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The impacts of observational learning and word-of-mouth learning on farmers' use of biogas in rural Hubei, China: does interpersonal trust play a role?

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Abstract

Background: Residue-based biogas is considered as a renewable energy that should be used to improve energy security and household livelihoods in rural areas. Observational learning and word-of-mouth learning are critical in the dissemination of knowledge about agricultural technologies. Yet, scholars have little understanding of the impacts of these learning methods on farmers' use of residue-based biogas. Using survey data from rural areas of Hubei China, this study estimates the impacts of observational learning and word-of-mouth learning from different subjects (i.e., relatives, neighbors, cadres, cooperative members, and technical instructors) on the use of residue-based biogas by farmers. Additionally, the moderating role of interpersonal trust in these relationships is explored.

Results: Results from logistic regression models show that observational learning from technical instructors significantly increases farmers' use of biogas. Furthermore, interpersonal trust significantly and positively influences the impact of observational learning on farmers' decisions to use biogas. Similarly, interpersonal trust significantly and positively moderates the influence of positive word-of-mouth learning on farmers' decision to use biogas. In contrast, a negative moderating role exists in the relationship between negative word-of-mouth learning and farmers' decision to use biogas. These impacts are further affirmed by robustness checks.

Conclusions: The results presented here show that enhancing farmers' interpersonal trust promotes the use of residue-based biogas by farmers. One important implication is that the government might promote the use of residue-based biogas by organizing technology demonstration activities, providing communication platforms, and enhancing mutual trust between farmers and relevant groups.

Background

Residue-based biogas is becoming increasingly attractive as a means to improve energy security and household livelihoods in rural areas [1–3]. However, it is still underutilized in rural areas around the world, especially in developing countries [4, 5]. For example, Clemens et al. [4] revealed that just 29% and 11% of the sampled households in Tanzania and Uganda, respectively, use biogas exclusively. According to Rahman et al. [5], only 32.5% of the surveyed households adopted the biogas technology in 2021 based on data from four districts in rural Bangladesh. Therefore, identifying the obstacles to biogas technology adoption is a formidable challenge for policymakers.

Empirical evidence suggests that the lack of relevant information is a major obstacle to the diffusion of biogas technology in many developing countries [6, 7].

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Generally, transportation is usually underdeveloped in rural areas in developing countries, and people live in congested geographical spaces [8, 9]. Accordingly, social learning among farmers has become prominent in the diffusion of agricultural technology [10–13]. For example, learning from neighbors [10, 11], extension agents [12], and "progressive" peers [13] all help in accelerating the transfer of information and increasing the use of technology by farmers.

The existing literature indicates that farmers often learn through two prominent social learning mechanisms: observational learning (OB) and word-of-mouth learning (WOM) [14–16]. In OB, individuals infer relevant information from the actions of other people indirectly through visual observations [14, 17]. In WOM, individuals extract relevant information from the opinion of other people directly through verbal communication [18]. These two types of learning occur in different ways. OB occurs when relevant subjects are facing similar shocks in making decisions, whereas WOM occurs when temporal, spatial, and social proximity among individuals exists [14]. Furthermore, WOM can be divided into positive WOM, meaning that it is explicitly from a subject with positive experiences, and negative WOM, which comes from a subject with negative experiences [19].

The effects of OB and WOM have been separately assessed in the extant empirical publications. For example, Jones et al. [20] showed that OB from other farmers has a causal effect on the uptake of the novel pigeon pea variety in the semi-arid areas of Mwea Division in the Eastern Province of Kenya. Conley and Udry [11] confirmed that farmers in Ghana choose fertilizer by observing the inputs and outputs of their neighbors. Based on sample potato farmers in Ecuador, Mauceri et al. [21] found that the diffusion of integrated pest management techniques is influenced by WOM. Similarly, Zilberman et al. [22] suggested that WOM could induce technology adoption. Although OB and WOM may coincide [23], few studies have disentangled the distinct effects of the two learning mechanisms against the same backdrop.

We are unaware of any research regarding the role of interpersonal trust in the investigation of the impacts of OB and WOM. Existing literature suggests that the extent to which social learning may speed up adoption is closely related to the connections among individuals [24]. Meaningful social connections create value typically in the form of interpersonal trust that helps individuals to learn information from others to improve different behaviors [25]. For example, farmers adopting aquaculture technologies and practices in the Mekong Delta, Vietnam [26], and behaviors of farmers toward individual and collective measures of controlling the western corn rootworm [27]. Interpersonal trust is the extent to which a person is confident in the words or actions of another [28]. As an essential ingredient of interpersonal ties, interpersonal trust can influence the extent to which farmers put the information acquired from others into practice, such as pesticides use [29], agricultural cultivation technology adoption [30], and the use of irrigation technology [31].

To address these research gaps, this study aims at accomplishing two objectives: (1) to examine the impacts of OB and WOM on farmers' use of residue-based biogas; and (2) to investigate whether and to what extent interpersonal trust can mediate the effects of OB and WOM. We contribute to the literature of technology adoption and social learning by providing the first field evidence of the various roles played by OB and WOM in the usage of residue-based biogas. We also contribute to the trust literature by identifying interpersonal trust as a mediating factor in the effects of social learnings. China is an interesting and relevant case study for empirically illustrating technology adoption concerns. In addition to the semi-closed geographical conditions in rural areas, the distinctive Chinese rural acquaintance society makes technology information to spread through observation and communication more conveniently [32]. Consequently, this study used a unique survey data set collected in rural areas of Hubei province in China. The outcomes of this study will help us better understand adoption decisions and develop strategies that leverage interpersonal trust to encourage the adoption of new technologies.

The remainder of this paper is organized as follows: The next section describes the overview of residue-based biogas in rural China. "Methods" section presents the data and methodology. "Results" section discusses the estimation results. "Discussion" section discusses and deals with policy implications and also identifies limitations and gives an outlook for future research. "Conclusions" section offers the conclusions.

Overview of residue-based biogas in rural China

Residue-based biogas is a mixture of methane, carbon dioxide, and other gases generated from agricultural residues through anaerobic processes in liquid–state/solid–state/liquid–solid two-phase digestions [33, 34]. This mixture is commonly used for cooking, generating power, and fueling vehicles among others [35, 36].

In China, residue-based biogas is increasingly gaining value, especially as a renewable and clean alternative cooking fuel in the rural areas [33]. As the largest developing country in the world, China has an abundance of agricultural residues. According to the Ministry of Agriculture and Rural Areas [37], more than 4.7 billion tons of agricultural residues have been produced annually in recent years, with 29.87% of available agricultural residues used to generate biogas that is mainly consumed by farmers according to the National 13th Five-Year Plan for Rural Biogas Development [38].

To promote the use of residue-based biogas in rural areas, effective policies such as the Pilot Scheme of Promoting the Resource Utilization of Agricultural Wastes [37] and Guiding Opinions on the Construction of Straw Gasification Clean Energy Utilization Project [39] have been implemented in the past decade. These top-down national policies not only promote biogas expansion by strengthening scientific–technological innovation and providing service guarantee, but they also set national short- and long-term targets for achieving sustainable use of residue-based biogas and call for efforts and actions from provincial governments. Notably, the national and local governments have already provided financial support for the use of residue-based biogas. During the 12th Five-Year Plan period (2011–2015), 14.2 billion RMB (equivalent to 2.25 billion USD) were invested in the construction of rural biogas projects for farmers [38]. In 2018, investment in small biogas projects for farmers in the sample province Hubei was 86.4 million RMB (equivalent to 12.55 million USD) [40]. Furthermore, each household in Hubei province that has a biogas digester has been subsidized with 1000 RMB (equivalent to 132.98 USD) since 2007 [41].

Despite the efforts by the national and provincial governments, farmers' use of biogas in rural China remains unsatisfactory [42]. It is estimated that the proportion of biogas farmers consumed in 2014 was only 3.31% [42]. Recently, numerous studies have identified predictions of residue-based biogas use in rural China [43–46]. The predictions include demographic factors (such as age, labor availability, and total household income), village basic infrastructure [43], personality traits [45], and energy-related command and control policies [44, 46]. However, no research has investigated the impacts of different types of social learning.

Methods

Data sources

Questionnaire design

This study was based on surveys conducted in rural areas of Hubei province, China. To obtain the data, we designed a detailed questionnaire, which was then modified by the relevant experts in agricultural resource economy from Hubei Rural Development Research Center. The experts considerably improved the logic and language. A pre-test was conducted among 20 farmers in our targeted area of study to boost the validity, accuracy, and credibility of our data. Based on the pre-test results, we deleted few invalid questions, modified the language, and added some interview questions to obtain the final version of the questionnaire, which had six parts.

The first part captured the details of infrastructure and living conditions in the villages, including the terrain where the households were located and the closest town or market. The second part entailed personal and household characteristics such as gender, age, education, and total household income. The third part covered rural biogas utilization such as social learnings, interpersonal trust, and the adoption of biogas utilization. The fourth part evaluated the extension of agricultural technologies, whereas the fifth part collected information on farmers' participation in social activities and their waste disposals. The final part mainly measured self-happiness of farmers and their perceptions of different situations. Additional file 1 is part of the survey questionnaire translated from Chinese into English.

Data collection

The data used in this study were collected from a household survey conducted in rural areas of Hubei province, China, in August 2018 using a multistage systematic random sampling procedure. First, four cities were randomly selected: Huanggang city, Wuhan city, Ezhou city and Jingmen city. Second, one to two counties or districts in each city were randomly selected. The selected counties or districts cover the main landforms in Hubei province, which range from hills to mountains and plain. The reason for selecting counties or districts at random with respect to the main landforms was that the use of biogas varies with household location in different landforms [2, 44]. Third, three to five towns in each county or district were randomly selected. Finally, one village in each town per county or district was randomly selected. In this stage, we obtained a household roster for each village from the local government and randomly selected households for interview. Interviews were conducted by team members from the School of Economics and Management, Huazhong Agricultural University. All the members had rich experience in rural investigation and were professionally trained before the survey was conducted. Supervised face-to-face interviews were conducted with an adult member of the sample households.

A total of 1084 observations were collected. The final sample for this study comprised 913 observations after excluding those with missing values. Observations from Huanggang city, Wuhan city, Ezhou city, and Jingmen city were 163, 328, 203, and 219, respectively, which accounted for 17.85%, 35.93%, 22.23%, and 23.99%, respectively.

Methodology

Model selection

In this research, the dependent variable was dichotomous, with 1 indicating that the ith farmer had used residue-based biogas ($y_i = 1$), and 0 indicating otherwise ($y_i = 0$). The binary logit model is one of the most widely used statistical models for dealing with the relationship between dichotomous dependent variable and multiple continuous or categorical independent variables [47]. Therefore, this paper used a binary logistic model to deal with discrete outcomes, assuming that the ith farmer had or had not used a distribution $\Pr(y_i)$. $\Pr(y_i)$ is believed to be affected by a vector of key explanatory variables (X_i) (e.g., OB, and positive and negative WOM), interpersonal trust (I_i), and the interaction terms between the learnings and interpersonal trust (X_iI_i). To avoid potential endogeneity due to omitted variable biases, we added other factors to the model as a vector of control variables (Z_i) that may explain the differences in the biogas use probability among the farmers. These factors included demographic variables, personal perceptions, and geographic locations [34, 48]. Furthermore, it is assumed that $\Pr(y_i)$ is influenced by an error term μ_i. The corresponding set of parameters is $\{\beta_1, \beta_2, \beta_3, \beta_4\}$, where β_0 is the intercept. It is considered that $\Pr(y_i)$ is determined by the aforementioned factors through a nonlinear link function F that maps the unbounded index.

$$y_i^* = \beta_0 + \beta_1 X_i + \beta_2 I_i + \beta_3 X_i I_i + \beta_4 Z_i + \mu_i \tag{1}$$

into bounded probability space [0,1]:

$$\Pr(y_i) = F(y_i^*) \tag{2}$$

where F is the logistic cumulative density function (Λ) that produces the logit model. Thus,

$$\Pr(y_i) = F(y_i^*) = \Lambda(y_i^*) = \frac{1}{1+\exp(y_i^*)} = \frac{\exp(y_i^*)}{1+\exp(y_i^*)} \tag{3}$$

Then, with (1) incorporated into (3), we get:

$$\begin{aligned}\Pr(y_i) &= F(y_i^*) = \Lambda(y_i^*)\\ &= \frac{1}{1+\exp[-(\beta_0 + \beta_1 X_i + \beta_2 I_i + \beta_3 X_i I_i + \beta_4 Z_i + \mu_i)}\\ &= \frac{\exp(\beta_0 + \beta_1 X_i + \beta_2 I_i + \beta_3 X_i I_i + \beta_4 Z_i + \mu_i)}{1+\exp(\beta_0 + \beta_1 X_i + \beta_2 I_i + \beta_3 X_i I_i + \beta_4 Z_i + \mu_i)}\end{aligned} \tag{4}$$

To investigate potential multicollinearity affecting the result, we calculated the variance inflation factor (VIF) for the binary logistic model with all variables included in the regression estimation except the interaction terms, and the calculated results are shown in Appendix 1. The VIF scores range from 1.04 to 3.24.[1] Campbell et al. [49] demonstrated that a multicollinearity problem exists when VIF is greater than 5. Thus, the multicollinearity test result was acceptable in our study. Furthermore, the robust standard error procedure was used in this paper in order to obtain unbiased standard errors under heteroscedasticity. We also used OLS and probit approaches to check the robustness of the binary logistic estimates.

According to previous studies, coefficients in nonlinear regressions (e.g., logit) cannot be used to infer the statistical significance of an interaction term and its underlying variables [50, 51]. The marginal effect of the interaction term varies not only in sign, but also in magnitude and statistical significance with the values of other explanatory variables [51]. The interpretation of logistic model coefficients has certain pitfalls and is less intuitive than linear model estimation. Hence, in this paper, the marginal effects were calculated using the "delta" method in Stata. As the relationship between the probability of social learning and residue-based biogas use is nonlinear, the marginal change could be presented by the tangent to the probability curve:

$$\begin{aligned}\frac{\partial \Pr(y_i)}{\partial X_i} &= \left(\frac{\partial \Pr(y_i)}{\partial y_i^*}\right)\cdot\left(\frac{\partial y_i^*}{\partial X_i}\right)\\ &= [\Lambda(y_i^*)(1-\Lambda(y_i^*))]\cdot(\beta_1 + \beta_3 I_i)\end{aligned} \tag{5}$$

Since only dummy variables were involved in the interaction terms, the marginal change in this paper was presented as follows:

$$\Delta y = \Pr(y_i|X, X_i = 1) - \Pr(y_i|X, X_i = 0) \tag{6}$$

For the main explanatory variables in this paper, OB refers to the process of observing as other individuals use residue-based biogas. Observing others is a behavior-based social interaction that farmers can use as a reference when making choices from an overwhelming number of options. OB may also update personal experience of farmers and beliefs about the profitability of the technology based on the profitable signal from the adoption behavior of others [52]. Consequently, although the profits and utility of others' use are unknown, OB may increase the probability of farmers using residue-based biogas.

Farmers in rural areas rely on various cues, including WOM, to acquire technology information in their immediate social circles. In this paper, positive WOM refers explicitly to the process of learning via communication from the positive experiences of others who have used

[1] As noted by Brambor et al. [51], any multicollinearity problem cannot be solved by centering the relevant variables. Therefore, the variables in this paper were involved in the interaction terms and were not centered in the logit estimation by subtracting their means.

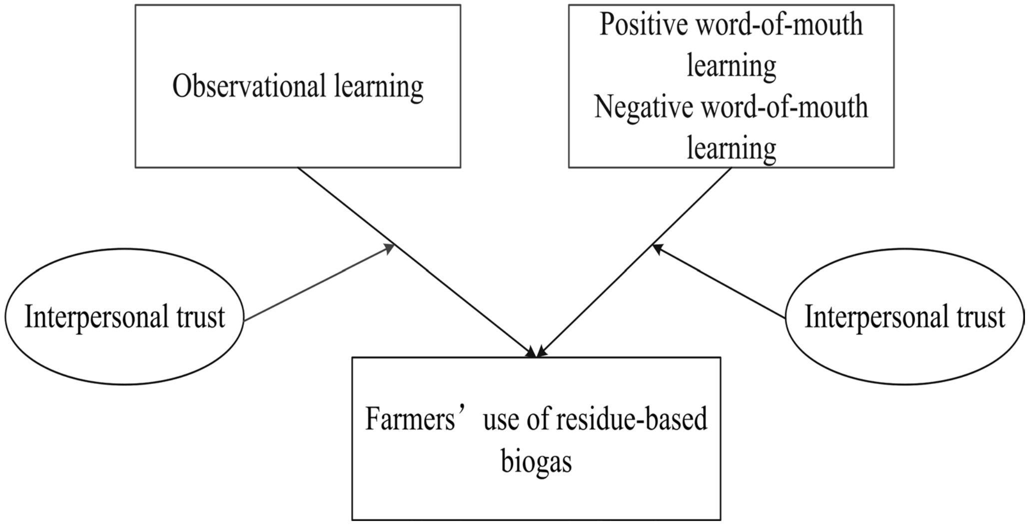


Fig. 1 Theoretical framework of this paper

residue-based biogas. This learning method may inform the beliefs of farmers about the strengths, expected quality or profit, and other positive effects of the technology. It could also increase the exante confidence of the farmers in the expected utility of the technology. Therefore, positive WOM may increase farmer use rates. On the contrary, negative WOM refers to the process of learning via communication from the negative experiences of farmers' use of residue-based biogas. This type of learning may enhance the perceptions of farmers on the disadvantages and potential problems of residue-based biogas. It may also constitute a noisy signal about the profitability of this technology, thus increasing use uncertainty among the farmers. Therefore, negative WOM may reduce the probability of farmers using the residue-based biogas.

In this paper, interpersonal trust is defined explicitly as farmers trust the opinion or decisions of others on residue-based biogas. According to Sol et al. [25], interpersonal trust facilitates the relationships between types of social learning and individual behaviors in the face of ambiguity and unstructured nature of decision-making problems. Embedded within cohesive groups marked with closure, farmers are likely to learn about residue-based biogas from others. This, in turn, can indicate that they have trust in other farmers, and the more individuals trust the information provider, the more likely they are to transform the knowledge obtained from the provider into practice. Consequently, the use behaviors of farmers tend to be consistent. Therefore, interpersonal trust may mediate the relationships between types of social learning and the use of residue-based biogas.

The relationships between the key independent variables, the trust variables, and the dependent variable are presented in summary in Fig. 1.

Variables and descriptive statistics

As aforementioned, the dependent variable was farmers' use of residue-based biogas, while the key independent variables were OB, positive and negative WOMs and the interaction terms between the learning types and interpersonal trust. Several factors serve as control variables to rule out alternative explanations. Gender, age and education of the respondents were controlled because the characteristics of farmers have been shown to inevitably correlate with the uptake of biogas technology [6, 34]. Furthermore, household labor and total household income were used as control variables because labor [43] and family income [48] are all determinants of clean energy consumption by households. Sun et al. [44] found that biogas subsidy is critical in biogas utilization, hence we included a dummy variable subsidy into the regression analysis. Moreover, risk and personal perceptions served as control variables because they promote biogas dissemination [53]. Meeks et al. [2] reported that biogas projects are generally unsuited for mountain regions due to temperature requirements to operate them, whereas Sun et al. [44] revealed that biogas users are more likely to be located in hilly areas than plains. Accordingly, in this study, we controlled household location heterogeneities to reduce the error in the regression analysis caused by landform factor disunity.

Variable definitions and descriptive statistics are presented in Table 1. According to Table 1, 22% of surveyed farm households had used residue-based biogas.

Table 1 Variable definitions and descriptive statistics

Variables	Definition	Mean (S.D.)
Adoption	1 if respondent has used residue-based biogas, 0 otherwise	0.22 (0.41)
OB from relatives (*OB_r*)	1 if respondent obtain observational learning from relatives' adoption of residue-based biogas, 0 otherwise	0.51 (0.50)
OB from neighbors (*OB_n*)	1 if respondent obtain observational learning from neighbors' adoption of residue-based biogas, 0 otherwise	0.59 (0.49)
OB from cadres (*OB_c*)	1 if respondent obtain observational learning from cadres'[1] adoption of residue-based biogas, 0 otherwise	0.54 (0.50)
OB from cooperative members (*OB_o*)	1 if respondent obtain observational learning from cooperative members' adoption of residue-based biogas, 0 otherwise	0.31 (0.46)
OB from technical instructors (*OB_t*)	1 if respondent obtain observational learning from technical instructors' adoption of residue-based biogas, 0 otherwise	0.32 (0.47)
Positive WOM from relatives (*WOM_rp*)	1 if respondent obtain positive word-of-mouth learning from relatives, 0 otherwise[a]	0.24 (0.43)
Positive WOM from neighbors (*WOM_np*)	1 if respondent obtain positive word-of-mouth learning from neighbors, 0 otherwise[a]	0.27 (0.44)
Positive WOM from cadres (*WOM_cp*)	1 if respondent obtain positive word-of-mouth learning from cadres[1], 0 otherwise[a]	0.13 (0.34)
Positive WOM from cooperative members (*WOM_op*)	1 if respondent obtain positive word-of-mouth learning from cooperative members, 0 otherwise[a]	0.04 (0.19)
Positive WOM from technical instructors (*WOM_tp*)	1 if respondent obtain positive word-of-mouth learning from technical instructors, 0 otherwise[a]	0.07 (0.25)
Negative WOM from relatives (*WOM_rn*)	1 if respondent obtain negative word-of-mouth learning from relatives, 0 otherwise[a]	0.21 (0.40)
Negative WOM from neighbors (*WOM_nn*)	1 if respondent obtain negative word-of-mouth learning from neighbors, 0 otherwise[a]	0.22 (0.42)
Negative WOM from cadres (*WOM_cn*)	1 if respondent obtain negative word-of-mouth learning from cadres[1], 0 otherwise[a]	0.11 (0.31)
Negative WOM from cooperative members (*WOM_on*)	1 if respondent obtain negative word-of-mouth learning from cooperative members, 0 otherwise[a]	0.03 (0.18)
Negative WOM from technical instructors (*WOM_tn*)	1 if respondent obtain negative word-of-mouth learning from technical instructors, 0 otherwise[a]	0.09 (0.29)
Trust in relatives (*Tr*)	1 if respondent trusts relatives, 0 otherwise[b]	0.41 (0.49)
Trust in neighbors (*Tn*)	1 if respondent trusts neighbors, 0 otherwise[b]	0.73 (0.45)
Trust in cadres (*Tc*)	1 if respondent trusts cadres[1], 0 otherwise[b]	0.62 (0.49)
Trust in cooperative members (*To*)	1 if respondent trusts cooperative members, 0 otherwise[b]	0.65 (0.47)
Trust in technical instructors (*Tt*)	1 if respondent trusts technical instructors, 0 otherwise[b]	0.58 (0.49)
Gender	1 if respondent is male; 0 if female	0.56 (0.50)
Age	Respondent's age	57.52 (10.94)
Education	Schooling of respondents (in years)	6.43 (3.75)
Labor	Number of individuals in the household that are aged 16 or more but below 65 years old	3.13 (1.41)
Household income	Total household income in 2017 (10 000 Yuan)[c]	6.96 (7.92)
Subsidy	1if subsidy is provided for those who use residue-based biogas	0.23 (0.42)
Risk perception	Risk perception of the adoption of residue-based biogas[d]	2.39 (1.01)
Cost-effective perception	Cost-effective perception of the adoption of residue-based biogas [d]	3.95 (0.89)
Plain	1 if household is located in plain, 0 otherwise	0.26 (0.44)
Hill	1 if household is located in hill, 0 otherwise	0.69 (0.46)
Mountains	1 if household is located in mountains, 0 otherwise	0.05 (0.22)

$N = 913$. [a]Following Ziegler [54], if the respondent has high or very high frequency of obtaining positive/negative word-of-mouth learning from these objects, we take value one; otherwise, we take value zero. [b]We take value one if the respondent have high or very high interpersonal trust in these objects, and otherwise, we take value zero. [c]Yuan is Chinese currency (1$ = 6.62 Yuan in 2018). [d]related to a 5-point-Likert scale, 1-very low; 5-very high. [1]Cadres refers to local governors who hold certain positions in the village's political organization, exercise local power, manage local affairs and provide local services, etc

Moreover, farmers who obtained OBs from relatives, neighbors, cadres, cooperative members, and technical instructors accounted for 51%, 59%, 54%, 31% and 32%, respectively. In addition, 24%, 27%, and 13% of the sample farmers obtained positive WOMs from relatives, neighbors, and cadres, respectively. However, much fewer farmers obtain this kind of learning from cooperative members (4%) and technical instructors (7%). Similarly, farmers who obtained negative WOMs from relatives, neighbors and cadres accounted for 21%, 22%, and 11% accordingly, which were all much higher than those of negative WOMs from cooperative members (3%) and technical instructors (9%). Table 1 shows that 73% and 65% of farmers trusted their neighbors and cooperative members, respectively. Farmers who trusted cadres, technical instructors, and relatives accounted for 62%, 58%, and 41%, respectively. Notably, during the interviews, interviewers clarified to the respondents that "relatives", "neighbors", "cadres", "cooperative members", and "technical instructors" refer to different types of generic and group concepts rather than specific individuals.

Results

Main results

To better understand the direct influences of OBs and WOMs on farmers' use of residue-based biogas and the moderating role of interpersonal trust in these influences, we constructed 5 models in which key independent variables and interaction terms into the models step by step. The results of the 5 binary logistic regression estimates are presented in Table 2, while all the estimation findings are given in Appendix 2.

In Table 2, model 1 exclusively tests the effects of interpersonal trust[2] and control variables on farmers' use of residue-based biogas. Model 2 adds the key independent variables to explore the direct effects of OBs and WOMs on farmers' use of residue-based biogas. Model 3 estimates the interaction between OBs and interpersonal trust, while model 4 tests the interaction between WOMs and interpersonal trust. Model 5, which was the preferred model, includes all the key explanatory variables, interaction terms, interpersonal trust, and control variables. Likelihood-ratio tests, AUC, and AIC results all suggested that models 2–5 were significantly better than the baseline model 1. When the pseudo-R^2s, AUC, and AIC in the models 1–5 were compared, it was noted that both models 4 and 5 had the most explanatory power. According to model 4, the effects of OB from relatives and neighbors on farmers' use were statistically significant, although the corresponding interaction terms were excluded. However, in model 5, the positive link between OBs from relatives and neighbors and the use behavior all become insignificant when the interaction terms were included. This emphasized the importance of interpersonal trust in mediating the relationships between OBs and adoption behavior, implying that focusing solely on the estimation results of model 4 is misleading. Therefore, the conclusions of the following analyses are mainly based on the results of model 5.

The impacts of OBs and WOMs on use of biogas by farmers

The coefficient for OB from technical instructors was positive and statistically significant at the 5% level, indicating that it significantly influenced the use behavior. However, the coefficient of the corresponding interaction term was not statistically significant, which suggested that OB from technical instructors significantly and directly increased the likelihood of the use by farmers. This finding is consistent with the study of Krishnan and Patnam [12], which demonstrated that OB from extension agents can effectively predict technology adoption, which is probably because technical instructors have professional technical skills. Therefore, obtaining OB from these instructors' adoption of residue-based biogas could be an efficient and reliable source that indicates the expected utility of this technology. Therefore, this type of learning greatly increases the probability of farmers using the technologies.

The moderating role of interpersonal trust

Interpersonal trust not only significantly strengthened the impact of OB from relatives on the use behavior, but it also statistically and significantly strengthened the relationships between positive WOMs from neighbors, cooperative members, technical instructors, and the use behavior. In contrast, interpersonal trust statistically and significantly weakened the links between negative WOMs from cadres, cooperative members, and the use behavior. As Brambor et al. [51] suggested, constructing marginal effect plots is an effective way to show how the estimated marginal effect of a variable on the probability varies with another. Furthermore, there is a need to plot the marginal effect of the interaction terms at the mean value [51] with all dichotomous variables involved in the interaction terms. Therefore, following the study of Franken et al. [55], we used figures to graphically depict the magnitude and significance of the interaction effects in model 5. The plots are presented in (a) ~ (f) in Fig. 2.

Moderating role of interpersonal trust on the relationships between OBs and adoption

The interaction coefficient of OB from relatives and trust in relatives was positive and statistically significant at the 5% level. A graph of this moderating effect, which is

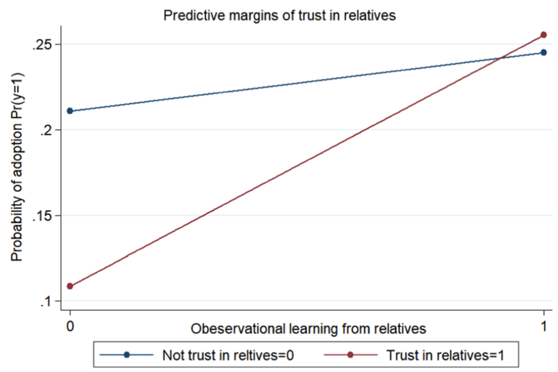
[2] The direct effects of different types of interpersonal trust on the use behavior were out of scope of this research.

Table 2 Evaluation statistics of the logistic model

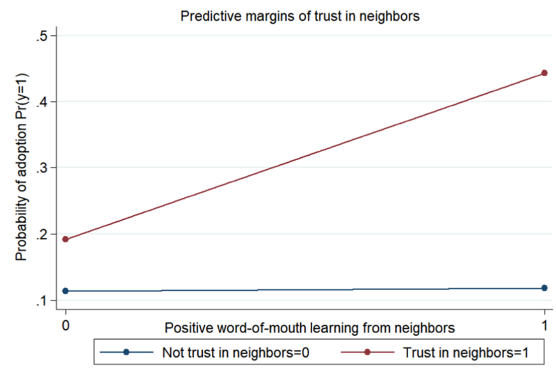
Variables	Model 1	Model 2	Model 3	Model 4	Model 5
OB_r		0.64**(0.27)	0.22 (0.30)	0.67**(0.28)	0.26 (0.31)
OB_n		0.83**(0.36)	0.56 (0.67)	0.86**(0.37)	0.81 (0.69)
OB_c		− 0.39 (0.35)	− 0.30 (0.44)	− 0.45 (0.37)	− 0.40 (0.45)
OB_o		− 0.22 (0.32)	− 0.05 (0.44)	− 0.28 (0.33)	− 0.05 (0.44)
OB_t		0.94***(0.33)	0.79**(0.39)	1.09***(0.34)	0.97**(0.40)
WOM_rp		0.25 (0.29)	0.23(0.29)	− 0.01 (0.36)	0.02 (0.35)
WOM_np		1.14***(0.30)	1.19***(0.31)	0.02 (0.65)	0.06 (0.65)
WOM_cp		0.99***(0.34)	1.00***(0.33)	1.27**(0.49)	1.29***(0.49)
WOM_op		1.11*(0.60)	1.08*(0.59)	− 0.97 (1.23)	− 1.19 (1.29)
WOM_tp		− 0.78 (0.58)	− 0.73 (0.56)	− 2.34***(0.80)	− 2.20***(0.79)
WOM_rn		0.02 (0.34)	0.04 (0.34)	0.13 (0.38)	0.15 (0.38)
WOM_nn		− 1.01***(0.34)	− 1.06***(0.34)	− 0.25 (0.76)	− 0.27 (0.75)
WOM_cn		− 0.87**(0.38)	− 0.91**(0.38)	− 0.76 (0.53)	− 0.74 (0.53)
WOM_on		0.72 (0.62)	0.62 (0.62)	3.10***(1.00)	3.12***(1.03)
WOM_tn		− 0.25 (0.41)	− 0.19 (0.41)	0.14 (0.47)	0.17 (0.46)
OB_r × *Tr*			1.11**(0.44)		1.12**(0.45)
OB_n × *Tn*			0.29 (0.63)		0.03 (0.65)
OB_c × *Tc*			0.03(0.44)		0.07 (0.45)
OB_o × *To*			− 0.23 (0.42)		− 0.31 (0.43)
OB_t × *Tt*			0.19 (0.40)		0.11 (0.41)
WOM_rp × *Tr*				0.56 (0.60)	0.42 (0.60)
WOM_np × *Tn*				1.58**(0.70)	1.56**(0.69)
WOM_cp × *Tc*				− 0.43 (0.70)	− 0.48 (0.68)
WOM_op × *To*				3.33**(1.43)	3.48**(1.47)
WOM_tp × *Tt*				3.60***(1.18)	3.36***(1.14)
WOM_rn × *Tr*				− 0.42 (0.63)	− 0.38 (0.64)
WOM_nn × *Tn*				− 1.06 (0.79)	− 1.09 (0.78)
WOM_cn × *Tc*				− 1.47*(0.82)	− 1.54*(0.79)
WOM_on × *To*				− 3.22***(1.21)	− 3.34***(1.22)
WOM_tn × *Tt*				− 1.06 (0.88)	− 0.92 (0.85)
Interpersonal trust variables	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes
Constant	− 1.39*(0.83)	− 3.43***(0.89)	− 2.78***(1.01)	− 3.05***(0.93)	− 2.66**(1.06)
Log likelihood	− 426.72	− 369.44	− 377.00	− 356.81	− 353.11
Pseudo-r^2	0.11	0.23	0.23	0.25	0.26
Prob > chi^2	0.00	0.00	0.00	0.00	0.00
Likelihood-ratio test		114.57***	122.41***	139.82***	147.23***
AUC	0.73	0.82	0.82	0.83	0.84
AIC	885.45	800.87	803.04	795.63	798.21

$N = 913$; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; standard errors are in parentheses; landform dummies are included in models 1, 2, 3, 4 and 5 with plains as the reference

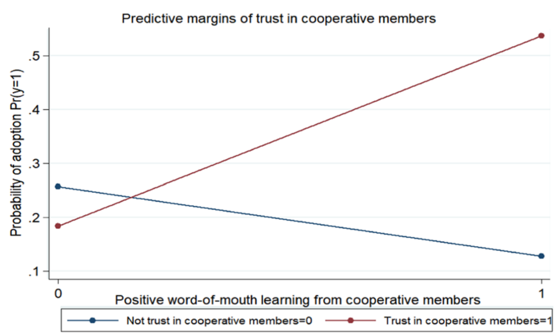
shown in Fig. 2a, allows further investigation. Specifically, there was a 15% increase in the use probability (from 0.11 to 0.26) by farmers who trusted and obtained OB from relatives. However, for farmers who did not trust their relatives, the increase in use probability was only 4% (from 0.21 to 0.25). One explanation for this phenomenon is that trusting relatives can make the information obtained via OB more salient, reliable, and persuasive. As a result, personal ambiguity about the technology can be greatly reduced if farmers trusted their relatives. Consequently, having trust in relatives may strengthen the relationship between OB from relatives and biogas use. Williams [56] noted that when trust is present, positive information may facilitate consistent behaviors like technology adoption, which requires little time and cognitive resources.



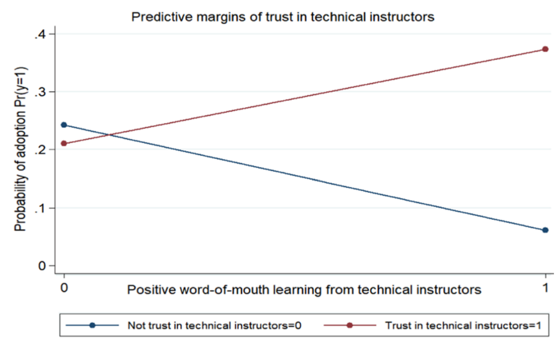
(a) Moderating effect of interpersonal trust on the relationship between OB from relatives and adoption



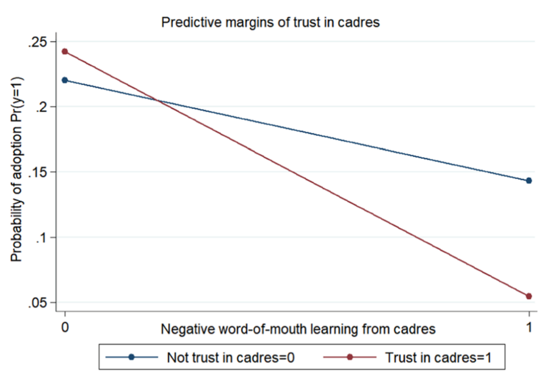
(b) Moderating effect of interpersonal trust on the relationship between positive WOM from neighbors and adoption



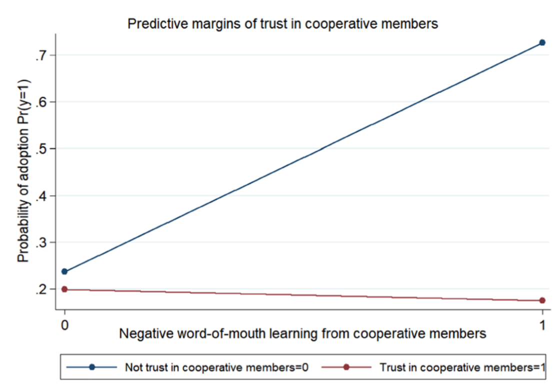
(c) Moderating effect of interpersonal trust on the relationship between positive WOM from cooperative members and adoption



(d) Moderating effect of interpersonal trust on the relationship between positive WOM from technical instructors and adoption



(e) Moderating effect of interpersonal trust on the relationship between negative WOM from cadres and adoption



(f) Moderating effect of interpersonal trust on the relationship between negative WOM from cooperative members and adoption

Fig. 2 Moderating effect of interpersonal trust on the relationships between WOMs/OBs and adoption

Moderating role of interpersonal trust on the relationships between WOMs and adoption

The interaction coefficient of positive WOM from neighbors with trust in neighbors was positive and statistically significant at the 5% level (Fig. 2b). Farmers who trusted their neighbors and acquired positive WOM from them had a 25% higher probability (from 0.19 to 0.44) of using residue-based biogas than those who did not trust their neighbors had only 1% (from 0.11 to 0.12) increase in use probability, which was in line with the study of Abrams et al. [57], who stated that interpersonal trust is a driver for the knowledge and experience sharing in networks, and makes knowledge exchanges less costly. The transformation of knowledge into actions could be greatly promoted if interpersonal trust exists. Farmers in rural China are closely interconnected with their neighbors, resulting in familiarity and frequent interaction with each other. Therefore, positive WOM from neighbors can enhance the perceptions of farmers on the advantages of residue-based biogas and neighbors' satisfaction with the adoption. Trust in neighbors helps to make these perceptions more profound, inducing their transformation into action.

The interaction coefficient of positive WOM from cooperative members with trust in cooperative members was also positive and statistically significant at the 5% level. This moderating effect is highlighted in Fig. 2c. Farmers who trusted cooperative members and acquired positive WOM from them had a 36% higher chance (from 0.18 to 0.54) of using residue-based biogas than those who trusted cooperative members but failed to obtain this type of learning. However, among farmers who did not trust cooperative members, those who obtained positive WOM from cooperative members had a 13% lower probability (from 0.26 to 0.13) of using residue-based biogas than those who did not obtain this type of learning. This finding has its particularity and rationality. Cooperative members in rural China are assumed to have better access to technical information because the specialized cooperative organizations provide their members with excellent technical services [58]. Therefore, farmers who trust these members can have confidence in the positive information accumulated by positive WOM from these members. On the contrary, farmers are not emotionally close to cooperative members because of different social identities [59], which could lead to a distrust in cooperative members. Against this backdrop, the side effect of total distrust in cooperative members may be greatly strengthened, resulting in a negative impact on the relationship between positive WOM and the use behavior.

The interaction coefficient of positive WOM from technical instructors with trust in technical instructors was positive and statistically significant at the 1% level. A graph illustrating this moderating effect is shown in Fig. 2d. Farmers who trusted technical instructors and acquired positive WOM from them had a 16% higher chance (from 0.21 to 0.37) of using residue-based biogas compared to those who trusted technical instructors but failed to obtain this type of learning. However, among the farmers who did not trust the technical instructors, those who obtained positive WOM from them had an 18% lower probability (from 0.24 to 0.06) of using residue-based biogas than those who did not. Technical instructors are expected to have a significant degree of technical information and to be skilled in agricultural technologies. Thus, trusting them can greatly help the transformation of positive WOM from technical instructors to real actions. However, technical instructors' work for the government in rural areas [12], and farmers distrust local government representatives, could exacerbate a negative influence. Therefore, the probability of biogas uses for farmers who do not trust technical instructors yet obtain positive WOM from them may be reduced.

Model 5 indicated that the interaction coefficient between the negative WOM from cadres and trust in cadres was negative and statistically significant at the 10% level. This moderating effect is shown in a graph (Fig. 2e). Farmers who trusted the cadres and as well obtained negative WOM from them had an 18% lower chance (from 0.24 to 0.06) of using residue-based biogas than those who trusted the cadres but did not obtain this type of learning. However, among farmers who did not trust the cadres, those who obtained negative WOM from the cadres had an 8% lower probability (from 0.22 to 0.14) of using residue-based biogas than those who failed to obtain this type of learning. This observation could be because village cadres in rural China represent power and authority, and are respected by rural farmers [60]. Trust in cadres can distinctively increase farmers' negative perceptions of residue-based biogas if they obtain this kind of learning from cadres, resulting in a low probability of use.

Model 5 suggests that the interaction coefficient of negative WOM from cooperative members with trust in cooperative members is negative and statistically significant at the 1% level. This moderating effect is shown in Fig. 2f. Specifically, farmers who trusted cooperative members and obtained negative WOM from them had a 3% lower probability (from 0.20 to 0.17) of using residue-based biogas than those who did not obtain this type of learning. In comparison, among farmers who did not trust cooperative members, those who obtained negative WOM from cooperative members had a 49% higher probability (from 0.24 to 0.73) of using residue-based biogas than those who did not obtain this type of learning. This seemingly contradictory result is not surprising for rural China. As stated before, cooperative members are assumed to have good technical information. Negative WOM may violate farmers' previous on the utility of this biogas given the asymmetric information in rural China [61]. Therefore, farmers who trust cooperative members have a lower use probability since cooperative members are not emotionally attentive to farmers. The lack of trust among farmers in cooperative members may have a reverse effect, i.e., the farmers' use probability will increase even though they receive negative WOM from cooperative members.

Robustness checks

To check the robustness of binary logistic estimates, OLS and probit methods were employed to examine the impact of OBs and WOMs on farmers' use of biogas, and the moderating role of interpersonal trust. The results of the obtained robustness are shown in Table 3. They indicate that the OB obtained from technical instructors significantly influences the use behavior and that interpersonal trust does moderate the relationships between OBs and use of biogas by farmers, and between WOMs and use of biogas by farmers. These results further support credibility of the binary logistic estimates present in Table 2.

Table 3 Robustness check results with OLS and probit model employed

Variables	OLS	Probit
OB_r	0.04 (0.05)	0.14 (0.18)
OB_n	0.02 (0.06)	0.39 (0.33)
OB_c	− 0.04 (0.06)	− 0.20 (0.25)
OB_o	0.02 (0.07)	− 0.03 (0.24)
OB_t	0.15^{**}(0.06)	0.55^{**}(0.23)
WOM_rp	0.05 (0.06)	0.04 (0.20)
WOM_np	− 0.00 (0.10)	0.02 (0.35)
WOM_cp	0.18^{**}(0.07)	0.71^{**}(0.28)
WOM_op	− 0.17 (0.21)	− 0.69 (0.74)
WOM_tp	-0.28^{***}(0.09)	-1.16^{***}(0.43)
WOM_rn	− 0.01 (0.06)	0.09 (0.22)
WOM_nn	− 0.04 (0.10)	− 0.19 (0.41)
WOM_cn	− 0.11 (0.08)	− 0.38 (0.30)
WOM_on	0.41^{**}(0.19)	1.79^{***}(0.60)
WOM_tn	0.02 (0.06)	0.11 (0.26)
OB_r × *Tr*	0.09 (0.05)	0.61^{**}(0.24)
OB_n × *Tn*	0.08 (0.05)	0.12 (0.32)
OB_c × *Tc*	0.02(0.06)	0.04(0.25)
OB_o × *To*	− 0.08(0.07)	− 0.17(0.24)
OB_t × *Tt*	− 0.00(0.06)	0.04(0.23)
WOM_rp × *Tr*	0.00(0.10)	0.20 (0.34)
WOM_np × *Tn*	0.24^{**}(0.11)	0.94^{**}(0.38)
WOM_cp × *Tc*	− 0.12(0.10)	− 0.24 (0.39)
WOM_op × *To*	0.51^{**}(0.23)	1.98^{**}(0.84)
WOM_tp × *Tt*	0.42^{***}(0.13)	1.85^{***}(0.62)
WOM_rn × *Tr*	− 0.04 (0.10)	− 0.24 (0.36)
WOM_nn × *Tn*	− 0.14 (0.11)	− 0.61 (0.43)
WOM_cn × *Tc*	− 0.07 (0.09)	-0.91^{**}(0.45)
WOM_on × *To*	-0.41^{*}(0.21)	-1.96^{***}(0.72)
WOM_tn × *Tt*	− 0.07 (0.09)	− 0.54 (0.48)
Interpersonal trust variables	Yes	Yes
Control variables	Yes	Yes
Constant	0.17 (0.11)	-1.46^{**}(0.58)
Prob > *F*/ Prob > chi^2	0.00	0.00

$N=913$; $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$; standard errors are in parentheses; landform dummies are included in OLS and Probit estimates with plains as the reference

Discussion

As a final discussion, after trying to explore the role of interpersonal trust in the effects of social learning on farmers' use of residue-based biogas, this paper obtains some general and main findings. The general findings are drawn as follows. Analysis of this survey data reveals that only 22% of the farmers surveyed used residue-based biogas, implying that the use rate is relatively low in rural Hubei, China. A large number of farmers receive OB from neighbors. Compared to the number of farmers who had access to OB, the number of farmers who obtained positive or negative WOMs is much less. Comparatively, interpersonal trust is generally high, and more than 70% of farmers trust their neighbors.

Main findings and policy implications

First, the empirical results presented here show that OB from technical instructors positively influences farmers' use of residue-based biogas. This implies that acquisition of OB from technical instructors can help promote adoption of residue-based biogas. Farmers may be uncertain about the utility and return effects of using residue-based biogas. However, if they obtain OB from others, especially from technical instructors, they are more likely to utilize biogas, and the demonstration activities are much more effective. Thus, it is necessary for local governments and their development partners to design and implement strategies aimed at encouraging farmers to obtain OB from technical instructors.

Second, the results reveal that interpersonal trust strengthens the relationship between OB from relatives and use behavior by farmers. That is, without farmers' trust in relatives, the transfer of technology from relatives through OB may be ineffective. Farmers are generally risk averse [62]. Thus, if they do not trust others, they are less likely to use residue-based biogas based on knowledge acquired via OB. Therefore, implementation of policies meant to increase farmers' use of residue-based biogas based on knowledge acquired through OB, policymakers and practitioners should first pay attention to the interpersonal trust levels among farmers. Mechanisms aimed at promoting mutual trust between farmers and relatives should be developed and implemented.

Third, this empirical study shows that interpersonal trust improves the relationship between positive WOM and use behavior. However, it weakens the relationship between negative WOM and the use behavior. When farmers trust others, dissemination of knowledge related to diffuse residue-based biogas via positive WOM becomes more effective. In contrast, when farmers trust others, acquisition of knowledge about residue-based biogas via negative WOM may fail. Therefore, policy practitioners should be cautious when implementing measures to promote biogas adoption through WOMs combined with interpersonal trust. Communication platforms should be built to inspire farmers who trust in others to actively participate in positive WOM. In addition, policy practitioners should advice farmers who trust others to critically value the information obtained from negative WOM.

Limitations and outlook for future research

Despite the interesting results presented in this study, we acknowledge that the generalizability of these results to the national level should be carefully considered since the study sample was only derived from of rural Hubei, China. Nevertheless, this study provides foundational data that can be used to establish national data. In addition, owing to the lack of time series data, this study was based on one-year data which do not capture the dynamic impacts of OB and WOM on technology adoption. Therefore, future empirical studies should aim to analyzing panel data to examine these dynamic effects. Furthermore, with data unavailable, we could not include the potential factors influencing residue-based biogas use such as the volume of agricultural waste production in our study. Future studies may explore the impacts of these potential factors on residue-based biogas use with relevant data at hand.

Conclusions

This paper is the first to incorporate the moderating role of interpersonal trust into the effects of social learning on farmers' use of residue-based biogas. Using data from representative household-based surveys in rural Hubei China comprising 913 farmers, we empirically examined and distinguished the impacts of OBs and WOMs on biogas use from different subjects (i.e., relatives, neighbors, cadres, cooperative members and technical instructors). It reveals that OB from technical instructors positively influences farmers' use of residue-based biogas, and that interpersonal trust strengthens the relationships between OB from relatives and use behavior by farmers, and between positive WOM and use behavior, but it weakens the relationship between negative WOM and the use behavior. These findings of this paper contribute to our understanding in the moderating role of interpersonal trust in the investigation of the impact of social learnings and to enriching the research field of farmers' use of biogas.

Appendix 1

See Table 4.

Table 4 Multicollinearity test results

Variables	VIF	1/VIF
OB_r	2.04	0.49
OB_n	3.06	0.33
OB_c	3.24	0.31
OB_o	2.56	0.39
OB_t	2.59	0.40
WOM_rp	2.43	0.41
WOM_np	2.47	0.41
WOM_cp	1.74	0.58
WOM_op	1.83	0.55
WOM_tp	1.95	0.51
WOM_rn	2.80	0.36
WOM_nn	2.68	0.37
WOM_cn	1.75	0.57
WOM_on	1.64	0.61
WOM_tn	1.65	0.61
Tr	1.14	0.87
Tn	1.04	0.96
Tc	1.28	0.78
To	1.26	0.79
Tt	1.29	0.78
Gender	1.24	0.81
Age	1.29	0.78
Education	1.46	0.68
Labor	1.14	0.88
Household income	1.17	0.86
Subsidy	1.11	0.90
Risk perception	1.19	0.84
Cost-effective perception	1.16	0.86
Hill	1.24	0.81
Mountains	1.24	0.81

$N = 913$; the VIF scores range from 1.04 to 3.24, and the multicollinearity test result was acceptable in our study

Appendix 2

See Table 5.

Table 5 Evaluation statistics of the logistic model

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
OB_r		0.64**(0.27)	0.22 (0.30)	0.67**(0.28)	0.26 (0.31)
OB_n		0.83**(0.36)	0.56 (0.67)	0.86**(0.37)	0.81 (0.69)
OB_c		− 0.39 (0.35)	− 0.30 (0.44)	− 0.45 (0.37)	− 0.40 (0.45)
OB_o		− 0.22 (0.32)	− 0.05 (0.44)	− 0.28 (0.33)	− 0.05 (0.44)
OB_t		0.94***(0.33)	0.79**(0.39)	1.09***(0.34)	0.97**(0.40)
WOM_rp		0.25 (0.29)	0.23(0.29)	− 0.01 (0.36)	0.02 (0.35)
WOM_np		1.14***(0.30)	1.19***(0.31)	0.02 (0.65)	0.06 (0.65)
WOM_cp		0.99***(0.34)	1.00***(0.33)	1.27**(0.49)	1.29***(0.49)
WOM_op		1.11*(0.60)	1.08*(0.59)	− 0.97 (1.23)	− 1.19 (1.29)
WOM_tp		− 0.78 (0.58)	− 0.73 (0.56)	− 2.34***(0.80)	− 2.20***(0.79)
WOM_rn		0.02 (0.34)	0.04 (0.34)	0.13 (0.38)	0.15 (0.38)
WOM_nn		− 1.01***(0.34)	− 1.06***(0.34)	− 0.25 (0.76)	− 0.27 (0.75)
WOM_cn		− 0.87**(0.38)	− 0.91**(0.38)	− 0.76 (0.53)	− 0.74 (0.53)
WOM_on		0.72 (0.62)	0.62 (0.62)	3.10***(1.00)	3.12***(1.03)
WOM_tn		− 0.25 (0.41)	− 0.19 (0.41)	0.14 (0.47)	0.17 (0.46)
OB_r × Tr			1.11**(0.44)		1.12**(0.45)
OB_n × Tn			0.29 (0.63)		0.03 (0.65)
OB_c × Tc			0.03 (0.44)		0.07 (0.45)
OB_o × To			− 0.23 (0.42)		− 0.31 (0.43)
OB_t × Tt			0.19 (0.40)		0.11 (0.41)
WOM_rp × Tr				0.56 (0.60)	0.42 (0.60)
WOM_np × Tn				1.58**(0.70)	1.56**(0.69)
WOM_cp × Tc				− 0.43 (0.70)	− 0.48 (0.68)
WOM_op × To				3.33**(1.43)	3.48**(1.47)
WOM_tp × Tt				3.60***(1.18)	3.36***(1.14)
WOM_rn × Tr				− 0.42 (0.63)	− 0.38 (0.64)
WOM_nn × Tn				− 1.06 (0.79)	− 1.09 (0.78)
WOM_cn × Tc				− 1.47*(0.82)	− 1.54*(0.79)
WOM_on × To				− 3.22***(1.21)	− 3.34***(1.22)
WOM_tn × Tt				− 1.06 (0.88)	− 0.92 (0.85)
Tr	− 0.33*(0.19)	− 0.23 (0.20)	− 0.98***(0.37)	− 0.36 (0.25)	− 1.08***(0.31)
Tn	1.07***(0.22)	1.25***(0.27)	1.02*(0.55)	0.96***(0.31)	0.95*(0.57)
Tc	− 0.03 (0.19)	0.12 (0.21)	0.11 (0.37)	0.23 (0.24)	0.22 (0.38)
To	− 0.24 (0.19)	− 0.32 (0.21)	− 0.24 (0.29)	− 0.44*(0.23)	− 0.33 (0.30)
Tt	− 0.16 (0.19)	− 0.06 (0.21)	− 0.14 (0.281)	− 0.19 (0.23)	− 0.24 (0.29)
Gender	− 0.16 (0.19)	− 0.10 (0.21)	− 0.08 (0.21)	− 0.19 (0.21)	− 0.17 (0.22)
Age	− 0.00 (0.01)	0.01 (0.01)	0.00 (0.01)	0.01 (0.01)	0.00 (0.01)
Education	0.08***(0.03)	0.08**(0.03)	0.07**(0.03)	0.09**(0.03)	0.08**(0.03)
Labor	0.04 (0.06)	0.06 (0.07)	0.06 (0.07)	0.07 (0.07)	0.07 (0.07)
Household income	− 0.00 (0.01)	− 0.01 (0.01)	− 0.01 (0.01)	− 0.01 (0.01)	− 0.01 (0.01)
Subsidy	0.44**(0.19)	0.25 (0.22)	0.29 (0.22)	0.23 (0.23)	0.27 (0.23)
Risk perception	− 0.46***(0.09)	− 0.29***(0.10)	− 0.29***(0.10)	− 0.31***(0.10)	− 0.32***(0.10)
Cost-effective perception	0.18*(0.10)	0.09 (0.11)	0.08 (0.12)	0.09 (0.12)	0.09 (0.12)
Hill	− 0.69***(0.19)	− 0.79***(0.22)	− 0.76***(0.22)	− 0.789***(0.23)	− 0.79***(0.23)
Mountains	− 0.60 (0.40)	− 0.57 (0.49)	0.64 (0.49)	− 0.65 (0.53)	− 0.72 (0.52)
Constant	− 1.39*(0.83)	− 3.43***(0.89)	− 2.78***(1.01)	− 3.05***(0.93)	− 2.66**(1.06)
Log likelihood	− 426.72	− 369.44	− 377.00	− 356.81	− 353.11

Table 5 (continued)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Pseudo-r^2	0.11	0.23	0.23	0.25	0.26
Prob > chi^2	0.00	0.00	0.00	0.00	0.00
Likelihood-ratio test		114.57***	122.41***	139.82***	147.23***
AUC	0.73	0.82	0.82	0.83	0.84
AIC	885.45	800.87	803.04	795.63	798.21

$N=913$; $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$; standard errors are in parentheses; terrain dummies are included in all models with plains as the reference

Supplementary Information

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Additional file 1. Part of the survey questionnaire.

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Author contributions
YZ was the main author responsible for the design, data collection, analysis, and interpretation of the results of this study. FQ complemented the discussion related to the cultural theory and provided relevant feedback for the improvement of the article's clarity. JZ complemented the design and data collection. All authors read and approved the final manuscript.

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Availability of data and materials
The datasets generated and analyzed in this paper are not publicly available due to confidentiality reasons. However, the transcripts of the anonymous interviews are available on reasonable request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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