AI-Embodied Agricultural Technologies, Population Aging, and Agricultural Economic Performance: Evidence from China

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Abstract

This paper examines how population aging shapes the economic return to AI-embodied agricultural technologies in China. Focusing on the adoption of unmanned aerial vehicles (UAVs), we use provincial data from 2018 and 2023 and a fixed-effects framework to analyze the relationship between UAV adoption, demographic structure, and agricultural economic performance.

The results show that UAV adoption is positively associated with agricultural performance on average. However, this relationship is significantly moderated by population aging. The interaction between UAV adoption and the share of the elderly population is negative and statistically significant, indicating that the economic gains from UAV adoption decline as regions become more aged. Marginal effect analysis further reveals a threshold pattern: the positive association between UAV adoption and economic performance becomes negligible and eventually turns negative in highly aged regions.

The findings are robust across alternative specifications, including lagged independent variables, alternative measures of agricultural performance, and controls for conventional mechanization and farm structure. The results suggest that AI-embodied agricultural technologies do not fully substitute for labor, but require complementary human capital. Overall, the paper provides new evidence that demographic structure shapes the returns to embodied AI adoption in agriculture.

Keywords: Artificial Intelligence; UAV adoption; Population aging; Agricultural economic performance; Agricultural exports; China
JEL Classification: O33, Q16, J11, F14

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1. Introduction

The diffusion of artificial intelligence (AI)-embodied technologies is transforming agricultural production systems. In China, the rapid adoption of unmanned aerial vehicles (UAVs) has introduced new opportunities to improve agricultural productivity, input efficiency, and export competitiveness. Unlike conventional agricultural machinery, UAVs combine automation with digital monitoring and precision application technologies, potentially enhancing both production productivity and product quality. As a result, AI-embodied agricultural technologies are increasingly viewed as an important source of agricultural modernization and rural structural transformation.

At the same time, China's agricultural sector faces substantial demographic challenges. Rural areas have experienced persistent out-migration of younger workers and a rising share of elderly laborers over recent decades (de Brauw et al., 2008). Existing research suggests that traditional mechanization, such as tractors and large-scale farming, can alleviate labor shortages by substituting for manual labor. However, whether AI-embodied technologies function in the same manner remains unclear. Unlike conventional machinery, AI-embodied technologies often require complementary digital and operational skills, implying that their economic effectiveness may depend critically on local demographic conditions.

This paper examines how population aging conditions the economic effect of AI-embodied agricultural technologies. Using panel data for 31 Chinese provinces, we investigate the relationship between UAV adoption and agricultural export performance, with particular attention to the interaction between UAV adoption and the elderly population share. To isolate the effect of AI technologies from broader structural transformation, the analysis controls for conventional mechanization and farm size. This distinction is important because UAV adoption may otherwise capture general deepening or farm consolidation rather than the independent contribution of AI-related technologies.

The empirical results reveal a consistent pattern. UAV adoption is positively associated with agricultural export performance on average. However, the marginal effect declines systematically as population aging increases. The estimated marginal effect becomes statistically insignificant and eventually negative once the elderly population share exceeds approximately 12.13 percent. These findings suggest that AI-embodied technologies are not perfect substitutes for labor. Instead, their effectiveness depends on the availability of complementary human capital, which may be relatively limited in aging rural regions.

The paper contributes to the literature in several ways. First, it distinguishes AI-embodied agricultural technologies from traditional mechanization, highlighting important differences in their interaction with labor and demographic structure. Second, it provides new evidence that demographic composition plays a critical role in shaping the economic returns to technological adoption, challenging the conventional view that technology uniformly offsets labor shortages. Third, by focusing on China, the paper contributes to a growing body of research on technological transformation, demographic change, and agricultural competitiveness in developing economies.

The findings also carry important policy implications. Policies promoting AI adoption in agriculture may generate uneven economic outcomes if demographic constraints are ignored. In aging regions, technological upgrading alone may be insufficient to sustain agricultural competitiveness without complementary investments in human capital, digital capability, and rural workforce revitalization.

2. Literature Review

2.1 AI-Embodied Technologies and Agricultural Transformation

The increasing adoption of artificial intelligence in agriculture has generated growing interest in how new forms of capital reshape production processes and economic outcomes. In contrast to traditional inputs, AI-embodied technologies such as UAVs integrate real-time data processing, automation, and precision application into agricultural production. These technologies are expected to improve input efficiency, crop monitoring, and product quality, although empirical evidence on AI-embodied agricultural capital remains limited.

More broadly, recent studies emphasize that digital technologies are reshaping agricultural production systems through precision farming, smart farming, and data-driven decision-making processes. Wolfert et al. (2017) review the role of big data and information and communication technologies (ICT) in smart farming, while Klerkx et al. (2019) examine the social science literature on digital agriculture, smart farming, and Agriculture 4.0.

While a large body of research has examined digital agriculture and ICT-based technologies, relatively less attention has been paid to the role of AI-embodied capital as a distinct category of production input. Unlike general digital technologies, AI-embodied capital is physically embedded in production processes and directly interacts with labor and land. This distinction suggests that its economic impact may differ from that of conventional digital tools, particularly in the context of agricultural modernization and large-scale production.

Evidence from precision agriculture also suggests that adoption patterns vary substantially across technologies and farm contexts, indicating that advanced agricultural technologies do not diffuse uniformly across producers (Lowenberg-DeBoer & Erickson, 2019). This reinforces the need to distinguish AI-embodied technologies from broader forms of digital agriculture and conventional mechanization.

2.2 Traditional Mechanization versus Intelligent Automation

More generally, the adoption of agricultural innovations depends on expected returns, complementary inputs, learning, and farm-level constraints (Feder et al., 1985; Foster & Rosenzweig, 2010). Within this broader literature, agricultural mechanization has long been examined as a major form of labor-saving technological change. The literature on agricultural mechanization has long emphasized the role of machinery in substituting for labor, particularly in response to rising wages and labor scarcity (Huang & Rozelle, 2018). Pingali (2007) shows that labor-saving mechanization has played an important role in raising agricultural productivity and

lowering unit production costs, especially in Asia. Conventional technologies such as tractors and harvesters increase productivity primarily by replacing physical effort and enabling economies of scale. In this framework, mechanization is generally viewed as a labor-saving process that mitigates the constraints imposed by declining labor availability.

However, the emergence of AI-embodied technologies represents a qualitative shift from traditional mechanization. Rather than simply substituting for labor, these technologies augment decision-making and require ongoing monitoring, calibration, and technical operation. Evidence from the broader automation literature suggests that advanced technologies can raise labor productivity and total factor productivity while also changing the composition of labor demand. Graetz and Michaels (2018), for example, find that industrial robots increased labor productivity and total factor productivity while reducing the employment share of low-skilled workers. This distinction is important because AI-embodied technologies may require complementary human capital rather than merely replacing labor.

This perspective is consistent with the broader literature on skill-biased technological change, which suggests that advanced technologies tend to complement skilled labor while substituting for routine tasks. Autor et al. (2003) show that computerization altered job skill demands by shifting demand away from routine tasks and toward non-routine cognitive tasks. In the agricultural context, this implies that AI-embodied technologies may be better characterized as skill-complementary inputs rather than pure labor substitutes.

2.3 Demographic Change and Technology Adoption

A growing literature highlights the role of demographic structure in shaping the adoption and effectiveness of new technologies. In rural China, demographic change is closely linked to sustained migration of younger and more educated workers from rural areas to off-farm and urban employment. de Brauw et al. (2002) show that migration became the most prevalent off-farm activity in rural China and was dominated by young and better-educated workers. This demographic transition has important implications for technological change.

Existing studies suggest that older farmers may face greater barriers to adopting new technologies due to lower digital literacy, higher adjustment costs, and shorter investment horizons. While traditional mechanization can partially offset labor shortages, the effectiveness of more advanced technologies may vary depending on the age composition and skill structure of the workforce.

Recent work on demographics and automation provides an important theoretical foundation for this argument. Acemoglu and Restrepo (2022) show that aging can lead to greater adoption of automation and robotics, suggesting that demographic pressure can shape technological change. However, the effectiveness of automation also depends on whether the required complementary skills are available. In the context of AI-embodied agricultural technologies, these insights suggest the presence of a potential human capital bottleneck. When the share of elderly workers becomes sufficiently high, the lack of younger and more technologically adaptable labor may limit the effective use of advanced technologies. This raises the possibility of non-linear or threshold effects in the relationship between technology adoption and economic performance.

2.4 Research Gap and Contribution

In China, agricultural transformation has also been closely linked to land use, farm structure, and productivity changes (Deng et al., 2006; Huang & Rozelle, 2018). Despite substantial progress in the literature, several gaps remain. First, existing studies on digital agriculture and agricultural technology adoption have largely focused on farm-level productivity, production efficiency, or income outcomes, with limited attention to aggregate regional economic performance such as exports. Second, the distinction between traditional mechanization and AI-embodied technologies has not been systematically incorporated into empirical analyses. Third, while the relationship between demographic change and technology adoption has received growing attention, less is known about how demographic structure conditions the economic returns to AI-embodied technologies at the regional level, particularly in the context of agricultural economic performance.

This paper contributes to the literature by integrating these strands of research. Specifically, it examines how AI-embodied agricultural technologies affect export performance and how this relationship is mediated by demographic structure. By distinguishing between traditional mechanization, farm structure, and AI-based capital, the analysis provides new evidence on the interaction between technology and demographics in shaping agricultural competitiveness in China.

3. Data and Methodology

3.1 Data Sources and Variable Construction

This study employs a balanced panel dataset covering 31 provincial-level regions in mainland China over the period from 2018 to 2023. The key explanatory variable, AI-embodied agricultural capital, is proxied by the number of unmanned aerial vehicles (UAVs). Data on UAVs are hand-collected from multiple editions of the China Agricultural Machinery Industry Yearbook. To benchmark AI-embodied technologies against conventional mechanization, we also collect data on tractor ownership and total agricultural machinery power from the same source.

Demographic characteristics are captured using the aging rate, defined as the share of the population aged 65 and above. These data are obtained from the National Bureau of Statistics (NBS).

The set of control variables includes provincial economic development, measured by log GDP per capita, and structural characteristics of the agricultural sector. In particular, we include measures of traditional mechanization, such as the large tractor shar, and farm structure, such as the proportion of large-scale farms, to distinguish the effects of AI-embodied technologies from conventional capital deepening and scale effects.

3.2 Empirical Strategy

To examine the impact of AI-embodied agricultural technologies on economic performance under demographic constraints, we estimate the following two-way fixed effects model:

$$\ln ex_gdp_{it} = \beta_1 \ln UAV_{it} + \beta_2 Aging_{it} + \beta_3 (lnUAVs_{it} \times Aging_{it}) + \gamma X_{it} + \alpha_i + \delta_t + \epsilon_{it}$$

Where i and t index province and year, respectively. ln(UAV_{it}) denotes the logarithm of UAV adoption, and $Aging_{it}$ denotes the share of the population aged 65 and above. The interaction term captures how the marginal effect of AI-embodied technologies varies with demographic structure.

X_{it} is a vector of control variables, including measures of traditional mechanization and farm structure. Province fixed effects (α_i) control for time-invariant heterogeneity, while year fixed effects (δ_t) capture common shocks across provinces. Standard errors are clustered at the provincial level. The coefficient of interest is β_3, which indicates whether population aging constrains the effectiveness of AI-embodied technologies.

3.3 Identification and Robustness

A central empirical concern in this study is the potential endogeneity of UAV adoption. Provinces with stronger export performance may have greater incentives or financial capacity to invest in advanced technologies, raising the possibility of reverse causality. To address this concern and to ensure the robustness of our findings, we implement a series of complementary empirical strategies.

First, we estimate a lagged specification in which UAV adoption and the aging rate are included with a one-period lag. This approach ensures that technological and demographic conditions precede observed economic outcomes, thereby mitigating simultaneity bias. The persistence of the main results under this specification provides evidence that the estimated relationships are not driven solely by reverse causality.

Second, we examine the sensitivity of our results to alternative measures of economic performance. In addition to agricultural exports, we use agricultural value added relative to provincial GDP as an alternative dependent variable. The consistency of results across these outcome measures suggests that the effects of AI-embodied technologies extend beyond trade performance and reflect broader economic impacts within the agricultural sector.

Third, we control for conventional agricultural mechanization to isolate the effect of AI-embodied technologies from general capital deepening. Specifically, we include measures such as tractor intensity and total agricultural machinery power. These specifications address the concern that UAV adoption may simply proxy for overall mechanization rather than representing a distinct technological channel.

Fourth, we incorporate farm structure variables, including the share of large-scale farms, to account for the possibility that UAV adoption is driven by scale advantages in agricultural production. Controlling for farm size allows us to distinguish the technological effect of UAV adoption from structural changes in agricultural organization.

Finally, we conduct marginal effect analysis to examine how the impact of UAV adoption varies across different levels of population aging. This analysis enables us to identify non-linearities and

threshold effects, providing direct evidence on how demographic structure conditions the effectiveness of AI-embodied technologies.

4. Empirical Results

4.1 Baseline Estimation Results

This section presents the baseline estimates of the relationship between AI-embodied agricultural technologies and agricultural export performance. The main objective is to examine whether UAV adoption contributes to agricultural export competitiveness and to examine how this relationship is conditioned by demographic structure. Table 1 presents the results from the two-way fixed effects model, controlling for time-invariant provincial heterogeneity and common year-specific shocks.

Table 1. Baseline Fixed-Effects Estimation Results for Agricultural Export Performance

Variables	Agricultural Export Performance
Log UAV Adoption	0.0760*** (0.0188)
Aging Rate	0.0977*** (0.0351)
UAV Adoption × Aging Rate	-0.0063*** (0.0020)
Log GDP per Capita	-0.7518*** (0.1996)
Large Tractor Share	-0.0769 (0.8498)
Constant	3.9896* (2.2761)
Observations	186
Within R-squared	0.6798
Number of Provinces	31
Province Fixed Effects	Included
Year Fixed Effects	Included

Notes: Robust standard errors clustered at the provincial level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

The results show that UAV adoption is positively associated with agricultural export performance. The coefficient on UAV adoption is positive and statistically significant at the 1 percent level, suggesting that provinces with greater adoption of UAV technologies tend to exhibit stronger agricultural export outcomes. This finding is consistent with the view that UAVs improve production efficiency, precision input application, and product quality.

The interaction term between UAV adoption and the aging rate is negative and statistically significant. This indicates that the positive association between UAV adoption and agricultural export performance weakens as population aging increases. The result suggests that the returns to AI-embodied agricultural technologies are not uniform across provinces but depend on

demographic conditions. In particular, UAV technologies may require complementary human capital and digital capability, which are likely to be more limited in regions with older rural populations.

The control variables are generally consistent with expectations. Log GDP per capita is negative and statistically significant, suggesting that higher-income provinces tend to experience structural transformation away from agriculture toward manufacturing and services. The coefficient on the large tractor share is not statistically significant, indicating that conventional mechanization alone does not explain differences in agricultural export performance once UAV adoption is accounted for.

Overall, the baseline results suggest that AI-embodied agricultural technologies are associated with improved agricultural export performance, but their effectiveness declines in more aged regions.

4.2 Robustness Checks

This section examines the robustness of the baseline findings using alternative specifications. We consider potential reverse causality, alternative outcome measures, additional controls for conventional mechanization, alternative measures of mechanization, and farm structure.

4.2.1 Lagged Independent Variables

A potential concern is reverse causality, whereby provinces with stronger export performance may have greater capacity to invest in advanced technologies. To address this concern, we estimate a specification in which the main explanatory variables are lagged by one period.

Table 2 reports the results of the lagged independent variable specification. The results remain consistent with the baseline findings. Lagged UAV adoption is positive and statistically significant, indicating that previous UAV adoption is associated with higher current agricultural export performance. The interaction term between lagged UAV adoption and the lagged aging rate remains negative and statistically significant. These results suggest that the baseline findings are unlikely to be driven solely by contemporaneous reverse causality.

Table 2. Lagged Independent Variable Specification

Variables	Agricultural Export Performance
Lagged Log UAV Adoption	0.0536***
	(0.0185)
Lagged Aging Rate	0.0897**
	(0.0363)
Lagged UAV Adoption × Lagged Aging Rate	-0.0052**
	(0.0020)
Lagged Log GDP per Capita	-0.4851**
	(0.1927)
Lagged Large Tractor Share	0.0907
	(0.8006)

Constant	1.2225 (2.2244)
Observations	155
Within R-squared	0.5956
Number of Provinces	31
Province Fixed Effects	Included
Year Fixed Effects	Included

Notes: Robust standard errors clustered at the provincial level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All explanatory variables are lagged by one period.

4.2.2 Alternative Dependent Variable: Agricultural Value Added

We next examine whether the results are robust to alternative measures of economic performance. Specifically, we replace agricultural export performance with agricultural value added relative to provincial GDP. This measure captures broader agricultural economic performance beyond trade outcomes.

Table 3 presents the results using agricultural value added relative to provincial GDP as an alternative dependent variable. The coefficient on UAV adoption remains positive and statistically significant, indicating that AI-embodied technologies are also associated with broader agricultural value creation. The interaction term between UAV adoption and the aging rate remains negative and statistically significant, consistent with the baseline results. This suggests that the moderating role of population aging is not limited to export performance but also applies to broader agricultural economic outcomes.

In this specification, conventional mechanization, measured by the large tractor share, becomes positive and marginally significant. This suggests that traditional mechanization may contribute to domestic agricultural production capacity, even though it does not appear to explain export performance once UAV adoption is included.

Table 3. Alternative Dependent Variable: Agricultural Value Added

Variables	Agricultural Value Added/GDP
Log UAV Adoption	0.1956** (0.0906)
Aging Rate	0.2278 (0.1457)
UAV Adoption × Aging Rate	-0.0167* (0.0092)
Log GDP per Capita	0.7002 (1.0362)
Large Tractor Share	9.3119** (3.6988)
Constant	-1.5791 (11.9296)
Observations	186

Within R-squared	0.6739
Number of Provinces	31
Province Fixed Effects	Included
Year Fixed Effects	Included

Notes: Robust standard errors clustered at the provincial level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

4.2.3 Controlling for Conventional Mechanization

To ensure that the estimated effect of UAV adoption is not capturing general trends in agricultural mechanization, we augment the baseline specification with additional machinery controls. These include harvesting equipment, irrigation machinery, precision seeders, and no-tillage seeders.

Table 4 reports the results after controlling for conventional agricultural mechanization. The main findings remain unchanged. UAV adoption continues to have a positive and statistically significant coefficient, while the interaction between UAV adoption and the aging rate remains negative and statistically significant. Although some conventional machinery variables are associated with export performance, their inclusion does not materially affect the estimated UAV coefficients.

These results indicate that the UAV effect is not simply capturing general mechanization. Instead, AI-embodied technologies appear to represent a distinct technological channel in agricultural production and export performance.

Table 4. Controlling for Conventional Agricultural Mechanization

Variables	Agricultural Export Performance
Log UAV Adoption	0.0841*** (0.0212)
Aging Rate	0.1153*** (0.0386)
UAV Adoption × Aging Rate	-0.0071*** (0.0021)
Log GDP per Capita	-0.7964*** (0.1660)
Large Tractor Share	-0.0139 (0.7677)
Log Harvesting Machinery	-0.0022 (0.0070)
Log Irrigation Machinery	-0.0233* (0.0115)
Log Precision Seeders	-0.0041 (0.0041)
Log No-Tillage Seeders	0.0120** (0.0044)
Constant	4.2809** (1.9204)
Observations	186

Within R-squared	0.7222
Number of Provinces	31
Province Fixed Effects	Included
Year Fixed Effects	Included

Notes: Robust standard errors clustered at the provincial level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

4.2.4 Alternative Measure of Mechanization

We further examine the robustness by using an alternative measure of traditional mechanization. Instead of the share of large tractors, we use total large tractor power as a proxy for mechanical capital intensity.

Table 5 reports the results using total large tractor power share as an alternative measure of mechanization. The results remain consistent with the baseline estimates. UAV adoption remains positive and statistically significant, and the interaction term between UAV adoption and the aging rate remains negative and statistically significant. This consistency suggests that the results are not sensitive to the choice of mechanization measure.

Table 5. Alternative Measure of Mechanization

Variables	Agricultural Export Performance
Log UAV Adoption	0.0796*** (0.0215)
Aging Rate	0.1029** (0.0394)
UAV Adoption × Aging Rate	-0.0066*** (0.0021)
Log GDP per Capita	-0.7559*** (0.1985)
Total Large Tractor Power Share	0.1039 (0.4959)
Constant	3.9585* (2.1930)
Observations	186
Within R-squared	0.6803
Number of Provinces	31
Province Fixed Effects	Included
Year Fixed Effects	Included

Notes: Robust standard errors clustered at the provincial level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

4.2.5 Controlling for Farm Structure

Another concern is that UAV adoption may reflect differences in farm structure rather than the effect of AI-embodied technologies. In China, land transfer reforms and farm consolidation may increase both the likelihood of adopting advanced technologies and agricultural export

performance. To address this issue, we include the share of large-scale farms as an additional control variable.

Table 6 reports the results after controlling for farm structure. The inclusion of farm structure does not alter the main results. UAV adoption remains positively associated with agricultural export performance, and the interaction between UAV adoption and the aging rate remains negative and statistically significant. The coefficient on the large farm share is not statistically significant, suggesting that farm scale alone does not explain differences in export competitiveness once technology adoption and other controls are included.

Overall, the robustness checks support the baseline interpretation that UAV adoption is associated with stronger agricultural economic performance, while population aging weakens this relationship.

Table 6. Controlling for Farm Structure

Variables	Agricultural Export Performance
Log UAV Adoption	0.0754***
	(0.0186)
Aging Rate	0.0984***
	(0.0350)
UAV Adoption × Aging Rate	-0.0062***
	(0.0019)
Log GDP per Capita	-0.7533***
	(0.2037)
Large Tractor Share	0.0920
	(0.8420)
Large-Scale Farm Share	-0.0057
	(0.0166)
Constant	4.2145*
	(2.4066)
Observations	186
Within R-squared	0.6812
Number of Provinces	31
Province Fixed Effects	Included
Year Fixed Effects	Included

Notes: Robust standard errors clustered at the provincial level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

4.3 Marginal Effects and Threshold Analysis

To interpret the interaction effect more directly, we compute the marginal effect of UAV adoption at different levels of population aging. While the regression results establish a negative interaction between UAV adoption and aging, the marginal effects show how the effect of UAV adoption changes across demographic conditions.

Table 7 reports the estimated marginal effects of UAV adoption across different aging rates for both the baseline and lagged specifications. The results show a clear declining pattern. At relatively low levels of aging, the marginal effect of UAV adoption is positive and statistically significant. This indicates that UAV adoption is associated with improved export performance in provinces with younger demographic structures. As the aging rate increases, however, the magnitude of the marginal effect declines steadily.

At aging rates near 10 percent, the marginal effect becomes statistically insignificant, particularly in the lagged specification. At higher levels of aging, the estimated marginal effect becomes negative and statistically significant. This pattern suggests that the benefits of UAV adoption are substantially reduced in more aged regions.

The implied threshold at which the marginal effect of UAV adoption equals zero is approximately 12.13 percent in the baseline specification and 10.33 percent in the lagged specification. These estimates indicate that the export-enhancing effect of UAV adoption is concentrated in provinces with relatively younger demographic structures.

Taken together, the marginal effect results reinforce the main finding of the paper: the economic returns to AI-embodied agricultural technologies depend critically on demographic conditions. UAV adoption can improve agricultural export performance, but its effectiveness is limited where population aging constrains the availability of complementary human capital and digital capability.

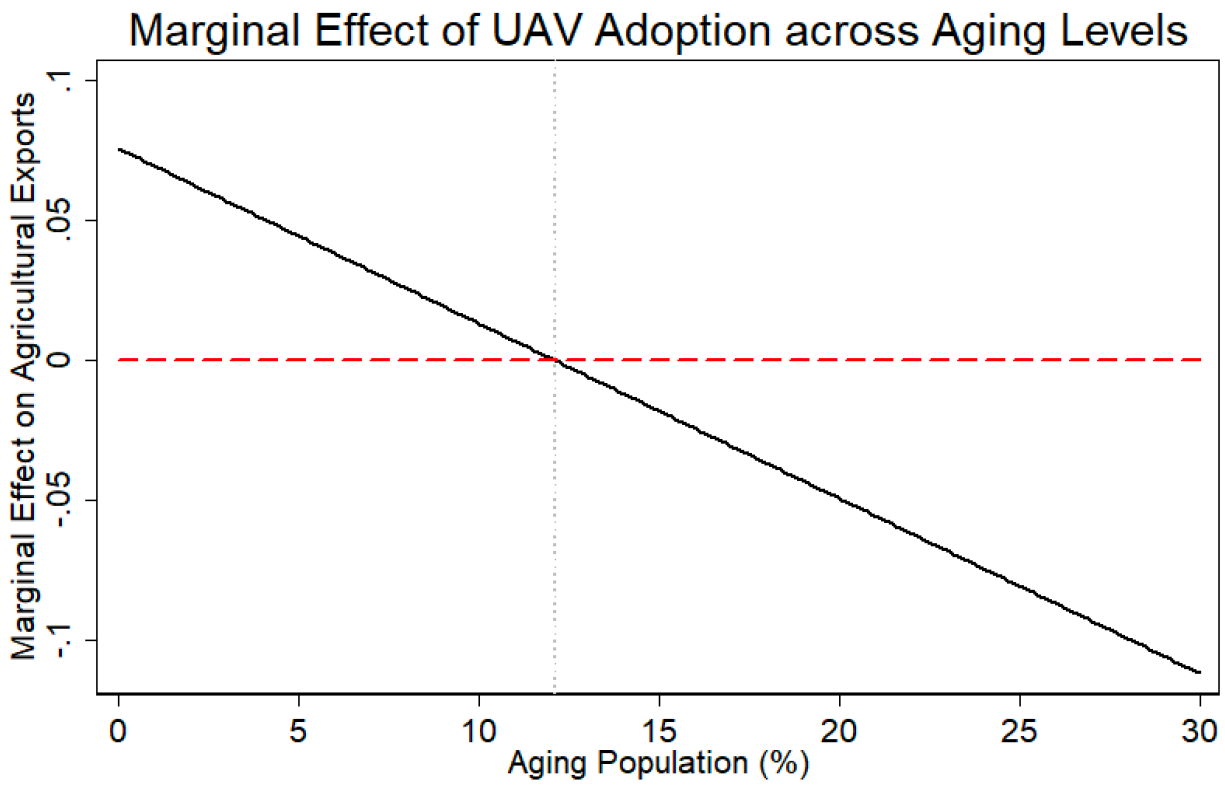
Table 7. Marginal Effect of UAV Adoption across Aging Rates

Aging Rate	(1) Marginal Effects (Baseline)	(2) Marginal Effects (Lagged)
0%	0.0760***	0.0536***
	(0.0188)	(0.0185)
5%	0.0446***	0.0276***
	(0.0105)	(0.0097)
10%	0.0133*	0.0017
	(0.0079)	(0.0066)
15%	-0.0180	-0.0242*
	(0.0144)	(0.0137)
20%	-0.0493**	-0.0501**
	(0.0233)	(0.0229)
25%	-0.0807**	-0.0761**
	(0.0327)	(0.0325)
30%	-0.1120***	-0.1020**
	(0.0423)	(0.0423)
Estimated Threshold	12.13%	10.33%
Observations	186	155

Notes: Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Column (1) reports the baseline specification, while Column (2) reports the lagged specification.

Figure 1 plots the marginal effect of UAV adoption across different levels of population aging. The figure shows that the marginal effect declines as the aging rate increases and crosses zero near the estimated threshold values. This visual evidence is consistent with the results in Table 7 and further supports the interpretation that demographic structure conditions the returns to AI-embodied agricultural technologies.

Figure 1. Marginal Effects of UAV adoption across Aging Rates



5. Conclusion and Policy Implications

5.1 Conclusion

This paper examines how AI-embodied agricultural technologies interact with demographic structure to shape agricultural economic performance. Using a provincial panel dataset for China over the period 2018-2023 and a two-way fixed effects framework, we document a robust association between UAV adoption and agricultural performance.

The results show that UAV adoption is positively associated with export outcomes on average. However, this effect is not uniform across regions. The interaction between UAV adoption and the aging rate is consistently negative, indicating that the effectiveness of AI-embodied technologies declines as population aging increases.

A key finding is the presence of a threshold pattern. The estimated marginal effects suggest that the positive impact of UAV adoption becomes negligible at aging rates around 10 - 12 percent and may turn negative at higher levels of aging. This pattern is robust across specifications, including lagged models, alternative outcome measures, and additional controls for conventional mechanization and farm structure.

These findings contribute to the literature by showing that AI-embodied technologies are not pure substitutes for labor. Instead, their economic effects depend on complementary human capital and demographic conditions. More broadly, the paper provides evidence that population aging can constrain the returns to technological adoption, offering a more nuanced perspective on agricultural modernization in aging economies.

5.2 Policy Implications

The results have several policy implications for economies seeking to promote advanced agricultural technologies under demographic constraints.

First, policies promoting the adoption of AI-embodied technologies should account for regional demographic conditions. In regions with relatively younger labor forces, supporting the diffusion of UAV technologies may generate meaningful gains. In more aged regions, however, policy efforts may need to focus on improving complementary conditions, such as training, technical support, and service provision, rather than solely subsidizing equipment adoption.

Second, strengthening human capital in rural areas is important for realizing the benefits of technological upgrading. Expanding vocational training programs related to digital agriculture, including UAV operation and farm management, can help improve the effective use of advanced technologies. Policies that encourage younger and technologically adaptable workers to participate in agriculture may also increase the capacity to adopt and utilize AI-embodied technologies.

Third, institutional and structural conditions remain important for agricultural transformation. Continued development of land transfer markets and farm consolidation can facilitate more efficient use of advanced equipment. At the same time, complementary social and labor policies may help reduce constraints associated with population aging and rural labor shortages.

Overall, the results suggest that technological adoption alone is not sufficient to improve agricultural economic performance. The returns to AI-embodied technologies depend critically on the interaction between technology and demographic conditions, underscoring the need for integrated policy approaches that combine technological upgrading with human capital development.

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Disclosure of Interest
The authors report there are no competing interests to declare.

Data availability statement

The data used in this study are compiled from multiple statistical sources, including the China Agricultural Machinery Industry Yearbook and the National Bureau of Statistics of China. The processed dataset and replication files are available from the corresponding author upon reasonable request.

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