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The Role of Internet and Social Interactions in Advancing Waste Sorting Behaviors in Rural Communities

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Abstract: Addressing the global challenge of sustainable waste management, this research investigates the influence of social dynamics and digital connectivity on rural residents' willingness to adopt waste classification practices, essential for sustainable environmental management. Through a comprehensive analysis of 5413 rural participants surveyed in the China Labor-force Dynamic Survey (CLDS), this study employs a novel mixed-methods approach. It integrates quantitative analysis with the Manski social interaction framework and a Recursive Bivariate Probit model to explore the intricate interplay between community interactions, internet access, and environmental behaviors. Our methodology stands out for its unique combination of social theory and econometric modeling to address a pressing environmental issue. Results highlight a significant effect of mobile internet use and social interactions within communities on enhancing willingness towards waste classification. Notably, digital connectivity emerges as a key facilitator of environmental engagement, mediating social influences, and fostering a collective approach to waste management. Considering these insights, we propose targeted policy interventions that blend digital strategies with traditional community engagement efforts. Recommendations include crafting digital literacy programs and leveraging social media to bolster community-centric environmental governance. By harnessing the synergistic potential of digital tools and social dynamics, these strategies aim to elevate the effectiveness of waste classification initiatives in rural China, offering a scalable model for environmental sustainability.

Keywords: social interaction; internet usage; rural waste classification; mobile internet; environmental governance

Citation: Wang, X.; Bravo, L.M.R.; Cosio Borda, R.F.; Quispe, L.A.M.; Rodríguez, J.A.P.; Ober, J.; Ahmed, N.; Khan, N.A. The Role of Internet and Social Interactions in Advancing Waste Sorting Behaviors in Rural Communities. *Resources* **2024**, *13*, 57. https://doi.org/10.3390/resources13040057

Academic Editors: Carlo Ingrao, Alberto Bezama, Annarita Paiano, Jakob Hildebrandt and Claudia Arcidiacono

Received: 14 February 2024
Revised: 30 March 2024
Accepted: 8 April 2024
Published: 9 April 2024

1. Introduction

Waste classification has emerged as a vital conduit for waste minimization, resource optimization, and environmental harm reduction. Currently, urban waste classification in China is progressing in an orderly manner, whereas rural areas are still in the exploratory stage of small-scale trials. Against the backdrop of a comprehensive victory in poverty alleviation and a shift in focus towards rural revitalization, accelerating the classification and management of rural household waste is crucial. This approach not only mitigates the adverse effects of waste on land occupation, soil contamination, water and air pollution, and residents' health but is also pivotal in constructing an ecologically habitable rural

environment. It represents a significant practice in implementing the rural revitalization strategy. It is crucial for enhancing the quality of the living environment and realizing people's aspirations for a better life [1,2].

Effective governance in rural areas has increasingly captured scholarly and governmental interests. Central to this is the multiparty governance model, which is spearheaded by the government and has garnered widespread scholarly endorsement [3,4]. This model synergistically incorporates social capital to tackle environmental challenges and is bolstered by cooperative strategies, such as government-led partnerships with private entities (PPP), to enhance administrative efficacy [5,6]. However, this model has shortcomings in rural applications, where a lack of active farmer participation often results in collective inaction [7,8]. In response, the concept of 'endogenous governance' has gained traction, promoting the empowerment of farmers as catalysts for environmental stewardship [9,10]. This approach is anticipated to evolve into a symbiotic governance model, where diversified stakeholders, shared responsibilities, and mutual benefits steer rural environmental management toward new horizons [11,12].

Rural autonomous governance, leveraging the unique strengths of local organizations in accessing information and self-regulation, has emerged as a promising avenue for realizing the vision of 'beautiful villages' [13,14]. The 'acquaintance society' inherent to rural areas, with its web of social relationships, underpins these governance strategies, with social trust and networked norms offering fresh paths for community mobilization [15,16]. Furthermore, the advent of the Internet has dramatically reshaped the landscape of traditional governance, infusing new life into social infrastructure and opening up channels for innovative governance approaches [17,18]. This technological infusion has been particularly impactful in poverty alleviation efforts where self-media networks and blockchain technology have offered novel solutions to longstanding challenges [19–21].

Moreover, internet technologies have effectively supported the development of rural residents' education, health, and social capital [22,23]. In the field of environmental governance, the "Internet + Recycling" model, centered around IoT technology, is becoming an important approach for developing China's recycling system [24,25]. In more developed rural areas, Internet-based monitoring systems have achieved precise regulation of the entire process of rural waste classification, collection, utilization, and disposal [26].

The academic community has reached a consensus on the effectiveness of a multiparty governance model under government leadership for rural environmental management. The challenge lies in how to mobilize the active participation of rural residents to enhance the governance efficiency or effectiveness of this model. The integration of internet technology into rural governance offers a novel tool. It means, demonstrating positive effects from the perspectives of both the governors and the impoverished groups in poverty governance. However, existing literature still shows limitations: (1) Although current studies have focused on social networks as a social foundation for rural environmental governance, they have not fully explained how to advance rural environmental management through social interactions, and few studies have explored the issue of rural residents' waste classification willingness or behavior from a social interaction perspective; (2) The integration of the internet in environmental or waste classification governance is mostly limited to the perspective of the governors, such as using technology for monitoring waste classification, transportation, and utilization, without fully considering the impact of the internet as a medium on individual rural residents, nor the effects of internet integration on the existing social interaction fields in rural areas.

Drawing on existing literature, this paper endeavors to examine the issue from the perspective of rural residents. Firstly, it employs a recursive bivariate Probit model to assess the influence of internet usage on rural residents' inclination towards waste classification. This involves an exploration of how the internet medium affects the willingness to engage in waste classification within the social interaction domain and an analysis of how various modes of internet connectivity differ in their impact on this willingness. Secondly, by applying the Manski interaction effects model and taking into account endogenous interac-

tion effects, contextual effects, and correlative effects, this study probes the role of social interaction in shaping rural residents' willingness to participate in waste classification.

2. Theoretical Analysis and Research Hypotheses

The concept underlying social interaction suggests that the dynamics and activities within a group are influenced by each other in a mutually dependent manner. Within a group, the intentions or behaviors of one individual can affect those of others, which in turn may influence individual intentions or behaviors, thereby contributing to the collective intentions or actions of the group. Manski [27] suggests that the identification strategy for interaction effects should elucidate the social interaction effects through three dimensions: endogenous interaction effects, contextual effects, and correlative effects. Endogenous interaction effects refer to the bidirectional interaction, whereby expectations formed by the group about an individual, and the individual's perceptions of the group, create a reciprocal interaction between the group and the individual. Therefore, from the perspective of such endogenous interaction effects, these could influence the residents' intentions to classify household waste in accordance with group intentions as well as affect the individual's perception of these intentions through the formation of expectations about the individual. The interplay of these factors culminates in the individual's intention to classify household waste. Most significantly, endogenous interaction effects are pivotal and should be emphasized in investigations of the impact of social interaction on rural residents' willingness to classify household waste [28–30].

Contextual effects exemplify unidirectional shaping, whereby the intentions or behaviors of a group determine those of an individual through normative constraints, leading to passive adaptation by the individual. Consequently, the collective will of the group exerts a decisive influence on individual members' intentions regarding waste sorting in this social environment [31]. Therefore, correlative effects highlight the influence of individual and family characteristics on the person, leading to shared changes in intentions or behaviors within groups due to both group dynamics and individual traits [32]. In essence, individual and family characteristics are aligned concerning the intention to engage in household waste sorting. Based on this, the following hypothesis is proposed:

Hypothesis H1: *The willingness of rural residents to classify household waste has a social interaction effect, with the community group's intentions to classify waste significantly influencing an individual's waste classification intentions.*

The impact that the internet has on rural residents' willingness mainly contains two aspects. First, it is the use of the internet in governance, which may offer technological empowerment to improve governance. "Internet +" plays a positive role in various processes of environmental governance and waste classification, including execution [26], supervision [33], and publicity. The internet helps, through effective policy diffusion, in forming public awareness for the protection of environmental concerns. Secondly, the internet significantly impacts individual cognition and behavior [34,35]. Unlike the mass media, new media on the internet creates a new "virtual field of interaction," through which rural residents can get in contact with urban residents, receive news, and become informed about the dynamics of classified household waste progress in urban areas through text, pictures, and video provided by many media.

Advanced concepts of urban environmental protection can transcend spatiotemporal boundaries and reach rural areas. The decentralized interactive function of the internet further highlights the agency of waste classification executors, with the development of the internet making new media one of the main mediums people rely upon. Media usage positively influences people's waste classification behavior [36]. Hence, internet-based new media mobilizes the intrinsic motivation of rural residents, promoting the formation of their willingness to classify waste. Therefore, the following hypothesis is proposed:

Hypothesis H2: *Internet usage promotes the formation of waste classification willingness among rural residents.*

Reference group theory suggests that individuals base their social and value judgments on the norms and standards of their reference groups [37]. Reference groups provide normative functions, set certain behavioral standards, and offer comparative standards for evaluating oneself or others [38]. Considering China's historical development, the dual development of urban and rural areas has led to rural areas lagging behind cities in terms of their economic and social aspects. Rural society, relatively isolated, was described by Fei Xiaotong [39] in the 1940s as a "familiar society" of neighbors. With the integration of urban and rural development, rural society has gradually become a "semi-familiar society" [40]. However, there is still room for improvement in the state of urban-rural division [41–43]. The widespread use of the internet breaks the spatiotemporal constraints, disrupting the traditional neighborhood community groups as reference groups. Therefore, internet usage plays a role in the process of social interaction, affecting individual intentions or behaviors. The internet partially "replaces" the influence of community group intentions (or behaviors) on individual intentions (or behaviors), meaning the internet weakens the endogenous interaction effect of rural residents' waste classification willingness. Thus, the following hypothesis is proposed:

Hypothesis H3: *While weakening the positive influence of group waste classification intentions on individual waste classification intentions, internet usage also promotes individual waste classification.*

3. Materials and Methods

3.1. Data Source

The data for this study is derived from the China Labor-Force Dynamic Survey (CLDS) conducted by Sun Yat-sen University. This survey, carried out every two years, tracks urban and rural communities and creates a comprehensive database focused on the labor force. It includes longitudinal and cross-sectional data at the individual, family, and community levels, providing high-quality foundational data for empirical theory and policy research. Considering the implementation time of waste classification in China and the availability of database variables, CLDS2016 data are used for empirical analysis. Individual and family-level data are merged using the Python programming language. After variable selection is missing and outlier value treatments are performed, a new dataset is formed. This dataset includes 13 provinces (cities and districts), 112 communities, and 5413 rural resident individual samples.

3.2. Variable Settings and Basic Descriptive Statistics

Table 1 presents the parameters used, their interpretations, and preliminary statistical analyses. The dependent variable is the willingness to classify waste. The mean indicates that most rural residents are willing to classify waste, suggesting potential for advancing rural waste classification work. The core explanatory variable is internet usage. With the development of mobile internet, the prevalence of internet in rural areas is high; about 47.6% of rural residents can connect to the internet via computers or mobile devices. Control variables include individual and family characteristics such as age, gender, years of education, health status, nature of work, personal income, marital status, and family size, as detailed in Table 1. Furthermore, based on the National Bureau of Statistics' division method for the eastern and northeastern regions of China, 13 provinces (cities, districts) of China are divided into these two regions. To control the impact of omitted variables and regional differences on model estimates, one dummy variable is set for whether it is in the eastern region, using the northeastern region as the reference.

Table 1. Descriptive statistics of the variables.

Variable (N = 5413)	Mode Value	Definition	Mean	Standard Deviation
Willingness to Classify Waste	Yes (3904)	Binary outcome, 1 = yes, 0 = no	0.721	0.359
Internet Usage	Yes (2577)	Binary variable, 1 = used, 0 = not used	0.476	0.449
Age	42	Continuous variable, years	43.214	11.868
Gender	Female (2608)	Binary variable, 1 = female, 0 = male	0.482	0.449
Years of Education	8	Continuous variable, years of schooling	6.531	3.413
Health Status	2	Ordinal variable, 1 = poor, 5 = excellent	2.219	0.904
Employment Nature	Employed (113)	Binary outcome, 1 = employed, 0 = not employed	0.021	0.136
Household Size	5	Continuous variable, number of people	7.921	2.389
Marital Status	Married (4400)	Binary outcome, 1 = married, 0 = not married	0.813	0.267
Regional Control Variable				
Eastern		Binary variable, 1 = east, 0 = not east	0.363	0.442

3.3. Econometric Strategy

3.3.1. Manski Interaction Effects Model

In the exploration of social dynamics influencing waste classification in rural communities, we employ the Manski Interaction Effects Model as a foundational analytical framework. This model is particularly suited to dissect the intricate social fabric of rural Chinese communities, highlighting how individual and collective environmental behaviors are shaped by the nuanced interplay of social interactions. As elucidated, the model divides social interaction effects into three distinct categories: endogenous, contextual, and correlative effects, each offering insights into different facets of social influence on waste classification intentions. Through this comprehensive approach, we directly address Hypothesis H1, positing that social interactions within communities significantly impact individuals' willingness to engage in waste classification practices. Following the requirements of Manski's social interaction effect identification strategy mentioned in the theoretical analysis, different variables of the three dimensions—endogenous interaction effects, contextual effects, and correlative effects—are included in the model. The specific equation form is shown in Equation (1):

$$y_i = \beta_0 + \beta_1 y^{a}_{-i} + \beta_{2k} x_{ik} + \beta_{3k} x^{a}_{-ik} + \beta_{4n} x_{in} + \xi_1 \quad (1)$$

In this equation, y_i represents the waste classification intention of an individual, $i = 1, 2, 3, \ldots, 5413$, y^{a}_{-i} represents the average waste classification intention of other residents in the same community as i, excluding i themselves, which corresponds to the endogenous interaction effect. The variable x_{ik} denotes the k individual and family characteristics of individual i representing the correlative effect, where $k = 1, 2, \cdots, 8$. The term x^{a}_{-ik} stands for the average of the individual and family characteristics of other residents in the same community as I, excluding i themselves, indicating the contextual effect. To reduce bias in model estimation, the model includes x_{in} as the n regional control variable, where $n = 1, 2, 3$. The parameters β_0, β_1, β_{2k}, β_{3k}, β_{4n} are to be estimated within the model. Lastly, ξ_1 represents the error term.

3.3.2. Recursive Bivariate Probit Model (RBP)

The Recursive Bivariate Probit Model (RBP) is deployed to meticulously assess Hypothesis H2, which conjectures that internet usage markedly bolsters rural residents' inclination towards waste classification. This econometric approach is adept at mitigating potential biases stemming from the non-random nature of internet adoption behaviors among individuals. By employing the RBP model, we seek to distill the pure effect of digital connectivity on environmental stewardship, thereby providing a nuanced understanding of how internet access influences waste management practices in rural settings.

Considering that internet usage is a self-selected rather than a random behavior and may be subject to self-selection bias, the use of ordinary binary variable regression models would yield biased estimates. To examine the effects of binary independent variables on binary outcomes, we employ a Recursive Bivariate Probit Model (RBP). The model equation is set as shown in Formula (2):

$$\begin{cases} \text{Inter}_i = \alpha_0 + \alpha_1 Z_i + \alpha_{2k} x_{ik} + \alpha_{3n} x_{in} + \xi_2 \\ y_i = \mu_0 + \mu_1 \text{Inter}_i + \mu_{2k} x_{ik} + \mu_{3n} x_{in} + \xi_3 \end{cases} \quad (2)$$

where Inter i represents whether a resident i uses the internet; Z_i represents the average Internet usage of other residents in the same community, excluding resident i, with the community as the reference group; $\alpha_0, \alpha_1, \alpha_2^k, \alpha_3^n, \mu_0, \mu_1, \mu_2^k, \mu_3^n$ are parameters to be estimated; ξ_2, ξ_3 are error terms.

4. Results and Discussion

4.1. Testing the Social Interaction Effect of Rural Residents' Willingness to Classify Waste

Table 2 reports the test results of the social interaction effect on rural residents' willingness to classify waste based on the Manski model. According to the test results of the Manski model, the endogenous interaction effect of rural residents' waste classification willingness is significant ($p < 0.01$). A 1-unit increase in the average waste classification intention of the community group increases the probability of an individual's participation in waste classification by 67.8%. This confirms the significant positive impact of the group's waste classification intentions and individual's perceptions of the group's intentions on individual waste classification willingness.

Table 2. Evaluation of Social Interaction's Effect on the Propensity for Household Waste Sorting Among Rural Residents via the Manski Framework.

	Variables	Manski Model Coefficient		Marginal Effects Model	
		Coefficient	Standard Error	Coefficient	Standard Error
Endogenous Interaction Effect	Average willingness to classify	2.940 **	0.086 **	0.678 **	0.017 **
Correlative Effect	Age	−0.0045 **	0.0018 **	−0.0009 **	0.000 **
	Gender	−0.0333 **	0.0315 **	−0.0081 **	0.0072 **
	Years of Education	0.018 **	0.0045 **	0.0045 **	0.0009 **
	Health Status	0.0045 **	0.0153 **	0.0009 **	0.0036 **
	Nature of Work	0.1854 **	0.1143 **	0.0432 **	0.0261 **
	Personal Income	0.0126 **	0.0054 **	0.0027 **	0.0009 **
	Marital Status	0.0999 **	0.0504 **	0.0234 **	0.0117 **
	Family Size	−0.0009 **	0.0081 **	−0.000 **	0.0018 **
Contextual Effect	Average Age	0.0081 **	0.0045 **	0.0018 **	0.0009 **
	Average Education	−0.0306 **	0.0144 **	−0.0072 **	0.0036 **
	Average Gender	−0.2592 **	0.252 **	−0.0594 **	0.0585 **
	Average Income	−0.0288 **	0.018 **	−0.0063 **	0.0045 **
	Average Family Size	−0.0054 **	0.0171 **	−0.0009 **	0.0036 **
	Average Health	−0.1467 **	0.0522 **	−0.0342 **	0.0117 **
	Average Marital Status	−0.2718 **	0.2502 **	−0.063 **	0.0576 **
	Average Nature of Work	0.6579 **	0.7704 **	0.1512 **	0.1773 **
Regional Control Variables	Eastern	−0.0099 **	0.0693 **	−0.0018 **	0.0162 **
Observations	Observations	5413			

Note: ** indicates significance at the 5% statistical level.

From the perspective of correlative effects, age has a significant negative impact on waste classification willingness ($p < 0.01$), with each additional year of age reducing the willingness to classify waste by 0.089%. Education level has a significant positive impact ($p < 0.01$), with each additional year of education increasing waste classification willingness by 0.045%. This aligns with the academic consensus that higher education levels positively influence public environmental behavior [44]. Personal income also has a significant positive impact ($p < 0.05$), suggesting that higher income levels facilitate the formation of

environmental awareness and behaviors [45]. Families in a sustained marital state exhibit a more significant willingness to classify waste ($p < 0.05$), 2.3% higher than families not in such a state, indicating that stable families are more sensitive to environmental issues caused by household waste.

In summary, these findings validate that individual, family, and environmental characteristics collectively cause common changes in the waste classification intentions of individuals within a group. In terms of contextual effects, the average age of the group has a significant positive impact on individual waste classification willingness ($p < 0.1$). The elderly members of the rural acquaintance society exert some normative influence on the younger group. However, this group, due to historical and generational reasons and lower education levels, has a lesser willingness to adopt environmental consciousness, leading to a significant negative impact of increased group education years on individual waste classification willingness ($p < 0.05$). Considering the lower prevalence of preventive medicine in rural areas and the reduced sensitivity to health issues caused by environmental degradation, a decline in the average health level of the group does not significantly positively impact individual environmental consciousness. Overall, in terms of social interaction effects, whether it is the focal endogenous inter-action effects or the contextual and correlative effects, all have an impact on individual waste classification willingness at different levels of significance. Hypothesis H1 is thus verified.

4.2. The Impact of Internet Usage on Rural Residents' Willingness to Classify Waste

Table 3 reports the test results regarding the impact of internet usage on the willingness of rural residents to classify waste. Model group 1, using the Probit model, indicates that internet usage has a significant positive effect on the waste classification willingness of rural residents ($p < 0.01$). Rural residents who use the internet demonstrate a 6.2% higher willingness to classify waste compared to those who do not use the internet, confirming that internet usage, empowered by new media, promotes the formation of waste classification willingness among rural residents. However, whether residents use the internet is not a random variable; individual characteristics and family features influence it. Failing to consider the self-selection bias of internet usage can impact the model's estimated results. To test the robustness of the impact of internet usage on rural residents' waste classification, a Recursive Bivariate Probit (RBP) model is constructed. Model group 2 reports these test results. Treating internet usage as the dependent variable and following the tool variable settings of Zuo Xiaofan et al. [46] and Guan Rui et al. [47], the internet usage of the group, excluding the individual, is chosen as the instrumental variable. The group's internet usage behavior directly influences individual internet usage without directly affecting residents' waste classification willingness, meeting the exclusivity constraint principle for selecting instrumental variables. Incorporating the average internet usage of the group into the first-stage regression equation, the model test results indicate that individual characteristics and family features have varying degrees of influence on whether rural residents use the internet. In contrast, the group's internet usage has a significant positive effect on individual internet usage.

Our application of the Recursive Bivariate Probit Model (RBP) reveals compelling evidence supporting Hypothesis H2. This model explains the positive, essential impact of internet use on the willingness of rural dwellers to engage in waste sorting activities. Thus, it points out that one of the main factors realized by digital connection should be counted on to promote environmental behavior. The findings confirm the hypothesized relationship between higher access to the internet and greater scope for environmental action, specifically in both physical space and digital strategies that need to be integrated into rural waste management policies to leverage the transformation potential internet connectivity offers. This study delves into the demographic impacts on willingness to classify waste, where age is a slight deterrent.

Table 3. Assessment of Internet Utilization's Influence on Rural Inhabitants' Tendency to Classify Domestic Waste.

Variables	Model 1: Probit		Model 2: RBP		
	Categorical Willingness	Marginal Effects	Internet Usage	Categorical Willingness	Marginal Effects
Internet Usage	0.231 ***	0.062 ***		0.416 ***	0.059 ***
	(0.027)	(0.007)		(0.009)	−0.007
Age	−0.0036 ***	−0.0009 ***	−0.0026 ***	−0.0018 ***	−0.0063 ***
	(0.001)	(0.001)	(0.002)	(0.000)	(0.00)
Gender	−0.030	−0.008	−0.024	−0.022 ***	−0.0081
	(0.026)	(0.009)	(0.025)	(0.007)	−0.009
Years of Education	0.010 **	0.003 **	0.041 ***	0.011 ***	0.0027 **
	(0.004)	(0.003)	(0.004)	(0.001)	−0.0027
Health Status	0.002	0.001	−0.058 ***	−0.013 ***	0.0009
	(0.013)	(0.004)	(0.006)	(0.002)	−0.0036
Nature of Employment	0.253 ***	0.069 ***	0.243 ***	0.023 **	0.0693 ***
	(0.095)	(0.026)	(0.094)	(0.024)	−0.0261
Personal Income	0.009 **	0.003 **	0.011 **	0.003 **	0.0027 **
	(0.005)	(0.002)	(0.004)	(0.002)	−0.0018
Marital Status	0.133 ***	0.037 ***	0.126 ***	0.038 ***	0.037 ***
	(0.012)	(0.013)	(0.042)	(0.005)	−0.0126
Household Size	−0.012 **	−0.004 **	0.051 ***	0.010 ***	−0.0036 **
	(0.005)	(0.002)	(0.005)	(0.002)	−0.0018
Whether Eastern Region	−0.186 ***	−0.051 ***	−0.207 ***	−0.029 **	−0.0513 ***
	(0.057)	(0.017)	(0.058)	(0.024)	−0.0171
Internet Usage	0.072	0.021	0.069	0.014	0.021 *
	(0.058)	(0.017)	(0.058)	(0.014)	0.041 ***
Average Internet Usage	–	–	2.142 ***	0.479 ***	−0.007
	–	–	(0.057)	(0.013)	−0.0009 ***
/athrho	–	–	−0.104 ***	–	0
	–	–	(0.040)	–	−0.0081
N	5413	5413	5413	5413	5413

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

It indicates that age has a slightly negative effect on willingness, decreasing 0.0009% for every year added ($p < 0.01$) according to the Probit model. This pattern appears to indicate that the younger generation is more attracted to pro-environmental behaviors, which have been generally agreed upon as originating from a higher level of environmental awareness and education—almost a duplication of the findings by Wiernik et al. [48]. The implication here is the critical need for environmental education from early years to all ages to develop a universally conscious society.

However, the level of education increases the willingness to engage in waste sorting. The level of education increases the willingness to sort waste by 0.003% ($p < 0.05$) for each additional year of schooling. This clearly defines the crucial role played by education in promoting environmental responsibility, an idea strongly affirmed by Otto and Kaiser [49], referring to the importance of education as the root for ensuring consciousness about the environment. The relationship between years of education and an intensified tendency toward waste sorting suggests that education clearly helps the individual to realize an increased level of awareness regarding environmental issues and their impacts. The same study also refers to gender differences in environmental behaviors. This indicates that men tend to be marginally less than women in categorizing waste (−0.022, $p < 0.01$), a result that aligns with the inferences made by Agarwal [50]. These findings suggest that gender-related environmental concerns and behaviors may be different and perhaps influenced by societal roles and perspectives of who should be responsible.

The other area of focus of the research was the substantial influence that economic indicators have on the Probit model to establish a positive relationship between employment status and personal income for the waste classification willingness. While the coefficients of employment status and personal income are at 0.253 ($p < 0.01$) and 0.009 ($p < 0.05$), respectively, this therefore means that financial stability has a positive influence on the ability and willingness to engage in environmentally friendly activities, according to Gifford and Nilsson [51]. This emanates from the provision of resources and mental capacity to participate

in sustainable activities. Sociodemographic variables related to family size, such as marital status and household size, play a significant role in influencing an individual's inclination to sort waste. Married individuals and those in larger households are more inclined to sort waste. This is in line with the position taken by Grùnhðj and Thðgersen [52] who argue that family and social institutions have a substantial influence on the development of environmental behavior.

Regional disparities are evident, with residents in eastern regions demonstrating lower waste classification willingness (−0.186, $p < 0.01$), pointing to the need for customized environmental policies that consider local cultural, economic, and infrastructural factors, as argued by Assa, B. [53]. Additionally, the study reveals the community effect, where average internet usage positively impacts waste classification willingness (2.142, $p < 0.01$) in the RBP model. This indicates the influential role of digital connectivity on environmental behaviors, stressing the importance of integrating communal internet usage patterns into policy-making to enhance waste classification willingness, especially in rural areas. Thus, both the Probit model and the RBP model confirm the significant positive impact of internet usage on rural residents' waste classification willingness, thereby validating Hypothesis H2.

4.3. The Impact of the Interaction between Social Interaction and Internet Usage on Waste Classification Willingness

According to reference group theory, the integration of the internet into social interactions changes residents' reference groups, potentially affecting the social interaction effect on waste classification willingness, especially the endogenous interaction effect. Therefore, an interaction model examining the impact of internet usage and the endogenous interaction effect of rural residents' waste classification willingness is constructed.

The findings from sections (1) to (3) in Table 4, derived using a gradual approach to integrating control variables, illustrate that both the general inclination towards waste sorting among rural populations and the influence of internet access significantly boost the motivation for individual waste sorting efforts ($p < 0.01$). The interaction terms have a significant negative impact ($p < 0.01$), indicating significant differences in the endogenous interaction effect on waste classification willingness between internet-using and non-internet-using rural residents. Specifically, internet usage among rural residents weakens the endogenous interaction effect of waste classification willingness, i.e., the influence of the community group's waste classification intention on the individual's intention is reduced. This validates the diminishing effect of internet usage on the endogenous interaction effect of rural residents' waste classification willingness, while internet usage itself significantly promotes individual waste classification through technological empowerment and new media ($p < 0.01$). Column (4) of Table 4 reports the second-step test results of the RBP model, which are consistent with the results in columns (1)-(3), and the auxiliary parameter/athrho test value passes the test, indicating the necessity of using the RBP model. Column (5) of Table 4 reports the marginal effects of Column (4), showing that a 1-unit increase in the average community group's waste classification willingness increases individual willingness by 34.6% ($p < 0.01$). For rural residents using the internet, compared to those not using it, waste classification willingness significantly increases by 4.2% ($p < 0.05$), consistent with the empirical test results mentioned earlier. The interaction term test results show that internet usage among rural residents weakens the positive effect of community endogenous interaction on waste classification willingness, with the weakening effect reaching 5.4% ($p < 0.01$). Considering the combined effect of internet usage, community endogenous interaction, and their interaction on waste classification willingness, the comprehensive effect for internet-using rural residents is 0.334 ($p < 0.05$), while for non-internet-using rural residents, it is 0.312 ($p < 0.01$). In other words, internet usage weakens the endogenous interaction effect of waste classification willingness on individual classification intentions while simultaneously exerting a positive promotional effect on individual waste classification willingness. However, this promotional effect is less than the weakening effect, leading to a net negative combined effect. On the one

hand, this result demonstrates the significant role of informal networks centered around social interaction in rural environmental governance. The positive significance of social interaction in forming collective actions within the community cannot be overlooked.

Table 4. Interplay Between Social Dynamics and Digital Connectivity's Effect on Household Waste Sorting Initiatives Among Rural Populations.

Variable	Model 1: Probit		Model 2: Recursive Bivariate Probit		
	(1)	(2)	(3)	(4)	(5)
Willingness to Sort Index	3.186 ***	3.137 ***	3.170 ***	3.176 ***	0.346 ***
	(0.116)	(0.117)	(0.119)	(0.118)	(0.015)
Frequency of Internet Use	0.657 ***	0.620 ***	0.602 ***	0.385 **	0.042 **
	(0.127)	(0.128)	(0.129)	(0.154)	(0.017)
Interaction Term	−0.548 ***	−0.543 ***	−0.495 ***	−0.5 ***	−0.054 ***
	(0.164)	(0.164)	(0.166)	(0.165)	(0.018)
/athrho	–	–	–	–	0.149 ***
					(0.058)
Control Variables (Category)	N	Y	Y	Y	Y
Control Variables	N	N	Y	Y	Y
Regional Control Variables	N	Y	Y	Y	Y
N	5413	5413	5413	5413	5413

Note: ***, and ** indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Numbers in parentheses represent standard errors. And Y and N denotes yes and no, respectively.

On the other hand, although the internet broadens media channels, the promotional effect of new media and virtual interaction spaces on rural residents' waste classification willingness is insufficient to offset the negative impact caused by the dissolution of social interaction effects within the community due to internet development. This finding not only provides insights for digital governance relying on the internet but also highlights the importance of community building as a means of governance in rural environmental management. Furthermore, it offers empirical evidence for policy formulation, combination, and execution in practical rural environmental governance. Thus, Hypothesis H3 is validated.

4.4. Heterogeneity Test: Gender, Regional Differences, and Internet Connectivity Channels

Table 5 details the examination results concerning the influence of social dynamics and digital access on the waste sorting inclination among rural populations, taking into account gender and geographic variances. Regarding gender differences, columns (1) and (2) of Table 5 report regression results for female and male sub-samples, respectively. The combined effect of internet usage on waste classification willingness for the female group reaches 0.713 ($p < 0.05$), an increase of 0.029 compared to non-internet-using females; for males, the combined effect reaches 0.831 ($p < 0.1$), an increase of 0.11 compared to non-internet-using males. The endogenous interaction (marginal) effect of waste classification willingness exhibits a higher characteristic in the male group than in the female group, while the positive effect of internet usage on waste classification willingness is more pronounced in the female group. Overall, the male group gains a higher combined effect on waste classification willingness from internet usage compared to the female group. +

Regarding regional differences, columns (3)–(6) of Table 5 report regression results for eastern and northeastern regions, respectively. The regression results for the eastern sample show that the combined effect of internet usage reaches 0.775 ($p < 0.05$), an increase of 0.035 ($p < 0.05$) compared to non-internet users, suggesting that in the economically developed eastern region, rural residents' overall willingness to participate in waste classification is enhanced by internet usage, with the promotional effect outweighing the weakening effect. The northeastern region samples show no significant effect of internet usage on the social interaction effect on rural residents' waste classification willingness. Overall, the influence

of social dynamics and digital access on the eagerness of rural inhabitants to engage in waste sorting demonstrates noticeable disparities based on gender and location.

Table 5. Disparities Based on Gender and Location: Evaluating the Combined Impact of Social and Digital Interactions on Waste Sorting Behavior in Rural Areas.

Variable	Gender Differences		Regional Differences			
	(1)	(2)	(3)	(4)	(5)	(6)
Willingness to Sort Index	3.1347 ***	3.2022 ***	3.1563 ***	3.3534 ***	2.9916 ***	3.4344 ***
	(0.1755)	(0.1611)	(0.2070)	(0.2547)	(0.1980)	(1.2816)
Frequency of Internet Use	0.7344 ***	0.4968 ***	0.6804 ***	0.5265 *	0.4851 *	1.4184
	(0.1917)	(0.1737)	(0.1953)	(0.2862)	(0.2511)	(1.2609)
Interaction Term	−0.6201 **	−0.3951 *	−0.5310 **	−0.5850 *	−0.2673	−1.7316
	(0.2457)	(0.2241)	(0.2601)	(0.3501)	(0.3240)	(1.5534)
Control Variables (Category)	N	N	Y	Y	Y	Y
Control Variables	N	N	N	N	N	N
Regional Control Variables	N	N	N	N	N	N
N	2511	2901	2184	1135	1796	297

Note: The asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The numbers in parentheses are standard errors. And Y and N denotes yes and no, respectively.

Table 6 reports the impact of the interaction between social interaction and internet usage on waste classification willingness, considering the heterogeneity of internet access channels. Internet connectivity channels are categorized into three types: mobile phones, computers, and simultaneous use of both mobile phones and computers. The test results in columns (1)–(3) of Table 6 uniformly show that regardless of the type of internet connectivity channel used, the community group's waste classification willingness significantly positively influences individual waste classification willingness ($p < 0.01$).

Table 6. Variability in Digital Access Methods: Exploring How Social Ties and Internet Usage Shape Waste Sorting Practices among Rural Communities.

Variables	(1)	(2)	(3)
Willingness to Sort Index	3.0042 ***	2.9538 ***	3.0240 ***
	(0.0972)	(0.0864)	(0.0981)
Mobile Internet	0.3708 **		
	(0.1512)		
Willingness Index × Mobile Internet	−0.3006		
	(0.1944)		
Broadband Internet		0.4608	
		(0.7524)	
Willingness Index × Broadband Internet		−0.9135	
		(0.9207)	
Cable Internet			0.4140 ***
			(0.1476)
Willingness Index × Cable Internet			−0.3357 *
			(0.1890)
Control Variables (Category)	N	N	N
Control Variables	N	N	N
Regional Control Variables	N	N	N
N	5413	5413	5413

Note: The asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Numbers in parentheses are standard errors. And Y and N denotes yes and no, respectively.

In terms of different internet connectivity channels, using only mobile phones as the internet connectivity channel significantly positively influences individual waste classification willingness ($p < 0.05$), but the interaction with the community's average classification willingness does not significantly impact individual willingness. Using only computers as the internet connectivity channel does not significantly affect individual waste classification

willingness, and its interaction with the community's average classification willingness also does not significantly impact individual willingness. However, using both mobile phones and computers as internet connectivity channels significantly positively influences individual waste classification willingness ($p < 0.01$), and its interaction with the community's average classification willingness has a negative effect on individual willingness ($p < 0.1$). The resulting combined effect is 0.713, indicating a 0.018 net effect increase compared to the non-internet-using group ($p < 0.1$). Conclusively, the effects of social engagement and online activity on the motivation of rural communities to classify waste differ notably among various digital access methods.

5. Conclusions and Policy Implications

5.1. Conclusions

Based on reference group theory, this study constructs a social interaction effect test model and an RBP model under the Manski social interaction framework to empirically analyze the impact and mechanisms of social interaction and internet usage on rural residents' waste classification willingness, yielding the following conclusions:

Rural residents' willingness to classify household waste exhibits significant social interaction effects, with endogenous interaction within the community positively impacting waste classification willingness. The test results of the Manski social interaction model show that the group's waste classification willingness significantly positively influences individual waste classification willingness. Correlative effects and contextual effects of certain variables at different significance levels impact rural residents' individual waste classification willingness differently. This result is also valid in the model that examines the interaction between internet usage and social interaction.

Internet usage has a significant positive impact on rural residents' household waste classification willingness. This result remains robust after considering individual selection biases, with mobile internet emerging as the primary internet connectivity channel driving waste classification. Test results of the model analyzing the impact of internet usage on rural residents' household waste classification willingness show that residents using the internet are more willing to classify waste than those not using the internet. After considering individual selection biases in internet usage, internet usage can enhance residents' willingness to classify household waste by 5.9%. The heterogeneity test for internet connectivity channels reveals that using mobile phones for internet access has a more significant impact on waste classification willingness compared to using computers.

The internet plays a significant role in the process of influencing rural residents' willingness to sort domestic waste through social interactions. While internet usage diminishes the positive impact of social interactions on individuals' willingness to sort domestic waste, it also exerts a promoting effect. Overall, the diminishing effect outweighs the promoting effect, but notable regional differences exist. Empirical test results show that both the average willingness to sort and internet usage significantly and positively affect individuals' willingness to sort domestic waste. The interaction term is significantly negative, and the negative effect it introduces is greater than the positive effect provided by internet usage. However, regional differences are evident. In the eastern regions, the diminishing effect is smaller than the promoting effect, while in the central regions, the results are consistent with the overall findings. In the western and northeastern districts, the presence of internet connectivity does not markedly affect the rural populace's readiness to segregate household waste.

The impact of social interaction, internet usage, and their interaction on rural residents' willingness to sort domestic waste varies significantly in terms of gender and internet connectivity channels. Regarding gender differences, the combined effect of internet usage on the waste sorting willingness of the male group is higher than that of the female group. As for the differences in internet connectivity channels, using only a computer as the channel does not significantly impact the willingness to sort domestic waste. In contrast, using mobile phones as the internet connectivity channel has a significant positive impact

on the willingness of rural residents to sort domestic waste. Moreover, using both mobile phones and computers as connectivity channels significantly affects individual willingness to sort domestic waste and exerts an interactive effect.

5.2. Policy Implications

The conclusions drawn from the analysis have certain policy implications for promoting waste sorting in rural areas and improving the level of rural environmental governance:

1. Strengthening community building will ignite the intrinsic motivation of rural residents to participate in environmental governance. Within the rural environmental governance framework of "villager-led, government-supported, and multi-party cooperation", it is crucial to leverage party-building leadership fully. This involves intensifying the informal networks within rural communities and advancing the processes of community self-organization, self-governance, and self-development. By fully mobilizing the subjective initiative of the principal actors in waste sorting, the endogenous motivation of rural residents can be harnessed. This approach fosters the formation of binding norms within the community, gradually advancing rural waste-sorting initiatives.
2. Enhancing the application of mobile internet to improve the digital governance capacity of rural environments. Although the internet plays a positive role in shaping the willingness of rural residents to sort waste, its current effectiveness is limited. Hence, there is a need to further capitalize on the convenience, precision, and immediacy of mobile internet. This involves strengthening the application of mobile internet in rural environmental governance. Firstly, establishing the concept of "Internet Plus" in environmental governance means achieving digital management across the entire chain of rural domestic waste sorting—collection, transportation, processing, supervision, and feedback. Secondly, utilizing the internet as a new medium for effective policy promotion and disseminating environmental conservation concepts through popular apps and social media platforms like WeChat, Weibo, and short video apps, which have a high dependency among rural residents.
3. Enhancing the innovation capacity of rural environmental governance to improve its efficacy. This involves promoting the construction of public health facilities in rural areas and improving the rural public service system. By innovating through various policy combinations and optimizing governance models like "Internet Plus" and community building, optimal efficacy in rural environmental governance can be achieved. Simultaneously, environmental governance authorities should fully consider the differences in economic foundations and resource endowments between regions. Tailoring strategies to local conditions and scientifically planning to develop localized models of rural environmental governance is crucial to avoiding the pitfall of blindly copying models from other contexts.
4. To effectively promote waste management practices in rural areas, it is essential to recognize the power of social norms as a driving force. This study has uncovered the influential role of community interactions and collective intentionality in enhancing individual commitment to waste classification. Therefore, the first implication is to leverage these social norms by encouraging practices that align with community expectations and values. Policies should support initiatives that not only inform but also culturally resonate with rural residents, reinforcing normative behavior towards waste management. Community leaders can play a pivotal role in this process by embodying and advocating for these norms, thus setting a precedent for others to follow. Integrating these efforts with digital tools will amplify their impact, ensuring that the message not only spreads widely but is also upheld by the collective digital endorsement of community members.

Author Contributions: Conceptualization, X.W., N.A. and N.A.K.; methodology, L.A.M.Q., R.F.C.B. and J.A.P.R.; software, J.O., X.W. and N.A.K.; validation, R.F.C.B., N.A., X.W., L.M.R.B., N.A.K. and J.O.; formal analysis, X.W., N.A. and N.A.K.; investigation, J.A.P.R. and N.A.; resources, N.A. and R.F.C.B.; data curation, R.F.C.B. and N.A.; writing—original draft preparation, N.A., J.O., L.M.R.B., X.W. and R.F.C.B.; writing—review and editing, R.F.C.B.; visualization, J.O., N.A., L.M.R.B. and X.W.; supervision, X.W. and N.A.; project administration, N.A.; funding acquisition, N.A. and J.O. All authors have read and agreed to the published version of the manuscript.

Funding: The research was partially funded by the Rector's pro-quality grant from the Silesian University of Technology, grant number: 13/020/RGJ23/0082.

Institutional Review Board Statement: According to our University Ethical Statement, the following shall be regarded as research requiring a favorable opinion from the Ethics Commission in the case of human research (based on a document in Polish: https://prawo.polsl.pl/Lists/Monitor/Attachments/7291/M.2021.501.Z.107.pdf (accessed on 10 January 2024)): Research in which persons with limited capacity to provide informed consent or research on persons whose capacity to provide informed or free consent to participate in research and who have a limited ability to refuse research before or during its implementation, in particular—children and adolescents under 12 years of age; persons with intellectual disabilities; persons whose consent to participate in the research may not be fully voluntary, including prisoners, soldiers, police officers, and employees of companies (when the survey is conducted at their workplace); and persons who agree to participate in the research on the basis of false information about the purpose and course of the research (masking instruction, i.e., deception) or do not know at all that they are subjects (in so-called natural experiments). Research in which persons particularly susceptible to psychological trauma and mental health disorders are to participate, in particular—mentally ill persons; victims of disasters, war trauma, etc.; patients receiving treatment for psychotic disorders; and family members of terminally or chronically ill patients. Research involving active intervention in human behavior aimed at changing that behavior without direct intervention in the functioning of the brain, e.g., cognitive training, psychotherapy, and psychocorrection (this also applies if the intervention is intended to benefit the subject (e.g., to improve his/her memory)). Research concerning controversial issues (e.g., abortion, in vitro fertilization, the death penalty) or requiring particular delicacy and caution (e.g., concerning religious beliefs or attitudes towards minority groups). Research that is prolonged, tiring, or physically or mentally exhausting. Our research was not conducted on humans meeting the abovementioned condition. None of the participants had a limited capacity to provide informed consent, were susceptible to psychological trauma, or had mental health disorders, and the research did not concern any of the abovementioned controversial issues and was not prolonged, tiring, or physically or mentally exhausting.

Informed Consent Statement: Informed consent was obtained from all subjects involved in this study.

Data Availability Statement: Data are openly accessed and freely available to everyone.

Conflicts of Interest: The authors declare no conflicts of interest.

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