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Research article

Does smartphone use encourage farmers to participate in centralized household waste disposal?

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ABSTRACT

The centralization of household waste disposal represents a significant stride toward achieving ecological viability in rural China. This initiative can substantially alleviate the grassroots government's burden of managing rural household waste. The proliferation and utilization of smartphones, a powerful tool that can expedite and reduce the cost of imparting environmental protection knowledge to producers, is a beacon of hope in the fight against waste. This article, utilizing Probit modeling and micro-survey data from 2126 agricultural households in China, examines the effect of smartphone usage on farmers' participation in centralized household waste disposal. The findings indicate that smartphone usage significantly enhances farmers' engagement in centralized domestic waste disposal, motivating them to participate actively. Notably, this finding persists even after robustness tests. Further heterogeneity analyses indicate that older and low-income populations exhibit a more pronounced level of engagement in centralized household waste disposal. This paper presents these findings and underscores the importance of the proposed policies to enhance farmers' consciousness regarding the environmental implications of smartphone usage. These policies are not just suggestions but urgent and necessary steps towards a more technologically advanced and efficient waste management system, and their implementation is crucial for the future of waste management.

1. Introductory

Waste disposal and utilization are critical to the Earth's ecosystem and sustainable human development. These issues are of global concern and are being actively addressed worldwide. The urgency of the global waste crisis is underscored by a World Bank report, which states that global waste increased from 2.01 billion tons in 2016 to 3.4 billion tons in 2018 and is projected to rise by 70 % by2050.[1] The United Nations Environment Program (UNEP), during the 2012 Global Partnership on Waste Management (GPWM) meeting, emphasized that waste is evolving into a global crisis [1]. This crisis is primarily driven by rapid urbanization and population growth [2,3]. The fundamental solution lies in the recycling and efficient disposal of waste. According to the China Bureau of Statistics (CBS), from 2009 to 2022, domestic waste disposal in China showed a steady upward trend, reaching 255.992 million tons by2022.[2]

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[1] Washington, DC: World Bank. http://hdl.handle.net/10986/30317.
[2] This data comes from the China Bureau of Statistics: www.stats.gov.cn.

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Approximately two-thirds of Chinese cities are surrounded by waste, with one-quarter lacking landfill capacity [4,5]. The imbalance between the rapid increase in urban waste and the inadequate growth in waste removal capacity has led to pressing issues such as environmental pollution [6].

In the 21st century, with socio-economic development, rural residents' lifestyles and consumption patterns have gradually changed, and rural environmental problems have become more pronounced [7,8]. This poses a significant barrier to achieving ecological sustainability in rural China. Despite the decreasing rural population due to urbanization, several studies have shown that rural domestic waste production is increasing, exhibiting a notable growth trend [9]. The substantial quantity of domestic waste in rural areas, combined with insufficient waste disposal infrastructure, negatively impacts living conditions and disrupts the balance of the rural ecosystem [10]. The accumulation of household waste detracts from rural communities' aesthetic appeal. It contributes to unsanitary conditions at centralized waste disposal sites, where mosquitoes, flies, and pathogens proliferate, posing health risks to the farming population [11]. However, many rural areas still rely on outdated waste disposal methods, such as unorganized landfills [12]. These rudimentary practices harm the rural ecosystem and adversely affect villagers' sense of well-being and community. Thus, establishing centralized recycling and waste disposal facilities in rural areas is essential for minimizing waste and ensuring environmentally safe disposal. Moreover, it is the foundation for constructing aesthetically pleasing and ecologically sustainable rural communities [13].

China is experiencing rapid digitization across a wide range of sectors and regions [14]. Rural digitization has gradually expanded as part of China's "digital countryside" strategy, with increased internet access and at least one smartphone in each household [15]. This digital transformation has immeasurable effects on farmers' access to information and daily lives. The introduction of China's mandatory waste sorting policy in 2019 to protect the environment has quickly gained attention online [16,17]. Despite clear standards for waste categorization, many urban residents still struggle to differentiate between types of household waste, and this challenge is even more pronounced in rural areas [18]. As a result, inefficiencies in rural waste sorting persist, leading to littering and improper waste disposal [19]. The main cause of this problem is the "information gap [20]," which prevents farmers from receiving timely and accurate information on waste separation. Since smartphones are a crucial channel for disseminating information, exploring their impact on farmers' willingness to centralize household waste disposal is essential. Do smartphones influence farmers' willingness to engage in centralized waste disposal? If so, what are the effects, and is there any heterogeneity among farmers? Therefore, studying the impact of smartphone use on farmers' willingness to centralize domestic waste disposal is essential.

By systematically reviewing policy and research, it becomes clear that the mechanisms through which smartphone use influences farmers' participation in centralized waste disposal, and the potential heterogeneity in these mechanisms require further investigation [21]. This study primarily examines the relationship between smartphone use and farmers' participation in centralized waste disposal, focusing on the extent of its impact on different groups. In addition to facilitating centralized domestic waste disposal in rural areas, this paper makes two key contributions. First, while previous research on waste classification has predominantly focused on the internet, this study examines smartphones, which are more accessible to the general population and more integrated into daily life. This allows for a more explicit analysis of the relationship between smartphone use and farmers' participation in centralized waste disposal. Second, the study systematically explores the heterogeneity of smartphone use, identifying the different behaviors of various groups after adopting smartphones. These findings can be used to develop targeted programs and guidelines for rural waste management, offering practical solutions to the pressing issue of waste disposal in rural areas [22].

This paper is divided into six main sections: the first section is the introduction, the second section is the literature review, the third section is the research background and theoretical framework, the fourth section is the research design, the fifth section is the empirical study, and the sixth section is the conclusion and recommendations.

2. Literature review

In the context of agricultural informatization rising to the level of national top-level design, integrating smartphones into rural public affairs governance represents a convergence of digital technology and rural life [23,24]. Centralized waste disposal, a critical aspect of rural public goods, is vital in rural areas. Effectively managing rural waste is essential for protecting the rural ecological environment. Understanding how smartphone usage influences farmers' perceptions and behaviors regarding centralized waste disposal is critical. Over time, smartphones have gradually induced or mandated institutional changes, altering external conditions and, potentially, farmers' cognition and behavior toward centralized waste management [25,26].

Current academic research primarily focuses on digital or intelligent technologies related to centralized waste disposal, particularly the technology, its implementation, and the resulting social benefits [27–29]. The complexity of waste types and components in rural China necessitates diversifying and integrating treatment technologies. Through intelligent centralized waste disposal terminals, precise classification can be achieved across all stages of waste management, including placement, collection, transportation, and disposal [30,31]. This study focuses on how smartphones contribute to centralized rural waste disposal, proposing three mechanisms: effective monitoring, accurate assessment, and decision-making support shaped by smartphone analysis [32]. However, successfully implementing digital technology for centralized waste disposal requires establishing "technical knowledge within power relations" and "technical knowledge within social relations" [33]. Although previous studies have explored the impact of the Internet on agricultural waste classification, smartphones offer greater convenience, speed, and accessibility. With internet access, farmers can use smartphones to obtain waste classification information anytime, anywhere, facilitating active participation in centralized waste disposal [34,35].

Numerous empirical studies demonstrate that smartphone use promotes farmers' participation in centralized waste disposal. Farmers can access environmental protection information through smartphones [36], enhancing their understanding of environmental issues. The availability of videos, graphics, and other visual content on environmental pollution shared online can inspire farmers to engage in environmental protection efforts [37,38]. Additionally, village administrators encourage farmers to participate in centralized waste disposal in line with national policies. Smartphones enable the dissemination of information, interactive communication, and mobilization, further motivating farmers to engage in waste disposal practices [38,39]. Moreover, smartphones facilitate interpersonal communication, transcending the limitations of time and space and fostering knowledge exchange regarding environmental protection. Social media also encourages farmers to actively participate in waste sorting by presenting environmental role models [18].

Previous literature indicates that smartphones influence farmers' participation in centralized waste disposal through direct and indirect effects. First, smartphones affect how farmers access information, increasing their knowledge and understanding of waste classification policies, thereby directly influencing their waste disposal behaviors. Second, smartphones alter farmers' perceptions, prompting them to promote centralized waste disposal proactively. Overall, smartphone use affects farmers' perceptions and behaviors regarding waste management.

3. Theoretical framework and background

3.1. Theoretical framework

Collective action, public goods, and autonomous governance theories underpin the centralized treatment of rural household waste. Collective action refers to actions taken by a group to pursue common interests [40,41], with the outcome dependent on the interdependence and trust among members. Through polycentric and hierarchical governance systems, opportunities and platforms can be created for individuals with diverse preferences to participate in governance [42,43]. This ensures cooperative provision of public goods through cost-sharing, benefit distribution, and self-governance rules, addressing challenges such as the "tragedy of the commons" and the "difficulty of collective action" [44].

Collective action has proven effective in implementing rural environmental policies, particularly addressing pollution in rural ecosystems [45]. As a rural public good and service, the centralized treatment of rural household waste requires both government intervention and farmer participation, emphasizing the advantages of autonomous governance. Farmers can directly communicate and build trust on more minor spatial scales, facilitating cooperative behaviors that support waste management efforts [46,47].

Public goods provision in rural areas currently follows a "top-down" approach, where decisions are driven by local policymakers rather than farmers' expressed needs [48]. This results in low levels of waste management supply and efficiency. Self-governance theory posits that through proper institutional design and community participation, users or occupants of resources can self-organize for effective governance and sustainable resource use. The government's clear rules for waste separation ensure that farmers understand their responsibilities. Strengthening environmental education and improving farmers' waste-sorting skills will enhance their participation in waste management [49].

In collective action and autonomous governance environments, external and subjective factors drive farmers' behaviors [50]. Rural household waste recycling and centralized treatment depend on internal and external conditions, with external factors being particularly decisive [51]. As rural residents increasingly use smartphones to access ecological knowledge, they learn about the negative consequences of improper waste disposal on the environment and public health [52,53].

Hypothesis 1. Smartphone use promotes farmers' participation in centralized waste disposal.

However, the rural population is highly heterogeneous, with household registration, education, and age variations [54,55]. Studies indicate that smartphone use has a more significant impact on urban residents' active waste disposal. Rural residents show a greater sense of novelty toward smartphones than urban dwellers, making them more influential in rural areas. Rural residents with higher education levels are more likely to use centralized waste disposal. Younger villagers are more open to adopting new technologies, while higher-income villagers can afford more advanced and personalized smartphones.

Hypothesis 2. Smartphone use has a heterogeneous impact on promoting farmers' participation in centralized waste disposal.

3.2. Background

There are significant differences between developed and developing countries regarding household waste management. Developed countries, such as Germany, Japan, and Sweden, typically have more mature and systematic waste management strategies, prioritizing the principles of Reduce, Reuse, and Recycle. These countries implement stringent regulations, community engagement, and incentive systems to ensure waste separation and recycling. In contrast, developing countries face lower waste collection rates and minimal recycling. For example, urban waste collection rates in low-income countries are around 48 %, with only 26 % in rural areas, and a mere 4 % of waste is recycled.

With its growing domestic waste output, China has introduced policies to address rural household waste. These include the "village collection, town transfer, county treatment" model, the National 13th Five-Year Plan for Rural Biogas Development, and the Action Plan for Agricultural and Rural Pollution Control. These initiatives aim to enhance rural waste governance and promote the rural revitalization strategy.

The "three rural areas" development has progressively improved over time, accelerated by reforms. Living and production conditions have become more convenient, and access to socialized ecological services has expanded. Additionally, rapid informatization has led to significant advancements in rural China's information infrastructure, making digital information more accessible. The widespread use of smartphones in rural areas (Fig. 1) has profoundly impacted farmers' values and habits and their access to information and life choices (Chen et al., 2022). This section examines the prevalence of smartphone use among rural residents and assesses how it facilitates the centralized disposal of household refuse in rural areas.

In the context of rural revitalization and the digital village strategy, the number of rural internet users has steadily increased, and rural internet coverage has expanded (Fig. 2) . By June 2022, all administrative villages in China had achieved total "county 5G, village broadband" coverage, with the proportion of villages with optical fiber increasing from less than 70 %–100 % and average download speeds surpassing 100 Mb/s. The internet penetration rate in rural areas was 58.8 %, with 293 million rural internet users. Mobile internet users in rural areas reached 348 million, accounting for 28.5 % of the national total. Despite this, the rural resident population made up 35.3 % of the national population in 2021, suggesting further potential for growth in rural internet users. The gender distribution of rural cell phone users closely mirrors the rural population, with 53.5 % male and 46.5 % female. However, 80 % of rural cell phone users are under 35, and only 7.6 % are over 46, indicating a need to increase smartphone usage among older people. The increasing use of smartphones in rural areas is closing the "digital divide" between urban and rural areas, profoundly affecting the lives of rural residents [56].

In 2000, per capita daily household waste in rural China was 0.48 kg/person-day; by 2020, this had risen to 0.80 kg/person-day. A study by Minsheng Securities reported that the rural domestic waste disposal rate reached 80 % by 2020. However, with rising living standards and increased consumption, rural domestic waste continues to grow. The unorganized disposal of large quantities of waste, often in open spaces, results in significant pollution, land degradation, and disease, affecting environmental health [57–59]. Therefore, centralized treatment of rural household waste has become a critical environmental issue. Establishing a centralized waste classification, collection, and transportation system is essential for sustainable rural development [60].

This paper focuses on how smartphones reshape rural residents' information access and values. Based on field survey data from rural China, it empirically analyzes how smartphone use impacts their willingness to participate in centralized household waste disposal.

4. Research design

4.1. Model setup

Probit or logistic models are typically used when assessing decisions between two variables, mainly when residual terms are relevant in binary choice models [61]. In this study, farmers are presented with two choices regarding the centralized treatment of rural waste: passive or active participation. These choices also represent the farmers' willingness to use smartphones. Given the binary nature of these choices, this study employs a probit model to assess the impact of smartphone use on farmers' participation in waste disposal.

Following the model from, the equation includes an unobservable latent variable, internet usage (the core explanatory variable), control variables, and influence coefficients for each variable. The residual term follows a standard normal distribution. The relationship between the latent variable and the observable behavior of farmers' waste disposal is represented by ordered probabilities, estimated using the maximum likelihood estimation model [62].

$$y_i^* = \beta_0 + \beta_1 internetuse + \sum_{j=2} \beta_j controls_j + \mu_i \tag{1}$$

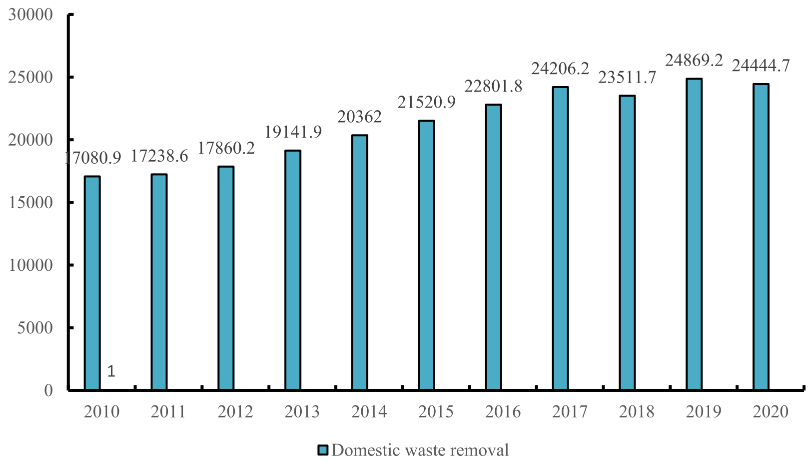

Fig. 1. Volume of domestic waste removal in China, 2010–2022.

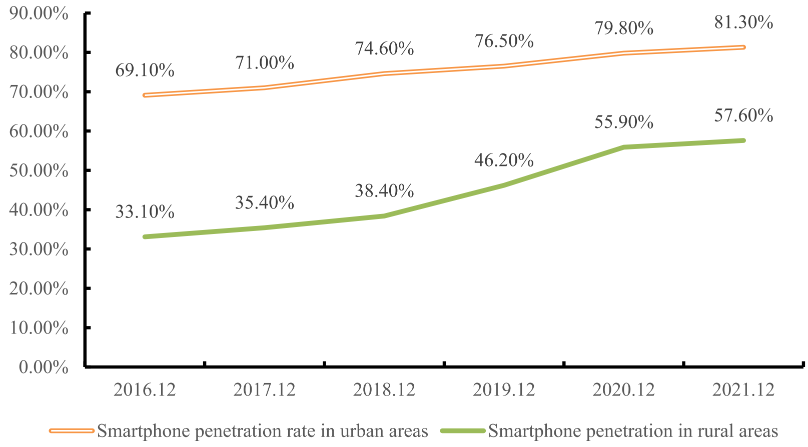

Fig. 2. Smartphone penetration in urban and rural China, 2016–2021.

In the formula, y_i^* it is an unobservable latent variable, a variable of internet use, which is the core explanatory variable of this paper and the control variable. Make conclusions more robust by adding possible control variables. β is the coefficient of influence of each variable, and μ is the residual term of the model, which follows a standard normal distribution. The relationship between the unobservable latent variable y_i^* in the sample and the behavioral variable γ of farmers' centralized household waste disposal is as follows:

$$y = 0, Non - adoption, if\ y^* \leq \gamma_0$$

$$y = 1, adoption, if\ y^* > \gamma_0 \tag{2}$$

γ_0 represent the unknown segmentation points of farmers' participation in centralized rural household waste disposal behavior. Based on this, it can be said that farmers are either involved in centralized rural household waste disposal or not. The probabilities of the two ordered choices are as follows:

$$p(y_i^* = 0|X) = \Phi\left(\gamma_0 - \beta_1 internetuse + \sum j = 2\beta_j controls_j\right)$$

$$p(y_i^* = 1|X) = \Phi\left(\gamma_1 - \beta_1 internetuse + \sum j = 2\beta_j controls_j\right) - \Phi\left(\gamma_0 - \beta_1 internetuse + \sum j = 2\beta_j controls_j\right) \tag{3}$$

In this formula, Φ represents the cumulative density function of the standard normal distribution, and the probit parameters are estimated in this paper using the great likelihood estimation model.

4.2. Data sources

Data for this study comes from a rural governance survey conducted by the Rural Governance Modernization Research Group at Ningbo University between April and July 2020. This nationwide survey covered over 400 villages in 26 provinces, with over 2300 returned questionnaires. The study utilized probability-ratio size sampling (PPS) to select cities, counties, townships, and villages randomly. After data processing, 2126 valid questionnaires were used, providing robust micro-data on rural governance challenges. The research primarily centers on inquiries about rural governance across multiple provinces and regions of China. It encompasses a more extensive selection of cities and provinces and a more substantial and all-encompassing dataset than alternative sources. As a result, it is better equipped to address the existing challenges in rural governance within China and furnish reliable micro-data for examining associated matters.

4.3. Variables and descriptive statistics

Rural households, the primary producers of domestic waste, generate waste of materials like paper, vegetable scraps, and leftovers [63]. In this paper, centralized waste disposal refers to farmers' willingness to participate in waste classification and disposal. If the village or household has the required technology for centralized waste disposal, their participation is rated 1; otherwise, it is rated 0. The core explanatory variable is smartphone usage, which is also binary [64].

Control variables are categorized into four components: personal attributes, operational characteristics, externalities, and geographical attributes. Personal attributes include gender, age, education, party membership, and village cadre status, as these factors influence farmers' awareness of waste management. Operational characteristics consider the importance of farming income, while externalities examine security cameras in villages, which play a role in public safety and management. Geographic attributes account for regional differences, with villages grouped into eastern, central, western, and northeastern regions. These control variables make the model comprehensive and improve its accuracy in assessing waste management behavior. Definitions and assignments for specific variables are shown in Table 1.

5. Empirical analysis

5.1. Basic regression analysis

Table 2 presents the probit regression results for the baseline model (1). Column (1) isolates the impact of smartphone usage on farmers' centralized rural domestic waste disposal, while columns (2) through (5) progressively add variables relating to farmer attributes, operational attributes, externalities, and regional attributes. Robust standard errors are reported for all regressions. The increasing R^2 values from columns (1) to (5) indicate that these variables contribute to explaining farmers' centralization of rural waste disposal. In all models, the coefficient for smartphone usage remains significantly positive, demonstrating that smartphone use substantially influences farmers' participation in centralized waste disposal. Specifically, the coefficient for smartphone usage in column (5) is 0.204 (significant at the 1 % level), indicating that smartphone users are 20.4 % more likely to participate in centralized waste disposal than non-users. These results align with the descriptive statistics in Table 1 and support the hypothesis posited in this paper. Additionally, gender, age, political identity, household economic status, and region significantly influence farmers' waste disposal behaviors.

5.2. Endogeneity test

To address potential endogeneity concerns, the study employs an instrumental variable approach. The variable "Share skills"—whether respondents share learned skills and knowledge via online platforms such as WeChat or Weibo—was used as an instrument for smartphone usage. Respondents who answered, "Never or Occasionally" were assigned a value of 0, while those answering "Often, Frequently, Always" were assigned a value of 1. This variable correlates strongly with smartphone usage but not directly with waste disposal, meeting the requirements for an instrumental variable. The two-stage least squares (2SLS) regression results in Table 3 show that "Share skills" is significantly related to smartphone usage in the first stage, and in the second stage, it positively influences waste disposal behavior, with a coefficient of 1.410 (significant at the 1 % level). This supports the original regression conclusion and addresses potential endogeneity concerns.

Table 1
Descriptive statistics.

Variable	Definition	Mean	SD
Smartphone use	Do you use smart mobile phones? Yes = 1; No = 0	0.792	0.406
Waste Disposal	Is your household waste sorted, collected, and disposed of by the village or town? Yes = 1; No = 0	0.565	0.496
Gender	Female = 0; Male = 1	0.535	0.499
Age in 2020		4.687	1.586
Age1	Under 18 = 1, 18–25 = 2. Yes = 1; No = 0	0.142	0.349
Age2	26~30 = 3, 31–40 = 4. Yes = 1; No = 0	0.249	0.433
Age3	41~50 = 5, 51–60 = 6. Yes = 1; No = 0	0.464	0.499
Age4	Above 60 = 7. Yes = 1; No = 0	0.145	0.352
Degree		2.432	1.084
Degree1	Primary school and below = 1. Yes = 1; No = 0	0.222	0.416
Degree2	Junior high school = 2. Yes = 1; No = 0	0.358	0.480
Degree3	High school/technical secondary school/technical school = 3. Yes = 1. No = 0	0.195	0.396
Degree4	College/undergraduate = 4, Graduate and above = 5. Yes = 1; No = 0	0.225	0.418
Village cadres	Yes = 1; No = 0	0.0588	0.235
Party member	Yes = 1; No = 0	0.163	0.37
Net income	The average net income of your family:	3.655	1.904
Income 1	5000 yuan = 1, RMB 5000–10000 = 2. Yes = 1; No = 0	0.366	0.482
Income 2	11000-15000 = 3. Yes = 1; No = 0	0.124	0.329
Income 3	16000-20000 = 4, 20000–30000 = 5. Yes = 1; No = 0	0.230	0.421
Income 4	Over 30000 = 6. Yes = 1; No = 0	0.281	0.450
Comes from planting	Does the family's main income come from farming? Yes = 1; No = 0	0.17	0.376
Eqs	Satisfaction with local environmental quality: Very dissatisfied = 1; Relatively dissatisfied = 2; General = 3; relatively satisfied = 4; Very satisfied = 5.	3.456	0.864
Security cameras installed	Do you know if there are any cameras in your village？ Yes = 1; No = 0	0.752	0.432
Area east	Yes = 1; No = 0	0.587	0.492
middle	Yes = 1; No = 0	0.265	0.441
west	Yes = 1; No = 0	0.148	0.355

Table 2
Basic regression analysis.

Variable	Dependent variable: Waste Disposal				
	(1)	(2)	(3)	(4)	(5)
Smartphone use	0.342***	0.381***	0.284***	0.246***	0.204**
	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)
Gender		0.027	−0.007	−0.015	−0.034
		(0.06)	(0.06)	(0.06)	(0.06)
Age in 2020 (taking “age1” as reference)					
age2		0.132	0.279***	0.237**	0.211**
		(0.09)	(0.10)	(0.10)	(0.10)
age3		0.222***	0.491***	0.431***	0.338***
		(0.08)	(0.10)	(0.10)	(0.11)
age4		0.199*	0.556***	0.497***	0.319**
		(0.11)	(0.13)	(0.13)	(0.14)
Degree (taking “degree1” as reference)					
degree2			0.274***	0.253***	0.211**
			(0.08)	(0.08)	(0.08)
degree3			0.335***	0.285***	0.222**
			(0.10)	(0.10)	(0.10)
degree4			0.590***	0.480***	0.303***
			(0.11)	(0.11)	(0.12)
Degree (taking “netincome1” as reference)					
netincome2				0.187**	0.131
				(0.09)	(0.09)
netincome3				0.130*	0.034
				(0.07)	(0.08)
netincome4				0.424***	0.247***
				(0.07)	(0.08)
Village cadres					−0.023
					(0.13)
Party member					0.274***
					(0.09)
Comes from planting					−0.139*
					(0.08)
Security cameras installed					0.254***
					(0.07)
Environmental quality satisfaction					0.206***
					(0.03)
Area (taking “West” as reference)					
east					0.301***
					(0.09)
middle					0.109
					(0.09)
_cons	−0.105*	−0.314***	−0.726***	−0.773***	−1.629***
	(0.06)	(0.10)	(0.13)	(0.13)	(0.19)
Pseudo R-squared	0.00894	0.0117	0.0222	0.0343	0.0696
chi2	26.04	34.07	64.55	100.00	202.6
N	2126	2126	2126	2126	2126

Notes: Standard errors in parentheses， ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$*, **, *** indicates the level of significance at the 10 %, 5 %, and 1 % level, respectively; *_cons* represents the constant term, a standard error of zero (or close to it) would indicate that the estimated value is precisely the actual value.

5.3. Robustness check

To verify the robustness of the results, three alternative methods were applied: changes in the measurement of the explanatory variable, explanatory variables, and model specifications. First, an ordinary logit model and ordinary least squares (OLS) were used to examine smartphone usage's effect on centralized rural waste disposal. The results in Table 4 confirm that smartphone usage significantly impacts centralized waste disposal in all models, consistent with the probit model results. The coefficient discrepancies across columns suggest that smartphone usage is more closely related to farmers' personal and business characteristics than externalities or geographic factors.

Next, robustness was checked by substituting the explanatory variable with “whether your household waste is classified.” The results in Table 5 confirm that smartphone usage positively influences waste disposal, consistent across probit, logit, and OLS models.

Additionally, replacing the explanatory variable “smartphone usage” with “whether your home has installed the internet” (with values of 1 for yes and 0 for no) shows that internet installation significantly affects farmers' centralized waste management. Table 6 presents this data, confirming that internet installation and waste classification positively impact smartphone usage and reaffirming the baseline findings.

Table 3
Two-stage instrumental variables test.

Variable	First Stage Second Stage	
	Smartphone use	Waste Disposal
	(1)	(2)
Share skills	0.186 ***	1.410***
	(0.00)	(0.00)
Control variables	No	No
Regional dummy variables	No	No
_cons	0.7004 ***	0.610 ***
	(0.012)	(0.001)
Adj R^2	0.05	
F	117.97	
N	2126	2126

Notes: Standard errors in parentheses , ***p < 0.01, **p < 0.05, *p < 0.1*, **, *** indicates the level of significance at the 10 %, 5 %, and 1 % level, respectively; *_cons* represents the constant term, a standard error of zero (or close to it) would indicate that the estimated value is precisely the actual value.

Table 4
Replacement of explanatory variables.

Variable	Dependent variable: Waste Disposal			
	(1) Logit	(2) Logit	(3) OLS	(4) OLS
Smartphone use	0.547***	0.335***	0.136***	0.077***
	(0.11)	(0.13)	(0.03)	(0.03)
Control variables	No	Yes	No	Yes
Regional dummy variables	No	Yes	No	Yes
R^2			0.01	0.09
Pseudo R-squared	0.00894	0.0696		
chi2	26.04	202.6		
N	2126	2126	2126	2126

Notes: Standard errors in parentheses , ***p < 0.01, **p < 0.05, *p < 0.1*, **, *** indicates the level of significance at the 10 %, 5 %, and 1 % level, respectively; *_cons* represents the constant term, a standard error of zero (or close to it) would indicate that the estimated value is precisely the actual value.

Table 5
Alternative explanatory variables.

Variable	Dependent variable: Waste Disposal					
	(1) Probit	(2) Probit	(3) Logit	(4) Logit	(5) OLS	(6) OLS
Smartphone use	0.603***	0.395***	0.980***	0.646***	0.225***	0.132***
	(0.07)	(0.09)	(0.12)	(0.14)	(0.03)	(0.03)
Control variables	No	Yes	No	Yes	No	Yes
Regional dummy variables	No	Yes	No	Yes	No	Yes
R^2					0.03	0.16
Pseudo R-squared	0.0257	0.128	0.0257	0.128		
chi2	75.04	373.8	75.04	374.2		
N	2126	2126	2126	2126	2126	2126

Notes: Standard errors in parentheses , ***p < 0.01, **p < 0.05, *p < 0.1*, **, *** indicates the level of significance at the 10 %, 5 %, and 1 % level, respectively; *_cons* represents the constant term, a standard error of zero (or close to it) would indicate that the estimated value is precisely the actual value.

5.4. Heterogeneity test

As smartphone use becomes more prevalent in rural areas, digital technologies are expected to facilitate rural ecosystem governance, improving waste disposal participation. This study examines individual villager-level heterogeneity, dividing farmers into age groups based on smartphone use [65]. Regression results in Table 7 show that smartphone usage significantly affects waste disposal behavior, particularly for individuals aged 40 and older. For the 40 to 60 age group, smartphone usage increases the log odds of waste sorting by 0.470, with an odds ratio of 1.60, meaning smartphone users are 1.60 times more likely to engage in waste sorting than non-users. Similarly, for individuals over 60, smartphone users are 1.37 times more likely to sort waste. These results indicate that smartphone use reduces knowledge gaps and enhances ecological behavior in older farmers.

An analysis of income structure, presented in Table 8, reveals that smartphone use significantly influences waste disposal

Table 6
Alternative explanatory variables.

Variable	Dependent variable: Waste Disposal					
	(1) Probit	(2) Probit	(3) Logit	(4) Logit	(5) OLS	(6) OLS
Internet cable	0.477***	0.292***	0.763***	0.470***	0.189***	0.109***
	(0.08)	(0.08)	(0.12)	(0.14)	(0.03)	(0.03)
Control variables	No	Yes	No	Yes	No	Yes
Regional dummy variables	No	Yes	No	Yes	No	Yes
R^2					0.02	0.09
Pseudo R-squared	0.0140	0.0716	0.0140	0.0715		
chi2	40.89	208.3	40.89	208.1		
N	2126	2126	2126	2126	2126	2126

Notes: Standard errors in parentheses，***p < 0.01, **p < 0.05, *p < 0.1*, **, *** indicates the level of significance at the 10 %, 5 %, and 1 % level, respectively; *_cons* represents the constant term, a standard error of zero (or close to it) would indicate that the estimated value is precisely the actual value.

Table 7
Heterogeneity 1, selection based on different age structures.

Variable	Dependent variable: Waste Disposal			
	(1) age≤25	(2) 25 <age≤40	(3) 40<age≤60	(4) age >60
Smartphone use	0.302	0.163	0.470***	0.318**
	(0.28)	(0.21)	(0.10)	(0.15)
Control variables	No	No	No	No
Regional dummy variables	No	No	No	No
_cons	−0.105*	−0.314***	−0.726***	−0.773***
	(0.06)	(0.10)	(0.13)	(0.13)
Pseudo R-squared	0.00280	0.000804	0.0164	0.0109
chi2	1.169	0.582	21.86	4.646
N	302	530	986	308

Notes: Standard errors in parentheses，***p < 0.01, **p < 0.05, *p < 0.1*, **, *** indicates the level of significance at the 10 %, 5 %, and 1 % level, respectively; *_cons* represents the constant term, a standard error of zero (or close to it) would indicate that the estimated value is precisely the actual value.

participation among rural residents with incomes below 15,000 yuan. This group, primarily engaged in agriculture, understands the ecological environment's importance and benefits from the spillover effects of digital technology. As a result, low-income farmers are more inclined to use smartphones for centralized waste disposal.

These findings demonstrate that digital technology reduces gaps caused by individual differences and motivates farmers to participate in waste management, supporting the rural digital governance agenda.

6. Conclusions and recommendations

6.1. Conclusions

The centralized management of household waste is crucial for achieving ecological sustainability in rural areas and improving the rural environment. As waste generators, rural residents directly benefit from effective waste disposal. Their willingness to participate in centralized waste classification is linked to broader governance and rural revitalization efforts. This study analyzed 2162 questionnaires from villagers surveyed by the Rural Governance Modernization Group of Ningbo University in 2021, using a probit model to assess the relationship between smartphone use and waste disposal behavior.

The results indicate that rural residents who use smartphones are 3.42 % more likely to engage in centralized waste disposal than non-users. This relationship remains significant even after robustness tests, supporting the hypothesis that smartphone usage positively influences waste management behavior. Age, income, and education levels also positively affect rural residents' willingness to engage in waste management.

Heterogeneity tests further reveal that wealthier and more educated villagers are more environmentally conscious and diligent in waste categorization.

6.2. Recommendations

Based on the findings, the following policy recommendations are proposed: First, governments should prioritize the role of smartphones in raising environmental awareness among rural residents when promoting digital technologies for environmental governance. Network administrators should also guide internet users toward responsible online behavior. Additionally, local

Table 8
Heterogeneity 2, choices based on different income structures.

Variable	Dependent variable: Waste Disposal			
	(1) Inc≤10000	(2) 10000 < Inc≤15000	(3) 15000< Inc≤30000	(4) Inc >30000
Smartphone use	0.287***	0.702***	0.087	0.242
	(0.10)	(0.21)	(0.14)	(0.15)
Control variables	No	No	No	No
Regional dummy variables	No	No	No	No
_cons	−0.251***	−0.391**	0.065	0.260*
	(0.09)	(0.19)	(0.13)	(0.14)
Pseudo R-squared	0.00764	0.0323	0.000551	0.00325
chi2	8.231	11.60	0.370	2.435
N	777	263	488	598

Notes: Standard errors in parentheses，***p < 0.01, **p < 0.05, *p < 0.1*, **, *** indicates the level of significance at the 10 %, 5 %, and 1 % level, respectively; *_cons* represents the constant term, a standard error of zero (or close to it) would indicate that the estimated value is precisely the actual value.

governments must address ecological risks in rural areas, which directly impact livelihoods in the digital age. Increased investment in education is also crucial to improving smartphone skills among rural residents, particularly older people, indirectly enhancing participation in waste disposal.

Two limitations of this study should be noted. First, it only examined smartphone usage without considering other digital technologies, such as big data or information communication technologies, which may also impact waste management behavior. Second, it did not explore the behavioral mechanisms underlying waste disposal participation. Future research should address these gaps by incorporating additional technologies and analyzing the mechanisms influencing farmers' waste disposal behavior.

CRediT authorship contribution statement

Zhongan Wu: Writing – original draft, Data curation, Conceptualization. **Toba Stephen Olasehinde:** Writing – review & editing, Investigation. **Fan Chen:** Writing – review & editing, Supervision, Project administration, Formal analysis, Conceptualization.

Data availability statement

All data generated or analyzed during this study are included in this published article.

Institutional Review Board statement

The study was conducted in accordance with the Declaration of Helsinki and approved by the Institutional Review Board of China Rural Policy and Practice Research Institute of Ningbo University (protocol code 20,200,005).Informed consent statement

Informed consent was obtained from all subjects involved in the study.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Reports a relationship with that includes: Has patent pending to. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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