

Article

Artificial Intelligence Exposure, Perceived Job Replaceability, and Perceived Income Change: The Moderating Role of Task Codifiability—Evidence from the China General Social Survey

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Abstract

This study examines how artificial intelligence (AI) exposure is associated with Chinese residents' perceived income change and how this association varies with Perceived Job Replaceability. Using a nationally representative sample of 6247 employed workers from the 2021 China General Social Survey matched with industry-level robot penetration data, we estimate ordered probit models and two-stage residual-inclusion control-function checks within an ordered-response framework. Three findings emerge. First, objective AI exposure is associated with a 4.2-percentage-point lower probability of reporting higher household income than last year for a one-standard-deviation increase in robot density, based on predicted-probability contrasts rather than raw ordered-probit coefficients. Second, workers reporting low Perceived Job Replaceability are 15.7 percentage points more likely to report higher household income than last year on the same probability scale. Third, task codifiability moderates this relationship: marginal-effect contrasts show that low Perceived Job Replaceability is associated with a 22.9 percentage-point increase in the probability of reporting higher household income than last year in low-codifiability occupations, compared with only 4.7 percentage points in high-codifiability occupations, indicating a polarization pattern in perceived income change outcomes. Heterogeneity analyses further show that medium-skill routine workers face the strongest negative exposure associations, whereas high-skill workers in low-codifiability occupations show the strongest positive low-replaceability contrast. Overall, the findings clarify how AI exposure, worker perceptions, and task structure are jointly associated with perceived income change in China and provide evidence relevant to more inclusive technological adjustment policies.

Keywords: artificial intelligence; job displacement; perceived job replaceability; perceived income change; China General Social Survey

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1. Introduction

The proliferation of artificial intelligence (AI) and industrial robotics has reignited longstanding debates over technology-related labor-market transformations. Unlike previous automation waves that primarily affected manufacturing assembly lines, contemporary AI systems demonstrate capabilities in pattern recognition, natural language processing, and even complex decision-making, domains once considered uniquely human. This technological leap has generated polarized narratives: some foresee mass unemployment and

rising inequality, while others anticipate productivity gains and the emergence of novel job categories. However, a critical blind spot persists in this discourse: how do workers assess the replaceability of their own jobs, and how are these assessments associated with recent household income change? The existing literature has extensively documented the objective susceptibility of occupations to automation [1], analyzed aggregate employment effects [2], and modeled skill-biased technological change [3]. Yet, the perceptual dimension, namely workers' own assessments of whether their work tasks are replaceable, remains comparatively understudied. This gap is consequential because perceived displacement risk can shape labor-market behaviors, including job searching, skill acquisition, and wage bargaining. The Chinese context offers a particularly compelling setting for investigating these dynamics. China has emerged as the world's largest industrial robot market, accounting for over half of global installations in 2024, with a robot stock exceeding two million units. Concurrently, the country is experiencing a profound economic transition from manufacturing-driven growth toward technology and service-oriented development. Chinese workers thus confront AI exposure not as a distant future scenario but as an immediate labor-market condition. Nevertheless, systematic evidence on how Chinese workers' perceived job replaceability is associated with income-change assessments remains scarce. This study addresses this gap by leveraging a nationally representative sample of 6247 employed workers from the 2021 China General Social Survey (CGSS), matched with objective industry-level industrial robot penetration data from the International Federation of Robotics (IFR). We develop three analytical innovations. First, we combine industry-level objective AI exposure with an individual-level measure of Perceived Job Replaceability, keeping structural exposure and self-reported replaceability analytically distinct. Second, we introduce a Task Codifiability Index to systematically distinguish between routine tasks susceptible to substitution and non-routine tasks amenable to human–AI complementarity. Third, we examine how Perceived Job Replaceability is associated with a perceived income change measure based on recent household income changes, thereby identifying an AI-related income polarization pathway. Our conceptual framework posits that AI's labor-market associations are not monolithic but differentiated by task structure. In occupations characterized by high task codifiability—where work can be reduced to explicit, repetitive rules—AI exposure is expected to align with less favorable perceived income-change assessments. Conversely, in low-codifiability roles requiring contextual judgment, emotional intelligence, or creative problem-solving, workers reporting low replaceability may be more likely to report favorable income-change assessments. This substitution–complementarity duality generates what we term the AI-related income polarization pathway: the same technology-diffusion environment may coincide with more favorable assessments among high-skill cognitive workers and less favorable assessments among middle- and low-skill routine workers. This study contributes to the literature in three ways. First, we provide a large-scale empirical assessment of Perceived Job Replaceability among Chinese workers using CGSS data, which contains rich modules on employment, wages, and technology use. Second, we extend prior research on automation and labor markets by explicitly modeling the perceptual mechanism linking AI exposure to perceived income change, rather than focusing solely on objective displacement probabilities. Third, our findings offer actionable insights for sustainable technology policies, workforce development strategies, and socially inclusive AI transitions in emerging economies undergoing rapid automation.

Figure 1 summarizes the conceptual structure of the argument developed in this study.

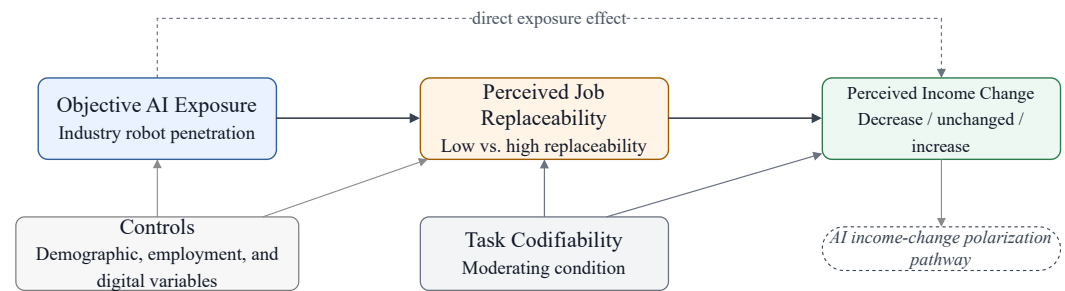


Figure 1. Conceptual framework for AI exposure, Perceived Job Replaceability, task codifiability, and perceived income change.

2. Literature Review

2.1. Automation, AI, and Labor Substitution

The relationship between technological advancement and employment has long occupied economists and sociologists. Early automation research focused on routine-biased technological change, arguing that computers and machinery systematically displace workers performing repetitive, codifiable tasks [4]. Prior work quantified this vulnerability, estimating that 47% of U.S. occupations face high automation risk [1]. Subsequent cross-national research has largely confirmed these patterns, though with important contextual variations [5]. However, equating AI with traditional automation risks oversimplification. While automation follows pre-programmed rules and excels at repetitive tasks, AI systems learn from data, adapt to novel inputs, and perform pattern recognition across diverse domains [6]. This expanded capability means AI penetrates cognitive and service occupations previously considered automation-proof. Related evidence shows that AI-related patents correlate with rising unemployment among medium-skilled workers across OECD countries, suggesting that AI's displacement effects extend beyond manufacturing floors [7].

2.2. The Complementary Perspective

A growing counter-narrative emphasizes AI's potential to complement rather than replace human labor. Prior work argued that the substitution–complementarity relationship depends critically on implementation context: when AI handles routine subtasks, human workers can focus on higher-order functions requiring judgment and interpersonal skills [8]. Other studies showed that AI and robotics solutions often augment professional capabilities rather than displacing them, particularly in knowledge-intensive sectors [9]. Empirical evidence from multiple countries supports this complementary view. Survey-based evidence from Portugal and Spain indicates that both consumers and producers often perceive AI as enhancing job efficiency and creating new opportunities rather than merely eliminating positions [10]. Similarly, workplace-tracking studies report productivity gains without proportional employment reduction [11]. The complementarity view is also consistent with evidence that automation can coexist with employment gains and that training institutions condition labor-market adjustment [12,13]. These findings suggest that the net effect of AI on employment depends on the balance between substitution and complementarity mechanisms.

2.3. Perceptual Mechanisms and Income-Change Assessments

While objective displacement risk has received substantial attention, workers' subjective perceptions constitute a distinct yet understudied mechanism. Perceived job insecurity can influence income-change assessments through several channels. Workers anticipating displacement may accept lower wages to retain employment (the bargaining power channel). Alternatively, those viewing AI as complementary may invest in skill

upgrading, enhancing their productivity and wage bargaining position (the human capital channel). Empirical research on perception–income linkages remains nascent. Existing evidence suggests that AI-enabled job characteristics influence innovative work behavior through perceived substitution crisis [14]. Research on livestream e-commerce likewise models behavior through perception-based constructs, including perceived product quality, perceived product scarcity, and perceived streamer’s product knowledge, showing that “perceived” indicators are commonly used to capture domain-specific subjective evaluations rather than direct objective attributes [15]. Related work also finds that AI exposure affects on-the-job learning, with heterogeneous effects across skill levels [16]. However, no study has systematically examined how Perceived Job Replaceability is associated with perceived income change in the Chinese context, where rapid automation coincides with institutional distinctiveness.

2.4. The Chinese Context

China presents a unique laboratory for studying AI–labor dynamics. The country has aggressively pursued automation-driven productivity growth, with industrial robot density reaching 470 units per 10,000 manufacturing employees in 2024, surpassing many developed economies. This technological push occurs alongside demographic pressures, including an aging workforce and shrinking labor pool, creating complex labor-market dynamics. Existing Chinese studies have documented automation’s employment effects using macro-level data [17] and industry-level analyses [18]. However, micro-level evidence on worker perceptions remains limited. Recent Chinese-language studies further show that AI and robots reshape occupational change, employment reallocation, skill composition, and inclusive growth across sectors and firms [19–23]. Recent work in *Mathematics* also examines AI-enabled productive-force transformation in Chinese enterprises through machine-learning and text-analytics methods [24], while related Chinese wage research in the same journal highlights the importance of nonlinear heterogeneity, sample selection, and endogeneity correction when evaluating income-related labor-market outcomes [25]. These studies establish the local relevance of automation and AI for China’s labor market, but their empirical emphasis remains largely focused on employment quantity, firm adjustment, occupational restructuring, aggregate skill demand, or objective wage structure. The present study complements this literature by moving the unit of analysis to individual workers and by examining how self-reported job replaceability is associated with perceived household income change. This micro-perceptual perspective is especially important in China because rapid robot diffusion, regional industrial upgrading, and uneven access to training may cause workers in similar exposure environments to form different income-change assessments. The CGSS dataset, which includes detailed employment modules and has been validated in prior research on technology and labor [26], offers an opportunity to fill this gap.

2.5. Research Gaps and This Study’s Contribution

Synthesizing the literature reveals three critical gaps. First, most studies focus on objective automation risk rather than subjective worker perceptions, despite theoretical reasons to expect perceptions to matter for labor-market behavior. Second, the income implications of AI exposure have received far less attention than employment effects, creating an incomplete picture of household income status. Third, the Chinese context—despite its global significance—remains empirically underexplored. This study addresses these gaps by (1) measuring both objective AI exposure and Perceived Job Replaceability; (2) examining perceived income change as a novel outcome variable; (3) using nationally representative Chinese micro-data; and (4) developing a task codifiability framework to

theorize when AI is more likely to substitute for or complement workers' tasks. Our integrated approach moves beyond the substitution–displacement dichotomy toward a nuanced understanding of AI's heterogeneous labor-market associations.

3. Data

3.1. Data Sources

This study draws on two principal data sources. The first is the 2021 China General Social Survey (CGSS), conducted by the National Survey Research Center at Renmin University of China. The CGSS employs a multistage stratified probability-proportional-to-size sampling design to generate nationally representative coverage of Chinese citizens aged 18 years and above. The 2021 wave contains 8,148 original survey records. Its sampling frame combines a certainty stratum consisting of the municipal districts of five major cities (Shanghai, Beijing, Guangzhou, Shenzhen, and Tianjin) with a sampled stratum covering the remaining urban and rural household population. The sampled stratum is further divided into 50 substrata, including 19 district strata and 31 county strata. The primary sampling units are streets in the certainty stratum and districts, county-level cities, or counties in the sampled stratum; according to the CGSS sampling documentation, 40 streets are selected in the certainty stratum, and 100 primary sampling units are selected from the sampled stratum. The survey contains comprehensive modules on employment status, occupational characteristics, monthly income, working hours, job autonomy, and digital technology use. The second source is the International Federation of Robotics (IFR) World Robotics database, which provides annual data on industrial robot installations and operational stock by country and industry sector. Following standard practice in the automation literature [2], we use 2020–2021 robot penetration data matched to CGSS respondents by industry sector. The analytical sample is constructed in four steps. First, respondents outside the working analytical population, including those who had never participated in work, are excluded. Second, we retain observations with non-missing values on perceived income change, Perceived Job Replaceability, the main covariates, and industry information, so missing data on model variables are handled through complete-case retention. Third, CGSS industry classifications and IFR sector data are harmonized using the Industrial Classification for National Economic Activities (2002 version). Fourth, the retained respondents' industries are matched to the corresponding IFR robot penetration sectors. The successful matching covers 14 manufacturing sub-sectors and matched non-manufacturing sectors, including agriculture, forestry, animal husbandry and fishery; mining; electricity, heat, gas, and water production and supply; construction; and education. This procedure yields a final CGSS–IFR matched analytical sample of 6247 observations. All regressions apply the CGSS survey weights, whose final weights combine design weights based on inverse selection probabilities and implementation-adjustment weights. Standard errors are clustered at the matched industry-sector level used for the CGSS–IFR exposure linkage.

3.2. Key Variables

3.2.1. Dependent Variable: Perceived Income Change

Based on the CGSS 2021 questionnaire item comparing each respondent's household income situation this year with that of last year, we construct a perceived income change variable for the analysis of AI exposure. Responses are coded on a three-point ordinal scale: 1 = lower than last year, 2 = basically unchanged, and 3 = higher than last year. This variable captures respondents' retrospective assessment of household income change rather than a direct forward-looking income expectation.

3.2.2. Independent Variables: AI Exposure and Perceived Job Replaceability

We construct two complementary measures of AI exposure. The objective AI exposure index is created by matching each respondent's industry sector (CGSS four-digit code) with IFR's industrial robot penetration (robots per 10,000 workers) for the corresponding sector. Higher values indicate greater automation potential. We construct Perceived Job Replaceability from CGSS 2021 items in which respondents report task conditions frequently encountered at work, including repetitive physical labor and other routine job requirements. This measure should not be read as a direct attitudinal item asking whether respondents welcome or fear AI. Rather, it is an individual-level self-reported assessment of task replaceability derived from workplace task conditions. To preserve the direction of the empirical estimates, the binary variable used in the regressions is reverse-coded: 1 denotes lower perceived job replaceability and 0 denotes higher perceived job replaceability. Lower perceived replaceability is interpreted as a complementarity-oriented condition, whereas higher perceived replaceability indicates substitution-oriented vulnerability.

This construct is distinct from the Task Codifiability Index. Perceived Job Replaceability is measured at the respondent level from self-reported task conditions, while the Task Codifiability Index is an occupation-level composite based on routine, abstract, and manual task profiles. The former captures how workers' own reported job conditions imply replaceability; the latter captures the structural codifiability of the occupation to which the respondent is matched. We therefore treat the two as related but analytically separate dimensions.

3.2.3. Task Codifiability Index

We construct a Task Codifiability Index based on occupational characteristics. Following the task-based framework in [27], we code occupations along three dimensions: (1) routine task intensity: the degree to which work follows explicit, repeatable procedures; (2) abstract task intensity: requirements for problem-solving, intuition, and persuasion; and (3) manual task intensity: physical manipulation and dexterity requirements. The three dimensions are derived from the CGSS occupational coding scheme through an occupation-level crosswalk. CGSS occupation codes are first mapped to broad occupational cells; each cell is then assigned routine, abstract, and manual task profiles using the closest task-description match. Comparable O*NET task descriptors are used as an external benchmark to check whether the ordering of occupations is conceptually consistent with established task measures. This procedure is used for construct validation rather than as an additional source of respondent-level data.

Let r_o , b_o , and m_o denote the raw routine, abstract, and manual task scores for occupation o . Each component is standardized across occupations before aggregation:

$$R_o = \frac{r_o - \bar{r}}{s_r}, \quad B_o = \frac{b_o - \bar{b}}{s_b}, \quad M_o = \frac{m_o - \bar{m}}{s_m}, \quad (1)$$

where bars denote occupational means, and s denotes the corresponding standard deviation. The main specification uses an equal-weight construction, $(\omega_R, \omega_B, \omega_M) = (1/3, 1/3, 1/3)$, so that no single task dimension mechanically dominates the index. Let R_o , B_o , and M_o denote the standardized routine, abstract, and manual task scores for occupation o , respectively. The raw codifiability score is defined as

$$S_o = \omega_R R_o - \omega_B B_o + \omega_M M_o, \quad \omega_R, \omega_B, \omega_M \geq 0, \quad \omega_R + \omega_B + \omega_M = 1, \quad (2)$$

where routine and manual rule-following components raise codifiability, while abstract task intensity lowers it. The respondent-level Task Codifiability Index is obtained by matching respondent i to occupation $o(i)$ and rescaling the raw score to the interval $[0, 10]$:

$$T_i = 10 \times \frac{S_{o(i)} - \min_{o \in \mathcal{O}} S_o}{\max_{o \in \mathcal{O}} S_o - \min_{o \in \mathcal{O}} S_o}. \quad (3)$$

The index ranges from 0 (least codifiable, highest complementarity potential) to 10 (most codifiable, highest substitution risk). The construction steps and sensitivity checks are summarized in Table 1. The sensitivity checks vary the task weights while preserving the same standardization, occupation crosswalk, and 0–10 rescaling rule.

Table 1. Task Codifiability Index construction summary.

Component	Operational Source	Role in TCI	Weighting
Routine task intensity	CGSS occupation-task crosswalk; O*NET routine benchmark	Raises codifiability for explicit, repetitive procedures	$\omega_R = 1/3$
Abstract task intensity	CGSS occupation-task crosswalk; O*NET problem-solving benchmark	Lowers codifiability for judgment, persuasion, and problem solving	$\omega_B = 1/3$
Manual task intensity	CGSS occupation-task crosswalk; O*NET physical-task benchmark	Raises codifiability when manual work is repetitive and rule-following	$\omega_M = 1/3$
Sensitivity definitions	Same standardized components and crosswalk	Tests dependence on weighting choices	$(0.50, 0.25, 0.25);$ $(0.25, 0.50, 0.25);$ $(0.25, 0.25, 0.50)$

This design makes the TCI an occupation-level structural measure. It differs from Perceived Job Replaceability, which is respondent-level and self-reported (Algorithm 1). The O*NET comparison is used only to assess whether the crosswalk produces a plausible occupational ordering; it does not alter individual CGSS responses or the dependent variable. For reproducibility, the construction can be viewed as a deterministic mapping from occupational task profiles and respondent occupation codes to respondent-level codifiability scores:

$$\mathcal{A}_{\text{TCI}} : \left(\{R_o, B_o, M_o\}_{o \in \mathcal{O}}, \{o(i)\}_{i=1}^N \right) \mapsto \left(\{T_i\}_{i=1}^N, \{G_i\}_{i=1}^N \right), \quad (4)$$

where $G_i \in \{\text{low}, \text{medium}, \text{high}\}$ denotes the tercile label assigned after rescaling. The tercile partition is defined by the empirical quantiles $q_{1/3}$ and $q_{2/3}$ of $\{T_i\}_{i=1}^N$:

$$G_i = \begin{cases} \text{low}, & T_i \leq q_{1/3}, \\ \text{medium}, & q_{1/3} < T_i \leq q_{2/3}, \\ \text{high}, & T_i > q_{2/3}. \end{cases} \quad (5)$$

3.2.4. Control Variables

Demographic controls include gender (male = 1), age (continuous), age-squared, and educational attainment (categorical: middle school or below, high school, some college, bachelor's degree or higher). Employment-related controls include monthly income (log-transformed), working hours per week, job tenure (years), and firm size (categorical: small <50 employees, medium 50–500, and large >500). Additionally, we control for internet usage frequency (scale 1–5) and remote work status (binary) as proxies for digital work environment exposure.

Algorithm 1 Construction of the Task Codifiability Index

Input: Occupation map $\{o(i)\}_{i=1}^N$, raw occupational task scores $\{r_o, b_o, m_o\}_{o \in \mathcal{O}}$, and weight vector $\omega = (\omega_R, \omega_B, \omega_M)$.

Output: Respondent-level Task Codifiability Index $\{T_i\}_{i=1}^N$, tercile labels, and sensitivity definitions.

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1: procedure BUILDTCI( $\mathcal{O}, \{o(i)\}_{i=1}^N$ )
2:   Map CGSS occupation codes to occupational task cells.
3:   Benchmark the task-cell ordering against comparable O*NET descriptors.
4:   Standardize raw task indicators as  $R_o = (r_o - \bar{r})/s_r$ ,  $B_o = (b_o - \bar{b})/s_b$ , and  $M_o = (m_o - \bar{m})/s_m$ .
5:   Set the main specification to equal weights,  $\omega = (1/3, 1/3, 1/3)$ .
6:   for all occupation  $o \in \mathcal{O}$  do
7:     Compute  $S_o = \omega_R R_o + \omega_B B_o + \omega_M M_o$  using Equation (2).
8:   end for
9:   Set  $S_{\min} = \min_{o \in \mathcal{O}} S_o$  and  $S_{\max} = \max_{o \in \mathcal{O}} S_o$ .
10:  for all respondent  $i = 1, \dots, N$  do
11:    Match respondent  $i$  to occupation  $o(i)$ .
12:    Compute  $T_i = 10(S_{o(i)} - S_{\min}) / (S_{\max} - S_{\min})$  using Equation (3).
13:  end for
14:  Partition  $\{T_i\}$  into low-, medium-, and high-codifiability terciles.
15:  Repeat the construction under routine-heavy, abstract-heavy, and manual-heavy weight vectors for sensitivity comparison.
16:  return  $\{T_i\}_{i=1}^N$ , codifiability tercile labels, and alternative-weight TCI definitions.
17: end procedure

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Figure 2 presents the sample construction and empirical workflow used to organize the analysis.

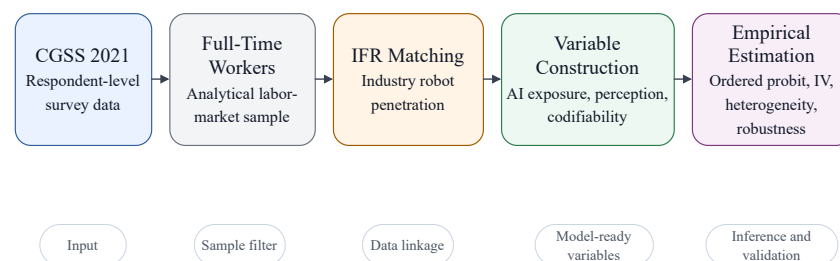


Figure 2. Sample construction, variable matching, and empirical estimation workflow.

4. Mathematical and Econometric Framework

This section formalizes the empirical design as a latent-response system in which objective AI exposure, Perceived Job Replaceability, and task codifiability jointly enter the probability distribution of perceived income change outcomes.

4.1. Baseline Ordered Probit Model

To formalize perceived income change as an ordered latent response, we employ an ordered probit model as the baseline specification. The latent variable framework can be expressed as follows:

$$Y_i^* = \beta_0 + \beta_1 A_i + \beta_2 R_i + \gamma' X_i + \varepsilon_i. \quad (6)$$

where Y_i^* denotes the latent propensity for a more favorable household income assessment, A_i is the objective industry-level robot penetration measure, R_i is the reverse-coded Perceived Job Replaceability indicator (0 = high perceived replaceability; 1 = low perceived replaceability), and X_i is the vector of demographic, employment, and digital behavior controls. The observed ordinal outcome relates to the latent variable through threshold

parameters $\tau_1 < \tau_2$. Let $\theta = (\beta_0, \beta_1, \beta_2, \gamma, \tau_1, \tau_2)$ collect the parameters of the baseline ordered-response model. Estimation proceeds by maximizing the sample log-likelihood

$$\ell(\theta) = \sum_{i=1}^N \sum_{j=1}^3 \mathbf{1}\{Y_i = j\} \log P_{ij}(\theta), \quad \hat{\theta} = \arg \max_{\theta} \ell(\theta), \quad (7)$$

where $P_{ij}(\theta) = P(Y_i = j \mid A_i, R_i, X_i; \theta)$. In the empirical implementation, survey weights are applied to the likelihood contribution and standard errors are clustered by industry. Because ordered probit coefficients are estimated on the normalized latent-response scale, they should not be interpreted directly as percentage-point changes in observed outcome probabilities. We therefore use coefficient estimates to assess the direction and statistical significance of associations in the latent perceived income change index, while substantive percentage-point interpretations are derived from predicted probabilities, and marginal-effect contrasts are computed from the ordered-response probability functions.

The notation used in the ordered-response framework is summarized in Table 2.

Table 2. Notation and variable definitions.

Symbol	Definition	Measurement	Expected Sign
<i>Outcome structure</i>			
Y_i	Observed perceived income change	1 = lower; 2 = unchanged; 3 = higher	–
Y_i^*	Latent perceived income change score	Ordered latent-response index	–
<i>AI exposure and perceived replaceability</i>			
A_i	Objective AI exposure	IFR robot density matched by industry	Negative
R_i	Perceived Job Replaceability indicator	Reverse-coded binary measure: 1 = low replaceability; 0 = high replaceability	Positive
T_i	Task codifiability index	Composite score ranging from 0 to 10	Negative
<i>Identification and controls</i>			
Z_i	Instrument for AI exposure	Industry-province mean AI exposure	Positive
X_i	Control vector	Demographic, job, and digital controls	Mixed

4.2. Extended Model with Task Codifiability Moderation

To test whether task codifiability moderates the relationship between Perceived Job Replaceability and perceived income change, we estimate a conditional process model:

$$Y_i^* = \beta_0 + \beta_1 A_i + \beta_2 R_i + \beta_3 T_i + \beta_4 (R_i \times T_i) + \gamma' X_i + \varepsilon_i. \quad (8)$$

$$Y_i = \begin{cases} 1, & Y_i^* \leq \tau_1, \\ 2, & \tau_1 < Y_i^* \leq \tau_2, \\ 3, & Y_i^* > \tau_2. \end{cases} \quad (9)$$

Let $\eta_i = \beta_0 + \beta_1 A_i + \beta_2 R_i + \beta_3 T_i + \beta_4 (R_i \times T_i) + \gamma' X_i$. Under the standard normality assumption for ε_i , the ordered-response probabilities are

$$\begin{aligned} P(Y_i = 1 \mid A_i, R_i, T_i, X_i) &= \Phi(\tau_1 - \eta_i), \\ P(Y_i = 2 \mid A_i, R_i, T_i, X_i) &= \Phi(\tau_2 - \eta_i) - \Phi(\tau_1 - \eta_i), \\ P(Y_i = 3 \mid A_i, R_i, T_i, X_i) &= 1 - \Phi(\tau_2 - \eta_i), \end{aligned} \quad (10)$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function. A negative interaction coefficient ($\beta_4 < 0$) indicates that the latent-index association between low Perceived Job Replaceability and perceived income change is weaker in high-codifiability occupations. In the nonlinear ordered-response model, however, the interaction coefficient alone is not treated as sufficient evidence of moderation on the probability scale; substantive

moderation is assessed through predicted-probability and marginal-effect contrasts. The moderation effect can be summarized on the latent-response scale as

$$\frac{\partial Y_i^*}{\partial R_i} = \beta_2 + \beta_4 T_i, \quad (11)$$

so that the latent-index low-replaceability association declines linearly with task codifiability when $\beta_4 < 0$. Because ordered-response coefficients are expressed on a latent scale, the reported substantive effects are computed as probability-scale contrasts. For outcome category $j \in \{1, 2, 3\}$ and codifiability level t , the Perceived Job Replaceability contrast is

$$\Delta_j(t) = \frac{1}{N_t} \sum_{i: T_i \in \mathcal{T}_t} [P(Y_i = j \mid R_i = 1, A_i, T_i, X_i) - P(Y_i = j \mid R_i = 0, A_i, T_i, X_i)], \quad (12)$$

where $\mathcal{T}_t$ denotes the low-, medium-, or high-codifiability tercile, and N_t is the number of observations in that tercile. Equation (12) links the formal ordered-response model directly to the marginal effects reported in the results section.

4.3. Control-Function Approach for Endogeneity Assessment

Concerns about reverse causality and omitted variable bias arise if workers with more favorable income-change assessments are systematically sorted into industries with different AI exposure. To assess this possibility, we use a two-stage residual-inclusion control-function approach within the ordered-response framework rather than a linear 2SLS estimator. The excluded instrument is industry-province average AI exposure, calculated as the mean robot penetration for all other workers in the same industry-province cell. Its relevance can be evaluated through the first-stage relationship with individual AI exposure. The exclusion restriction is maintained as a conditional identifying assumption: after controlling for observed individual, employment, regional, and industry characteristics, local industry-province robot diffusion is assumed to affect perceived income change through the respondent's AI exposure channel rather than through unobserved individual income-assessment shocks. The first-stage equation is as follows:

$$A_i = \pi_0 + \pi_1 Z_i + \delta' X_i + v_i. \quad (13)$$

Formally, the control-function check relies on the pair of moment conditions

$$\text{Cov}(Z_i, A_i) \neq 0, \quad \text{Cov}(Z_i, \varepsilon_i) = 0, \quad (14)$$

which correspond to instrument relevance and conditional exclusion, respectively. The second condition is not directly testable and is therefore interpreted as an identifying assumption rather than as an empirically proven fact. Because the outcome model is nonlinear, the endogeneity adjustment is implemented as a two-stage residual-inclusion specification. After estimating Equation (13), we compute $\hat{v}_i = A_i - \hat{A}_i$ and include this residual in the ordered-response equation:

$$Y_i^* = \beta_0 + \beta_1 A_i + \beta_2 R_i + \beta_3 T_i + \beta_4 (R_i \times T_i) + \gamma' X_i + \rho \hat{v}_i + \varepsilon_i. \quad (15)$$

The ordered probit specification normalizes the latent-error scale by assuming $\varepsilon_i \sim N(0, 1)$. Under the control-function formulation, the residual coefficient ρ provides an exogeneity diagnostic analogous to a Hausman-type test in the ordered-response setting. The null hypothesis is

$$H_0 : \rho = 0, \quad (16)$$

which indicates no residual evidence that A_i is endogenous after conditioning on the included controls and the first-stage residual. A statistically significant ρ would instead support retaining the residual-inclusion correction. We interpret this procedure as an endogeneity assessment and robustness check, not as a complete solution to all possible violations of the exclusion restriction.

$$ME_R(T_i) = \frac{\partial P(Y_i = 3)}{\partial R_i} = \phi(\tau_2 - \eta_i)(\beta_2 + \beta_4 T_i), \quad (17)$$

where $\phi(\cdot)$ denotes the standard normal density. This expression shows that the probability-scale low-replaceability effect depends jointly on the interaction slope $(\beta_2 + \beta_4 T_i)$ and the local density around the upper threshold.

Algorithm 2 summarizes the complete estimation procedure from sample construction and variable matching to baseline estimation, moderation analysis, and robustness checks.

Algorithm 2 Estimation Procedure for AI-Related Perceived Income Change Associations

Input: CGSS individual-level data and IFR industry-level robot penetration data.

Output: Estimated coefficients, marginal effects, and subgroup results.

1: **procedure** ESTIMATEAIINCOMECHANGEFFECTS($\mathcal{D}_{\text{CGSS}}, \mathcal{D}_{\text{IFR}}$)

Stage I: Sample construction and data integration

- 2: Start from the 8148 original CGSS 2021 records and exclude respondents outside the working analytical population.
- 3: Retain complete-case observations with non-missing outcome, perception, control, and industry-code information.
- 4: Harmonize CGSS and IFR industry classifications using the 2002 national industry classification and match respondents' industry codes with IFR robot penetration data at the sector level.

Stage II: Variable construction

- 5: Construct the objective AI exposure measure A_i .
- 6: Construct the Perceived Job Replaceability variable from task-condition items, including repetitive physical labor, and reverse-code it as R_i where 1 denotes low perceived replaceability.
- 7: Compute the Task Codifiability Index T_i using Algorithm 1.
- 8: Assemble the control vector X_i and the industry-province instrument Z_i .

Stage III: Ordered-response estimation

- 9: Estimate the baseline ordered probit model in Equation (6).
- 10: Estimate the moderation model in Equation (8).
- 11: Recover threshold-based outcome probabilities using Equation (10).

Stage IV: Identification and association decomposition

- 12: Estimate the first-stage IV relation in Equation (13).
- 13: Assess first-stage relevance and state the conditional exclusion assumption summarized in Equation (14).
- 14: Compute the first-stage residual $\hat{v}_i$ and estimate the 2SRI ordered-response model in Equation (15).
- 15: Compute Perceived Job Replaceability marginal effects with Equation (17).

Stage V: Validation and heterogeneity

- 16: Conduct subgroup estimation by skill level and occupational category, while retaining digital behavior measures as controls.
 - 17: Run robustness checks with alternative exposure, alternative estimator, propensity-score matching, placebo reassignment, and COVID-sensitive subsample restriction.
 - 18: **return** coefficient estimates, category probabilities, marginal effects, and validation results
 - 19: **end procedure**
-

Figure 3 consolidates the full analytical pathway from data integration to latent-response estimation, identification, and validation.

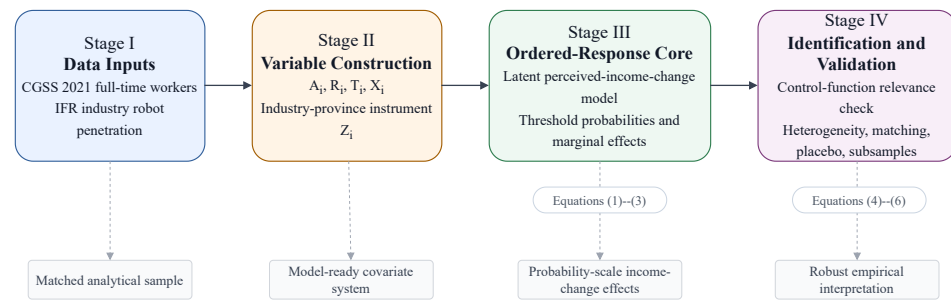


Figure 3. Main-text identification and estimation architecture, linking data integration, variable construction, ordered-response modeling, and validation procedures.

4.4. Heterogeneity Analysis

To uncover heterogeneous patterns across theoretically central worker subgroups, we partition the sample along two dimensions: (1) skill level: low (middle school or below), medium (high school or some college), and high (bachelor’s or above); and (2) occupational category: manufacturing, service, professional/technical, and managerial. These two dimensions correspond to the human-capital and task-structure channels emphasized in the theoretical framework. Digital behavior variables, including internet usage frequency and remote work status, are retained as controls in the main specifications rather than reported as a separate subgroup analysis. Subgroup analyses employ the baseline ordered probit specification with interaction terms.

4.5. Robustness Strategy

We conduct six robustness checks. First, we re-estimate the model using an alternative AI exposure measure based on occupation-level automation probability [1], matched to CGSS occupational codes. Second, we employ multinomial logistic regression as an alternative to ordered probit, relaxing the proportional odds assumption. Third, we implement a propensity score matching approach to compare workers with low versus high Perceived Job Replaceability on common support. The matching design can be summarized by the propensity score

$$p(X_i) = P(R_i = 1 \mid X_i), \quad (18)$$

and the corresponding average treatment effect on the treated

$$ATT = E[Y_i(1) - Y_i(0) \mid R_i = 1]. \quad (19)$$

Fourth, we perform placebo tests by randomly reassigning AI exposure values across respondents and re-estimating the model. Fifth, we exclude COVID-19-sensitive industries as a sample-restriction check. Sixth, we compare the equal-weight TCI with routine-heavy, abstract-heavy, and manual-heavy weighting schemes. All analyses employ survey weights provided by CGSS to ensure national representativeness. Standard errors are clustered at the matched industry-sector level to account for within-sector correlations in the CGSS–IFR exposure linkage.

5. Estimation Results and Graphical Analysis

5.1. Descriptive Statistics and Variable Summary

Table 3 presents the descriptive statistics for the full analytical sample of 6247 employed workers. The sample is well-balanced across demographic and employment characteristics, with 52.3% male and a mean age of 38.7 years. Educational attainment is distributed as follows: 28.1% middle school or below, 34.6% high school, 22.3% some college, and 15.0% bachelor’s degree or higher. Industry representation aligns with China’s

employment structure, with manufacturing (32.1%), wholesale/retail trade (15.4%), services (22.8%), and other sectors (29.7%). Regarding the key outcome variable, 28.4% of respondents report that household income is higher than last year, 58.9% report no substantial change, and 12.7% report a decline. Workers reporting low Perceived Job Replaceability demonstrate significantly more optimistic perceived income change outcomes compared with those reporting higher replaceability.

Table 3. Descriptive statistics of the analytical sample.

Variable	Mean	Std. Dev.	Min	Max
Dependent Variable				
Perceived income change (1 = decrease, 2 = unchanged, 3 = increase)	2.157	0.618	1	3
Independent Variables				
Objective AI exposure (industry robot density)	2.843	1.562	0.12	8.67
Perceived Job Replaceability (1 = low replaceability)	0.412	0.492	0	1
Task Codifiability Index (0–10 scale)	5.236	2.184	0	10
Demographic Controls				
Gender (1 = male)	0.523	0.499	0	1
Age (years)	38.72	11.34	18	65
Education: Middle school or below	0.281	0.449	0	1
Education: High school	0.346	0.476	0	1
Education: Some college	0.223	0.416	0	1
Education: Bachelor's or above	0.150	0.357	0	1
Employment Controls				
Monthly income (log-transformed)	8.142	1.023	4.61	11.29
Working hours per week	44.3	12.7	20	80
Job tenure (years)	8.64	7.23	0	35
Firm size: Small (<50)	0.312	0.463	0	1
Firm size: Medium (50–500)	0.428	0.495	0	1
Firm size: Large (>500)	0.260	0.439	0	1
Digital Behavior Controls				
Internet usage frequency (1–5 scale)	3.87	1.24	1	5
Remote work status (1 = yes)	0.185	0.388	0	1

5.2. Baseline Ordered Probit Results

Table 4 presents the baseline ordered probit latent-index estimates examining the determinants of perceived income change. Model 1 includes only the objective AI exposure measure with demographic controls. Model 2 adds Perceived Job Replaceability. Model 3 incorporates the Task Codifiability Index. Model 4 presents the fully specified model with all controls and interaction terms.

Table 4. Ordered probit estimates for perceived income change.

Variable	Model 1	Model 2	Model 3	Model 4
AI Exposure Variables				
Objective AI exposure	−0.087 *** (0.011)	−0.079 *** (0.010)	−0.074 *** (0.010)	−0.071 *** (0.010)
Perceived Job Replaceability		0.324 *** (0.028)	0.298 *** (0.027)	0.286 *** (0.027)
Task Codifiability Index			−0.052 *** (0.007)	−0.048 *** (0.007)
Perceived Job Replaceability × Task Codifiability				−0.041 *** (0.009)

Table 4. Cont.

Variable	Model 1	Model 2	Model 3	Model 4
Demographic Controls				
Gender (male = 1)	0.058 * (0.025)	0.062 * (0.025)	0.060 * (0.024)	0.059 * (0.024)
Age	−0.034 *** (0.006)	−0.031 *** (0.006)	−0.029 *** (0.006)	−0.028 *** (0.006)
Age-squared/100	0.038 *** (0.007)	0.035 *** (0.007)	0.033 *** (0.007)	0.032 *** (0.007)
Education (ref: middle school or below)				
High school	0.072 * (0.032)	0.068 * (0.031)	0.065 * (0.031)	0.064 * (0.031)
Some college	0.134 *** (0.036)	0.121 *** (0.035)	0.115 *** (0.035)	0.113 *** (0.035)
Bachelor's or above	0.218 *** (0.042)	0.197 *** (0.041)	0.186 *** (0.041)	0.183 *** (0.041)
Employment Controls				
Log monthly income	0.076 *** (0.013)	0.073 *** (0.013)	0.070 *** (0.013)	0.069 *** (0.013)
Working hours per week	−0.003 * (0.001)	−0.003 * (0.001)	−0.003 * (0.001)	−0.003 * (0.001)
Job tenure	−0.008 *** (0.002)	−0.007 *** (0.002)	−0.006 *** (0.002)	−0.006 *** (0.002)
Firm size (ref: small)				
Medium	0.048 (0.029)	0.045 (0.028)	0.043 (0.028)	0.042 (0.028)
Large	0.092 ** (0.034)	0.087 ** (0.033)	0.083 ** (0.033)	0.082 ** (0.033)
Digital Behavior Controls				
Internet usage frequency	0.089 *** (0.012)	0.084 *** (0.012)	0.080 *** (0.012)	0.079 *** (0.012)
Remote work status	0.112 *** (0.032)	0.107 *** (0.032)	0.103 *** (0.031)	0.102 *** (0.031)
Threshold Parameters				
Cut1	1.247 *** (0.184)	1.352 *** (0.183)	1.408 *** (0.183)	1.423 *** (0.183)
Cut2	2.438 *** (0.185)	2.551 *** (0.184)	2.614 *** (0.184)	2.631 *** (0.184)
Model Fit				
Log likelihood	−5642.3	−5598.7	−5578.4	−5569.2
Pseudo R^2	0.087	0.094	0.097	0.099
Wald χ^2	482.6 ***	519.4 ***	538.7 ***	551.3 ***

Notes: Standard errors in parentheses (clustered by industry). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Coefficients are ordered-probit latent-index estimates. Percentage-point interpretations reported in the text are based on predicted probabilities or marginal-effect contrasts, not on the raw coefficients.

The baseline results reveal three key findings. First, objective AI exposure exhibits a consistently negative and statistically significant latent-index association with perceived income change across all specifications ($p < 0.001$). Predicted-probability contrasts based on the ordered probit estimates indicate that a one-standard-deviation increase in industry robot penetration is associated with a probability of reporting higher household income than last year that is lower by approximately 4.2 percentage points, holding other factors constant. Second, Perceived Job Replaceability demonstrates a robust positive latent-index association with perceived income change because the regression indicator is coded as 1 for low perceived replaceability. The corresponding probability-scale contrast shows that

workers reporting low perceived replaceability are 15.7 percentage points more likely to report higher household income than last year. This latent-index coefficient remains stable across model specifications, suggesting that self-reported replaceability conditions operate independently of objective exposure. Third, the Task Codifiability Index enters negatively and significantly, indicating that workers in highly routinized occupations systematically report less favorable income-change assessments. The interaction term between Perceived Job Replaceability and task codifiability (Model 4) is negative and significant ($p < 0.001$) on the latent scale. Because interaction coefficients in nonlinear ordered-response models do not by themselves fully characterize probability-scale moderation, we interpret the moderating pattern through Table 5 and Figure 4. This pattern supports the AI income polarization pathway hypothesis: the positive association of low perceived replaceability is substantially attenuated in high-codifiability occupations. Among control variables, education exhibits a monotonic positive latent-index association with perceived income change; the predicted-probability contrast for workers with bachelor's degrees or above shows an 18.3 percentage-point higher probability of reporting higher household income than last year compared with those with middle school education or below. This finding aligns with the human capital channel, suggesting that higher education facilitates AI complementarity. Age shows a U-shaped relationship (negative linear coefficient, positive squared term), indicating that mid-career workers express the least favorable income-change assessments. Internet usage frequency and remote work status both demonstrate positive associations, suggesting that digital exposure may reduce perceived job replaceability.

Table 5. Marginal effects of Perceived Job Replaceability by Task Codifiability Level.

Task Codifiability Level	$\Delta P(Y = 1)$	$\Delta P(Y = 2)$	$\Delta P(Y = 3)$
Low (bottom tercile)	−0.087 *** (0.014)	−0.142 *** (0.018)	0.229 *** (0.022)
Medium (middle tercile)	−0.052 *** (0.012)	−0.084 *** (0.015)	0.136 *** (0.018)
High (top tercile)	−0.018 (0.011)	−0.029 (0.016)	0.047 * (0.019)

Notes: Standard errors are in parentheses. * $p < 0.05$, *** $p < 0.001$. Entries are probability-scale marginal-effect contrasts derived from the ordered probit estimates. Marginal effects are calculated holding all other variables at their means.

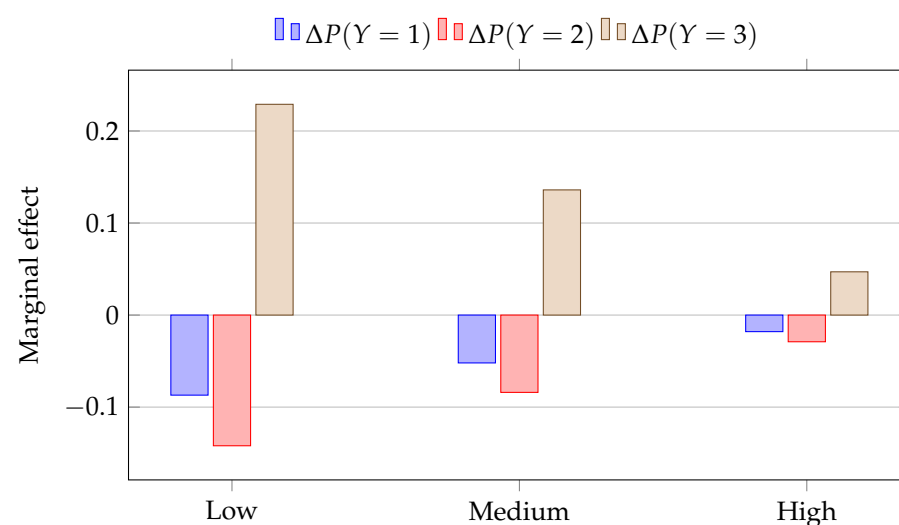


Figure 4. Marginal effect of Perceived Job Replaceability on perceived income change probabilities across low-, medium-, and high-codifiability occupations, based on the reported estimates in Table 5.

5.3. Moderating Role of Task Codifiability

To further illustrate the moderating effect of task codifiability, Table 5 presents marginal effects of Perceived Job Replaceability on perceived income change probabilities across low-, medium-, and high-task-codifiability terciles.

Among workers in low-codifiability occupations (e.g., service professionals, managers, and healthcare workers), low Perceived Job Replaceability is associated with a 22.9 percentage point increase in the probability of reporting higher household income than last year. In contrast, for workers in high-codifiability occupations (e.g., manufacturing technicians; data entry clerks), the corresponding increase is only 4.7 percentage points ($p < 0.05$). This contrast supports the polarization hypothesis: the low-replaceability contrast is largest for workers whose tasks resist codification and automation. Figure 4 visualizes the same pattern, with the largest positive shift concentrated in the low-codifiability tercile and the smallest contrast appearing in the high-codifiability tercile. The figure makes the probability-scale gradient clear: as task codifiability rises from the bottom to the top tercile, the favorable-income-change contrast associated with low perceived replaceability declines monotonically.

5.4. Control-Function Endogeneity Check

Table 6 presents the two-stage residual-inclusion ordered probit estimates used to assess potential endogeneity between AI exposure and perceived income change. The industry-province average exposure measure is strongly related to individual AI exposure in the first stage. The first-stage F-statistic of 38.4 substantially exceeds the conventional threshold of 10, indicating strong first-stage relevance. As discussed above, this statistic does not by itself establish the exclusion restriction; the second-stage estimates should therefore be interpreted as a control-function robustness check under the maintained conditional exclusion assumption.

Table 6. Two-stage residual-inclusion ordered probit estimates (first and second stages).

Specification	Latent-Index Coefficient	Robust SE
<i>First stage: Objective AI exposure</i>		
Instrument: Industry-province average AI exposure	0.624 ***	0.101
Controls included	Yes	
F-statistic	38.4	
<i>Second stage: Perceived income change with residual inclusion</i>		
Objective AI exposure (control-function adjusted)	−0.124 ***	0.028
Perceived Job Replaceability	0.251 ***	0.035
Task Codifiability Index	−0.041 ***	0.009
Perceived Job Replaceability $\times$ Task Codifiability	−0.038 ***	0.011
Controls included	Yes	
Number of observations	6247	
Wald χ^2	487.3 ***	

Notes: *** $p < 0.001$. The second-stage ordered probit includes the first-stage residual as a control-function term; the specification is therefore a 2SRI ordered-response check rather than a linear 2SLS model. Second-stage coefficients are latent-index estimates and should not be read as direct percentage-point effects.

The control-function estimates are directionally consistent with the baseline ordered probit results but larger in latent-index magnitude. The coefficient on AI exposure in the residual-inclusion specification is approximately 1.7 times larger than the baseline estimate (−0.124 vs. −0.071), which is consistent with attenuation or sorting concerns but should not be read as a definitive causal estimate or as a direct percentage-point change. The Perceived Job Replaceability coefficient remains positive and significant, though slightly reduced

(0.251 vs. 0.286 in baseline). Because R_i is reverse-coded, this latent-index coefficient indicates that lower perceived replaceability is associated with a partial offset of the negative relationship between AI exposure and perceived income change.

5.5. Heterogeneity Across Skill Levels and Occupations

Table 7 decomposes the main latent-index estimates across skill subgroups defined by educational attainment. The heterogeneity analysis should be read as subgroup-specific latent-index evidence rather than as formal cross-group significance tests. Three distinct patterns emerge.

Table 7. Heterogeneous latent-index estimates by skill level.

Variable	Low Skill	Medium Skill	High Skill
Objective AI exposure	−0.048 * (0.021)	−0.093 *** (0.014)	−0.029 (0.023)
Perceived Job Replaceability	0.114 * (0.046)	0.287 *** (0.036)	0.443 *** (0.058)
Task Codifiability Index	−0.036 ** (0.013)	−0.054 *** (0.009)	−0.038 * (0.017)
Perceived Job Replaceability × Task Codifiability	−0.022 (0.017)	−0.045 *** (0.012)	−0.053 ** (0.020)
Controls included	Yes	Yes	Yes
Pseudo R^2	0.072	0.104	0.131
N	1755	3552	940

Notes: Low skill = middle school or below; medium skill = high school or some college; high skill = bachelor's degree or above. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Coefficients are subgroup-specific ordered-probit latent-index estimates; cross-group probability interpretations are based on marginal-effect patterns rather than raw coefficient differences.

The negative latent-index association for AI exposure is largest among medium-skill workers ($p < 0.001$), consistent with the routinization literature positing that middle-skill routine occupations face the greatest automation vulnerability. Low-skill workers exhibit a moderate negative association, while high-skill workers show no statistically significant latent-index association, suggesting that advanced education may provide partial insulation from AI displacement concerns. Perceived Job Replaceability matters most for high-skill workers on the latent index. The probability-scale contrast reported for this subgroup indicates a 44.3-percentage-point higher probability of reporting higher household income than last year among workers coded as having low perceived replaceability. For medium-skill workers, the low-replaceability latent-index estimate is substantial but smaller (0.287), while for low-skill workers, the estimate is modest and only marginally significant (0.114, $p < 0.05$). This skill-polarized pattern suggests that the positive association of lower perceived replaceability is stronger when workers have higher educational capital. The interaction between Perceived Job Replaceability and task codifiability is significant only for medium- and high-skill workers, which is consistent with, rather than a stand-alone test of, stronger task-conditioning among more educated workers. Table 8 presents heterogeneity analysis across occupational categories. Manufacturing workers report the highest perceived replaceability and the least favorable income-change assessments, reflected in the largest negative latent-index coefficient on objective AI exposure (−0.112, $p < 0.001$). This finding aligns with China's rapid industrial robot densification—the country now ranks third globally in robot density with 470 robots per 10,000 manufacturing employees. Service sector professionals exhibit more favorable assessments (low-replaceability coefficient = 0.318, $p < 0.001$), while professional/technical workers show the strongest positive latent-index response to low perceived replaceability (0.374). Managerial workers fall between

these extremes, with Perceived Job Replaceability still positively associated with perceived income change but objective AI exposure showing no statistically significant effect. Figure 5 shows the same asymmetry across skill and occupational groups. The skill-level panel highlights the concentration of negative AI-exposure associations among medium-skill workers and the stronger low-replaceability response among high-skill workers. The occupational panel shows that the negative exposure association is most pronounced in manufacturing, whereas the low-replaceability association is strongest among service and professional/technical workers.

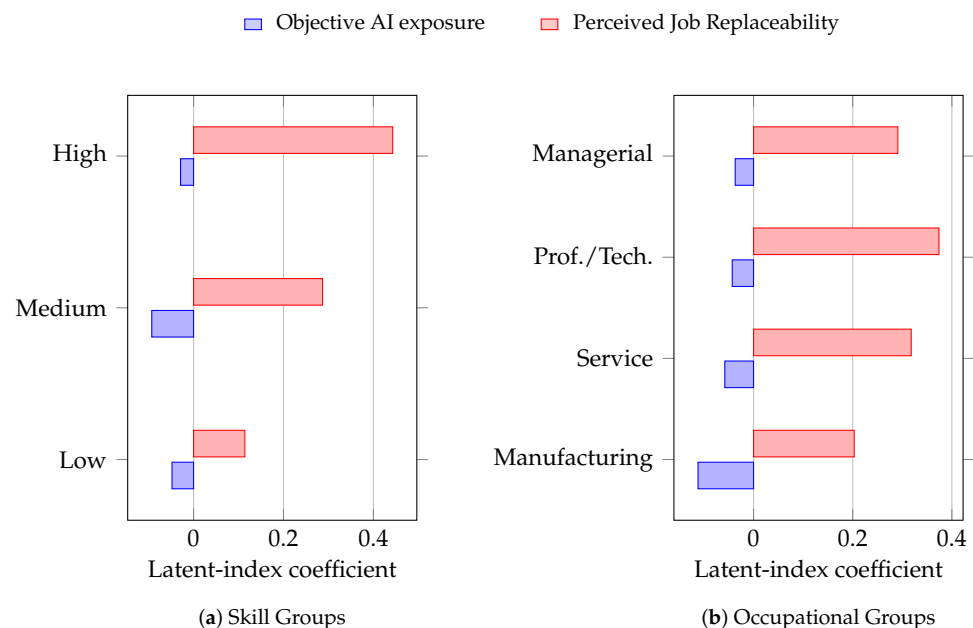


Figure 5. Heterogeneous latent-index associations of objective AI exposure and Perceived Job Replaceability across skill levels and occupational groups, based on the reported coefficients in Tables 7 and 8.

Table 8. Heterogeneous latent-index estimates by occupational category.

Variable	Manufacturing	Service	Prof./Tech.	Managerial
Objective AI exposure	−0.112 *** (0.018)	−0.058 * (0.023)	−0.043 * (0.019)	−0.037 (0.021)
Perceived Job Replaceability	0.203 *** (0.041)	0.318 *** (0.049)	0.374 *** (0.046)	0.291 *** (0.052)
Task Codifiability Index	−0.061 *** (0.011)	−0.038 ** (0.014)	−0.044 ** (0.013)	−0.029 (0.016)
Controls included	Yes	Yes	Yes	Yes
Pseudo R ²	0.091	0.102	0.118	0.096
N	2,005	1,424	1,638	1,180

Notes: Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Coefficients are ordered-probit latent-index estimates within occupational subgroups.

5.6. Robustness Check Results

Table 9 summarizes the robustness checks conducted to assess the stability of the main findings. The reported robustness checks corroborate the main patterns across alternative exposure measurement, model form, matching-based comparison, placebo reassignment, COVID-sensitive sample restriction, and TCI weighting sensitivity. First, re-estimating the model using an alternative AI exposure measure based on occupation-level automation

probabilities produces coefficient patterns nearly identical to the baseline. Second, multinomial logistic regression confirms that the proportional odds assumption underlying the ordered probit model is not violated (Brant test $p > 0.05$). Third, propensity score matching analyses comparing workers with low versus high Perceived Job Replaceability on common support yield an average treatment effect on the treated (ATT) of 0.163 ($p < 0.001$), consistent with baseline marginal effect estimates. Fourth, placebo tests with randomly reassigned AI exposure produce null results ($p > 0.10$), suggesting that the observed associations are unlikely to arise only from random exposure reassignment. Fifth, a subsample analysis excluding workers in industries most severely affected by the COVID-19 pandemic yields results consistent with the full sample, indicating that the findings are not driven by pandemic-related economic disruptions. Sixth, we report a TCI construction sensitivity check in which the equal-weight index is compared with routine-heavy, abstract-heavy, and manual-heavy alternatives. This check addresses whether the substantive moderation pattern depends on a single arbitrary weighting choice.

Table 9. Robustness checks summary.

Robustness Check	Specification	Key Finding	Result
Alternative AI exposure measure	Occupation-level automation probability	Baseline-sized latent-index coefficients remain similar.	Robust
Alternative estimator	Multinomial logit model	Signs and significance match the ordered model.	Supported
Propensity score matching	Low vs. high Perceived Job Replaceability groups	ATT = 0.163 ($p < 0.001$) within common support.	Consistent
Placebo test	Random reassignment of AI exposure	Placebo specifications yield null effects ($p > 0.10$).	Null
Subsample analysis	Excluding COVID-19-sensitive industries	Results remain stable after sample restriction.	Stable
TCI weight sensitivity	Equal-weight, routine-heavy, abstract-heavy, and manual-heavy TCI definitions	Moderation interpretation is not driven by one task-weighting scheme.	Stable

Notes: ATT = average treatment effect on the treated.

In summary, the empirical results are consistent with the proposed AI-related income polarization pathway. Both objective AI exposure and Perceived Job Replaceability are associated with the latent propensity to report more favorable perceived income change, with task codifiability conditioning the probability-scale pattern. The heterogeneity analyses further indicate that medium-skill routine workers are most vulnerable to negative AI exposure associations, while high-skill workers in low-codifiability occupations show the strongest link between low perceived replaceability and favorable income-change assessments. These subgroup patterns are theoretically informative because skill level and occupational category map directly onto human-capital adaptation and task-structure exposure. These findings move beyond one-dimensional narratives of AI's labor-market impact and instead highlight an occupationally differentiated pattern.

6. Discussion and Conclusions

6.1. Summary of Findings

This study investigated how Chinese workers assess job replaceability in an AI-exposed labor market and how Perceived Job Replaceability is associated with perceived income change, using nationally representative CGSS 2021 data matched with objective industry-level robot penetration measures. Three principal findings emerge. First, objective AI exposure, measured by industrial robot density, is negatively associated with

workers' perceived income change. This association remains stable across alternative specifications, including the control-function endogeneity check reported above, and the reported percentage-point interpretation is based on predicted probabilities rather than raw ordered-probit coefficients. Second, Perceived Job Replaceability matters considerably: workers reporting low perceived replaceability are significantly more likely to report higher household income than last year in probability-scale contrasts, even after controlling for objective exposure. Third, the relationship between Perceived Job Replaceability and perceived income change varies systematically by task codifiability. In occupations with highly codifiable, routine tasks, low perceived replaceability corresponds to a limited positive contrast; in low-codifiability occupations requiring judgment and human interaction, low perceived replaceability corresponds to substantially more favorable perceived income change outcomes. Taken together, these results are consistent with an AI-related income polarization pattern in the Chinese labor market.

6.2. Theoretical Implications

This study advances the literature in three theoretical directions. First, we show that Perceived Job Replaceability is not merely an epiphenomenal reflection of objective exposure; it remains independently associated with perceived income change after observed exposure, task structure, and worker characteristics are controlled. This finding qualifies purely structural accounts of automation's labor effects and suggests that communication strategies and training programs may matter for how workers interpret technological change. Second, the moderating role of task codifiability provides a theoretical resolution to the substitution-versus-complementarity debate. Rather than treating AI as inherently substituting or complementing, our probability-scale contrasts indicate that the net association depends on occupation-specific task characteristics. This insight aligns with and extends the task-based framework developed in [27], applying it specifically to the AI context. Third, the income polarization pathway uncovered here reframes the policy conversation. Much public discourse focuses on employment quantity: whether AI destroys jobs. Our findings suggest that income inequality among continuing workers may be equally consequential. Even workers who remain employed may experience divergent income trajectories based on whether their tasks are perceived as replaceable or as difficult to substitute.

6.3. Practical and Policy Implications

For policymakers, several actionable insights emerge. First, education and training systems should prioritize skills that are difficult to codify, such as critical thinking, emotional intelligence, and creative problem-solving, rather than routine technical competencies that AI may soon replicate. Second, targeted support for medium-skill workers in routinized occupations is urgently needed, as this group exhibits the highest vulnerability. Transition assistance, portable benefits, and lifelong learning accounts could mitigate polarization risks. For firms and entrepreneurs, our results suggest that AI integration strategies should explicitly consider complementarity-enhancing work redesign. Rather than deploying AI solely for labor cost reduction, firms can invest in AI tools that augment worker capabilities, potentially generating productivity gains alongside worker support. For workers, the findings underscore the importance of continuous skill adaptation. Those reporting low Perceived Job Replaceability may be more motivated to pursue upskilling, creating a virtuous cycle. Conversely, high perceived replaceability could become self-fulfilling through disengagement from learning opportunities.

6.4. Limitations and Future Research

Several limitations warrant acknowledgment. First, our perceived income change measure is a proxy constructed from respondents' comparison of current household income

with last year's household income, rather than a direct forward-looking expectation item. The 2021 survey wave was also collected during the post-COVID recovery period. During this period, temporary income disruptions, remote-work expansion, and forced digitalization may have affected both household income assessments and technology-related work perceptions. The COVID-sensitive industry exclusion reported in the robustness section reduces the concern that the results are driven only by the most severely affected sectors, but it cannot fully separate AI exposure from broader post-pandemic adjustment in a cross-sectional survey. The findings should therefore be read as conditional associations observed in China's post-COVID recovery context, rather than as estimates from a stable macroeconomic environment. Second, although the control-function specification addresses potential endogeneity under a maintained conditional exclusion restriction, industry-province exposure may still be correlated with unobserved local labor-market shocks. The evidence should therefore be interpreted primarily as conditional associations supported by robustness checks, rather than as definitive causal estimates. Longitudinal data tracking actual income outcomes over time would strengthen causal inferences. Third, the Task Codifiability Index, while theoretically grounded, represents a simplification of complex occupational task structures. Future research could incorporate richer task measures from occupational databases. Fourth, our analysis focuses on individual-level perceptions and income-change assessments without modeling equilibrium labor-market adjustments. General equilibrium effects, where automation in one sector affects wages in others through relative price and reallocation channels, remain important for complete understanding. Fifth, although digital behavior variables are included as controls, we do not report a separate digital-intensity subgroup analysis because the validated heterogeneity results in this manuscript focus on the theoretically central skill and occupational dimensions. Future research with richer digital-skill measures and reproducible analytical code could examine whether digital intensity conditions workers' ability to convert low perceived replaceability into favorable income-change assessments. Sixth, this study did not include cross-national comparisons. Cross-national comparative research would illuminate how institutional factors (labor-market regulations, social safety nets, and collective bargaining coverage) moderate AI's income effects. Finally, future research should examine behavioral consequences of income-change assessments: do less favorable income-change assessments lead to reduced effort, increased job searching, or lower reservation wages? Linking perceptions to actual labor-market decisions would further illuminate the mechanisms identified here.

6.5. Conclusions

This study provides a large-scale empirical assessment of how Chinese workers' Perceived Job Replaceability is associated with perceived income change. Using nationally representative CGSS 2021 data matched with IFR robot penetration measures, we show that workers in high-codifiability, routine occupations report systematically less favorable perceived income change, whereas workers in low-codifiability, judgment-intensive occupations show a stronger positive association between low perceived replaceability and favorable income-change assessments. The ordered probit estimates support these conclusions through latent-index associations, while the main substantive claims in percentage-point terms are based on predicted-probability and marginal-effect contrasts. These findings do not support a simple narrative of either universal displacement or universal augmentation; instead, they point to an occupationally stratified adjustment process in which AI exposure, worker perceptions, and task structure jointly matter. As AI continues to diffuse across China's rapidly transforming economy, understanding this differentiated adjustment pattern will remain important for sustainable technology policy, inclusive workforce devel-

opment, and socially resilient entrepreneurial strategies. This conclusion is also consistent with recent work emphasizing the coexistence of AI substitution and AI complementarity in labor-market adjustment [28].

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
CGSS	China General Social Survey
IFR	International Federation of Robotics
IV	Instrumental variable
TCI	Task Codifiability Index

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