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NONLINEAR EFFECTS OF AGEING POPULATION AND AI ON CHINA'S GDP GROWTH: A THRESHOLD ANALYSIS

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Abstract. This research empirically explores the influences of ageing on China's GDP growth, incorporating Artificial Intelligence (AI) as a moderating factor. Specifically, industrial robot penetration was used as a proxy for AI adoption. This research selects panel data in 31 provinces of China (2000–2022). The non-linear association between ageing population and GDP growth is examined using panel threshold regression models, while threshold variables are ageing and AI adoption, respectively. To verify the robustnes, the old-age dependency ratio is utilized as a proxy of ageing population. According to the findings, GDP growth is initially negatively affected by ageing population. However, when AI adoption surpasses a critical threshold, this negative effect is significantly mitigated. This finding highlights the importance of AI adoption in managing the economic challenges brought by ageing. Therefore, some valuable recommendations have been put forward to support inclusive and sustainable economic development. These include greater investment in research and expansion concerning AI, promoting AI-driven robotics in key sectors, and offering targeted skilling programs for elderly employees. Further suggestions are to invest in digital infrastructures and the industry of ageing, as well as to leverage and develop elderly human capital.

Keywords: panel threshold regression, ageing population, Artificial intelligence (AI), China's GDP growth, panel data, sustainable economic development.

JEL Classification: O11, O47.

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1. Introduction

One of the major challenges to society's sustained growth is ageing population, which occurs due to longevity and a low birth rate. This can result in several challenges such as a shrinking labour force, higher social dependency, and heavier pension burdens, all of which slow economic growth (Hu et al., 2021; Liu & McKibbin, 2022). These major demographic changes present a major obstacle to reaching Sustainable Development Goal (SDG) 8: ongoing economic progress based on inclusivity and sustainability. Meanwhile, AI is becoming more prominent within the global economy amid an aging global population.

According to endogenous economic growth theories, technological development enhances productivity, leads to economic expansion (Arrow, 1962). Today, AI has become the driving force behind an emerging era of scientific and technical innovation and industrial development, much like the steam engine did during the Steam Age, the electricity supply during the Electric Age, and the use of computers and the internet during the Age of Information (Denning & Lewis, 2017). Thus, advancements in AI are expected to boost GDP growth.

China, while being at the forefront of technological advancement, is simultaneously facing the challenges of ageing. This raises a critical question: Can AI adoption mitigate the negative influence of ageing on its GDP growth? Understanding this complex relationship is vital for China's economic planning, as well as other developing countries facing similar demographic and technological transitions. Hence, this study aims to examine how ageing population and AI adoption affect GDP growth in China. The remainder of the research is organised with the following structure: Section 2 introduces the research background; Section 3 gives the literature review; Section 4 focuses on the empirical research methodology; and Section 5 provides the empirical results and discussion. The last part establishes a set of conclusions, recommendations for policy, and implications for theory and practice. The limitations of the work and future directions for research are also outlined.

2. Research background

China is experiencing the rapid growth of both its ageing population and the development of AI (Khanthawithoon et al., 2021). China's economy maintained a strong growth rate of 8% to 10% in previous decades. However, as presented in the World Bank (2024), the country's annual economic development has been slowing since 2010. According to Figure 1, the GDP growth rate decreased from 10.6% to 6% between 2010 and 2019. The COVID-19 epidemic led to the GDP increasing at rates of just 2.2% in 2020, 8.4% in 2021, and 3.0% in 2022. Furthermore, after COVID-19, GDP growth was just 5.2% in 2023, lower than it had been in 2019. Two trends offering cause for concern are the yearly increases in the proportion of the population aged 65 and above and the ratio of old-age dependency. Between 2010 and 2023, the former factor rose from 8.6% to 15.4%, while the latter grew from 11.9% to 22.5%. China's population growth is accelerating, while the ageing trend is rising.

China is also advancing rapidly in AI applications, having the world's highest number and fastest percentage growth of AI-powered robot installations (International Federation of Robotics [IFR], 2024). As shown in Figure 2, the number of industrially intelligent robots installed in China has increased dramatically since 2013. Starting in 2021, China installed more of these robots than any other market combined for three consecutive years, with the maximum number of installations reaching 290,144 units in 2022. Based on these developments, the indication is that China is becoming a world leader in AI development.

The ageing population in China poses substantial risks to its long-term demographic sustainability and economic resilience. Hsu et al. (2022) claimed that this demographic ageing will result in a decline in productivity due to a reduced labour force and a rise in old-age dependence. To mitigate the economic problems linked to this ageing population, several fields of industry could be altered by integrating AI into robotics and automating production procedures. These include boosting production, optimizing processes, and improving consumer interactions, which can alleviate the adverse impacts of ageing on economy (Rakholia et al., 2024; Licardo et al., 2024).

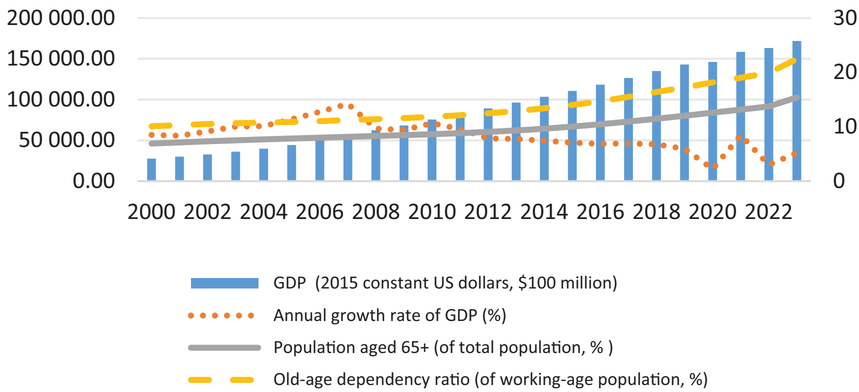


Figure 1. Annual growth rate of GDP and old-age dependency ratio in China (2000–2023) (source: World Bank, 2024)

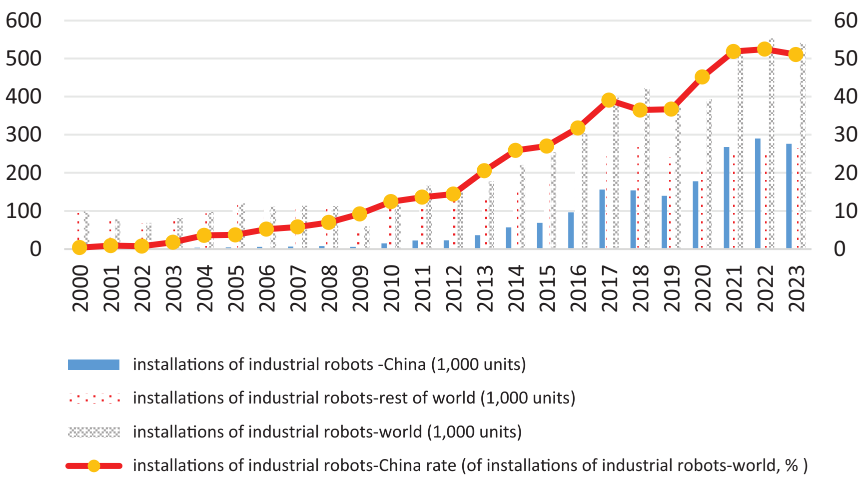


Figure 2. Installations of industrial robots: China vs the World (2000–2023) (source: IFR, 2024)

Despite the positive outlook on the integration of AI, the empirical evidence supporting that AI mitigates the adverse impacts of ageing population on GDP growth remains limited in the context of China. Amid these uncertainties, further empirical research is needed to explore the association between ageing population, AI, and economic development in China.

3. Literature review

According to some previous researches, ageing population promotes positive GDP growth. For instance, Mamun et al. (2020) utilise a model of bivariate endogenous growth to explore the connection between economic development and the ageing population, based on time series data taken between 1972 and 2015 in Bangladesh. Their study reveals a long-run positive relationship between ageing and real GDP per capita. Similarly, Bawazir et al. (2021) deploy a static panel data model to investigate the links between ageing population and economic development. They use a panel of 10 separate Middle East countries between

1996 and 2016. The findings suggest that ageing has a positive effect on GDP growth. Additionally, based on the entropy method, Chen et al. (2022) discover that economic growth is substantially positively affected by ageing population, according to their measurement of the provincial ageing population index in China between 2008 and 2019. These studies argue that the ageing has a positive effect on economic development in recent years.

Nevertheless, the outcomes of most studies indicate that GDP growth is negatively affected by ageing population. For instance, Lee and Shin (2021) contend that GDP growth is hampered by an ageing population, having identified lower Total Factor Productivity (TFP) expansion in 35 OECD countries where considerable ageing was experienced between 1960 and 2017, according to the Cobb-Douglas production function. Meanwhile, Maestas et al. (2023) indicate that a rise in the ageing population may lead to lower GDP per capita across various states, based on a causal model in the U.S. using data between 1980 and 2010. This is mainly attributable to diminished productivity growth and reduced opportunities for employment. Moreover, using the Solow model to examine ASEAN countries from 2001 to 2021, Thanh Trong et al. (2024) find that old-age dependency adversely affects GDP growth. The finding is consistent with the situation in Malaysia identified by Yip et al. (2024). With regard to the China context, Liu et al. (2023) find that ageing population negatively impacts economic growth for 30 provinces between 2000 and 2019 due to industrial structure upgrading, through static and dynamic panel, and mediating effect models. The finding is also in accordance with the results obtained by Yang and Qi (2024).

The disparities in this research arise from an assumption that ageing has a linear impact on GDP growth. However, this relationship is more complex. In its early stages, both the elderly and working-age populations grow, offsetting the economic burden of ageing and supporting GDP growth. In the later stages, the elderly population expands rapidly, raising dependency ratios, straining economic productivity, healthcare, and pensions, and, ultimately, hindering growth (Lee & Shin, 2019). Therefore, the linear model can only represent a portion of the data when examining the influence of ageing population on GDP growth, indicating the existence of a non-linear relationship. Studies such as the work of Galappaththi et al. (2023) examine the causal relationship between economic growth and ageing population, covering 84 countries between 1961 and 2020 through wavelet coherence analysis. They find that the causal relationship and its direction has been changing over time for majority of countries.The finding corresponds to those obtained by Jayawardhana et al. (2023a) for 15 Asian countries and Jayawardhana et al. (2023b) for 15 European countries. Meanwhile, Mihajlović and Miladinov (2024) examined eight expanding economies in Central and Eastern Europe, finding a nonlinear association between ageing populations and economic development. They reveal short-term benefits and long-term detrimental effects. Likewise, Lobo and Falleiro (2024) identify a nonlinear assocation between ageing and economic growth across 72 countries between 1990 and 2019 using the fixed effects method. In relation to China, Ye et al. (2021) find that GDP growth decreases by 2% for every 10% rise in ageing population. This result is based on the deployment of the interactive fixed effects model for provincial panel data between 1990 and 2015. The adverse influence of ageing on GDP growth has been intensifying since 2000. Furthermore, Liang et al. (2023) find that the effects of various threshold factors vary significantly, based on a panel threshold regression in 31 provinces of China between 2002 and 2019.

In addition, technological innovation is now driven by AI, serving as a stimulus for productivity and economic development. A growing tendency is to resort to the application of AI to address various challenges related to an ageing population (Wu et al., 2022). Some scholars find that AI can improve economic growth. Scholars such as Rammer et al. (2022) insist that the widespread AI adoption enhances innovation output, according to firm-level data from Germany in 2018. Meanwhile, for 77 countries from 1993 to 2019, Gong et al. (2023) find that industrial robots can boost economic development by substituting labour and improving Total Factor Productivity (TFP). Likewise, Socol et al. (2024) believe that AI adoption has positive correlations with GDP growth and net income per capita for the European Union (EU-27) in 2021. With regard to the China context, Wang et al. (2024) find that AI has positive and regional heterogeneity impacts on economic growth for China between 2011 and 2019. Nevertheless, only rarely have researchers made the claim that the adverse influence of ageing on economic development can be lessened by AI. For example, Li et al. (2022) illustrate this point through an examination of 30 provinces and using data from 2007 to 2018. The finding about the impact of regional heterogeneity on economic growth accords with that obtained by Yang and Wang (2023) in 30 provinces of China between 2011 and 2019. Moreover, Li et al. (2022) argue that a higher level of AI development can mitigate the negative economic impact of ageing population, based on a threshold panel model.

However, significant concerns remain about labour displacement and inequalities when AI applications are introduced. AI is also assumed to divide the workplace between middle- and lower-skilled workers (Tyson & Zysman, 2022), potentially leading to job losses that affect economic development. Despite improvements in digital literacy among older adults, barriers to access and participation in AI-driven health initiatives persist, potentially limiting the benefits of AI for this demographic.

Based on previous studies, the nexus between an ageing population, AI, and GDP growth remains highly debatable. Few scholars, with some exceptions such as Liang et al. (2023) and Li et al. (2022), have conducted panel threshold regression to examine how ageing population and AI influence GDP growth. A major research gap is highlighted by the paucity of empirical research that has integrated these elements,underscoring that further investigation is needed to understand the complex interactions between ageing population, AI adoption, and GDP growth in China.

4. Model specification

The original Solow model, which accounts for capital, labour, and exogenous technological progress, does not distinguish between human and physical capital. As a result, it offers limited insight into the underlying causes of technological advancement and increasing returns. To address this, researchers have progressively modified the model in line with human capital theory (Schultz, 1961). For instance, Mankiw et al. (1992) introduced human capital into the Solow model. The first step in the current study is to apply a model of endogenous growth, utilising an expanded Cobb-Douglas function in which the inputs of physical capital, labour, and human capital are integrated:

$$Y = AK^{\alpha}L^{\beta}H^{\gamma}, \tag{1}$$

where Y indicates total output, K indicates physical capital, L indicates labour, and H indicates human capital. α, β, γ indicates the elasticity of output in relation to the three inputs. A represents the knowledge level (Jones & Williams, 1998).

Eq. (1) is divided by L to calculate the output for each unit of labor. The right-hand side is multiplied by $\frac{L^{\alpha+\gamma}}{L^{\alpha+\gamma}} = \frac{L^{\alpha}}{L^{\alpha}} \cdot \frac{L^{\gamma}}{L^{\gamma}} = 1$. Assuming consistent returns for scale, $\alpha + \beta + \gamma = 1$, resulting in Eq. (2):

$$\frac{Y}{L} = A\left(\frac{K^{\alpha}}{L^{\alpha}}\right)\left(\frac{H^{\gamma}}{L^{\gamma}}\right) = A\left(\frac{K}{L}\right)^{\alpha}\left(\frac{H}{L}\right)^{\gamma}. \quad (2)$$

Small letters are substituted for the per unit of labour variables for simplicity, as shown in Eq. (3):

$$y = Ak^{\alpha}h^{\gamma}. \quad (3)$$

Technological element A is referred to as the current knowledge supply available at period t. In this regard, since knowledge is a non-rival input, researchers can simultaneously use the stock of current knowledge at the same time (Romer, 1990). Eq. (4) is produced by combining all the previous individual research efforts:

$$\dot{A} = \delta R^{\theta} A, \quad (4)$$

where R indicates the effort or sources spent on the study; it is assumed that the function is growing in R. However, Jones and Williams (1998) point out that Eq. (4) may produce an increase or decrease in A, depending on how earlier theories influence a current study.

To demonstrate how a rise in R leads to increased innovation, a fundamental assumption is that the parameter θ is set to 1 (Jones & Williams, 1998). Research productivity is represented by the coefficient θ, as put forward by Romer (1990), and Jones and Williams (1998).

The equation is converted into its natural log format to estimate Eq. (3).

Additionally, the growth ratio was calculated using the differenced natural logged form of Eq. (3).

$$\Delta \ln y = \Delta \ln A + \alpha \Delta \ln k + \gamma \ln h. \quad (5)$$

The growth ratio of y is referred to $g_y = \frac{\dot{y}}{y}$, where $\dot{y} = \frac{dy}{dt}$. The term $\dot{y}$ indicates the variation in output per worker (the change in t) between two time periods. The growth ratio can also be further denoted as $g_y = \frac{dy/dt}{y} = \frac{d\ln y}{dt} = \frac{\ln y_{t - \ln y_{t-s}}}{s}$. As a result, the growth ratio equation is obtained by multiplying Eq. (5) by the variation in t:

$$\frac{\dot{y}}{y} = \frac{\delta R^{\theta} A}{A} + \alpha \frac{\dot{k}}{k} + \gamma \frac{\dot{h}}{h}. \quad (6)$$

The expression of the growth ratio of y is given as follows:

$$g_y = \delta R + \alpha g_k + \gamma g_h. \quad (7)$$

This study concentrates on determining the influence of China's ageing and AI adoption on its GDP growth. Consequently, the level of AI application serves as a proxy for the variable R, given by the density of industrial robot adoption in each region over a period of time.

Next, the threshold analysis was adopted in accordance with Hansen's (1999) panel threshold regression methods to estimate the non-linear effects of the ageing population on China's GDP, based on different levels of ageing population and AI adoption.

The fundamental model of Panel Threshold Regression (PTR) has two regimes, as follows:

$$Z_{it} = \alpha_0 + \alpha_1 x_{it} \cdot I_{it}\left(q_{it} \le \gamma\right) + \alpha_2 x_{it} \cdot I_{it}\left(q_{it} > \gamma\right) + \varepsilon_{it}, \tag{8}$$

where i=1..., N; t=1..., T; Z_{it} indicates the dependent variable, x_{it} indicates both the regime-dependent and the independent variable; q_{it} indicates the threshold variable; γ indicates the threshold value; and $I(.)$ indicates the indicator function. Meanwhile, ε_{it} indicates the error term (which is identically and independently distributed).

The empirical study, according to Hansen (1999), only searched for non-duplicate values in the threshold variable, arranged these values in ascending order, ignored about 1% of the observed values before and afterwards, and only took the middle 98% samples as the candidate scope of the threshold; that is, between 1% and 99% of the zones were searched.

To make the threshold estimation more precise, this study uses the Hansen threshold "grid search method" in threshold regression to obtain the threshold value γ. First, 0.0025 is used as the grille level to grid the threshold limit range. Then, every grid point obtained following the gridding is used as the candidate threshold value γ so that the model can be estimated one by one. The total of the residual squares is obtained, and the threshold value that corresponds to the minimum total of the residual squares is selected. This is given as the threshold estimate value $\dot{r}$.

Firstly, to identify any non-linear effect of ageing on GDP growth in China, a single threshold model is utilized. The ageing population is the threshold variable in Eq. (9) of model 1:

$$g_{it} = \alpha_0 + \alpha_1 Ag_{it} \cdot I_{it}\left(Ag_{it} \le \gamma_1\right) + \alpha_2 Ag_{it} \cdot I_{it}\left(Ag_{it} > \gamma_1\right) + \alpha_3 X_{it} + \varepsilon_{it}. \tag{9}$$

The threshold regime can occur in more than one threshold, hence the division into three subsamples. The basis for this was the assumption of a double threshold model when obtaining the panel threshold regression. This is given in Eq. (10) of model 1:

$$\begin{aligned} g_{it} &= \alpha_0 + \alpha_1 Ag_{it} \cdot I_{it}\left(Ag_{it} \le \gamma_1\right) + \alpha_2 Ag_{it} \cdot I_{it}\left(\gamma_1 \le Ag_{it} \le \gamma_2\right) + \\ &\alpha_3 Ag_{it} \cdot I_{it}\left(Ag_{it} > \gamma_2\right) + \alpha_4 X_{it} + \varepsilon_{it}. \end{aligned} \tag{10}$$

Thereafter, a single threshold model is used, involving AI as the threshold variable for the effect on GDP growth of China's ageing population. This is given in Eq. (11) of model 2:

$$g_{it} = \alpha_0 + \alpha_1 Ag_{it} I_{it}\left(AI_{it} \le \gamma_1\right) + \alpha_2 Ag_{it} \cdot I_{it}\left(AI_{it} > \gamma_1\right) + \alpha_3 X_{it} + \varepsilon_{it.} \tag{11}$$

Similarly, a double threshold effect model is used, with AI as the threshold variable for the effect of ageing on GDP growth in China, as shown in Eq. (12) of model 2 as follows:

$$\begin{aligned} g_{it} &= \alpha_0 + \alpha_1 Ag_{it} I_{it}\left(AI_{it} \le \gamma_1\right) + \alpha_2 Ag_{it} \cdot I_{it}\left(\gamma_1 < AI_{it} \le \gamma_2\right) + \\ &\alpha_3 Ag_{it} \cdot I_{it}\left(AI_{it} > \gamma_2\right) + \alpha_4 X_{it} + \varepsilon_{it}, \end{aligned} \tag{12}$$

where the subscript i and t represent provinces and years in China, respectively. g_{it} refers to economic growth and is denoted as the dependent variable; Ag refers to ageing population and is denoted as the independent variable and the regime-dependent variable, is the threshold variable in model 1. Artificial intelligence adoption is represented as AI and is the model 2 threshold variable, while X_{it} are linked control variables. These include the Regional Gross

Capital Formation (RGCF) as the Cobb-Douglas function's physical capital indicator; Labour Productivity (LP) as the Cobb-Douglas function's labour indicator; and Human Capital (HC) as the Cobb-Douglas function's human capital indicator. Meanwhile, ε is the error term. These research variables are displayed in Table 1.

Table 1. Definition of research variables

Variables	Definition	Source
g	GDP growth, which is proxied by the GDP per capita of every province in China.	World Bank (2024)
Ag	Ageing population, which is proxied by the proportion of the population aged 65 and above.	National Bureau of Statistics of China (NBSC, 2025)
	Ageing population, is the old-age dependency ratio, which is proxied by the ratio of the population aged 65 and above to the population aged 15–64.	NBSC (2025)
AI	Artificial intelligence, which is proxied by robot penetration, reflects the distribution density of industrial robots.	IFR (2024), NBSC (2025)
RGCF	Regional Gross Capital Formation rate, which is proxied by the ratio of the gross capital formation in a certain period to the regional GDP.	NBSC (2025)
LP	Labour productivity is proxied by the ratio of regional GDP to the number of employed persons at the end of every province.	NBSC (2025)
HC	Human capital accumulation is proxied by the growth rate of the average number of years of schooling in every province in China.	NBSC (2025)

Note: This study selects the panel data for 31 provinces of China (2000–2022) (excluding Hong Kong, Macao, and Taiwan regions in China). The relevant data are logarithmised, and some missing data are inserted by interpolation.

Industrial robots are among the most significant applications of AI technology, with their adoption rapidly expanding across various fields (Zhou et al., 2024; Malik et al., 2024; Zatsu et al., 2024). These modern robots incorporate advanced AI attributes like machine learning, computer vision, and decision-making autonomy, while their extensive deployment indicates clearly how AI has been integrated into industry (Rakholia et al., 2024; Licardo, 2024; Pillai et al., 2021; Shen & Zhou, 2024). Several studies have employed the number of industrial robot installations as stated by IFR as a proxy for AI application levels (Leigh et al., 2020; Wei et al., 2021; Wu et al., 2022; Dai & Wang, 2023; Zhang et al., 2024).

Since IFR reports only contain robot data at the "country-industry" level and lack micro-data at the provincial level, Acemoglu and Restrpo (2020) used the "Bartik instrumental variable" (Bartik, 1991) to build regional-level "robot penetration" in the United States. They assumed the uniform distribution of industrial robots across all sectors, while the density of industrial robots in a region depended on the employment share of different industries in that region (Wang et al., 2022; Lin & Li, 2023). In subsequent related studies, similar methods have been used to construct robot penetration at the regional level (Faber, 2020; Yu & Cong, 2023; Javed, 2023; Qi et al., 2024; Luo & Qiao, 2024). The same method is adopted in this new study for calculating provincial-level robot penetration in China. Several measurement methods are used: the IFR classification of sub-industries is matched with those listed in the "China Statistical Yearbook". The weight is the employment share of these sub-industries by province, and the weighted total is calculated using the industrial robot stock within each sub-industry across the individual provinces. The expression for robot penetration is as follows:

$$AI_{it} = \sum_{j=1}^{3} \frac{L_{ijt}}{L_{it}} \times \frac{R_{jt}}{L_{jt}}, \tag{13}$$

where AI_{it} indicates the density of industrial robot installations for province i during period t; L_{ijt} indicates the employed people for province i, industry j during period t, L_{it} indicates the employed people for province i during period t, $\frac{L_{ijt}}{L_{it}}$ indicates the proportion of employed people for province i, industry j during period t (i.e. weight); R_{jt} indicates the industrial robot stock for industry j during period t, L_{jt} indicates the employed people for industry j during period t, and $\frac{R_{jt}}{L_{jt}}$ is the density of robot installations for industry j during period t.

5. Results and discussion

The values of the core variables in different quantiles are reported in Table 2. These are highly useful for studying conventional heterogeneity effects and grouping in the sample.

Table 2. Values of core variables in different quantiles using descriptive statistics

Variable	Min	P25	P50	P75	Max
lnration65	1.446	2.050	2.223	2.426	2.997
lndependency65	1.816	2.370	2.542	2.747	3.360
RoboticAI	0.008	0.124	0.548	2.379	15.370

Note: Computed by author using the instruction "tabstat" in Stata16.

First, for model 1, the threshold effect and F tests are undertaken, with ageing population set as the threshold variable, as well as the core independent and regime-dependent variables. The ageing population is found to have a single threshold effect on China's GDP growth. The matching ageing population threshold value is 2.5879, with the results illustrated in Table 3.

Table 3. Significance test of threshold effect (model 1)

Threshold test type	F-stat	P-value	Critical value of F		
			10%	5%	1%
Single threshold	43.27*	0.0833	42.2920	50.0924	65.3744
Double threshold	20.40	0.1767	22.8759	25.7643	35.2116

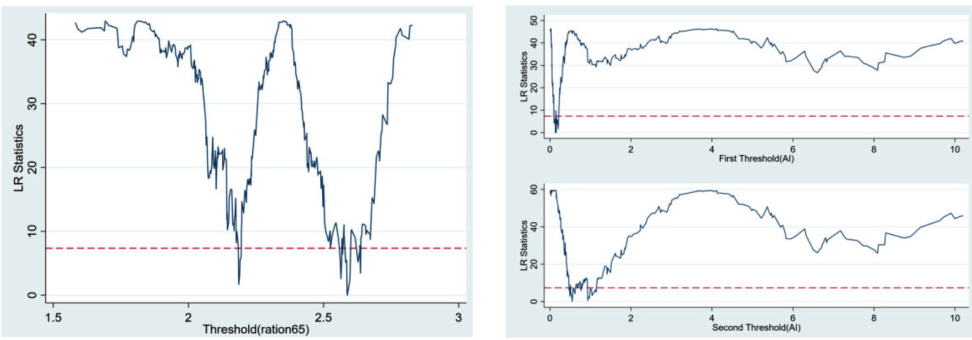
Note: Computed by the author. Using the instruction "xthreg" in Stata16, (*) indicates significant at the 10% level, (**) indicates significant at the 5% level, and (***) indicates significant at the 1% level. F-stat is the F statistic with both single and double threshold effect tests, and P-values are obtained by repeating the bootstrap processes 300 times for each one of these two bootstrap tests.

Subsequently, the threshold effect and F tests were conducted for model 2, with AI adoption set as the threshold variable, ageing population as the core independent variable and regime-dependent variable. This result indicates that ageing population has a double threshold effect on GDP development in China. The P-value for the third threshold test is 0.2867, which exceeds the 0.1 significance level, indicating that a triple threshold effect does not exist. The estimated threshold values for AI adoption are 0.1343 and 0.5497, as reported in Table 4. These findings align with the likelihood ratio test results illustrated in Figure 3.

Table 4. Significance test of threshold effect (model 2)

Threshold test type	F-stat	P-value	Critical value of F		
			10%	5%	1%
Single threshold	37.40**	0.0367	29.7161	36.1410	47.5117
Double threshold	49.90***	0.0000	24.5661	28.8589	33.6971
Triple threshold	29.52	0.2867	38.4516	43.8550	60.6754

Note: Computed by author. Using the instruction "xthreg" in Stata16, others as noted in Table 3.



Note: The dashed line indicates the 5% critical value, the curve indicates the likelihood ratio estimator, the intersection is the confidence interval estimator of the threshold value.

Figure 3. Likelihood ratio statistic of the threshold

Based on the above test results, the estimated results concerning the threshold effects on Eq. (9) of model 1 and Eq. (12) of model 2 are summarised in Table 5. Firstly, the study analyses Eq. (9) of model 1, which is the single threshold influence of ageing population on China's GDP growth, with ageing population as the threshold variable. As displayed in Table 5 in the second column, two interval changes were noted for the coefficient of the influence of China's ageing population on its GDP development. That is, the threshold variable of ageing population divides the sample into two regimes, for areas with a lower ageing population (threshold value ≤2.5879) and those with a higher ageing population (threshold value >2.5879). With a low degree of ageing population (that is, if it is under the 2.5879 threshold value or in the first regime), GDP growth in China is negatively impacted by the ageing population (α_1 = –0.0255) but not to the point of statistical significance. When the ageing population exceeds the 2.5879 threshold value or is in the second regime, the influence of ageing population on GDP growth remained negative (α_2 = –0.0563), became greater and significant at the 5% level. This suggests that the negative effects of China's ageing population on its GDP growth only become evident at higher ageing levels, aligning with Lee and Shin's findings (2019). The challenges that ageing population poses to economic development include a shrinking labour force, a rising dependency ratio, and rising healthcare and social security costs (Maestas et al., 2023).

Table 5. Tests for threshold effects of ageing population affecting GDP per capita

Threshold value	Estimated threshold (Ag)		Estimated threshold (AI)	
Single	2.5879	3.0301	0.1343	0.2082
95% Confidence interval	(2.5816,2.5976)	(3.0080,3.0350)	(0.1153,0.1385)	(0.1943,0.2121)
F-stat	43.27* (0.0833)	53.25* (0.0733)	37.40** (0.0300)	40.57** (0.0233)
Double			0.5497	0.9365
95% Confidence interval			(0.5191,0.5499)	(0.9219,0.9413)
F-stat			49.90*** (0.0000)	55.42*** (0.0000)
Coefficients	Coeff. Inration65	Coeff. Independency65	Coeff. Inration65	Coeff. Independency65
α_1	–0.0255 (0.2738)	–0.0378 (0.0231)	–0.1756 (0.2598)	–0.0268 (0.0211)
α_2	–0.0563** (0.2530)	–0.0673*** (0.0214)	0.0143 (0.2544)	0.0048 (0.0215)
α_3			0.0501* (0.2692)	0.0359* (0.0218)
R-sq	0.9791	0.9766	0.9808	0.9810

Notes: Computed by author.

Then, the study analyses Eq. (12) of model 2, which is the double threshold influence of ageing population on China's GDP growth, with AI adoption as the threshold variable. The fourth column in Table 5 displays the estimated outcomes. The threshold variable of AI adoption divides the sample into three regimes, which are divided into lower (threshold value ≤0.1343), medium (0.1343 < threshold value ≤ 0.5497), and higher AI adoption levels (threshold value >0.5497). When AI adoption is at a lower level or in the first regime, that is, when the threshold value is below 0.1343, the ageing population negatively impacts (α_1 = –0.1756) China's GDP growth, but this isn't statistically significant. In the second regime (that is, with threshold values from 0.1343 to 0.5497), the influence of China's ageing population on its GDP growth turns from negative to positive (α_2 = 0.0143). However, this is also of no statistical significance. When the AI adoption level exceeds the threshold value of 0.5497, entering the third regime, the positive influence of ageing population on China's GDP growth (α_3 = 0.0501) becomes greater, and this is significant at the 10% level. This suggests that higher levels of AI adoption can effectively mitigate the adverse effects of ageing population on GDP growth, findings that are in line with Li et al. (2022). AI-driven automation, such as robotic systems in manufacturing or AI powered diagnostic tools in healthcare, compensates for the lack of employees imposed by an ageing workforce and significantly enhances productivity (Park et al., 2022). For instance, the "X-Eye" automated inspection system, developed by Xiaomi Car in China using large AI models, replaces human visual inspection and increases efficiency by several dozen times. This AI-driven method not only saves significant labour hours but also maintains a high level of inspection quality (Beijing Science and Technology News, 2025). These advantages ensure that production lines operate smoothly without being affected by the declines in efficiency and accuracy typically associated with an ageing inspection workforce, such as reduced physical strength and visual acuity.

To ensure the tests are robust, the influence of ageing population is also estimated using the old-age dependency ratio instead of the proportion of the population aged 65 and above as a proxy. The third and fifth columns of Table 5 show the outcomes. The result shown in the third column reveals that the influence on China's GDP growth of the ageing population, represented by the old-age dependency ratio in model 1 and with ageing population as the threshold variable, also has two intervals of change. The negative impact aligns with the result shown in the second column in Table 5. The coefficient α_2 measures the threshold effect of a higher degree of an ageing population. The result indicates that the magnitude of the negative effect becomes larger(from –0.0563 to –0.0673) and statistically significant at the 1% level. This outcome had been anticipated since the proportion of the population aged 65 and above is smaller than the old-age dependency ratio. To some degree, this demonstrates the robustness of the findings.

Similarly, the results in the fifth column, show that the effect of ageing, proxied by the old-age dependency ratio in Model 2 and with AI as the threshold variable, exhibits three distinct phases of change in GDP per capita. The results indicate that the first threshold shows a negative impact, which later shifts to a positive effect, consistent with the findings displayed in the fourth column of Table 5. At the third threshold, the coefficient α_3, which captures the threshold effect of a higher level of AI adoption, indicates that the negative effect of ageing on GDP growth becomes slightly weaker. This result is expected, as the old-age dependency ratio is higher than the proportion of the population aged 65 and above, indicating that the findings are robust.

6. Conclusions

6.1. Findings

This research examine the nonlinear connection between ageing and GDP growth, with ageing and AI adoption as threshold variables, based on panel data for 31 provinces of China (2000–2022). The findings are as follows: firstly, ageing population has threshold effects on China's GDP growth. Secondly, ageing population negatively affects China's GDP growth once it surpasses a certain threshold, and its negative effect intensifies as ageing increases. Conversely, the findings highlight AI's capacity to serve as a booster to increase GDP growth. More precisely, once AI surpasses the second threshold, it begins to significantly lessen the negative effects of ageing.

6.2. Policy recommendations

Based on these findings, this research presents various policy recommendations. To mitigate the negative influence of ageing, it is essential to increase investment in AI research and development. Government policies can focus on supporting innovation in AI technologies, particularly those that can enhance productivity in sectors with an ageing workforce, such as manufacturing, healthcare, and services. This might be accomplished by supporting research projects, providing tax incentives to companies that invest in AI, and encouraging public-private collaborations to accelerate AI adoption.

It's also critical to support the deployment of AI-driven robotics in key sectors and provide training that enhances AI applications. The government could help the industrial robot industry and pass legislation that fosters it, such as by supporting the development of intelligent and industrial robots, as well as promoting their widespread application. Additionally, it is imperative to develop and enhance training programs, especially for the elderly, who might find it more difficult to adjust to new technology than their younger ones. Cases such as the Learning, Training, Assistance – Formats, Issues, Tools (LTA-FIT) model in the context of Germany's Industry 4.0 highlight the necessity of comprehensive training programs catered to all employee levels, with a particular focus on digital competencies for elderly workers.

Improving digital infrastructure is essential to allowing new technologies and making sure they are age-friendly. Given that many smart technologies, such as robots, rely on remote network-based operation, a strong digital foundation is essential for functionality and accessibility. Furthermore, as stated by China's Ministry of Industry and Information Technology, age-friendly digital policies should be systematically adopted aiming to narrow the digital divide among the elderly.

Finally, increasing investment and development of the ageing industry is essential. As ageing population intensifies,the "silver economy" brings new opportunities for economic growth. The government should increase fiscal spending on the ageing industry as well as create appropriate policies for guidance and support its development. For instance, according to the State Council of China, "the Opinions on Developing the Silver Economy and Enhancing the Well-being of the Elderly" emphasise that there is a need to promote the integrated application of next-generation information technologies and smart devices. This includes mobile terminals, wearables, and service robots in domestic, community, and institutional elderly care scenarios. In addition, it is crucial to fully leverage and develop elderly human capital by fostering an environment that supports their social participation. For example, according to the Ministry of Civil Affairs of China, "the Guiding Opinions on Supporting the Social Participation of the Elderly and Promoting the Realization of the Elderly Leading a Useful Life" recommends creating diverse and personalised opportunities for employment that specifically focus on elderly people. These initiatives should be integrated into the growth of emerging sectors, including the silver and digital economies, to cultivate new drivers of inclusive and sustainable development.

6.3. Theoretical and practical implications

This research not only enriches the academic literature, but also enhances endogenous economic growth theories by extending the classical Cobb-Douglas function to incorporate ageing and AI. For policymakers, such research can offer evidence-based policy suggestions and practical advice that address the economic challenges associated with ageing population by leveraging AI-driven technological advancements. This research can also serve as theoretical guidance for other developing nations facing demographic challenges.

6.4. Limitations and future research directions

There are some limitations to this research. Firstly, due to data limitations, AI is measured only using industrial robot penetration as a proxy. Although industrial robot represents a practical indicator of AI-driven applications, it doesn't fully capture the extent of AI development and adoption. Therefore, future studies could use different indicators to measure AI, such as the AI patent grants. Secondly, future studies could adopt methodologies like Data Envelopment Analysis, to evaluate the efficiency of AI applications in mitigating the economic impacts of ageing population across Chinese provinces.

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There are no conflicting interests to disclose.

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