5–25), then categorized as: 1 (5–10; low), 2 (11–15; moderate), 3 (16–20; high), and 4 (21–25; very high).	1	69.5
		2	27.14
		3	3.37
Kessler Psychological Distress Scale (K6)	An ordinal index (1–3) of psychological distress based on the 6-item Kessler Scale (K6) raw score (0–24). Categorized following Kessler et al. (2003): 1 (0–4; low/no distress), 2 (5–12; moderate), and 3 (13–24; severe).	1	55.46
		2	30.89
		3	13.66

Note: The number of observations is 9,117 for all variables.

Table 2: Variable Definitions and Descriptive Statistics of the Main Explanatory Variable, Excluded Exogenous Variables, and Control Variables

Variable	Summary	Max	Min	Index	Distribution (%)
AI job replacement anxiety (scale: 1=Strongly disagree, 2=Disagree, 3=Somewhat disagree, 4=Neither agree nor disagree, 5=Somewhat agree, 6=Agree, 7=Strongly agree)				1	46.92
				2	15.19
				3	8.13
				4	12.83
				5	11.13
				6	4.26
				7	1.54
the Global Index of Occupational Exposure to Generative AI	0.407 (0.139)	0.103	0.621		
Automation Risk Index (ARI)	0.275 (0.085)	0.139	0.545		
Anxiety score regarding falling behind in the AI era (scale: 1 = strongly disagree to 7 = strongly agree)				1	36.11
				2	14.14
				3	9.22
				4	14.41
				5	16.95
				6	6.3
				7	2.87
Pricing plan for AI used at work (1 = no use, 2 = free plan, 3 = paid plan)				1	34.46
				2	50.56
				3	14.97
Age	39.750 (13.407)	15	83		
Sex (1=Male, 2=Female)				1	55.37
				2	44.63
Educational attainment (1=High school graduate or less, 2=Vocational school or junior college, 3=University graduate or above, or 4=Others)				1	15.58
				2	16.23
				3	67.85
				4	0.34
Annual household income collapsed into 6 categories (1=less than JPY 4 million, 2=JPY 4 million to less than JPY 8 million, 3=JPY 8 million to less than JPY 14 million, 4=JPY 14 million or more, 5="I don't want to answer", or 6="I don't know")				1	17.93
				2	35.97
				3	25.47
				4	6.3
				5	6.87
				6	7.47
Company size (number of employees) (1=less than 30, 2=30 to less than 100, 3=100 to less than 1,000, 4=1,000 or more, or 5="I don't know")				1	20.15
				2	13.83
				3	26.72
				4	33.64
				5	5.66
Employment type (1=regular employment, 2=non-regular employment, or 3=self-employment)				1	71.89
				2	6.44
				3	21.67
Daily working hours on-site collapsed (1=less than 5 hours, 2=5 hours to less than 9 hours, 3=9 hours or more, or 4="I don't know")				1	23.09
				2	54.51
				3	21.31
				4	1.09
Remote work status dummy (1=No or 2=Yes)				1	67.8
				2	32.2

Notes:
The number of observations is 9,117 for all variables.
For continuous variables, means are reported with standard deviations in parentheses. For discrete variables, their distributions are presented.

Table 3: The Impact of AI Job Replacement Anxiety on Labor Motivation and Mental Well-Being

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Work engagement	Job satisfaction	Work meaningfulness	Turnover intention	Quiet quitting	K6
Panel A: Outcome equation						
AI job replacement anxiety (Base category=1: Strongly disagree)						
2.Disagree	-0.7316***	-0.2561	-0.7482***	0.7459***	0.0763	0.3588
	(0.0602)	(0.1964)	(0.0726)	(0.0879)	(0.1430)	(0.6984)
3.Somewhat disagree	-1.0499***	-0.4405*	-1.1203***	1.1301***	0.1967	0.5546
	(0.0856)	(0.2605)	(0.0862)	(0.0978)	(0.1701)	(0.9236)
4.Neither agree nor disagree	-1.2283***	-0.5297*	-1.3286***	1.3113***	0.1194	0.5198
	(0.0958)	(0.3197)	(0.1043)	(0.1038)	(0.2107)	(1.1859)
5.Somewhat agree	-1.5119***	-0.5538	-1.6159***	1.4995***	0.2213	0.4706
	(0.1198)	(0.4429)	(0.1202)	(0.1426)	(0.2903)	(1.5604)
6.Agree	-2.0253***	-0.7052	-2.0754***	1.9691***	0.5625	0.6986
	(0.1430)	(0.5404)	(0.1490)	(0.1785)	(0.3525)	(1.9578)
7.Strongly agree	-2.3464***	-0.7948	-2.5454***	2.3974***	0.6050	0.6835
	(0.2571)	(0.7621)	(0.2171)	(0.2245)	(0.4799)	(2.4841)
Prefecture dummy	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Endogenous covariate equation						
	AI job replacement anxiety (1: Strongly disagree, 2: Disagree, 3: Somewhat disagree, 4: Neither agree nor disagree, 5: Somewhat agree, 6: Agree, 7: Strongly agree)					
Global Index of Occupational Exposure to Generative AI	0.8350***	0.7151***	0.9242***	0.5263***	0.7098***	0.7044***
	(0.0976)	(0.1081)	(0.0936)	(0.1276)	(0.1163)	(0.1055)
Prefecture dummy	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Correlation of the error terms	0.5528***	0.1652	0.5735***	-0.5186***	-0.0460	-0.0527
	(0.0449)	(0.1747)	(0.0406)	(0.0527)	(0.1094)	(0.6139)
Observations	9,117	9,117	9,117	9,117	9,117	9,117

Notes:

This table reports the estimation results from the simultaneous equation system, comprising the outcome equations (Panel A) and the endogenous covariate equation (Panel B). Panel A presents the raw coefficients on AI job replacement anxiety, with “1: Strongly disagree” serving as the reference category. Panel B reports the raw coefficients from the endogenous covariate equation. For brevity, the coefficients on the control variables are omitted. The reported error term correlation in each column represents the correlation between the stochastic disturbances of the outcome and the endogenous covariate equations.

Standard errors in parentheses are clustered at prefecture level.

*** p<0.01, ** p<0.05, * p<0.1

Table 4: The Impact of AI Job Replacement Anxiety (Alternative Excluded Exogenous Variable)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Work engagement	Job satisfaction	Work meaningfulness	Turnover intention	Quiet quitting	K6
Panel A: Outcome equation						
AI job replacement anxiety (Base category=1: Strongly disagree)						
2.Disagree	-0.7298***	-0.2913	-0.7217***	0.7951***	0.0481	0.6503***
	(0.0615)	(0.1804)	(0.0796)	(0.0807)	(0.1810)	(0.1919)
3.Somewhat disagree	-1.0440***	-0.4862**	-1.0822***	1.1906***	0.1589	0.9378***
	(0.0868)	(0.2408)	(0.0941)	(0.0812)	(0.2186)	(0.2303)
4.Neither agree nor disagree	-1.2241***	-0.5895**	-1.2824***	1.3937***	0.0710	1.0188***
	(0.0997)	(0.2949)	(0.1153)	(0.0846)	(0.2669)	(0.3142)
5.Somewhat agree	-1.5089***	-0.6342	-1.5562***	1.6148***	0.1579	1.1353***
	(0.1224)	(0.4099)	(0.1333)	(0.1160)	(0.3675)	(0.4109)
6.Agree	-2.0145***	-0.8051	-1.9922***	2.1082***	0.4819	1.5322***
	(0.1466)	(0.5024)	(0.1682)	(0.1481)	(0.4525)	(0.4948)
7.Strongly agree	-2.3317***	-0.9208	-2.4377***	2.5737***	0.5037	1.7376***
	(0.2574)	(0.6945)	(0.2383)	(0.1834)	(0.5891)	(0.6311)
Prefecture dummy	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Endogenous covariate equation						
	AI job replacement anxiety (1: Strongly disagree, 2: Disagree, 3: Somewhat disagree, 4: Neither agree nor disagree, 5: Somewhat agree, 6: Agree, 7: Strongly agree)					
Automation Risk Index	0.8026***	0.6217***	0.8321***	0.5524***	0.5761***	0.6694***
	(0.1699)	(0.1800)	(0.1577)	(0.1663)	(0.1864)	(0.1737)
Prefecture dummy	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Correlation of the error terms	0.5482***	0.1960	0.5458***	-0.5626***	-0.0210	-0.3144**
	(0.0458)	(0.1593)	(0.0465)	(0.0405)	(0.1395)	(0.1576)
Observations	9,117	9,117	9,117	9,117	9,117	9,117

Notes:

This table reports the estimation results from the simultaneous equations system, comprising the outcome equations (Panel A) and the endogenous covariate equation (Panel B). Panel A presents the raw coefficients for AI job replacement anxiety, taking "1: Strongly disagree" as the reference category. Panel B reports the raw coefficients from the endogenous covariate equations. For brevity, the coefficients on the control variables are omitted. The reported error term correlation in each column represents the correlation between the stochastic disturbances of the outcome and the endogenous covariate equations.

Standard errors in parentheses are clustered at prefecture level.

*** p<0.01, ** p<0.05, * p<0.1

Table 5: The Impact of AI Job Replacement Anxiety Llinear Two-Stage Least Squares (2SLS))

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Work engagement	Job satisfaction	Work meaningfulness	Turnover intention	Quiet quitting	K6
Panel A: Second stage of two-stage least squares						
AI job replacement anxiety	-2.1193***	-0.2330***	-1.0194***	0.0056	0.7207***	0.8239
	(0.3205)	(0.0870)	(0.1584)	(0.0919)	(0.2509)	(0.6086)
Prefecture dummy	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: First stage for AI job replacement anxiety						
	AI job replacement anxiety					
Global Index of Occupational Exposure to Generative AI	0.7853***					
	(0.1024)					
Prefecture dummy	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
F test of excluded instrument	58.79					
Observations	9,117	9,117	9,117	9,117	9,117	9,117

Notes:

This table reports the estimation results from the linear two-stage least squares (2SLS) regressions, with Panel A presenting the second-stage results and Panel B presenting the first-stage results. In Panel A, AI job replacement anxiety is treated as a quasi-continuous variable. Panel B reports only the coefficient on the excluded exogenous variable (the Global Index of Occupational Exposure to Generative AI). Note that the first stage is identical across all specifications. The first-stage F-statistic for the excluded instrument is also reported.

Standard errors in parentheses are clustered at prefecture level.

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Heterogeneous Impacts of AI Job Replacement Anxiety on Work Motivation and Mental Well-Being (by Age Group)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Work engagement			Work meaningfulness		
	Age≤35	36≤Age≤55	56≤Age	Age≤35	36≤Age≤55	56≤Age
Panel A: Outcome equation						
AI job replacement anxiety (Base category=1: Strongly disagree)						
2.Disagree	-0.7904***	-0.7184***	-0.9750***	-0.8156***	-0.7635***	-0.9210***
	(0.0517)	(0.0841)	(0.0993)	(0.0643)	(0.0918)	(0.1074)
3.Somewhat disagree	-1.1438***	-1.1098***	-1.3723***	-1.2358***	-1.1785***	-1.4021***
	(0.0561)	(0.1358)	(0.1476)	(0.0638)	(0.1478)	(0.1098)
4.Neither agree nor disagree	-1.3974***	-1.2212***	-1.4678***	-1.5380***	-1.2896***	-1.5680***
	(0.0681)	(0.1379)	(0.1876)	(0.0778)	(0.1491)	(0.1620)
5.Somewhat agree	-1.7846***	-1.5408***	-1.6423***	-1.9303***	-1.5740***	-1.8297***
	(0.0941)	(0.1553)	(0.2303)	(0.0879)	(0.1854)	(0.1777)
6.Agree	-2.3837***	-2.0498***	-2.2084***	-2.5111***	-1.9705***	-2.2460***
	(0.1024)	(0.1973)	(0.3574)	(0.1308)	(0.2504)	(0.2933)
7.Strongly agree	-2.8207***	-2.4123***	-2.4602***	-3.0179***	-2.5686***	-2.8191***
	(0.2443)	(0.2909)	(0.3836)	(0.1665)	(0.3428)	(0.4166)
Panel B: Endogenous covariate equation						
	AI job replacement anxiety (1: Strongly disagree, 2: Disagree, 3: Somewhat disagree, 4: Neither agree nor disagree, 5: Somewhat agree, 6: Agree, 7: Strongly agree)					
Global Index of Occupational Exposure to Generative AI	0.7671***	0.8973***	0.8849***	0.8666***	0.9495***	1.1073***
	(0.1284)	(0.1455)	(0.2349)	(0.1139)	(0.1363)	(0.2165)
Correlation of the error terms	0.6701***	0.5446***	0.5984***	0.8666***	0.5476***	0.6715***
	(0.0356)	(0.0566)	(0.0671)	(0.1139)	(0.0645)	(0.0497)
Observations	4,234	3,521	1,362	4,234	3,521	1,362

	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	Turnover intention			K6		
	Age≤35	36≤Age≤55	56≤Age	Age≤35	36≤Age≤55	56≤Age
Panel A: Outcome equation						
AI job replacement anxiety (Base category=1: Strongly disagree)						
2.Disagree	0.7892***	-0.3971***	0.9538***	0.9068***	0.5145	-0.2854
	(0.0774)	(0.1250)	(0.1274)	(0.1479)	(0.5280)	(0.4156)
3.Somewhat disagree	1.2130***	-0.3944**	1.6810***	1.2903***	0.7680	-0.2333
	(0.1013)	(0.1770)	(0.2080)	(0.2065)	(0.6481)	(0.5650)
4.Neither agree nor disagree	1.4907***	-0.7943***	1.7680***	1.4519***	0.8608	-0.5324
	(0.1148)	(0.1851)	(0.1956)	(0.2731)	(0.8791)	(0.6503)
5.Somewhat agree	1.7470***	-1.2576***	2.0139***	1.7132***	0.9361	-0.7625
	(0.1538)	(0.2448)	(0.2291)	(0.3514)	(1.1836)	(0.7960)
6.Agree	2.3162***	-1.5087***	2.5543***	2.3579***	1.1994	-1.0884
	(0.1919)	(0.2802)	(0.3409)	(0.4338)	(1.4350)	(1.0498)
7.Strongly agree	2.8240***	-2.0110***	3.3208***	2.6437***	1.5066	-1.2858
	(0.2458)	(0.3367)	(0.8164)	(0.5700)	(1.8578)	(1.5530)
Panel B: Endogenous covariate equation						
	AI job replacement anxiety (1: Strongly disagree, 2: Disagree, 3: Somewhat disagree, 4: Neither agree nor disagree, 5: Somewhat agree, 6: Agree, 7: Strongly agree)					
Global Index of Occupational Exposure to Generative AI	0.4531**	0.6473***	0.3918*	0.5941***	0.7562***	0.4787*
	(0.2011)	(0.1334)	(0.2333)	(0.1816)	(0.1429)	(0.2793)
Correlation of the error terms	-0.6242***	0.5638***	-0.6540***	-0.5617***	-0.2051	0.4527
	(0.0577)	(0.0877)	(0.0677)	(0.1303)	(0.4714)	(0.3088)
Observations	4,234	3,521	1,362	4,234	3,521	1,362

Notes:

This table reports the estimation results from the simultaneous equation system, comprising the outcome equations (Panel A) and the endogenous covariate equation (Panel B) for the three age groups (under 36, 36–55, and 56 and older), respectively. Panel A presents the raw coefficients on AI job replacement anxiety, with "1: Strongly disagree" serving as the reference category. Panel B reports the raw coefficients from the endogenous covariate equation. For brevity, the coefficients on the control variables are omitted. The reported error term correlation in each column represents the correlation between the stochastic disturbances of the outcome and the endogenous covariate equations.

Standard errors in parentheses are clustered at prefecture level.

*** p<0.01, ** p<0.05, * p<0.1

Table 7: Heterogeneous Impacts of AI Job Replacement Anxiety on Work Motivation and Mental Well-Being (by Education Group)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES		Work engagement			Work meaningfulness	
	High school graduate or less	Vocational school or junior college	University graduate or above	High school graduate or less	Vocational school or junior college	University graduate or above
Panel A: Outcome equation						
AI job replacement anxiety (Base category=1: Strongly disagree)						
2.Disagree	-0.7613***	-0.6795***	-0.7657***	-0.7100***	-0.5776***	-0.8104***
	(0.1068)	(0.1093)	(0.0710)	(0.1335)	(0.1423)	(0.0746)
3.Somewhat disagree	-1.2849***	-0.8472***	-1.0715***	-1.3310***	-0.9240***	-1.1294***
	(0.1280)	(0.1501)	(0.1047)	(0.1365)	(0.1692)	(0.1056)
4.Neither agree nor disagree	-1.3489***	-1.1418***	-1.2604***	-1.4474***	-1.0898***	-1.3623***
	(0.1507)	(0.1665)	(0.1163)	(0.1799)	(0.1886)	(0.1238)
5.Somewhat agree	-1.5035***	-1.4996***	-1.5765***	-1.8861***	-1.4234***	-1.6336***
	(0.1976)	(0.1995)	(0.1484)	(0.2126)	(0.2238)	(0.1434)
6.Agree	-1.9264***	-1.9986***	-2.1188***	-2.1500***	-1.6979***	-2.1693***
	(0.2946)	(0.3131)	(0.1749)	(0.2787)	(0.2955)	(0.1786)
7.Strongly agree	-2.1953***	-2.0161***	-2.5426***	-2.5786***	-1.8834***	-2.7117***
	(0.3670)	(0.4695)	(0.2918)	(0.4419)	(0.4750)	(0.2580)
Panel B: Endogenous covariate equation						
	AI job replacement anxiety (1: Strongly disagree, 2: Disagree, 3: Somewhat disagree, 4: Neither agree nor disagree, 5: Somewhat agree, 6: Agree, 7: Strongly agree)					
Global Index of Occupational Exposure to Generative AI	0.3298	1.2299***	0.8663***	0.4200*	1.4088***	0.9224***
	(0.2490)	(0.2408)	(0.1290)	(0.2517)	(0.2538)	(0.1380)
Correlation of the error terms	0.5810***	0.5192***	0.5753***	0.6565***	0.4916***	0.5767***
	(0.0722)	(0.0772)	(0.0537)	(0.0790)	(0.0860)	(0.0528)
Observations	1,420	1,480	6,186	1,420	1,480	6,186

	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES		Turnover intention			K6	
	High school graduate or less	Vocational school or junior college	University graduate or above	High school graduate or less	Vocational school or junior college	University graduate or above
Panel A: Outcome equation						
AI job replacement anxiety (Base category=1: Strongly disagree)						
2.Disagree	0.8666***	0.7073**	0.7248***	-0.2688	0.2433	0.6155
	(0.1553)	(0.3533)	(0.0915)	(0.3541)	(0.4412)	(0.3869)
3.Somewhat disagree	1.5036***	0.9218*	1.1004***	-0.2279	0.3607	0.8862*
	(0.1554)	(0.4717)	(0.1218)	(0.4537)	(0.5979)	(0.5089)
4.Neither agree nor disagree	1.3925***	1.0091*	1.3377***	-0.5143	0.4566	0.9130
	(0.2271)	(0.6088)	(0.1202)	(0.5893)	(0.7197)	(0.6658)
5.Somewhat agree	1.7233***	0.9312	1.5430***	-0.8319	0.0933	1.0254
	(0.3060)	(0.8083)	(0.1722)	(0.8024)	(0.9316)	(0.9001)
6.Agree	2.0435***	1.3834	2.0491***	-1.1569	0.5934	1.4045
	(0.3609)	(0.9504)	(0.2211)	(0.9317)	(1.1764)	(1.1195)
7.Strongly agree	2.7474***	1.4892	2.5062***	-0.9301	0.2057	1.5311
	(0.5171)	(1.0908)	(0.2887)	(1.2973)	(1.5013)	(1.4054)
Panel B: Endogenous covariate equation						
	AI job replacement anxiety (1: Strongly disagree, 2: Disagree, 3: Somewhat disagree, 4: Neither agree nor disagree, 5: Somewhat agree, 6: Agree, 7: Strongly agree)					
Global Index of Occupational Exposure to Generative AI	0.0312	1.0790***	0.5318***	0.3420	1.1862***	0.6778***
	(0.2438)	(0.3383)	(0.1849)	(0.2448)	(0.2771)	(0.1637)
Correlation of the error terms	-0.5731***	-0.3604	-0.5307***	0.3918	-0.0037	-0.2459
	(0.1174)	(0.3112)	(0.0653)	(0.3040)	(0.3692)	(0.3502)
Observations	1,420	1,480	6,186	1,420	1,480	6,186

Notes:

This table reports the estimation results from the simultaneous equation system, comprising the outcome equations (Panel A) and the endogenous covariate equation (Panel B) for three educational attainment groups (high school graduate or less, vocational school or junior college, and university graduate or above), respectively. Panel A presents the raw coefficients on AI job replacement anxiety, with "1: Strongly disagree" serving as the reference category. Panel B reports the raw coefficients from the endogenous covariate equation. For brevity, the coefficients on the control variables are omitted. The reported error term correlation in each column represents the correlation between the stochastic disturbances of the outcome and the endogenous covariate equations.

Standard errors in parentheses are clustered at prefecture level.

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Heterogeneous Impacts of AI Job Replacement Anxiety on Work Motivation and Mental Well-Being (by Employment Status)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Work engagement			Work meaningfulness		
	Regular employment	Non-regular employment	Self-employment	Regular employment	Non-regular employment	Self-employment
Panel A: Outcome equation						
AI job replacement anxiety (Base category=1: Strongly disagree)						
2.Disagree	-0.7180***	-0.7316***	0.8085***	-0.7541***	-0.7986***	-0.8247***
	(0.0592)	(0.0985)	(0.1200)	(0.0681)	(0.1460)	(0.2009)
3.Somewhat disagree	-1.0049***	-1.1510***	0.6585***	-1.1263***	-1.2679***	-1.3660***
	(0.0869)	(0.1586)	(0.1820)	(0.0862)	(0.1636)	(0.3251)
4.Neither agree nor disagree	-1.2486***	-1.1280***	1.3866***	-1.3739***	-1.3984***	-1.2509***
	(0.1099)	(0.1118)	(0.1586)	(0.1128)	(0.1538)	(0.3104)
5.Somewhat agree	-1.5717***	-1.3099***	1.8991***	-1.7172***	-1.5208***	-1.6442***
	(0.1386)	(0.1763)	(0.2010)	(0.1256)	(0.2340)	(0.4664)
6.Agree	-2.1259***	-1.8068***	2.4275***	-2.1811***	-2.1122***	-1.8536***
	(0.1580)	(0.2145)	(0.3155)	(0.1573)	(0.2646)	(0.5791)
7.Strongly agree	-2.3640***	-2.2636***	2.8855***	-2.7027***	-2.3651***	-2.9882***
	(0.3053)	(0.2951)	(0.4432)	(0.2669)	(0.3883)	(0.6891)
Panel B: Endogenous covariate equation						
	AI job replacement anxiety (1: Strongly disagree, 2: Disagree, 3: Somewhat disagree, 4: Neither agree nor disagree, 5: Somewhat agree, 6: Agree, 7: Strongly agree)					
Global Index of Occupational Exposure to Generative AI	0.9406***	0.5832***	0.0973	1.0413***	0.5899***	0.7782***
	(0.1412)	(0.1800)	(0.2818)	(0.1297)	(0.1754)	(0.2986)
Correlation of the error terms	0.5682***	0.4850***	-0.7844***	0.5988***	0.5557***	0.6339***
	(0.0501)	(0.0582)	(0.0454)	(0.0432)	(0.0764)	(0.1366)
Observations	6,554	1,976	587	6,554	1,976	587

	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	Turnover intention			K6		
	Regular employment	Non-regular employment	Self-employment	Regular employment	Non-regular employment	Self-employment
Panel A: Outcome equation						
AI job replacement anxiety (Base category=1: Strongly disagree)						
2.Disagree	0.7723***	0.5784	-0.8065***	0.6121	-0.2582	1.0253**
	(0.0838)	(0.3803)	(0.1157)	(0.3985)	(0.7506)	(0.4512)
3.Somewhat disagree	1.1697***	0.9057*	-1.0680***	0.8313	-0.0705	1.3741***
	(0.0884)	(0.4813)	(0.2000)	(0.5336)	(1.1024)	(0.4246)
4.Neither agree nor disagree	1.3868***	0.9540*	-1.4104***	0.9083	-0.4151	1.6888***
	(0.1067)	(0.5759)	(0.2422)	(0.7194)	(1.2147)	(0.5809)
5.Somewhat agree	1.6092***	1.1067	-2.0423***	1.0009	-0.7377	1.7657**
	(0.1441)	(0.7484)	(0.2916)	(0.9359)	(1.6092)	(0.6906)
6.Agree	2.1833***	1.2769	-2.6455***	1.3434	-0.7853	2.2933***
	(0.1770)	(0.9535)	(0.3329)	(1.1647)	(2.1345)	(0.7965)
7.Strongly agree	2.5394***	1.8208	-3.1492***	1.4886	-1.2228	2.7126**
	(0.2314)	(1.1726)	(0.4655)	(1.4495)	(2.5881)	(1.2954)
Panel B: Endogenous covariate equation						
	AI job replacement anxiety (1: Strongly disagree, 2: Disagree, 3: Somewhat disagree, 4: Neither agree nor disagree, 5: Somewhat agree, 6: Agree, 7: Strongly agree)					
Global Index of Occupational Exposure to Generative AI	0.5605***	0.3463	0.0541	0.7390***	0.4543**	0.6640*
	(0.1671)	(0.2864)	(0.3221)	(0.1497)	(0.2085)	(0.3621)
Correlation of the error terms	-0.5729***	-0.3016	0.8649***	-0.2415	0.3597	-0.4955*
	(0.0523)	(0.3114)	(0.1077)	(0.3571)	(0.6703)	(0.2849)
Observations	6,554	1,976	587	6,554	1,976	587

Notes:

This table reports the estimation results from the simultaneous equation system, comprising the outcome equations (Panel A) and the endogenous covariate equation (Panel B) for for three employment types (regular employment, non-regular employment, and self-employment), respectively. Panel A presents the raw coefficients on AI job replacement anxiety, with "1: Strongly disagree" serving as the reference category. Panel B reports the raw coefficients from the endogenous covariate equation. For brevity, the coefficients on the control variables are omitted. The reported error term correlation in each column represents the correlation between the stochastic disturbances of the outcome and the endogenous covariate equations. Standard errors in parentheses are clustered at prefecture level.

*** p<0.01, ** p<0.05, * p<0.1

Appendix 1: Construction of AI exposure measures as excluded exogenous variables

This appendix details the construction of the two AI exposure measures used in this study. Section 1 explains how the JACSIS questionnaire captures industry-occupation cells. Section 2 describes the primary excluded exogenous variable—the Global Index of Occupational Exposure to Generative AI (GIOE) from Gmyrek et al. (2025)—which enters the first-stage equation (3) in our main analysis. Section 3 describes the alternative excluded exogenous variable employed in the robustness checks (Section 4.2.2): the Automation Risk Index (ARI) from Fukao et al. (2025a, 2025b). Both excluded exogenous variables assign a predetermined, cell-level AI exposure score to individual \$i\$ based solely on their industry-occupation cell, ensuring independence from any unobserved individual psychological traits.

1 Industry and occupation classification

The JACSIS survey classifies respondents along two dimensions. Industry affiliation is captured by Question 6 (Q6), which categorizes respondents into 20 distinct industry sectors: Agriculture / Forestry / Fishing (Q6 = 1), Mining (Q6 = 2), Construction (Q6 = 3), Manufacturing (Q6 = 4), Electricity / Gas / Heat / Water Supply (Q6 = 5), Information and Communication / IT (Q6 = 6), Transport (Q6 = 7), Wholesale (Q6 = 8), Retail (Q6 = 9), Finance / Insurance (Q6 = 10), Real Estate (Q6 = 11), Food and Beverage — with alcohol (Q6 = 12), Food and Beverage — without alcohol (Q6 = 13), Lodging / Accommodation (Q6 = 14), Medical Services — on-site (Q6 = 15), Medical Services — visiting / off-site (Q6 = 16), Welfare / Social Services (Q6 = 17), Education / Learning Support (Q6 = 18), Other Services (Q6 = 19), and Government / Public Sector (Q6 = 20). Occupation type is captured by Question 7 (Q7), which categorizes respondents into nine distinct occupational classes: Professional / Technical (Q7 = 1), Clerical / Administrative (Q7 = 2), Sales (Q7 = 3), Service (Q7 = 4), Security / Protective (Q7 = 5), Production / Manufacturing (Q7 = 6), Transport / Machine

Operation (Q7 = 7), Construction / Mining (Q7 = 8), and Elementary / Cleaning / Packing (Q7 = 9). Each respondent is assigned to one of 20 × 9 = 180 industry-occupation cells defined by the intersection of their Q6 and Q7 responses. Both excluded exogenous variables then map the predetermined exposure score of the corresponding cell to each individual.

2 Main excluded exogenous variable: GIOE (Gmyrek et al., 2025)

2.1 Data source

The Global Index of Occupational Exposure to Generative AI (GIOE) is sourced from Gmyrek et al. (2025). The GIOE is constructed using a task-based framework that estimates the automation potential of specific occupational tasks by integrating expert and worker survey judgments with Large Language Model (LLM) predictions. Scores are mapped to the ISCO-08 4-digit occupational classification, ranging from 0 (indicating that a task cannot be automated by current generative AI technology) to 1 (indicating that a task can be fully automated). Crucially, Gmyrek et al. (2025) document that workers in high-exposure occupations report significantly greater subjective concern regarding AI job replacement, thereby satisfying the relevance condition required for our instrumental variable approach.

2.2 Construction

For each Q6 × Q7 cell, the closest 4-digit ISCO-08 occupations are manually mapped (as detailed in Section 3.3). The cell-level GIOE score is calculated as the simple average of the individual ISCO-08 exposure scores across the occupations matched to that cell. Consequently, the instrument value assigned to individual i in prefecture p is defined as:

$$GIOE_{ip} = GIOE_{q6(i),q7(i)} = \left(\frac{1}{n_{q6(i),q7(i)}}\right) \times \sum_{k} GIOE_{k}^{ILO}$$

where k indexes the ISCO-08 occupations assigned to the Q6 × Q7 cell of individual i, $n_{q6(i),q7(i)}$ is the number of such occupations, and $GIOE_{k}^{ILO}$ is the exposure score from Gmyrek et al. (2025) for occupation k. Crucially, all 180 cells have at least one mapped ISCO-08 occupation, meaning that no data imputation is required. The resulting cell-level values are reported in Table A.1.

Table A.1: GIOE cell values ($GIOE_{ip}$)

Industry (Q6) \ Occupation type (Q7)	Q7=1 Prof./Tech.	Q7=2 Clerical	Q7=3 Sales	Q7=4 Service	Q7=5 Security	Q7=6 Prod.	Q7=7 Transport	Q7=8 Constr.	Q7=9 Elem.
Q6=1: Agriculture/Forestry/Fishing	0.2190	0.6130	0.3830	0.2000	0.2000	0.1720	0.1250	0.1400	0.1070
Q6=2: Mining	0.2820	0.6180	0.4950	0.2400	0.1930	0.2330	0.1730	0.2130	0.1730
Q6=3: Construction	0.3370	0.5820	0.4770	0.2430	0.1930	0.2680	0.1700	0.1460	0.0980
Q6=4: Manufacturing	0.3500	0.6060	0.4560	0.2400	0.1930	0.2170	0.1700	0.1770	0.1600
Q6=5: Utilities	0.3390	0.6150	0.4800	0.2400	0.1930	0.2740	0.1880	0.1920	0.1330
Q6=6: IT/Telecommunications	0.5060	0.6210	0.4920	0.2430	0.2000	0.2450	0.1900	0.2120	0.1400
Q6=7: Transport	0.3080	0.5600	0.5000	0.2500	0.2100	0.2430	0.2180	0.1880	0.2440
Q6=8: Wholesale	0.4930	0.5660	0.4660	0.3250	0.2000	0.2870	0.3370	0.1800	0.2280
Q6=9: Retail	0.4680	0.4720	0.3830	0.3260	0.2000	0.2100	0.2400	0.1800	0.2180
Q6=10: Finance/Insurance	0.5270	0.5790	0.5450	0.2430	0.1800	0.2400	0.2600	0.1800	0.2300
Q6=11: Real Estate	0.4020	0.6040	0.4270	0.2330	0.2000	0.2850	0.2600	0.1840	0.1030
Q6=12: Food/Beverage with Alcohol	0.3280	0.6000	0.4100	0.2070	0.2000	0.1880	0.2600	0.1800	0.1340
Q6=13: Food/Beverage without Alcohol	0.3280	0.6000	0.4100	0.2000	0.2000	0.1880	0.2600	0.1800	0.1340
Q6=14: Lodging/Accommodation	0.4140	0.5740	0.4780	0.2560	0.2000	0.1530	0.2600	0.1680	0.1340
Q6=15: Medical: On-site	0.2890	0.5770	0.4770	0.2000	0.1930	0.2680	0.2500	0.1880	0.1250
Q6=16: Medical: Off-site/Visiting	0.2430	0.5870	0.4650	0.2100	0.2000	0.2400	0.2500	0.1900	0.1200
Q6=17: Welfare/Social Services	0.3070	0.5950	0.4650	0.2110	0.2000	0.2600	0.2800	0.1630	0.1330
Q6=18: Education/Learning Support	0.2850	0.5280	0.4400	0.2480	0.2000	0.2230	0.2600	0.1550	0.1280
Q6=19: Other Services	0.4110	0.5920	0.4470	0.2220	0.2000	0.2290	0.2570	0.1760	0.1180
Q6=20: Public Sector/Government	0.3450	0.6100	0.3920	0.2350	0.1820	0.2570	0.2070	0.2050	0.1420

Note: Values are simple means of ISCO-08 occupation-level GIOE scores (Gmyrek et al., 2025) within each industry × occupation-type cell. All 180 cells have observed data (no imputation).

3 Alternative excluded exogenous variable: ARI (Fukao et al., 2025a, Fukao et al., 2025b)

3.1 Data source

The 2024 Automation Risk Index (ARI) score measures the susceptibility of a given Japanese occupation to automation by AI and robotics. It is constructed from two primary sources: the JobTag-OID database developed by the Japan Institute for Labour Policy and Training (JILPT), which provides detailed skill and ability profiles for over 500 Japanese occupations across 53 items (39 skills, 5 abilities, and 9 job adaptability attributes), and an expert survey conducted jointly by the Research Institute of Economy, Trade and Industry (RIETI) and the Nomura Research Institute in 2024. In this survey, experts assessed the extent to which AI and robotics could substitute for each of these skills, abilities, and attributes. The resulting ARI scores are bounded between 0 and 1, with higher values indicating greater vulnerability to technological automation.

3.2 Construction

For each Q6 × Q7 cell, the relevant JSOC occupations from the ARI (JobTag-OID) database are manually mapped based on industry and occupation-type correspondence. The cell-level ARI score is calculated as the simple average of the 2024 ARI scores across the occupations matched to that cell. Consequently, the instrument value assigned to individual i in prefecture p is:

$$ARI_{ip} = ARI_{q6(i),q7(i)} = \left(\frac{1}{n_{q6(i),q7(i)}}\right) \times \sum_{k} ARI\_2024_k$$

where k indexes JSOC occupations in the Q6 × Q7 cell of individual i, $n_{q6(i),q7(i)}$ is the number of such occupations, and ARI_2024_k is the score from Fukao et al. (2025a, 2025b).

3.3 Coverage and imputation

164 of the 180 Q6 × Q7 cells have at least one JSOC occupation from the ARI (JobTag-OID) database mapped to them. The remaining 16 cells — Q6 = 1 (Agriculture) for Q7 = 5, 6, 7, 8; Q6 = 10 (Finance / Insurance) for Q7 = 8; Q6 = 15 (Medical On-site) and Q6 = 16 (Medical Off-site) for Q7 = 8; and all nine Q7 categories for Q6 = 20 (Government) — have no JSOC occupations mapped to them in the ARI database. For these 16 cells the instrument value is imputed from the closest available industry with mapped occupations in the same Q7 category, as follows. For Q6 = 1 (Agriculture), the imputed source is Q6 = 3 (Construction) for Q7 = 5 (Security / Protective), Q7 = 7 (Transport / Machine Operation), and Q7 = 8 (Construction / Mining), and Q6 = 4 (Manufacturing) for Q7 = 6 (Production / Manufacturing), reflecting the closest industries with comparable manual and production occupations. For Q6 = 10 (Finance / Insurance) Q7 = 8 (Construction / Mining), the value is borrowed from Q6 = 11 (Real Estate) Q7 = 8 (Construction / Mining). For Q6 = 15 (Medical On-site) and Q6 = 16 (Medical Off-site) Q7 = 8 (Construction / Mining), the value is borrowed from Q6 = 17 (Welfare / Social

Services) Q7 = 8 (Construction / Mining). For Q6 = 20 (Government / Public Sector), all nine Q7 categories — Q7 = 1 (Professional / Technical), Q7 = 2 (Clerical / Administrative), Q7 = 3 (Sales), Q7 = 4 (Service), Q7 = 5 (Security / Protective), Q7 = 6 (Production / Manufacturing), Q7 = 7 (Transport / Machine Operation), Q7 = 8 (Construction / Mining), and Q7 = 9 (Elementary / Cleaning / Packing) — are imputed using the values from Q6 = 19 (Other Services), as no ARI-coded JSOC occupations exist for the public sector. These imputed cell values are indicated in italics in Table A.2.

Table A.2: ARI cell values (ARI_{ip})

Industry (Q6) \ Occupation type (Q7)	**Q7=1 Prof./Tech.**	**Q7=2 Clerical**	**Q7=3 Sales**	**Q7=4 Service**	**Q7=5 Security**	**Q7=6 Prod.**	**Q7=7 Transport**	**Q7=8 Constr.**	**Q7=9 Elem.**
Q6=1: Agriculture / Forestry / Fishing	0.1575	0.3511	0.2162	0.3426	*0.3939*	*0.3066*	*0.3542*	*0.2730*	0.5454
Q6=2: Mining	0.1446	0.3086	0.2122	0.2873	0.5097	0.2852	0.3846	0.2546	0.5036
Q6=3: Construction	0.1468	0.3324	0.2565	0.3648	0.3939	0.2924	0.3542	0.2730	0.5036
Q6=4: Manufacturing	0.1710	0.3324	0.2402	0.3736	0.3939	0.3066	0.3661	0.2730	0.4925
Q6=5: Utilities	0.1393	0.3238	0.2565	0.3552	0.3939	0.2714	0.3522	0.2490	0.4929
Q6=6: IT / Telecom	0.1655	0.3324	0.2561	0.3598	0.5097	0.2637	0.3587	0.1467	0.5212
Q6=7: Transport	0.1698	0.3324	0.2503	0.3469	0.3939	0.3115	0.3524	0.2569	0.4925
Q6=8: Wholesale	0.1676	0.3324	0.2458	0.3685	0.3939	0.3021	0.3552	0.2782	0.4925
Q6=9: Retail	0.1773	0.3400	0.2420	0.3646	0.3939	0.2863	0.3971	0.2490	0.5036
Q6=10: Finance / Insurance	0.1694	0.3324	0.2573	0.3479	0.5097	0.2805	0.3917	*0.2782*	0.4929
Q6=11: Real Estate	0.1728	0.3324	0.2561	0.3700	0.3939	0.2562	0.3706	0.2782	0.5036
Q6=12: F&B with Alcohol	0.1792	0.3348	0.2575	0.3794	0.5097	0.2706	0.4047	0.2596	0.5036
Q6=13: F&B no Alcohol	0.1792	0.3348	0.2575	0.3794	0.5097	0.2706	0.4047	0.2596	0.5036
Q6=14: Lodging / Hotels	0.1828	0.3314	0.2583	0.3717	0.3939	0.2909	0.4191	0.2075	0.5036
Q6=15: Medical — In-facility	0.1741	0.3211	0.2599	0.3705	0.3939	0.2855	0.4069	*0.1467*	0.5036
Q6=16: Medical — Visiting / Home Care	0.1741	0.3211	0.2599	0.3705	0.3939	0.2855	0.4069	*0.1467*	0.5036
Q6=17: Welfare / Social Care	0.1729	0.3257	0.2585	0.3705	0.3939	0.2728	0.4069	0.1467	0.5036
Q6=18: Education	0.1684	0.3191	0.2566	0.3648	0.3939	0.2981	0.4191	0.1467	0.4942
Q6=19: Other Services	0.1678	0.3324	0.2420	0.3700	0.3939	0.3066	0.3524	0.2730	0.4925
Q6=20: Government / Public Sector	*0.1678*	*0.3324*	*0.2420*	*0.3700*	*0.3939*	*0.3066*	*0.3524*	*0.2730*	*0.4925*

Note: Values are simple means of ARI score of 2024 (Fukao et al., 2025a, Fukao et al., 2025b) across JSOC occupations in each industry × occupation-type cell. Italics = imputed values (16 cells).

Appendix 2: The Impact of AI Job Replacement Anxiety (linear two-stage least squares (2SLS), IV: ARI)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Work engagement	Job satisfaction	Work meaningfulness	Turnover intention	Quiet quitting	K6
Panel A: Second stage of two-stage least squares						
AI job replacement anxiety	-3.3050***	-0.6169***	-1.4666***	0.2458**	1.2089**	5.8408***
	(0.9128)	(0.1965)	(0.4463)	(0.1251)	(0.5045)	(2.0351)
Prefecture dummy	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: First stage for AI job replacement anxiety						
	AI job replacement anxiety					
Automation Risk Index	0.6316***					
	(0.1972)					
Prefecture dummy	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
F test of excluded instrument	10.25					
Observations	9,117	9,117	9,117	9,117	9,117	9,117

Notes:

This table reports the estimation results from the linear two-stage least squares (2SLS) regressions, with Panel A presenting the second-stage results and Panel B presenting the first-stage results. In Panel A, AI job replacement anxiety is treated as a quasi-continuous variable. Panel B reports only the coefficient on the excluded exogenous variable (the Automation Risk Index). Note that the first stage is identical across all specifications. The first-stage F-statistic for the excluded instrument is also reported.

Standard errors in parentheses are clustered at prefecture level.

*** p<0.01, ** p<0.05, * p<0.1