Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Research on the impact of artificial intelligence development on fertility intentions in China

Yunjiang Yu
Shanghai Normal University
Xiaohan Xia
1000588741@smail.shnu.edu

Shanghai Normal University

Article

Keywords:

Posted Date: November 23rd, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11103595/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Research on the impact of artificial intelligence development on fertility intentions in China

Abstract

The rapid development of artificial intelligence (AI) is reshaping labour markets and may also affect household fertility intentions. Using data from the China Family Panel Studies and an occupation-level index of AI exposure, this study examines whether technological exposure is associated with individuals' ideal number of children and investigates three potential mechanisms: employment instability, marital satisfaction and value change. The results indicate that greater occupational AI exposure is associated with lower fertility intentions. This relationship remains after a series of robustness checks and instrumental-variable analyses. The negative association is stronger among middle-aged, less-educated and lower-income respondents. Mechanism analyses are consistent with employment instability and lower marital satisfaction as possible pathways, while evidence of value change is mixed. Financial assets moderate the association; evidence for housing assets is weaker. By incorporating technological change into the study of fertility intentions, the analysis provides evidence on how labour-market transformation may shape demographic decision-making and informs the design of fertility-support policies in the AI era.

Introduction

Following the general patterns of population change, birth rates will decline over time as an economy reaches a certain stage (Cai 2024; Wang and Liu 2019). Since the 1990s, China's total fertility rate has consistently remained below the replacement level and has continued to decline, with its impact manifested not only in a shrinking population but also in reduced labour supply and accelerated population ageing, which significantly constrain economic growth potential and the social security system (Zhai and Jin 2023). To address the challenge of low fertility, China's policies have gradually shifted from restrictive to encouraging, but the effectiveness of these policies remains significantly below expectations (Li and Sheng 2025). As policy restrictions on childbearing are relaxed, further research is needed on how fertility intentions are formed and what influences them, given their role in linking population-level patterns to household decisions (Wu 2020).

Existing research on low fertility has focused extensively on economic, educational, policy, and cultural factors. Classic economic theories treat children as durable goods that provide utility to parents. This perspective explains the formation and evolution of fertility intentions through household decision-making (Becker and Lewis 1973; Barro and Becker 1989). On this basis, a substantial body of literature emphasises the decisive role of income and child-rearing costs in

shaping fertility intentions from the perspective of economic constraints (Guo et al. 2021; Wang and Bai 2024). At the same time, educational expansion has a profound impact on reproductive behaviour by enhancing human capital returns and changing individuals' opportunity costs (Li 2014; Li 2025). Other research identifies changes in culture and values as an important driver of sustained fertility decline in postmodern societies (Lesthaeghe 1983). This conceptual change is specifically reflected in greater emphasis on individual rights, higher parenting standards and expectations, and a decline in the perceived utility of children (Song and Chen 2022). Specifically, women who hold individualistic values have significantly lower fertility intentions than women who place greater emphasis on traditional family values (Miller and Pasta 1993). In addition, in the Chinese context, increasing motherhood penalties and constraints on career development have significantly suppressed women's fertility intentions and childbearing (Yang 2019; Xu 2021).

Although these studies explain low fertility from several perspectives, they have not fully incorporated the rapid development of artificial intelligence into its analytical frameworks. Current research focuses on examining the economic effects of artificial intelligence, with particular attention to issues such as job substitution, task restructuring, and wage distribution gaps (Autor et al. 2015). Based on the theory of task-based technological change, artificial intelligence tends to replace routine, highly codifiable tasks, thereby triggering a systematic adjustment of the structure of labour demand (Acemoglu and Restrepo 2020). To characterise the heterogeneous impact of technological shocks, existing studies have identified the impact of technology at the occupational level by constructing an AI Occupational Exposure (AIOE) index (Felten et al. 2018; Acemoglu et al. 2022). Related studies have shown that the increase in the penetration of artificial intelligence not only exacerbates employment instability and occupational mobility, but also changes individuals' expectations of future economic conditions through increased income uncertainty and career development risks (Chen et al. 2024; Zhang et al. 2025).

Although fertility intentions are subjective, they are shaped by existing economic conditions, marital relationships, and values (Shi and Wang 2024). However, existing literature lacks empirical research to systematically identify this mechanism of action at the micro level. Based on the above analysis, this article examines employment uncertainty, marital relationships, and changes in values as potential mechanisms linking artificial intelligence to household fertility

intentions. Specifically, this article attempts to answer the following questions: Will the development of artificial intelligence technology significantly affect individual fertility intentions? Through which channels might this influence operate? Does this influence differ across demographic groups and households with different resources?

This article makes three contributions. First, it extends the analysis of fertility intentions to technological change, offering an explanation for low fertility from the perspective of artificial intelligence. Previous studies have mostly explained the decline in fertility rates from the perspectives of economic constraints, policy systems, and changes in values (Shi et al. 2024; Li 2025), but there has been insufficient attention paid to technological progress, especially the rapid development of artificial intelligence. Second, it uses occupational AI exposure to examine fertility intentions as occupational risks evolve. Previous studies have mostly analysed fertility intentions based on static income levels or current employment status (Wu 2020), which makes it difficult to reflect changes in the uncertainty individuals face in their careers. This article combines occupational AI exposure with individual employment mobility to characterise workers' exposure to technological substitution risks. Third, it examines employment uncertainty, marital satisfaction, and changes in values as mechanisms through which artificial intelligence may affect fertility intentions. Although existing research has focused on the impact of income level and employment stability on fertility (Ranjan 1999), there is a lack of systematic analysis on how technological development affects fertility intentions through multiple channels such as the labour market, marital relationships, and values.

Theoretical framework and hypotheses

AI exposure and fertility intentions

The development of artificial intelligence has broken through existing occupational boundaries and promoted the reorganisation of tasks (Acemoglu and Restrepo 2019; Yao et al. 2024). In the AI era, whether workers can benefit from technological changes and to what extent they can withstand technological shocks is no longer solely determined by their occupational category, but also depends on the structure of tasks and skill requirements within their occupations (Wu et al. 2026).

Regarding the labour market effects of artificial intelligence, the theory of task-based technological change points out that the substitution effect of artificial intelligence technology

mainly affects routine tasks with clear rules and standardised processes, whereas its capacity to replace abstract tasks requiring creativity and judgement or manual tasks requiring physical flexibility is limited. This feature directly leads to a significant reduction in the demand for workers engaged in routine tasks in the labour market (Autor et al. 2015; Acemoglu et al. 2022; Yu et al. 2026). Therefore, workers engaged in occupations dominated by routine tasks are more susceptible to the impact of technological substitution compared to other groups, and thus face higher risks of technology-related unemployment and declining income. The perceived risks associated with this technological change will, in turn, influence household fertility decisions.

The desire to have children, shaped by individuals' circumstances, is highly sensitive to income stability and future expectations. Even if firms reassign workers displaced by AI rather than dismissing them, these workers may struggle to maintain their previous earnings. Therefore, the occupational substitution risk and income uncertainty caused by artificial intelligence can suppress individuals' fertility intentions by changing their expectations of future economic conditions.

> *Based on this, we propose Hypothesis 1: Occupational AI exposure has a significant negative impact on individuals' desire to have children.*

Heterogeneous effects of AI exposure

As a transformative technology, artificial intelligence does not have a uniform impact on fertility decisions. Instead, its effects are heterogeneous, varying based on individual characteristics and family backgrounds.

Firstly, age groups differ in their career stages and childbearing timelines (Qing and Wen 2025). The middle-aged group is in a stage of life where career development overlaps with childbearing and child-rearing. They have accumulated professional experience but may find it difficult to update established skills. At the same time, this group needs to balance their career development and family caregiving responsibilities. The time and energy required for childbearing, as well as the risk of career interruption, have a greater impact on them (Vignoli et al. 2012). Intensified workplace competition associated with artificial intelligence can therefore more readily suppress their willingness to have children (Yu and Sun 2018). However, the career development path of young people is not yet fully stable, and their reproductive decisions are mostly in the planning stage. Their awareness of AI-related occupational risks is less developed, and their reproductive

concepts are becoming more diversified. They have not yet faced immediate time constraints on childbearing and practical parenting pressures, and the inhibitory effect of artificial intelligence is difficult to fully manifest. Secondly, there are differences in occupational characteristics and reproductive attitudes among different educational groups. The less-educated group is more likely to engage in low-skilled and highly repetitive routine positions (Acemoglu and Restrepo 2019), which are key areas for artificial intelligence replacement. Their employment stability and income security are more affected by technological shocks, and their willingness to have children is relatively strong. They are more sensitive to changes in the cost of childbirth and economic pressure caused by occupational shocks, and their willingness to have children is easily suppressed. Highly educated workers have more specialised skills and greater career flexibility, but their fertility willingness is more influenced by subjective factors such as self-actualisation and quality of life. Their fertility preferences are lower and less flexible, making them less likely to change substantially in response to career risks. Finally, there are differences in the economic foundation and capacity to withstand risk among different income groups (Shi and Wang 2024). The low-income group has a weak economic foundation, and the cost of raising children has already accounted for a large proportion of household expenses. The occupational substitution risk caused by artificial intelligence will further exacerbate their economic burden and uncertainty about the future, thereby strongly suppressing their willingness to have children.

> *Based on this, we propose Hypothesis 2: The impact of AI-related job displacement on reproductive decisions exhibits significant group differences, with middle-aged individuals, those with lower levels of education, and low-income individuals experiencing more pronounced negative effects.*

Potential mechanisms

The relationship between occupational AI exposure and fertility intentions may involve three parallel pathways: labour-market conditions, the quality of marital relationships, and changes in attitudes.

First, employment instability. Existing research indicates that technological progress often accompanies job substitution and employment structure adjustment, thereby increasing the probability of unemployment for some workers. Unemployment can reduce an individual's current income, while unemployment risk heightens uncertainty about future economic conditions. In this situation, individuals often postpone or abandon their family planning because

of risk aversion (Ranjan 1999). Technological shocks are usually accompanied by job transitions and career path adjustments. Frequent career mobility can disrupt household routines and stability, increasing uncertainty about future plans (Busetta et al. 2019). When there is significant uncertainty in future income and career development paths, individuals are more likely to adopt delayed decision-making strategies, thereby reducing their willingness to have children.

Second, marital satisfaction. The displacement risks and income uncertainty brought about by artificial intelligence can affect marital quality through two pathways: the first involves economic pressure, whereby job and income instability exacerbate the financial burden on families, which in turn is a major source of marital conflict and decreased satisfaction (Bertrand et al. 2015). The second involves evaluations of family roles, whereby individuals may question their economic contribution within the family due to technological disruption, leading to a decline in their subjective evaluation of the marriage. Existing research shows that marital quality and relationship stability are important positive predictors of the desire to have children (Mao et al. 2026). Therefore, artificial intelligence may indirectly suppress the desire to have children through reduced marital satisfaction.

Third, changes in values. The willingness to have children is largely shaped by individual value orientations and attitudes towards childbearing. The second demographic transition theory points out that modernisation often accompanies a shift in fertility values from traditional utilitarianism to individualism (Lesthaeghe 2014). The technological transformation and social individuation driven by artificial intelligence have, on the one hand, strengthened individualistic value orientations and elevated the priority of career development and self-realisation in personal life; on the other hand, improvements in social security and more diverse elder-care arrangements weaken utilitarian motivations for childbearing, such as securing support in old age and continuing the family line (Wang and Peng 2015). When traditional familistic concepts such as continuing the family line and family fulfilment give way to a focus on individual development, individuals' desire to have more children and continue the family line declines accordingly (Chen and Hu 2020). Based on this, artificial intelligence may indirectly suppress the desire to have children by weakening traditional concepts of childbirth.

Based on this, this paper proposes Hypothesis 3: Occupational AI exposure suppresses individuals' willingness to have children through three channels: employment instability, reduced marital satisfaction, and weaker traditional views on childbirth.

Moderating role of household assets

In the context of rising uncertainty, the role of family assets in the willingness to have children is not only reflected in direct impacts but may also play an important moderating role by buffering external shocks. Existing studies mainly examine the impact of family assets on fertility behaviour from the perspective of the wealth effect (Wei 2023), but have paid little attention to the mechanisms by which household wealth interacts with technological change and fertility intentions.

Functionally, the impact of family assets on fertility intentions is mainly reflected in risk-buffering and expectation-stabilising effects. Household assets, as accumulated wealth, can provide basic security for families in the event of income interruption or decline, thereby reducing the impact of uncertainty on fertility intentions. Related studies have shown that households with higher asset levels have smaller fluctuations in consumption and living standards when facing employment shocks, demonstrating stronger capacity to withstand risk (Zhang et al. 2015). Higher levels of household assets can enhance individuals' confidence in future economic conditions, reduce anxiety caused by uncertainty, and thus increase their acceptance of long-term household investments. Especially in the context of technological changes exacerbating labour market volatility, the stable expectations provided by assets have become an important psychological foundation to support fertility intentions (Bueno and Brinton 2019).

Furthermore, there may be differences in the moderating effects of different types of household assets. Housing assets and financial assets, as the two main forms of household wealth, have different mechanisms of action. On the one hand, housing assets enhance individuals' sense of life security by providing stable living conditions and access to public services. A stable living environment not only reduces the uncertainty of spatial mobility for families, but also enhances their long-term development expectations through the availability of resources such as education and healthcare. Therefore, the higher the level of housing assets, the easier it is for individuals to make reproductive decisions based on a stable living foundation, thereby weakening the negative impact of occupational AI exposure. On the other hand, financial assets provide households with more flexible risk response tools through their liquidity and return characteristics. Financial assets can not only compensate for income fluctuations in the short term, but also generate expectations of wealth growth through investment returns.

Based on this, this paper proposes Hypothesis 4: Housing assets and financial assets moderate the relationship between occupational AI exposure and households' willingness to have children.

Data and methods

Data sources

To examine the impact of AI exposure on family fertility intentions, this paper uses survey data from the China Family Panel Studies (CFPS) in 2018 and 2022 to construct an individual-level sample for quantitative analysis. CFPS is a biennial follow-up survey conducted by the Institute of Social Science Survey at Peking University. The survey officially began in 2010 and covers 25 provinces, municipalities, and autonomous regions nationwide, with a nationally representative sample. The data used in this article come from family members, household economic questionnaires, and individual self-response questionnaires. The AI data come from AI patents screened in the patent database of the National Intellectual Property Administration. Provincial-level control variables are sourced from the corresponding year's China Statistical Yearbook.

Variables

Dependent variable

The key variable in this study is fertility intentions. This study uses the ideal number of children as the measure of fertility intentions, based on the question "Considering no policy restrictions, how many children would you ideally like to have?" from the CFPS personal questionnaire. The possible values are limited to 0 to 10.

Explanatory variable

The explanatory variable in this article is occupational AI exposure. With the proposal of deep learning theory in 2006 and the breakthrough of deep convolutional neural networks (CNN) in 2012, artificial intelligence technology quickly entered the stage of industrialization and large-scale application. The main focus of this article is the widespread penetration of artificial intelligence technology with deep learning as its core in the labor market and its economic and social impact. After the release of the New Generation Artificial Intelligence Development Plan in 2017, the application of artificial intelligence technology in manufacturing, finance, Internet platforms and other fields has accelerated, and the structure of professional tasks and employment patterns have changed significantly. Therefore, this article chooses 2018 and 2022

as research windows, which can better capture the real impact of the diffusion of artificial intelligence technology on employment uncertainty and family fertility decisions.

Drawing on the task-based framework (Autor et al. 2003), this article argues that the impact of artificial intelligence on the labour market depends on the compatibility between technology supply and occupational task demand. In terms of measurement methods, this article does not use traditional keyword matching methods because keyword methods struggle to capture the deep penetration of artificial intelligence into complex cognitive tasks. Referring to Webb (2020) and recent research in China (Chen et al. 2024; Zhang et al. 2025), this paper adopts a semantic mapping method based on natural language processing. An advantage of this method is that it not only focuses on whether the technology exists, but also measures the distance between patent descriptions and job tasks in the semantic space through the BGE deep learning model. This addresses limitations of traditional measures in handling ambiguous terms and identifying the potential of emerging technologies.

On the demand side, this paper uses the O*NET database to construct a matrix of job tasks. Unlike previous research, which simply aggregated tasks, this paper draws on the approach of Zhang et al. (2025), using task importance and task ranking to calculate a standardised weight for each specific work activity within a particular profession. This approach aligns better with economic intuition; even if two professions share the same tasks, if one task is central to an accountant's role while being peripheral to a construction worker's role, the level of technological disruption they face will clearly differ. In the context of China, this paper further maps the aforementioned task characteristics to the Chinese occupational classification system using a SOC-ISCO-CNSO cross-matching table.

Regarding the technical aspect, this paper uses patent abstracts extracted from the China National Intellectual Property Administration (CNIPA) database as a proxy for technological impact. To capture the potential for technological advances to substitute for tasks, this paper employs a non-linear aggregation strategy (Jiang et al. 2024). The Log-Sum-Exp (LSE) operator is used to calculate the strength of the technological signal for each occupation in each year:

$$E_{o,t} = \sum_{k \in K_o} \omega_{o,k} \left[\tau \cdot ln \left(\sum_{p \in P_t} exp \left(\frac{\mathrm{sim}(V_k, V_p)}{\tau} \right) \right) \right] \quad (1)$$

The formula calculates the cosine similarity between the task vector and the patent vector. The introduction of the LSE operator aims to simulate the decision-making logic of a company when

facing new technologies: the degree of exposure of a task is primarily influenced by its proximity to the most relevant cutting-edge technologies. Furthermore, in the calculation process, this paper uses large language models such as DeepSeek to disambiguate and clean descriptions of some tasks, providing an additional check on automated matching and the accuracy of semantic embeddings in specialised occupations. The results show that professions such as software engineering and financial auditing, which require high-level cognitive skills, exhibit a high degree of exposure, which is consistent with Chen et al.'s (2024) findings regarding the technological advancements driven by AI.

Control variables

Because fertility intentions reflect individual preferences, household characteristics, and broader socioeconomic conditions, the analysis controls for these factors when assessing the impact of artificial intelligence. Therefore, this article refers to the research of Wang et al. (2022) and controls for relevant variables at three levels: individual, family, and province. At the individual level, it includes age, gender, education level, spouse's education level, health status, medical insurance status, and household registration type; at the family level, it includes household size, ownership of additional properties, per-capita household income and its squared term; at the provincial level, it includes the level of economic development, financial support, social consumption level, and advanced industrial structure. Variable definitions are provided in Table 1.

The sample includes married male and female respondents aged 20–45 who have completed their education. To ensure data quality, this article further excludes samples with missing or abnormal values in key variables such as educational attainment and household income. Finally, this article uses respondents' current main occupation, identified by the occupational codes in the CFPS individual questionnaire. The occupation-level AI exposure index is assigned to individuals using their occupational codes, yielding 11,766 matched observations.

Descriptive statistics for the relevant variables are presented in Table 1. The results indicate that the average number of children desired by respondents in 2018 was 1.939, while in 2022, it was 1.938. Regarding the characteristics of individual respondents, the average age was 35.6 years. The average for the gender variable was 0.475, indicating a relatively balanced gender

distribution. The average family size was 4.864, reflecting a generally medium-sized family structure.

Table 1. Descriptive statistics

Variable	Definition and coding	Sample size	Mean	Standard deviation	Minimum	Maximum
Ideal number of children	Ideal number of children under no policy restrictions (0–10)	11,766	1.939	0.675	0.000	10.000
Occupational AI exposure	Occupation-level index constructed by semantic mapping	11,766	−0.731	1.005	−2.576	2.501
Age	Current age (years)	11,766	35.617	5.868	20.000	45.000
Gender	1 = male; 0 = female	11,766	0.475	0.499	0.000	1.000
Education level	Eight-category education measure (1 = lowest; 8 = highest)	11,766	3.420	1.372	1.000	8.000
Spouse's education level	Eight-category education measure (1 = lowest; 8 = highest)	11,766	3.404	1.374	1.000	8.000
Health status	1 = very healthy; 5 = unhealthy	11,766	2.726	1.064	1.000	5.000
Medical insurance	1 = insured; 0 = not insured	11,766	0.937	0.243	0.000	1.000
Agricultural hukou	1 = agricultural; 0 = non-agricultural	11,766	0.750	0.433	0.000	1.000
Household size	Number of household members	11,766	4.864	1.949	1.000	21.000
Other property	1 = owns property besides current residence; 0 = no	11,766	0.262	0.440	0.000	1.000
Per-capita household income	CNY 100,000 per person	11,766	0.302	0.726	0.000	41.000
Per-capita household income squared	(CNY 100,000 per person)²	11,766	0.618	20.919	0.000	1,681.000
Economic development	Log provincial GDP per capita	11,766	11.028	0.430	10.380	12.505
Fiscal support	General fiscal expenditure / regional GDP	11,766	0.241	0.097	0.110	1.273
Consumer spending	Retail sales of consumer goods / regional GDP	11,766	0.395	0.045	0.180	0.496
Industrial upgrading	Tertiary-sector output / secondary-sector output	11,766	1.391	0.480	0.756	5.283

Model specification

This paper aims to investigate the impact of occupational exposure to artificial intelligence on fertility intentions, providing empirical evidence to understand the formation of low birth rates in the context of technological change. Therefore, the following model is specified:

$$Fertility_{ijt}=\beta_0+\beta_1 AI_{it}+\beta_2 X_{ijt}+\theta_t+\tau_j+\varepsilon_{ijt} \quad (2)$$

Specifically, 'i', 'j', and 't' represent the individual, the province where the individual resides, and the year the individual was surveyed, respectively. The dependent variable represents the individual's desire to have children in year 't', specifically, the individual's ideal number of children at that time. The key explanatory variable is the individual's occupational exposure to artificial intelligence, measuring the intensity of AI technology penetration in their field. The control variables include three levels: individual, family, and province. A year fixed effect is included to control for time trends unrelated to individual characteristics. A province fixed effect

controls for features that do not change over time at the provincial level. An error term represents random factors affecting family decisions on having children, which are not included in the model.

All coefficient tests are two-sided Wald tests of the null hypothesis that the coefficient equals zero, with $\alpha = 0.05$. Exact *P* values are reported to three decimal places ($P < 0.001$ for smaller values), together with the analysis-specific sample size and standard error. Baseline linear models use heteroskedasticity-robust standard errors and province and year fixed effects; Poisson regression is used as a count-outcome robustness check, probit models are used for binary outcomes, and high-dimensional fixed-effects models absorb the indicated effects. Alternative inference specifications cluster standard errors by person or occupation–province. Double/debiased machine learning uses five-fold cross-fitting with random forests and seed 42, and the instrumental-variable model uses heteroskedasticity-robust two-stage least squares.

Results

Baseline regression

This article first explores the association between artificial intelligence exposure and fertility intention, and Table 2 reports the baseline regression results. Column (1) includes only the core explanatory variable, column (2) includes fixed effects of year and province, and column (3) further introduces individual, household, and province-level control variables. For fertility intention, without controlling for any fixed effects or control variables, the artificial intelligence exposure coefficient is significantly negative at the 1% significance level. After further adding all control variables, the absolute value of the coefficient further decreased, and the significance remained at the 1% level. In the fully adjusted model, a one-unit increase in AI exposure is associated with a 0.021 decrease in the ideal number of children ($P < 0.001$). The baseline results are consistent with Hypothesis 1.

Table 2. Baseline regression results

Variable	(1)	(2)	(3)
Occupational AI exposure	−0.084***	−0.073***	−0.021***
	(0.006)	(0.006)	(0.006)
P value (two-sided)	<0.001	<0.001	<0.001
Controls			Yes
Year fixed effects		Yes	Yes
Province fixed effects		Yes	Yes
Observations	11,766	11,766	11,766
R^2	0.016	0.127	0.188

Note: Entries are unstandardised coefficients; heteroskedasticity-robust standard errors are in parentheses. *P* values are from two-sided Wald tests of H_0: coefficient = 0. ***, ** and * denote $P < 0.01$, $P < 0.05$ and $P < 0.10$, respectively.

Robustness checks

To assess the robustness of the findings, this study re-estimates the association between AI exposure and fertility intentions using alternative regression models and fixed effects, different clustering levels, restricted samples and an instrumental-variable strategy.

Alternative regression model

In the benchmark regression section of this article, a linear OLS model is used. However, the ideal number of children for the dependent variable is a non negative discrete count variable with values ranging from 0 to 10, and there is a clear concentration of values in its distribution. The linear OLS model may result in setting errors. Therefore, this article replaces the regression model with Poisson regression to test the robustness of the core results and avoid unreliable conclusions caused by model bias. Table 3 shows that the coefficient of artificial intelligence exposure remains significantly negative in all three models. Through a significance test at the 1% level, it is consistent with the baseline regression results, indicating that the negative effect is not affected by the choice of regression model. Compared with the coefficients after controlling for all variables in benchmark regression, the absolute values of the coefficients after controlling for all variables in Poisson regression have decreased, but the negative effects and significance have not changed. This is because Poisson regression has a semi elastic and nonlinear boundary effect on the regression coefficients of count variables.

Table 3. Poisson regression estimates

Variable	(1)	(2)	(3)
Occupational AI exposure	-0.044***	-0.039***	-0.012***
	(0.003)	(0.003)	(0.003)
P value (two-sided)	<0.001	<0.001	<0.001
Controls			Yes
Year fixed effects		Yes	Yes
Province fixed effects		Yes	Yes
Observations	11,766	11,766	11,766
Pseudo-R^2	0.001	0.011	0.016

Note: Entries are Poisson coefficients; heteroskedasticity-robust standard errors are in parentheses. P values are from two-sided Wald tests of H_0: coefficient = 0. ***, ** and * denote P < 0.01, P < 0.05 and P < 0.10.

Alternative fixed effects and clustering levels

The benchmark regression controlled for year and province fixed effects and used heteroskedasticity-robust standard errors. This paper further examines robustness against two potential threats. First, province fixed effects absorb only time-invariant province characteristics; province-by-year fixed effects therefore address province-specific time-varying shocks. Second, repeated observations of individuals and the occupational construction of AI exposure may induce correlated errors. Table 4 consequently reports person-clustered and occupation–province-clustered standard errors. The coefficient remains negative across these specifications; the corresponding estimates and *P* values are reported in Table 4.

Table 4. Alternative fixed effects and clustering levels

Variable	Province–year FE	Person-clustered SE	Occupation–province-clustered SE
Occupational AI exposure	-0.021***	-0.021***	-0.021**
	(0.006)	(0.007)	(0.009)
P value (two-sided)	<0.001	0.002	0.021
Controls	Yes	Yes	Yes
Year fixed effects		Yes	Yes
Province fixed effects		Yes	Yes
Province–year fixed effects	Yes		
Observations	11,766	11,766	11,766
R^2	0.190	0.188	0.188

Note: Entries are unstandardised coefficients. Column 1 uses heteroskedasticity-robust standard errors; Columns 2 and 3 cluster by person and occupation–province, respectively. P values are two-sided tests of H_0: coefficient = 0. ***, ** and * denote P < 0.01, P < 0.05 and P < 0.10.

Restricted samples

Table 5 reports robustness checks using restricted samples. First, the analysis focuses on younger respondents of reproductive age. The regression results for respondents aged 22 to 35 show that the coefficient of artificial intelligence exposure is still significantly negative, consistent with the core conclusion of the benchmark regression. Second, in order to reduce the influence of the distinctive economic conditions in the four municipalities directly under the central government, this article excluded samples from Beijing, Shanghai, Tianjin and Chongqing. The AI-exposure coefficient remains negative and statistically significant in the remaining sample.

Table 5. Restricted-sample robustness checks

Variable	Ages 22–35	Excluding four municipalities
Occupational AI exposure	-0.022**	-0.023***
	(0.009)	(0.007)
P value (two-sided)	0.012	<0.001
Controls	Yes	Yes
Year fixed effects	Yes	Yes
Province fixed effects	Yes	Yes
Observations	5,790	11,035
R^2	0.163	0.173

Note: Each restriction is applied independently to the full analysis sample. Entries are unstandardised coefficients; heteroskedasticity-robust standard errors are in parentheses. P values are two-sided Wald tests of H_0: coefficient = 0. ***, ** and * denote P < 0.01, P < 0.05 and P < 0.10.

Double/debiased machine learning

The primary linear model treats the ideal number of children as a continuous outcome. To relax functional-form restrictions in the nuisance components, the analysis applies double/debiased machine learning with random forests and five-fold cross-fitting (one validation fold and four training folds per iteration). As shown in Table 6, the estimated AI-exposure coefficient remains negative ($\beta = -0.012$, $P = 0.047$), providing a complementary robustness check.

Table 6. Double/debiased machine learning estimates

Variable	Ideal number of children
Occupational AI exposure	−0.012**
	(0.006)
P value (two-sided)	0.047
Controls	Yes
Year fixed effects	Yes
Province fixed effects	Yes
Observations	11,766

Note: The estimate uses five-fold cross-fitting with random forests (seed 42). The robust standard error is in parentheses; the *P* value is from a two-sided Wald test of H_0: coefficient = 0. ** denotes $P < 0.05$.

Endogeneity and instrumental-variable analysis

In the baseline regression, AI exposure may be endogenous for two main reasons: one is reverse causality, where there is a correlation between reproductive decisions and career choices. If an individual has a clear reproductive plan, they may actively avoid jobs with fierce competition and high exposure to artificial intelligence, and instead choose more stable jobs, making fertility plans an antecedent of occupational AI exposure; the second is omitted-variable bias, such as individual risk preferences, career planning, and other unobserved variables, which simultaneously affect the exposure of artificial intelligence and fertility decisions.

To address potential endogeneity, this paper uses US occupational AI exposure as an instrumental variable and estimates a heteroskedasticity-robust two-stage least-squares model. The empirical results are reported in Table 7. Regarding instrument relevance, as a leading country in the research and application of artificial intelligence technology, the United States has significant global spillover effects in its technological development, which are closely related to China's exposure to artificial intelligence. The coefficient of occupational exposure to artificial intelligence in the United States is significantly positive at the 1% significance level. The Kleibergen–Paap rk LM statistic is 1009.035, which is significant at the 1% level and indicates rejection of underidentification. The Kleibergen–Paap rk Wald F statistic is 1245.728, supporting instrument relevance.

The exclusion restriction requires US occupational AI exposure to affect Chinese fertility intentions only through domestic occupational AI exposure, conditional on the included controls. This assumption cannot be directly verified, and common occupational or global economic shocks may threaten it. The second-stage AI-exposure coefficient remains negative and statistically significant at the 1% level ($P = 0.007$), consistent with the baseline results.

Table 7. Instrumental-variable estimates

Variable	First stage: AI exposure	Second stage: ideal number of children
US occupational AI exposure	0.260***	
	(0.007)	
P value (two-sided)	<0.001	
Occupational AI exposure		−0.057***
		(0.021)
P value (two-sided)		0.007
Controls	Yes	Yes
Year fixed effects	Yes	Yes
Province fixed effects	Yes	Yes
R^2	0.323	0.079
Kleibergen–Paap rk Wald F	1,245.728	
Kleibergen–Paap rk LM $\chi^2(1)$	1,009.035	
LM *P* value	<0.001	
Stock–Yogo 10% critical value	16.380	
Observations	11,326	11,326

Note: Heteroskedasticity-robust standard errors are in parentheses. Coefficient *P* values are from two-sided Wald tests; the rank LM test uses the upper tail of the chi-squared distribution. *** denotes $P < 0.01$. The Stock–Yogo value is the 10% maximal-IV-size critical value for one endogenous regressor and one excluded instrument.

Heterogeneity analysis

This article systematically examines heterogeneity in the impact of artificial intelligence on fertility decision-making from three dimensions: age, education level, and household income. The empirical results are reported in Tables 8–10.

From an age perspective, the sample is divided into respondents aged 20–29, 30–39, and 40–45. The coefficient is not distinguishable from zero among those aged 20–29 (P = 0.136), is negative among those aged 30–39 (P = 0.017), and is suggestively negative among those aged 40–45 at the 10% level (P = 0.070). The evidence therefore points most clearly to the 30–39 group, rather than to a uniform effect across everyone aged 30–45.

Table 8. Heterogeneity by age

Variable	Ages 20–29	Ages 30–39	Ages 40–45
Occupational AI exposure	−0.023	−0.020**	−0.021*
	(0.016)	(0.008)	(0.012)
P value (two-sided)	0.136	0.017	0.070
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Observations	1,985	6,201	3,580
R^2	0.156	0.205	0.217

Note: Entries are unstandardised coefficients; heteroskedasticity-robust standard errors are in parentheses. *P* values are from two-sided Wald tests of H_0: coefficient = 0. ***, ** and * denote $P < 0.01$, $P < 0.05$ and $P < 0.10$, respectively.

Table 9 divides respondents into lower-secondary-or-less, upper-secondary, and tertiary-education groups. The AI-exposure coefficient is negative in the least-educated group ($\beta = -0.047$, $P < 0.001$), but is not distinguishable from zero in the upper-secondary or tertiary group. This pattern is consistent with greater exposure to routine-task displacement and lower capacity to buffer labour-market risk among less-educated workers.

Table 9. Heterogeneity by education

Variable	Lower secondary or less	Upper secondary	Tertiary
Occupational AI exposure	−0.047***	−0.009	−0.007
	(0.009)	(0.013)	(0.012)
P value (two-sided)	<0.001	0.484	0.550
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Observations	7,148	2,080	2,538
R^2	0.196	0.165	0.163

Note: Entries are unstandardised coefficients; heteroskedasticity-robust standard errors are in parentheses. *P* values are from two-sided Wald tests of H_0: coefficient = 0. ***, ** and * denote $P < 0.01$, $P < 0.05$ and $P < 0.10$, respectively.

Table 10 divides respondents into tertiles of per-capita household income. The AI-exposure coefficient is negative in the lowest tertile ($\beta = -0.037$, $P = 0.004$), but is not distinguishable from zero in the middle or highest tertile. This pattern is consistent with household resources buffering technological risk.

Taken together, the subgroup patterns are broadly consistent with Hypothesis 2, with the clearest negative associations among respondents aged 30–39, those with lower education, and those in the lowest income tertile.

Table 10. Heterogeneity by household income

Variable	Low income	Middle income	High income
Occupational AI exposure	−0.037***	−0.002	−0.007
	(0.013)	(0.010)	(0.010)
P value (two-sided)	0.004	0.823	0.486
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Observations	3,922	3,923	3,921
R^2	0.205	0.176	0.141

Note: Entries are unstandardised coefficients; heteroskedasticity-robust standard errors are in parentheses. *P* values are from two-sided Wald tests of H_0: coefficient = 0. ***, ** and * denote $P < 0.01$, $P < 0.05$ and $P < 0.10$, respectively.

Mechanism analysis

The extent to which the impact of artificial intelligence on career stability affects fertility intentions is the central question this article aims to address. Based on theoretical analysis, the article examines three parallel channels: job instability, marital satisfaction, and changing attitudes.

Employment-instability mechanism

This article measures employment uncertainty at three levels: occupational mobility, spatial mobility, and time investment, using three indicators: job change, workplace location, and working hours. The results are presented in Table 11.

The employment-change indicator is generated from the survey question, “Did your previous job continue into the most recent year?” A response of “no” is coded 1 and “yes” is coded 0. Workplace distance is coded from 1 to 7, ranging from the current village/community to a workplace outside mainland China (including Hong Kong, Macao and Taiwan). The separate response “no fixed workplace” is excluded because it is not an eighth distance category. Weekly working time is measured in hours. Because employment change refers to change since the previous survey, lagged occupational AI exposure is used in the job-change probit model.

Table 11 shows positive associations between AI exposure and job-change propensity, workplace distance among respondents with a fixed workplace, and weekly working hours (all $P < 0.001$). The estimated probit coefficient for job-change propensity is 0.068. The job-change coefficient is a probit index coefficient and should not be interpreted as a percentage-point

marginal effect. Together, the estimates are consistent with occupational, spatial and temporal dimensions of employment instability.

These associations suggest two possible links to fertility intentions. The first is economic expectations: frequent job and spatial mobility may disrupt the stability and predictability of household income. The second is time constraints: extended work hours directly reduce the time and energy available for raising children.

Table 11. Employment-instability mechanisms

Variable	Job change	Workplace distance	Weekly working hours
Occupational AI exposure	0.068***	0.099***	3.892***
	(0.016)	(0.018)	(0.220)
P value (two-sided)	<0.001	<0.001	<0.001
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Observations	8,992	8,858	11,049
Pseudo-R^2 / R^2	0.056	0.062	0.079

Note: Entries are unstandardised coefficients; heteroskedasticity-robust standard errors are in parentheses. *P* values are from two-sided Wald tests of H_0: coefficient = 0. ***, ** and * denote $P < 0.01$, $P < 0.05$ and $P < 0.10$, respectively. Column 1 is a probit coefficient and reports pseudo-R^2; Columns 2–3 are linear fixed-effects estimates. Workplace category 8 ("no fixed workplace") is excluded.

This paper categorises employers based on the nature of their employment units, treating government departments, state-owned enterprises, and public institutions as public sector entities, and private companies and individual businesses as private sector entities. The probit coefficient for AI exposure in the job-change model is negative for public sector employees and positive for private sector employees. This pattern may reflect that public sector employees, with their job security and established positions, experience a different adjustment logic in response to technological penetration compared to private sector employees, who are more sensitive to market-driven adjustments.

The analysis also distinguishes self-employed respondents from employees. The estimated probit coefficient for AI exposure is 0.078 among the self-employed ($P = 0.022$) and −0.107 among employees ($P < 0.001$; Table 12). Together with the positive estimate in the non-public sector, these patterns are consistent with greater adjustment pressure outside institutional employment.

Table 12. Heterogeneity in employment-instability mechanisms

Variable	Public sector	Non-public sector	Self-employed	Employee
Occupational AI exposure	−0.153***	0.105***	0.078**	−0.107***
	(0.055)	(0.018)	(0.034)	(0.022)
P value (two-sided)	0.005	<0.001	0.022	<0.001
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes
Observations	1,336	7,649	3,630	5,354
Pseudo-R^2	0.123	0.057	0.076	0.069

Note: Entries are unstandardised coefficients; heteroskedasticity-robust standard errors are in parentheses. *P* values are from two-sided Wald tests of H_0: coefficient = 0. ***, ** and * denote $P < 0.01$, $P < 0.05$ and $P < 0.10$, respectively. All estimates are probit coefficients; the final row reports pseudo-R^2.

Marital-satisfaction mechanism

This paper uses two subjective evaluations - marital satisfaction and satisfaction with the partner's economic contribution - to illustrate the quality of marital relationships. Satisfaction with marital life was measured using the question, "Overall, how satisfied are you with your current marriage/cohabitation?" with a rating scale of 1 to 5. Satisfaction with the partner's financial contribution to the household was measured using the question, "How satisfied are you with your partner's financial contributions to the family?" with a rating scale of 1 to 5. The results are presented in Table 13.

AI exposure is negatively associated with marital satisfaction ($\beta = -0.024$, $P = 0.006$) and satisfaction with the partner's economic contribution ($\beta = -0.027$, $P = 0.009$). These associations are consistent with economic insecurity affecting both role evaluations and broader assessments of marriage.

Family-pressure and gender-role perspectives provide possible explanations for these associations. Economic insecurity may increase emotional stress and weaken couple interaction, while perceived economic contribution can shape an individual's role evaluation within marriage. Declining marital satisfaction may in turn reduce positive expectations about long-term family investment, and dissatisfaction with economic contributions may reinforce the perception that the household is not ready to provide for children. The negative associations in Table 13 are consistent with this proposed pathway.

Table 13. Marital-satisfaction mechanisms

Variable	Marital satisfaction	Partner's economic contribution
Occupational AI exposure	−0.024***	−0.027***
	(0.009)	(0.010)
P value (two-sided)	0.006	0.009
Controls	Yes	Yes
Year fixed effects	Yes	Yes
Province fixed effects	Yes	Yes
Observations	11,758	11,754
R^2	0.089	0.064

Note: Entries are unstandardised coefficients; heteroskedasticity-robust standard errors are in parentheses. *P* values are from two-sided Wald tests of H_0: coefficient = 0. ***, ** and * denote $P < 0.01$, $P < 0.05$ and $P < 0.10$, respectively.

Value-change mechanism

The preceding analyses concern employment and marital outcomes; the value-related analysis uses three indicators: the desired number of sons (0–10), the importance of lineage continuation (1–5), and the importance of family harmony (1–5). The regression results are presented in Table 14.

The estimated coefficients of artificial intelligence exposure for the three indicators indicate that the increase in exposure systematically weakens individuals' traditional reproductive concepts. The preference for boys and the concept of passing on the family line are the most traditional utilitarian and directly aimed at the desire to have more children and sons to continue the family line. They are closely linked to the function of family continuity and intergenerational security in pre modern society, and therefore have the greatest degree of relaxation and weakening in the face of the rise of individualistic values; In contrast, although the orientation towards a happy family belongs to the category of traditional familism, its connotation is broader and more compatible with modern lifestyles. The above findings provide micro empirical evidence from the perspective of technological change for the theory of the second demographic transition. Therefore, the exposure of artificial intelligence indirectly suppresses individual fertility intentions by weakening traditional fertility concepts, forming the third transmission path of hypothesis 3.

Table 14. Value-change mechanisms

Variable	Desired number of sons	Lineage continuation	Family harmony
Occupational AI exposure	−0.002	−0.026*	−0.018**
	(0.007)	(0.015)	(0.009)
P value (two-sided)	0.804	0.080	0.046
Controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Observations	6,313	7,144	7,145
R^2	0.129	0.076	0.025

Note: Entries are unstandardised coefficients; heteroskedasticity-robust standard errors are in parentheses. *P* values are from two-sided Wald tests of H_0: coefficient = 0. ***, ** and * denote $P < 0.01$, $P < 0.05$ and $P < 0.10$, respectively. The non-numeric desired-sons response −3 ("no preference") is treated as missing.

Moderating role of household assets

This paper further includes separate interaction terms between AI exposure and log household financial assets, and between AI exposure and log net housing assets to reveal the moderating effect of family assets in fertility decisions.

Table 15 reports models using log financial assets and log net housing assets; observations with non-positive values are excluded from the corresponding model. The financial-asset interaction is positive ($\beta = 0.011$, $P = 0.004$), indicating attenuation of the negative AI-exposure association at higher financial-asset levels. The housing-asset interaction is also positive but weaker and statistically suggestive only at the 10% level ($\beta = 0.007$, $P = 0.089$).

Family assets can play a moderating role essentially because they provide important support during childbirth and child-rearing. Wealthy families often enjoy more comfortable living conditions, more living space and better access to educational resources, while those with limited assets face significant affordability constraints when facing high-cost housing in desirable school districts and other substantial child-rearing investments.

Table 15. Moderating role of household assets

Variable	Financial assets	Net housing assets
Occupational AI exposure	−0.136***	−0.110**
	(0.041)	(0.055)
P value (two-sided)	<0.001	0.044
Log household assets	−0.001	−0.014*
	(0.005)	(0.008)
P value (two-sided)	0.807	0.072
AI exposure × log assets	0.011***	0.007*
	(0.004)	(0.004)
P value (two-sided)	0.004	0.089
Controls	Yes	Yes
Year fixed effects	Yes	Yes
Province fixed effects	Yes	Yes
Observations	9,701	10,756
R^2	0.190	0.192

Note: Entries are unstandardised coefficients; heteroskedasticity-robust standard errors are in parentheses. *P* values are from two-sided Wald tests of H_0: coefficient = 0. ***, ** and * denote $P < 0.01$, $P < 0.05$ and $P < 0.10$, respectively. Asset variables are logged; non-positive asset values are excluded from the corresponding model.

Conclusions and policy implications

This study uses data from the China Family Panel Studies (CFPS) in 2018 and 2022, focusing on married individuals of reproductive age. It develops an index to measure exposure to artificial intelligence at the occupational level, and then examines the impact of AI technology on family fertility intentions, from three perspectives: job instability, marital satisfaction, and changes in attitudes. The main findings of the study are as follows.

First, occupational AI exposure is negatively associated with fertility intentions in the baseline model ($\beta = -0.021$, $P < 0.001$), and the direction is maintained in the Poisson, fixed-effects, clustering, restricted-sample, DDML ($P = 0.047$), and instrumental-variable ($P = 0.007$) checks. Second, AI exposure is associated with greater job-change propensity in the non-public sector and among self-employed respondents, and with lower marital evaluations. The value-related evidence is mixed: lineage-continuation and family-harmony ratings are lower, but corrected son-preference responses show no association ($P = 0.804$). Heterogeneity estimates are strongest for respondents aged 30–39, those with lower education, and those in the lowest income tertile. Finally, the financial-asset interaction provides evidence of moderation ($P = 0.004$), whereas the housing-asset interaction is weaker and only suggestive at the 10% level ($P = 0.089$).

Based on the research findings, this paper proposes policy considerations concerning employment security, targeted support and household resources. Their effectiveness in increasing fertility would require separate policy evaluation.

First, strengthen employment security in the AI era to alleviate the employment uncertainty caused by technological shocks. Firstly, make vocational skills training more targeted and forward-looking, focus on workers in routine occupations with high risks of artificial intelligence substitution, provide training that helps workers use artificial intelligence, help workers move into emerging occupations and skills-based roles, and reduce occupational substitution risks from the source. Secondly, improve the system for protecting employment rights and interests, strictly regulate employment discrimination against the childbearing age group, and establish a support mechanism for re-employment after career interruptions due to childbirth. Thirdly, differentiate and improve the protection system for different employment groups. Targeting those most affected by technological shocks such as the private sector and self-employed groups, expand the coverage of unemployment insurance and flexible employment social security, increase insurance subsidy standards, and enhance their ability to resist occupational risks.

Second, tailor fertility-support policies to different groups and address their main constraints on childbearing. For the middle-aged, low-income, and less-educated groups, increase universal support for childbirth, expand the coverage and distribution standards of childbirth subsidies and childcare allowances, and focus on reducing essential child-rearing costs such as education, healthcare, and childcare. At the same time, by providing vocational skills training and employment assistance, policies can improve income stability and strengthen the economic foundation for childbearing.

Third, leverage the benefits of family assets to provide a risk buffer and support family planning. Broaden the channels for family financial asset allocation, and enhance financial knowledge and investor education to improve residents' financial literacy and asset allocation capabilities, enabling the potential value of financial assets to better support family planning economically and psychologically.

This study has several limitations. First, the ideal number of children measures stated preferences rather than subsequent childbearing. Second, the sample covers married respondents aged 20–45 in two survey waves, limiting generalisation to unmarried people, other age groups and later AI

developments. Third, occupational AI exposure captures potential technological exposure rather than individual adoption or actual displacement, and cross-country task mapping may introduce measurement error. Finally, occupational selection and unobserved preferences may remain relevant despite the controls and instrumental-variable analysis; the exclusion restriction is not directly testable. Future research could use longer panels and directly observed AI adoption to examine these issues.

References

Acemoglu D, Restrepo P (2019) Automation and new tasks: how technology displaces and reinstates labor. J Econ Perspect 33(2):3–30. https://doi.org/10.1257/jep.33.2.3

Acemoglu D, Restrepo P (2020) Robots and jobs: evidence from US labor markets. J Polit Econ 128(6):2188–2244. https://doi.org/10.1086/705716

Acemoglu D, Autor D, Hazell J, Restrepo P (2022) Artificial intelligence and jobs: evidence from online vacancies. J Labor Econ 40(S1):S293–S340. https://doi.org/10.1086/718327

Autor DH, Dorn D, Hanson GH (2015) Untangling trade and technology: evidence from local labour markets. Econ J 125(584):621–646. https://doi.org/10.1111/ecoj.12245

Autor DH, Levy F, Murnane RJ (2003) The skill content of recent technological change: an empirical exploration. Q J Econ 118(4):1279–1333. https://doi.org/10.1162/003355303322552801

Barro RJ, Becker GS (1989) Fertility choice in a model of economic growth. Econometrica 57(2):481–501. https://doi.org/10.2307/1912563

Becker GS, Lewis HG (1973) On the interaction between the quantity and quality of children. J Polit Econ 81(2, Part 2):S279–S288. https://doi.org/10.1086/260166

Bertrand M, Kamenica E, Pan J (2015) Gender identity and relative income within households. Q J Econ 130(2):571–614. https://doi.org/10.1093/qje/qjv001

Bueno X, Brinton MC (2019) Gender egalitarianism, perceived economic insecurity, and fertility intentions in Spain: a qualitative analysis. Popul Stud 73(2):247–260. https://doi.org/10.1080/00324728.2019.1604979

Busetta A, Mendola D, Vignoli D (2019) Persistent joblessness and fertility intentions. Demogr Res 40:185–218. https://doi.org/10.4054/DemRes.2019.40.8

Cai F (2024) How does social mobility affect fertility? Sociol Stud 39(1):45–63.

Chen L, Gao Y, Yu L (2024) How is artificial intelligence shaping firms' labour demand? Evidence from big data on recruitment platforms. Manag World 40(6):74–93. https://doi.org/10.19744/j.cnki.11-1235/f.2024.0067

Chen T, Hu A (2020) Individualism or familism? An analysis of the effect of different fertility motives on fertility behavior. Jiangsu Soc Sci 2020(2):28–38. https://doi.org/10.13858/j.cnki.cn32-1312/c.20200319.004

Felten E, Raj M, Seamans R (2018) A method to link advances in artificial intelligence to occupational abilities. AEA Pap Proc 108:54–57. https://doi.org/10.1257/pandp.20181021

Guo K, Yan S, Li S (2021) Structural transformation, fertility choice and demographic transition. J World Econ 44(1):106–125. https://doi.org/10.19985/j.cnki.cassjwe.2021.01.006

Jiang Y, Wang X, Sam TH, Vasudevan A (2024) Digital transformation, equity pledge and labor income share. Finance Res Lett 64:105451. https://doi.org/10.1016/j.frl.2024.105451

Lesthaeghe R (1983) A century of demographic and cultural change in Western Europe: an exploration of underlying dimensions. Popul Dev Rev 9(3):411–435. https://doi.org/10.2307/1973316

Lesthaeghe R (2014) The second demographic transition: a concise overview of its development. Proc Natl Acad Sci USA 111(51):18112–18115. https://doi.org/10.1073/pnas.1420441111

Li C (2014) Educational experiences and inequality of opportunity among China's post-1980 generation: a comment on "The Silent Revolution". Soc Sci China 2014(4):66–77.

Li J (2025) Fertility decisions in Chinese families oriented towards intergenerational development. Soc Sci China 2025(2):63–83+205–206.

Li J, Sheng H (2025) Re-examining low fertility in China from the perspective of dynamic structural differences. Chin Popul Sci 39(2):12–28.

Mao Z, Wan L, Luo Z (2026) The logic of constructing a new marriage and childbearing culture under low fertility: a family resilience perspective. Popul Econ 47(3):15–26. https://doi.org/10.3969/j.issn.1000-4149.2026.00.022

Miller WB, Pasta DJ (1993) Motivational and nonmotivational determinants of child-number desires. Popul Environ 15(2):113–138. https://doi.org/10.1007/BF02209405

Qing S, Wen M (2025) China's fertility level and age pattern from a gender perspective. Sociol Stud 40(5):111–134+228–229.

Ranjan P (1999) Fertility behaviour under income uncertainty. Eur J Popul 15(1):25–43. https://doi.org/10.1023/A:1006106527618

Shi Z, Wang Z (2024) Socioeconomic status and fertility: an analytical framework for fertility inequality. Popul J 46(4):5–23. https://doi.org/10.16405/j.cnki.1004-129X.2024.04.001

Shi Z, Wang Z, Wei S, Yang G (2024) Incentive and minimum-guarantee effects of fertility subsidies: evidence from a field experiment. Econ Res J 59(11):175–191.

Song J, Chen W (2022) Realisation of fertility intentions among couples of childbearing age and the influence of family characteristics: evidence from a three-dimensional fertility perspective. Popul Res 46(5):3–18.

Vignoli D, Drefahl S, De Santis G (2012) Whose job instability affects the likelihood of becoming a parent in Italy? A tale of two partners. Demogr Res 26:41–62. https://doi.org/10.4054/DemRes.2012.26.2

Wang J, Liu J (2019) Seeking consensus amid disagreement: research on low fertility and the evolution of population policy in China. Sociol Stud 34(2):219–241+246. https://doi.org/10.19934/j.cnki.shxyj.2019.02.010

Wang T, Peng X (2015) The effect of social security on fertility intentions: evidence from the New Rural Cooperative Medical Scheme. Econ Res J 50(2):103–117.

Wang W, Fu Y, Liu F (2022) Fertility policy, fertility intentions and age at first birth. Econ Res J 2022(9):116–136.

Wang Y, Bai Y (2024) Multi-child fertility intentions among people of childbearing age from the material–ideational perspective: evidence from a CGSS 2021 survey experiment. Soc Sci 2024(1):158–168. https://doi.org/10.13644/j.cnki.cn31-1112.2024.01.007

Webb M (2020) The impact of artificial intelligence on the labor market. Working paper, revised 11 January 2020. Stanford University, Stanford, CA. https://doi.org/10.2139/ssrn.3482150

Wei W (2023) Resource advantage or security tie? Housing status, property rights and happiness. Sociol Stud 38(3):159–179+229.

Wu F (2020) Research on fertility intentions: theory and empirical evidence. Sociol Stud 35(4):218–240+246. https://doi.org/10.19934/j.cnki.shxyj.2020.04.011

Wu Y, Ge T, He G (2026) Digital transformation and income distribution from the perspective of changes in occupational task structure. Soc Sci Dig 2026(3):88–90.

Xu Q (2021) From the fatherhood wage premium to the motherhood wage penalty: the effects of parenthood on men's and women's wages in China, 1989–2015. Sociol Stud 36(5):1–24+226.

Yang J (2019) The dual penalties of gender and motherhood and gender differences in labour-market participation. Popul Res 43(1):36–51.

Yao J, Zhang K, Guo L, Feng X (2024) How does artificial intelligence improve firm productivity? The perspective of workforce skill restructuring. Manag World 40(2):101–116+133+117–122. https://doi.org/10.19744/j.cnki.11-1235/f.2024.0018

Yu W-H, Sun S (2018) Fertility responses to individual and contextual unemployment: differences by socioeconomic background. Demogr Res 39:927–962. https://doi.org/10.4054/DemRes.2018.39.35

Yu Y, Chen Y, Gao X, Liu J (2026) The impact of artificial intelligence development on the long-term residence intentions of China's floating population. Popul Res 50(1):68–85.

Zhai Z, Jin G (2023) Negative population growth in China: characteristics, challenges and responses. Popul Res 47(2):11–20.

Zhang D et al. (2025) Measuring artificial-intelligence exposure in China and its effect on labour demand: new evidence from large language models. Manag World 41(7):59–75. https://doi.org/10.19744/j.cnki.11-1235/f.2025.0092

Zhang X, Li L, Chai C, Ma S (2015) Does housing increase happiness through its investment or residential attributes? J Financ Res 2015(10):17–31.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- dta.dta