Proceedings of the 4th International Conference on Global Politics and Socio-Humanities
DOI: 10.54254/2753-7048/2026.33311

Smart Elderly Care and Older Adults' Care Choices

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Abstract. This study looks at how smart elderly care affects older adults' care choices, we use panel data from four waves of the China Longitudinal Study of Aging, covering 2014 to 2020, we treat the rollout of smart elderly care demonstration zones as a quasiexperiment, then apply a multiperiod differenceindifferences model for our empirical analysis, a few findings stand out, results show smart elderly care has a clear positive impact on older adults' care choices, this holds up across a series of robustness checks, the influence works through three channels, it reduces information search costs, that eases information frictions between supply and demand, it helps maintain cognitive abilities, which strengthens the ability to compare and evaluate different care options, it also expands social networks, which shifts how people think about care choices, this study pushes the theoretical boundaries of care decisionmaking from an institutional embeddedness perspective, it offers empirical evidence to help finetune smart elderly care policies and agefriendly improvements, and it speaks to a realworld tension, where policy shows strong enthusiasm but the market remains lukewarm.

Keywords: Smart elderly care, Elderly care choice, Difference-in-differences

1. Introduction

China's population is aging rapidly. Smart elderly care has become a major policy priority. Local governments nationwide are investing heavily in demonstration bases. The goal is using technology to fix service gaps. But something isn't working. Even with more policy support and new bases opening constantly, older adults simply aren't adopting these solutions. Expensive devices sit unused. Digital platforms can't get users engaged. This raises an uncomfortable question: can demonstration-based policies actually change how older adults choose their care?

The problem runs deeper than just implementation challenges. Academic research has missed something important. Policy studies mostly look at resource allocation and whether programs work at the aggregate level. They don't show how interventions affect individual decisions. Technology adoption research focuses on individual characteristics but treats older adults as if they make choices without any institutional context. Neither approach explains why policy supply and individual demand don't match up. Neither asks whether demonstration bases really expand choice sets or just add technology to existing options.

This study treats demonstration-based policy as the main explanatory variable. We built a framework connecting policy intervention, cognitive restructuring, and behavioral response. Then

DOI: 10.54254/2753-7048/2026.33311

we tested it using micro-survey data on care choices. The innovation is bringing institutional analysis into care decision-making models. This shows how policy interventions reshape both cognitive frameworks and choice constraints. Using a technology-institutional co-construction perspective helps move beyond the technological determinism versus social constructivism debate. It offers a new way to understand smart elderly care's institutional dilemmas.

Theoretically, this expands care decision-making theory through institutional embeddedness. It bridges macro-policy and micro-behavior research. Practically, the findings support more precise policy adjustments. They identify specific bottlenecks in how policies transmit effects. They point toward making demonstration-based operations more sustainable. The evidence suggests shifting from technology-driven supply toward demand-responsive service delivery.

What follows: Section 2 reviews literature, Section 3 develops hypotheses, Section 4 covers methods, Section 5 presents results, Section 6 concludes.

2. Literature review

In recent years, digital technology has become deeply intertwined with an aging society, more and more researchers have begun to emphasize the importance of smart elderly care, research on the effects of smart elderly care in the existing literature primarily follows two lines of inquiry, first, exploring the multidimensional impact of smart elderly care on the well-being of the elderly, second, analyzing the development of the smart elderly care industry and its driving mechanisms.

Regarding the former, scholars have found that the adoption of smart elderly care services has a positive and beneficial effect on both the physical and mental health of the elderly [1], further research indicates that smart health and elderly care, as a typical practice integrating digital technology with elderly care services, can significantly improve the health status of the elderly population and effectively curb the growth of medical expenses, these effects are primarily transmitted through four dimensions, technological penetration, service integration, environmental adaptation, and cultural drivers [2].

From the perspective of social well-being, the accessibility, applicability, and scalability of smart elderly care at the household level can significantly improve older adults' life satisfaction, the level of digitalization in urban services is positively correlated with older adults' life satisfaction, smart elderly care can enhance well-being by expanding older adults' family, friendship, and social networks [3].

In the consumer sector, internet usage has been shown to significantly stimulate elderly consumption, with mechanisms including improved physical health, the creation of positive life experiences, enhanced social interaction, and increased reliance on smart elderly care [4].

At the same time, research has also revealed the complex dimensions of smart aging, pointing out that smart aging services in the era of artificial intelligence possess the dual characteristics of high convenience and high risk, there are six major risk dimensions, technical security risks, device idling risks, human-machine interaction risks, psychological and emotional risks, regulatory and ethical risks, and social polarization risks, among which the risk level of device idling is particularly prominent [5].

Complementing research on the effects of smart aging is a body of literature focusing on the factors influencing elderly care choices, there is far less consensus about the drivers of elderly care choices, as a critical decision for older adults, elderly care choices are shaped by multiple interrelated factors.

From an institutional perspective, participation in pension insurance effectively influences elderly care choices by altering perceptions of aging and enhancing trust in the government [6].

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From a cultural perspective, residents in rice-growing regions, who are more strongly influenced by collectivism, tend to prefer family-based care, residents in wheat-growing regions, who are less influenced by collectivism, tend to prefer community-based care, the underlying mechanism lies in the fact that collectivism affects individuals' willingness to participate in pension insurance and their level of social trust [7].

From the perspective of individual-environment fit, older adults living in communities with a high degree of facility and service fit exhibit a stronger preference for aging in place, economic resources play a moderating role in this relationship, insufficient assets weaken the positive effect of high fit on the willingness to age in place, high expenditure levels reinforce the preference for institutional care among older adults in communities with low fit [8].

From the perspective of cognitive shifts, older adults' perceptions of caregiving responsibilities present a complex landscape where traditional and modern views intertwine, children providing care remains widely accepted, new care models such as government-provided care, self-care, and a tripartite sharing of caregiving responsibilities are gaining greater recognition, this shift is both a rational choice based on individual circumstances and the result of the combined influence of value-based preferences regarding the distribution of responsibilities [9].

The two lines of research mentioned above have yielded substantial findings regarding the effects of smart aging and the determinants of care choices, respectively, the mechanism between smart elderly care and elderly care choices is still unclear.

Among the few cross-disciplinary studies, some scholars have focused on a specific policy intervention, smart health and elderly care demonstration bases, to evaluate its value-based healthcare effects, they found that the pilot policy significantly improved the health status of the elderly and reduced healthcare expenditures, with more pronounced effects among rural populations, those with lower educational attainment, and elderly individuals with inadequate pension security, highlighting the inclusive nature of smart elderly care [2], this study treated health status as an outcome variable and did not address older adults' care choices.

Another study examined the impact of new-quality productive forces on the development of the smart elderly care industry, finding that such forces significantly promote the industry's growth, with survival-oriented and development-oriented needs playing positive moderating and innovation-guiding roles, respectively, the study also revealed that the coordination mechanism still suffers from supply-demand mismatches, structural consumption contradictions, and scenario failures [10], this implies that there may be a systemic misalignment between policy provision for smart elderly care and the actual needs of the elderly.

A review of the above literature reveals a gap worthy of reflection, existing research confirms the positive effects of smart aging on the health, well-being, and consumption of older adults, it also highlights how their choices regarding elderly care are influenced by multiple factors including institutional, cultural, and environmental factors, there is a scarcity of direct empirical evidence addressing the core question of how smart aging policies actually influence these choices.

This gap directly addresses the paradox highlighted in the introduction, against the backdrop of continuously intensifying smart elderly care policies and the proliferation of demonstration bases, why has the actual adoption of smart elderly care by older adults remained lukewarm, is it because policy interventions have failed to effectively influence older adults' decision-making space, or because the outcome variables selected in existing studies have failed to capture the full picture of policy effects.

This study aims to investigate the effects of smart elderly care on older adults' care choices, by treating smart health and elderly care demonstration-based policies as the core explanatory variable

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and the elderly's care choices as the outcome variable, we establish a direct theoretical link between policy intervention and micro-level behavior, this approach addresses the dual shortcomings of existing literature, which tends to emphasize the effects of smart elderly care while neglecting changes in care choices, and focuses on factors influencing care choices while overlooking the effects of policy intervention, this research framework not only aids in understanding the bottlenecks and disconnects in the transmission of smart elderly care policies but also offers a potential theoretical approach to resolving the practical dilemma of policy enthusiasm versus market indifference.

3. Mechanism analysis and hypothesis formulation

How does smart aging change how older adults choose their care? It starts with information problems. Right now there's a big mismatch between what policies offer and what elderly people actually need. Under traditional care systems, seniors don't know enough about service providers, what kinds of care are out there, or whether prices match quality.

These information gaps make them default to family-based care. Smart aging technologies change this equation. Digital platforms pool care resources together, making it much cheaper and easier to search for and compare options. When information barriers drop, older adults can judge for themselves whether socialized care works for them. Family care becomes less of a default. Other options become real choices.

Then there's the cognitive side. Picking a care model means looking ahead and weighing different options against future needs. That takes real mental effort. But aging typically dulls mental sharpness and information-processing ability. This makes it hard to accept unfamiliar care models. Smart aging technologies push back against this. Using smart devices and online services keeps the brain stimulated. It helps maintain cognitive function. When older adults stay sharp, they can compare alternatives more effectively. They're not locked into default choices anymore.

Social networks matter too. Care decisions don't happen in a vacuum. They're shaped by social interactions and cultural norms. Older adults' traditional networks are mostly family and neighbors. These tight circles tend to reinforce family-based care through shared information and values. Smart aging technologies break these patterns. Care platforms with social features expand network boundaries. They connect older adults with peers using different care models. Exposure to different experiences and attitudes shifts what people see as acceptable care options.

So we propose H1: smart elderly care has a significant positive effect on older adults' care choices. It helps them move beyond default family-based care toward more diversified, socialized models.

4. Variable definition and model selection

4.1. Data sources

This study draws primarily on the China Longitudinal Study of Aging (CLASS) database, organized and implemented by Renmin University of China. The survey features large-scale national coverage of elderly populations combined with longitudinal tracking design. Data collection spans multiple domains: basic personal characteristics, health status and medical service utilization, socioeconomic conditions, care arrangements and social support, psychological and emotional well-being, family structure and intergenerational relationships, plus daily activities and lifestyle patterns. The sample covers 29 provinces, municipalities, and autonomous regions across the country. It has strong

DOI: 10.54254/2753-7048/2026.33311

national representativeness. This study uses data from the CLASS survey. We include four waves: 2014, 2016, 2018, and 2020. We build an unbalanced panel dataset. After excluding samples with missing values for core variables, the final sample includes 39,368 observations. County-level control variables come from several sources. These include the China County Statistical Yearbook, the National Economic and Social Development Bulletins of districts and counties, and microdata from the Sixth National Population Census.

4.2. Model selection

To examine the impact of the Smart Elderly Care Demonstration Base policy on older adults' care choices, we employed a difference-in-differences (DID) regression model, constructing the following regression model (1)

$$y_{it} = \beta_0 + \beta_1 \times DID_{it} + \sum \alpha_k controls_{it} + \lambda_t + \mu_i + \varepsilon_{it} \tag{1}$$

ε_{it} represents the random disturbance term; i and t denote the firm and year, respectively, while controlling for annual fixed effects λ_t and firm-specific fixed effects μ_i ; k denotes the number of control variables; β_0 denotes the constant term; β_1 denotes the coefficient of the independent variable.

4.3. Variable definition

The dependent variable in this study is smart elderly care (oac). It is measured by the implementation of policies in smart health and elderly care demonstration bases.The control variables are: economic development level (economy), measured by per capita GDP; local government fiscal capacity (gov_budget), measured by general public budget expenditure; and household income (revenue), measured by per capita disposable income;and the degree of local population aging (old), measured by the proportion of the population aged 60 and over in the permanent resident population. Individual-level control variables include: age (age), marital status (marriage), household registration type (registration), participation in the urban and rural residents' pension insurance (insurance), and household size (socialize), measured by the number of people living together.

5. Empirical analysis

5.1. Descriptive statistics

Table 1 reports descriptive statistics. The smart elderly care variable (did) has a mean of 0.0378, meaning about 3.78% of individuals in the full sample live in smart elderly care demonstration base policy coverage areas. This figure reflects the policy's phased and gradual rollout nature. Elderly care choice shows a mean of 0.0546—approximately 5.46% of sampled elderly have selected institutional care. Family-based care remains dominant at this stage. Nevertheless, institutional care has reached a level sufficient to examine how policy interventions affect care choices. Control variable statistics align with existing literature findings, indicating the selected sample has good representativeness and validity.

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Table 1. Descriptive statistics

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
did	39,368	0.0378	0.191	0	1
oac	38,623	0.0546	0.227	0	1
economy	38,160	5.761	4.876	0.880	30.31
gov_budget	38,160	711,639	1.300e+06	88,000	8.204e+06
revenue	34,256	26,330	8,389	14,691	57,912
old	36,973	13.55	3.362	1.450	23.61
socialize	39,318	2.924	1.757	0	99
age	39,368	70.33	7.066	57	113
marriage	39,355	0.716	0.451	0	1
registration	39,358	0.536	0.499	0	1
insurance	39,199	0.339	0.473	0	1

5.2. Baseline regression

Table 2 reports the baseline regression results, showing that smart elderly care has a positive effect on older adults' care choices. In Column 1, we include only individual and time fixed effects without any control variables. The did coefficient is 0.038 and is significant at the 1% level, which offers initial support for the policy effect.

After adding control variables in Column 2, the did coefficient drops slightly to 0.035. It remains significant at the 5% level, suggesting that the policy effect holds even when individual characteristics are taken into account. In Column 3, we adjust the standard errors by clustering at the individual level. The did coefficient stays at 0.035, and significance remains at 5%, further supporting the reliability of the results.

The did coefficient of 0.035 also carries meaningful economic implications. With other factors held equal, the policy raises the probability of choosing socialized care by 3.5 percentage points for elderly individuals living in the coverage areas. Given the baseline probability observed in the sample, this increase is economically significant.

The control variables generally perform as expected. Their relationships with care choices are consistent with findings from existing research, indicating that the model is well specified and the estimates are credible. Taken together, these results provide strong support for hypothesis H1.

Table 2. Baseline regression

	(1)	(2)	(3)
VARIABLES	oac	oac	oac
did	0.038***	0.035**	0.035**
	(4.12)	(2.52)	(2.26)
Constant	0.064***	0.277	0.277
	(41.67)	(1.06)	(1.41)
Observations	38,623	28,315	28,315

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Table 2. (continued)

R-squared	0.008	0.011	0.011
Number of ind_id_2020	21,834	17,885	17,885
Controls	NO	YES	YES
ind_id_2020 FE	YES	YES	YES
wave FE	YES	YES	YES
Clustered Standard Errors	NO	NO	YES

t-statistics in parentheses

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

5.3. Parallel trends test

We conducted a parallel trends test revealing that prior to smart elderly care demonstration base policy implementation, treatment and control groups exhibited similar elderly care choice trends with insignificant period-specific coefficients, confirming group comparability before policy intervention and satisfying the parallel trends assumption, thereby providing a reliable foundation for difference-in-differences model identification of causal policy effects.

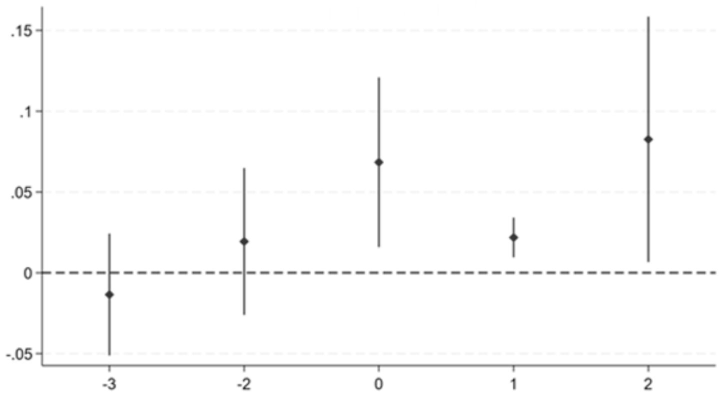

Figure 1. Parallel trends test

5.4. Placebo test

A placebo test helped rule out unobservable factors through random treatment group assignment across 500 simulated regressions generating a distribution of false policy effects where estimated coefficients from random samples clustered around zero while the true baseline regression coefficient of 0.035 fell at the distribution's upper tail with only two simulation results exceeding it, yielding an empirical p-value of 0.004—these results demonstrating the policy's effect on elderly care choices stems neither from omitted variables nor random chance, confirming baseline conclusion robustness.

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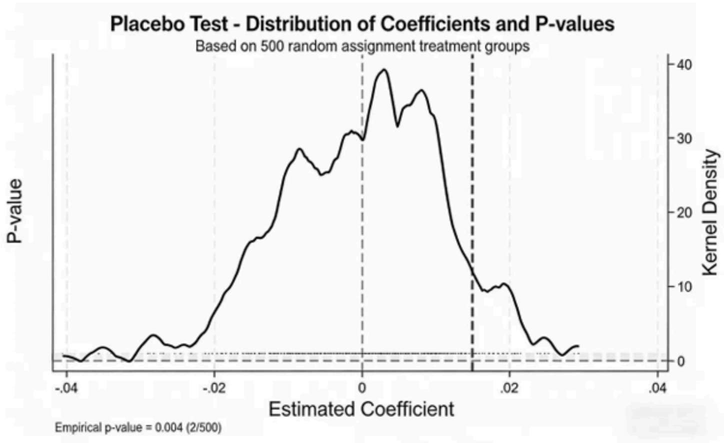

Figure 2. Placebo test

6. Conclusions and recommendations

Using 2014–2020 CLASS panel data, we treat smart elderly care demonstration policies as a quasi-natural experiment and apply a multi-period DID model to study their effects on older adults' care choices. Results show a significant positive impact: those in policy-covered areas are 3.5 percentage points more likely to choose socialized care (a 64% rise from the sample baseline), with robustness confirmed by parallel trend and placebo tests that exclude unobservable or random interference. The policy works via three channels: cutting elderly care information search costs to ease supply-demand frictions, preserving cognitive abilities for rational care assessment, and expanding social network diversity to reshape care choice cognition, driving a shift from traditional family care to diversified socialized models.

There's a huge gap between policy support and actual adoption. Bridging it means shifting focus. Stop pushing technology for technology's sake. Start with what elderly people actually need. Demonstration bases should spend less time showcasing fancy gadgets and more time figuring out real care needs and building feedback loops.

Information platforms can help. A unified regional system that pulls resources together and makes service quality transparent would cut search costs significantly. So would age-friendly product design and basic digital training for older adults. The social aspect matters too. Platforms need spaces where older adults share experiences with different care models. Peer discussions gradually shift perceptions about acceptable options.

This study has limitations. Measuring smart elderly care through policy coverage alone misses actual technology use. We can't see if effects differ between areas with coverage versus actual user engagement. Future work needs data on real usage behavior, not just policy presence. Long-term tracking would help too. Policy effects might fade over time, or strengthen. We don't know. Combining surveys with in-depth interviews could also reveal the psychological mechanisms at play—why some older adults embrace new care models while others resist.

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