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Analysis of Influencing Factors on Farmers' Willingness to Pay for the Use of Residential Land Based on Supervised Machine Learning Algorithms

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Abstract: Aimed at advancing the reform of the Paid Use of Residential Land, this study investigates the willingness to pay among farmers and its underlying factors. Based on a Logistic Regression analysis of a micro-survey of 450 pieces of data from the Sichuan Province in 2023, we evaluated the effects of three factors, namely individual, regional and cultural forces. Further, Random Forest analysis and SHAP value interpretation refined our insights into these effects. Firstly, the research reveals a significant willingness to pay, with 83.6% of sample farmers being ready to participate in the reform, and 53.1% of them preferring online payment (the funds are mostly expected to be used for village infrastructure improvements). Secondly, the study implies that Individual Force is the most impactful factor, followed by regional and cultural forces. Thirdly, the three factors show different effects on farmers' willingness to pay from different income groups, i.e., villagers with poorer infrastructure and lower clarity of homestead policy systems tend to be against the reform, whereas farmers with strong urban identity and collective pride support it. Based on these findings, efforts should be made to increase the publicity of Paid Use of Residential Land. Moreover, we should clarify the reform policies, accelerate the development of the online payment platform, use the funds for village infrastructure improvements, and advocate for care-based fee measures for disadvantaged groups.

Keywords: paid use of rural residential; willingness; farmers; distributed cognition; machine learning

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1. Introduction

Efficiency and fairness represent the primary value objectives in the ongoing reform of Rural Residential Land Use System. The use right system of residential land, characterized by "free acquisition, free retention, and one residence for one family" [1], originated from the planned economy era. However, in the current socio-economic context, this system has manifested significant negative externalities. The concurrent over-occupation [2] and idleness [3] of the residence bases, disputes over the residential bases [4], the encroachment of arable land for construction [5], and the peasants' concept of private ownership of residential bases [6] collectively imply that the gratuitous use system is increasingly incompatible with the realities of the new era. It struggles to address the fairness and efficiency in land resource allocation.

In 2010, the Ministry of Land and Resources issued the Notice on Further Improving the Rural Residential Base Management System and Effectively Safeguarding the Rights and Interests of Farmers, which allows village collectives, particularly in areas with better economic conditions and notable contravention in the supply of land resources, to implement a pilot program for the Paid Use of Residential Bases within households who are applying for new residential bases. Consequently, the reform of Paid Use of Residential Land, initiated in the early 1990s and quickly halted, has re-emerged into the spotlight.

Currently, the academic community has not yet clearly defined The Paid Use of Residential Land. Combined with the academic perspectives, this study posits that The Paid

Utilization of Residential Land, in its strictest sense, mainly refers to Paid Acquisition of Homestead Land and Paid Retention of Residential Base. The Paid Acquisition of Residential Base mainly refers to the selection fee of the newly acquired residential land based on factors such as area and geographical location, while Paid Retention of Residential Land typically refers to the fees for the use of existing residential land. This primarily encompasses three categories: residential land that is occupied beyond the standard due to historical reasons, additional properties owned by households with multiple residences, and residential land possessed by non-members of the local collective economic organization through inheritance or other forms of acquisition. Given that the majority of pilot regions for The Paid Utilization of Residential Land prioritize 'retention over acquisition', and only a handful are implementing reforms of 'Paid Acquisition of Homestead Land', this paper concentrates its discussion on the Paid Retention of Residential Land aspect of Residential Land Use Reform exclusively. Therefore, this paper delves into the scenario of Paid Retention within the context of Residential Land Use Reform.

The literature review reveals that current research on Paid Retention of Homestead Land primarily focuses on the establishment of market-oriented pathways [7], the evaluation of reform effect [8], the exploration of the theoretical frameworks [9–11], etc. However, the existing studies still exhibit several deficiencies: (1) most of the studies on Paid Retention of Homestead Land are confined to theoretical explorations with a lack of quantitative analyses; (2) a very small number of empirical studies have placed the Paid Use (retention) and Paid Withdrawal in the same decision-making framework when, in fact, it is not a simple choice between the two (a few studies have examined the influencing factors of farmers' willingness to pay for the use of homesteads); (3) a convincing logical framework for variable selection in empirical econometric models is needed; (4) while previous literature has explored the heterogeneity of location and topography, it has failed to consider the heterogeneous effects of households' income on their willingness to pay for the use of residential land; and (5) existing studies predominantly adopt traditional econometric models, neglecting the need for a diverse research methodology. This limitation makes it challenging to address the endogeneity problem of linear models as well as the inaccurate outcomes due to non-linearity and interaction.

The theoretical framework of Distributed Cognition (DC) employed in this paper underscores the dispersion of cognition among cognitive subjects and environments [12]. Diverging from conventional cognitive science, Distributed Cognition addresses the limitations of traditional cognitive perspectives by considering individual's interactions with the others, the geographical environments, and the socio-cultural contexts [13]. Thus, Distributed Cognition emerges as a novel lens through which all cognitive phenomena can be understood, offering a robust explanatory power for individuals' cognitive activities in intricate social scenarios [14].

Therefore, based on the theoretical foundation of Distributed Cognition, this paper integrates the utilization of diverse models in Supervised Machine Learning algorithms to achieve synergies between models and improve the effectiveness of analysis process. It explores the key factors affecting farmers' willingness to pay for homestead utilization and examines the variability of farmers' income levels. The objective is to elucidate the inherent mechanisms underpinning farmers' cognitive processes and provide decision-making references for the enhancement and optimization of the system of Paid Use of Homesteads.

2. Theoretical Analysis and Research Hypothesis

2.1. Distributed Cognition

Distributed Cognition serves as a robust theoretical framework for analysis, with its applicability spanning a diverse array of domains such as neural brain activity [15], team-based tasks [16], healthcare activities [17], human–computer interactions [18], and collaborative work [19]. Hatch and Gardner proposed a model of concentric circles grounded in distributed cognition theory [14]. The three circles of the concentric circle model represent three cognitive subsystems: (1) Individual Force, the central circle, emphasizing human subjectivity and cognition formed through direct influence from past experiences, tendencies, and individual characteristics and abilities; (2) Regional Force, a circle of significant interest in distributed cognition, symbolizing cognition derived from subject interactions with surrounding people, resources, and environmental elements; and (3) Cultural Forces, the outermost circle, emphasizing the indirect influence of practices, activities, beliefs, evaluations, and other non-material elements on individual cognition. These forces operate independently while interacting, contributing to the development of individual cognitive processes.

Farmers, as cognitive subjects, have their willingness to pay for Homestead Utilization shaped by a multitude of factors, including personal attributes, family profiles, homestead characteristics, village resource endowments, value perceptions, and the policy and market environment [20]. This aligns with the cognitive hierarchy underscored by Distributed Cognition Theory, confirming its applicability. Hence, this study constructs a cognitive analysis framework, grounded in Distributed Cognition Theory and the concentric circle model, to explore farmers' willingness to pay for Homestead Use, as illustrated in Figure 1.

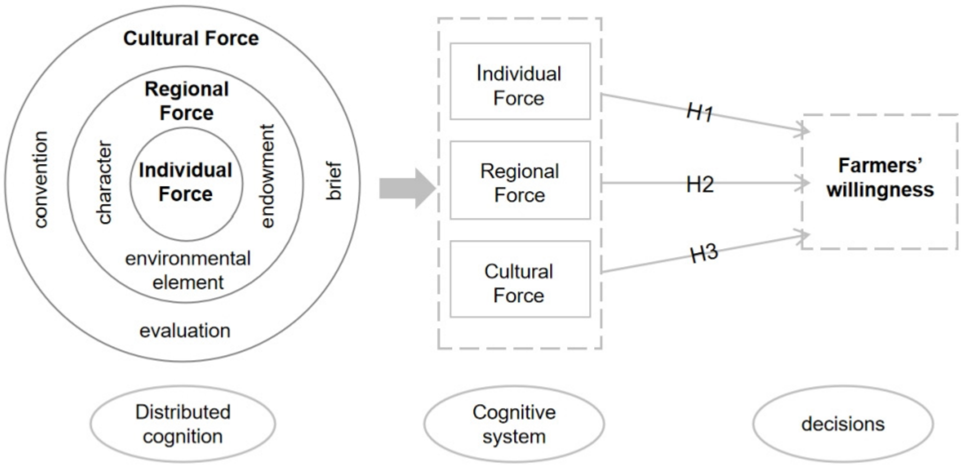

Figure 1. An analytical framework of farmers' willingness based on Concentric Circle Modeling.

2.2. Hypothesis

The Cognitive Behavioural Theory posits that the cognitive interpretations of an individual's behaviour significantly impact their ultimate decisions or actions. The varied behavioral decisions of farmers stem from distinct cognitive processes, and farmers' inclination to utilize homesteads with paid fee can be viewed as the ultimate manifestation of cognitive processing. Building upon the preceding analysis, this paper presents the following hypotheses, firmly grounded in the principles of Distributed Cognition Theory, for thorough examination:

H1: Individual Force has a significant impact on farmers' inclination to pay for the Utilization of Residential Land. Individual Force underscores the influence of a person's past experiences, inclinations, abilities, and their acquired environmental knowledge on their cognition. The selection of individual characteristic variables mainly aims to gauge the subtle, profound impact of an individual's past experiences on Distributed Cognition. In terms of individual tendencies, capabilities, and possessed environmental knowledge, the focus is primarily on the ability to tolerate risk and the level of comprehension of land policies. In the specific distributed cognitive activity related to the Paid Use of Homesteads, there exist individual characteristic differences among farmers, such as age, education level, risk resilience, and understanding of land policies. These differences inevitably lead to diverse cognitions regarding the ownership, function, and value of homesteads, which directly influence their decision-making willingness. More specifically, age influences an individual's acceptance level of new things, while education level also impacts a farmer's cognitive level to some extent, and differences in farmers' understanding of policies can lead to diverse interpretations, thereby influencing their decision-making willingness. Moreover, existing research reveals notable intentional disparities among farmers residing in cities, engaged in an urban-rural dual lifestyle, and living in rural areas when dealing with homestead issues [21]. Significantly, those farmers with elevated risk resilience often possess a broader range of employment and residential options that is attributed to their superior adaptability and transformability in the face of economic, social, environmental, and institutional shocks and pressures [22]. Consequently, the risk resilience of farmers may not only influence their choice to reside or work in their native villages or elsewhere but also their willingness to pay for the paid use of homesteads.

H2: Regional Force plays a crucial role in shaping farmers' inclination to pay for Residential Land Use. Regional Force underscores the local resource endowment, constraints, and the direct impact of the surrounding community on individual perceptions. Concerned with the perceptions of Paid Utilization of Residential Land, the key regional social environmental and resource factors for farmers include family resource endowment, homestead, characteristics, and village location. Consequently, the attributes of farmers' households, homesteads and villages are chosen to gauge the Regional Force dimension. Gender Psychology reveals variations in risk attitudes, decision-making approaches, and perspectives between men and women [23]. The household head holds a cardinal role within the family, exerting considerable influence on the ultimate decisions of the household. Therefore, the gender of the household head could be a crucial factor influencing the willingness to choose. Given that village cadres possess a deeper understanding of policies and a commitment to setting an example, their presence within households may impact the inclination towards certain choices. In alignment with relevant studies, factors such as the number of migrant workers [24], homestead characteristics [25] and village location [20] are considered. Specifically, the distance between the village and town will impact the convenience for farmers to engage in town livelihoods and their personal experience in utilizing existing homesteads, thereby influencing their willingness to pay for using homesteads to some extent.

H3: Cultural Forces have a substantial impact on farmers' inclination to pay for Homestead Use. Cultural Forces underscore the indirect impact of non-material elements, such as practices, rules, activities, and beliefs on individual cognitive processes. Related researches suggest that factors like local attachment [26], individual herd mentality in rural communities [27], concern for social reputation [28], and formal or informal institutions [29] can significantly influence individual cognition. Within the cognitive framework of paying for Homestead Use, an amplified understanding among farmers regarding the security function of homesteads, their empathy towards disadvantaged groups, and the existence of land plots may foster the belief that the reform towards Paid Homestead Use would disrupt their time-honoured practice of utilizing ancestral homes without fiscal obligation. This could engender their resistance towards endorsing the concept of Paid Use of Homesteads. Furthermore, farmers' perceptions of the property function of the homestead, policy identity, collective pride, as well as other values [30], can also serve as cultural determinants that mould their perceptions towards activities related to Paid Homestead Use.

3. Materials and Methods

3.1. Data Sources and Sample Description

The data employed in this investigation were obtained from a focused research effort on the governance of Residential Bases undertaken by our team in July 2023. This research spanned three administrative divisions within the Sichuan Province: the Pidu District and Chongzhou City in Chengdu, and Lu County in Luzhou, as shown in Figure 2. The Pidu District and Lu County were among the first phase of the 33 pilot counties (including cities and districts) in the Rural Residential Base Reform, with Lu County leading the way in implementing a paid-use system for Residential Bases. Thus, the selected study areas offer a degree of representativeness.

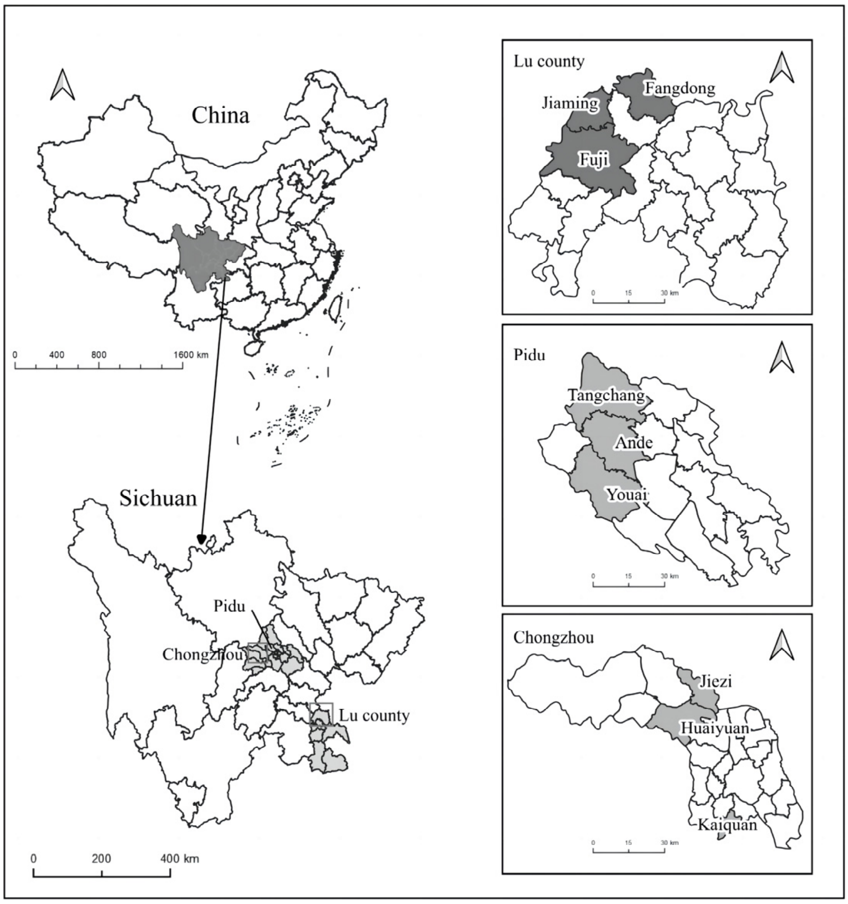

Figure 2. Investigation area.

We employed a mixed-method sampling strategy for this study, utilizing stratified and random sampling. In each county (including cities and districts), we randomly selected three townships, from which we chose two to three administrative villages (or communities). In each village, we selected 20 to 30 households at random for individual interviews and questionnaire surveys with farmers.

Prior to conducting the formal survey, we executed a small-scale interview to refine the questions in the initial questionnaire. This included streamlining the scale, modifying excessively specialized terminologies, standardizing the scale dimensions, etc., aiming to enhance the reliability and validity of the scale. Additionally, we incorporated similar or contrasting queries within various sections of the questionnaire to assess the consistency of responses. Following a Cronbach's alpha reliability assessment, the overall measure yielded an alpha coefficient of 0.818, with each dimension scoring above 0.7. This indicates that the selected variables in our study exhibit robust reliability.

In total, we distributed 500 questionnaires, collecting 450 valid responses for an effective response rate of 90.0%. Table 1 presents the descriptive statistical characteristics of the sampled farm households and homesteads.

Table 1. Characteristics description of samples.

Indicator	Classification Criteria	Frequency /Household	Frequency /%
Gender	Male	349	77.6
	Female	101	22.4
Age	≤35	19	4.2
	36~45	36	8.0
	46~55	133	29.6
	56~65	146	32.4
	≥66	116	25.8
Education Level	Illiterate	19	4.2
	Elementary School	164	36.4
	Junior High School	191	42.4
	High School	50	11.1
	College and above	26	5.8
Social Class	Ordinary Villager	367	81.6
	Village Cadre	83	18.4
Willingness for Paid Use	Willing	376	83.6
	Not Willing	74	16.4
Expected Usage Fee Purpose	Village Infrastructure	390	86.7
	Village Public Services	322	71.6
	Compensation for Exiting Rural Residential Land	85	18.9
	Cadre Performance Reward	28	6.2
	Other (Villager Bonus)	6	1.3
Fee Collection Method for Expected Residential Land Use	Online Self-payment	231	51.3
	Village Residents Pay at Village Committee	52	11.6
	Village Cadres Collect Payment Door-to-Door	167	37.1
Number of Homesteads	One	417	92.6
	Two or more	33	7.3
Homestead Area	0~90 m^2	73	16.2
	91~120 m^2	101	22.4
	121~150 m^2	70	15.6
	151~200 m^2	86	19.1
	201 m^2 and above	120	26.7
Construction Cost of Homestead	0~5 ten thousand	135	30.0
	6~15 ten thousand	143	31.8
	16~30 ten thousand	118	26.2
	31 ten thousand and above	54	12.0
Year of Homestead Completion	Within 10 years	160	35.6
	11~20 years	154	34.2
	21~30 years	95	21.1
	31 years and above	41	9.1
Region	Chongzhou City	143	31.8
	Lu County	154	34.2
	Pidu District	153	34.0

3.2. Variable Selection and Scale Design

Drawing on the Distributed Cognition framework, and guided by variable and indicator selection in relevant studies, we have developed 21 analytical indicators for this research. These indicators cover three cognitive dimensions: Individual Force, Regional Force, and Cultural Force. Table 2 provides detailed information on variable selection and assignment.

Table 2. Variable selection and design.

Dimensionality	Category	Observational Variable	Variable Code	Variable Settings and Assignment Instructions
Individual Force (IF)	Individual Characteristics	Age	age	1: 35 years and below, 2: 36~45, 3: 46~55, 4: 56~65, 5: 66 years and above
		Educational Level	edu	1: Illiterate, 2: Primary School, 3: Junior High School, 4: High School, 5: College and above
	Risk Tolerance	Confidence in Urban Settlement	cityconfid	1: Yes, 0: No
		Willingness for Non-agricultural Employment	nonagri	1: Yes, 0: No
	Land Policy Awareness	Understanding of Local Homestead System	poliknowled	1: No understanding at all, 2: No understanding, 3: Average, 4: Understanding, 5: Very understanding
		Clarity of Village Collective Homestead Management System	clarity	1: Completely disagree, 2: Disagree, 3: Average, 4: Agree, 5: Completely agree
		Adequacy of Propaganda on Village Collective Homestead Reform	advocay	1: Completely disagree, 2: Disagree, 3: Average, 4: Agree, 5: Completely agree
Regional Force (RF)	Family Characteristics	Is there a Village Cadre in the Household?	cadres	1: Yes, 0: No
		Number of Migrant Workers	migrant	/
		Household Head's Gender	gender	1: Male, 2: Female
	Homestead Characteristics	Excessive Occupation of Homestead	overoccupy	1: Yes, 0: No
		Per Capita Homestead Area	perlandarea	/
	Village Characteristics	Village−Town Distance	distance	/
		Level of Infrastructure Development	insfra	1: Very poor, 2: Poor, 3: Average, 4: Good, 5: Very good
Cultural Force (CF)	Empathy	Support for Exemption of Homestead Over-occupation Fee for Vulnerable Groups	empathy	1: Completely disagree, 2: Disagree, 3: Average, 4: Agree, 5: Completely agree
	Perception of Multifunctional Value of Homestead	Homestead Property Function—Whether your own homestead still has appreciation potential	propersen	1: Yes, 0: No
		Homestead Security Function—Importance of Homestead for Residency Support of Rural Farmers	safeguasen	1: Completely unimportant, 2: Unimportant, 3: Average, 4: Important, 5: Very important
	Land Plots	Intention to Rely on Rural Homestead for Retirement	emotieland	1: Yes, 0: No
	Herd Mentality	If others withdraw from the rural homestead, I will do the same	herdment	1: Yes, 0: No
	Policy Identification	Agreement with Local Government's Propaganda on Homestead System	policyident	1: Completely disagree, 2: Disagree, 3: Average, 4: Agree, 5: Completely agree
	Collective Pride	Pride in Being a Villager of My Hometown	collepride	1: Completely disagree, 2: Disagree, 3: Average, 4: Agree, 5: Completely agree

3.3. Methodology

Within the domain of Supervised Machine Learning, a multitude of methodologies are deployed to tackle issues of classification. These encompass an array of models, ranging from Logistic Regression and Support Vector Machines (SVM) to Random Forests (R-Forest) and Decision Trees, with the latter category further bifurcating into classical Decision Trees (D-Tree) and Conditional Inference Trees (C-Tree).

The Logistic Regression analysis was conducted using the Statistical Package for the Social Sciences (SPSS) software, version 27. SPSS was chosen for its robust statistical capabilities and user-friendly interface, which is conducive to executing logistic regressions effectively. For the implementation of Random Forests, Decision Trees, and SVM algorithms, the R statistical programming environment was utilized, specifically version 4.3.2. R was selected because of its extensive library of machine learning packages, such as 'randomForest', 'e1071' for SVM, and 'rpart' and 'party' for Decision Trees, which are pivotal to carrying out advanced machine learning procedures. This combination of SPSS and R coding ensures reproducibility of results and enables other researchers to build upon the findings of this study.

A comprehensive investigation conducted by a global consortium of researchers evaluated the efficacy of 179 classifiers spanning 17 families, employing 121 distinct datasets. The assessment revealed that Random Forests consistently outperformed their counterparts, with SVMs trailing closely behind [31]. Both models demonstrated superior predictive accuracy, coupled with a capacity to mitigate model misconfiguration risks via data-driven strategies. Additionally, Random Forests facilitate the evaluation of feature importance, while SVMs excel in handling high-dimensional data and unravelling intricate nonlinear relationships. However, these models are often characterized as non-interpretable black-box entities, thereby presenting formidable challenges in deciphering their internal mechanics without the aid of interpretable machine models.

Conversely, Decision Trees and the Logistic Regression models are lauded for their high interpretability. Decision Trees, renowned for their intuitive and interpretable nature, can adeptly capture nonlinear relationships but are susceptible to data overfitting. Despite Logistic Regression inheriting the constraints of linear models—where increasing nonlinearity and interactions tend to degrade both model accuracy and interpretability—it boasts distinct advantages. These include the capacity to ascertain the directionality of influence that independent variables exert on the dependent variable, a capability that eludes both visual models such as Decision Tree and non-visual models like Random Forest and SVM, thereby distinguishing Logistic Regression.

Each model under consideration possesses unique strengths in terms of predictive accuracy, interpretability, and generalizability. This study, therefore, innovatively amalgamates multiple models within Supervised Machine Learning algorithms, capitalizing on their collective strengths to amplify prediction accuracy, deepen feature interpretation, and circumvent the limitations intrinsic to a single model approach. The research methodology is delineated in Figure 3.

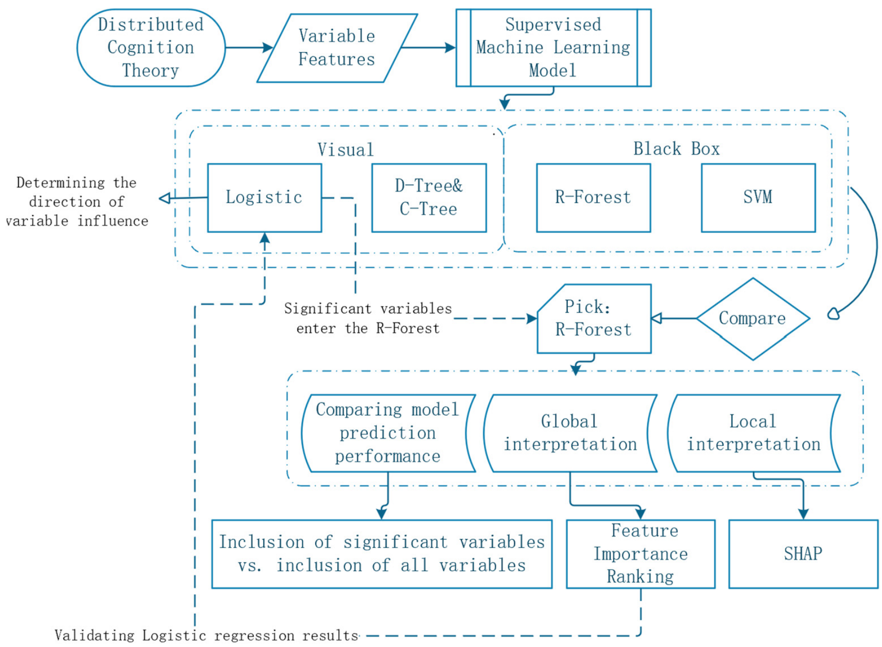

Figure 3. Machine learning flowchart.

Initially, a comprehensive set of 21 characteristic variables—selected in accordance with the Distributed Cognition Theory—were integrated into the conventional logistic model. The output of this logistic model was subsequently leveraged to scrutinize three correlation hypotheses rooted in the "three forces" dimension, as well as to evaluate the heterogeneity in income levels among farming households.

The logistic model is articulated as follows:

$$\text{Logisitc}(\mathrm{P}|y=1)=\ln[\frac{p}{1-p}]=\beta_0+\beta_1X_1+\beta_2X_2+\beta_nX_n+\varepsilon=\beta_0+\sum_{i=1}^{n}\beta_iX_i+\varepsilon \quad (1)$$

In this equation, P symbolizes the probability of farmers expressing willingness to participate in Paid Homestead Usage; X_i represents the explanatory variable; β_i corresponds to the coefficient of the influencing factor; β_0 designates the intercept term; and Ɛ denotes the error term.

Following this, the data is partitioned into training and test sets in a 7:3 ratio. All variables, inclusive of the significant ones identified within the logistic model, are integrated into D-Tree, C-Tree, R-Forest, and SVM models within the Supervised Machine Learning domain for individual training. Each model then undergoes a rigorous validation process using the allocated test set. The performance of these diverse classifiers is meticulously examined using an array of parametric metrics. These include 'Sensitivity' or 'Recall', quantifying the proportion of correctly identified actual positives; 'Specificity', evaluating the fraction of true negatives accurately identified; 'Precision', assessing the proportion of true positives within all positive predictions; and 'Accuracy', measuring the proportion of total observations correctly classified. The predictive performance of these classifiers is scrutinized with precision using these metrics to ensure a comprehensive evaluation. The model demonstrating the most robust and superior performance based on these parameters is then earmarked for further, more detailed analysis.

Lastly, the study employs SHAP, a model-independent post hoc interpretation technique, to shed light on the influence of input variables on the predictions rendered by the most optimized machine learning model. By means of evaluation and intuitive interpretation of SHAP values, we are able to delve into a deeper comprehension of the predictive outcomes generated by intricate models, such as Random Forests and SVM.

4. Logistic Regression Results and Analysis

4.1. Results of Regression Analyses

To further validate the appropriateness of the logistic model, this study employs the Tolerance and Variance Inflation Factor (VIF) to diagnose whether there exists severe multicollinearity among explanatory variables. Included in these variables are dimensions of individual, regional, and cultural forces, as well as regional dummy variables. The dummy variables, 'Chongzhou_dummy' and 'Pidu_dummy', are constructed based on geographical categorizations, aiming to capture potential structural differences across regions. A value of 1 for 'Chongzhou_dummy' indicates that the observation originates from the Chongzhou region, whereas a value of 1 for 'Pidu_dummy' signifies an observation from the Pidu region. In the case where both variables read as 0, the observation is inferred to be from the reference group, i.e., the Lu County region.

Generally speaking, a VIF exceeding 10 suggests a serious multicollinearity problem; Tolerance, being the reciprocal of VIF, is more ideal as it approaches 1. The test results shown in Table 3 indicate that all Tolerance values are greater than 0.1, and the maximum VIF among the independent variables is 2.009, which is far less than 10. This suggests that the model does not have a multicollinearity problem and passes the test.

Table 3. Diagnostic results of multicollinearity of explanatory variables.

Dimensionality	Variables	Tolerance	VIF
Individual force	Age X1	0.619	1.615
	Educational level X2	0.599	1.669
	Urban foothold confidence X3	0.856	1.168
	Non-farm employment intention X4	0.821	1.218
	Homestead system understanding degree X5	0.692	1.444
	Clarity of village collective housing land system X6	0.662	1.511
	Village collective "homestead reform" publicity power X7	0.593	1.688
Regional force	Whether there are village cadres at home X8	0.861	1.161
	Number of migrant workers X9	0.861	1.161
	Gender of household head X10	0.929	1.076
	Whether the homestead is over-occupied X11	0.646	1.548
	Per capita homestead area X12	0.633	1.579
	Village—township distance X13	0.737	1.357
	The degree of infrastructure improvement X14	0.777	1.287
Cultural force	Empathy X15	0.900	1.111
	Homestead property function perception X16	0.861	1.161
	Homestead security function perception X17	0.787	1.271
	Land complex X18	0.841	1.190
	Herd mentality X19	0.886	1.129
	Policy identity X20	0.693	1.443
	Collective pride X21	0.787	1.271
Regional dummies	Chongzhou_dummy	0.498	2.009
	Pidu_dummy	0.522	1.916

The Omnibus test was used for a general global test of the model, and the results showed that the chi-square value in Omnibus was significant, at $p = 0.000 < 0.05$. This indicates that the OR value of at least one variable included in the fitted model is statistically significant, meaning that the model is overall meaningful.

The Hosmer—Lemeshow (HL) test method was used to test the goodness of fit of the model. The significance level of the model is 0.945, much greater than 0.05, indicating that the model does not reject the null hypothesis, and the fitted equation has basically no deviation from the real equation.

The model underwent tests for Multicollinearity, Omnibus, and Hosmer—Lemeshow diagnostics, and all tests passed, indicating no issues in multicollinearity and satisfying the assumptions of the Logistic Regression Model.

The results of the Logistic Regression analysis are shown in Table 4.

Table 4. Logistic model regression results.

Dimensionality	Variable	B	S.E.	Wald	Sig.	Exp (B)
Individual Force	Age X1	−0.338 *	0.186	3.299	0.069	0.713
	Educational level X2	−0.155	0.209	0.553	0.457	0.856
	Urban foothold confidence X3	−0.448 **	0.212	4.476	0.034	0.639
	Non-farm employment intention X4	0.199	0.369	0.292	0.589	1.221
	Homestead system understanding degree X5	0.288	0.181	2.532	0.112	1.334
	Clarity of village collective housing land system X6	0.429 **	0.183	5.479	0.019	1.535
	Village collective "homestead reform" publicity power X7	0.040	0.200	0.039	0.843	1.040
Regional Force	Whether there are village cadres at home X8	0.065	0.421	0.024	0.878	1.067
	Number of migrant workers X9	−0.329 **	0.127	6.683	0.010	0.719
	Gender of household head X10	−0.225	0.359	0.393	0.531	0.799
	Whether the homestead is over-occupied X11	0.056	0.392	0.021	0.885	1.058
	Per capita homestead area X12	−0.005	0.005	1.034	0.309	0.995
	Village−township distance X13	0.162 ***	0.060	7.303	0.007	1.176
	The degree of infrastructure improvement X14	0.919 ***	0.218	17.685	0.000	2.506
Cultural Force	Empathy X15	−0.582 ***	0.207	7.948	0.005	0.559
	Homestead property function perception X16	0.333	0.275	1.463	0.226	1.395
	Homestead security function perception X17	−0.424	0.267	2.517	0.113	0.655
	Land complex X18	−0.314	0.453	0.480	0.488	0.731
	Herd mentality X19	0.734	0.554	1.756	0.185	2.084
	Policy identity X20	−0.559 ***	0.170	10.885	0.000	0.572
	Collective pride X21	−0.661 ***	0.204	10.512	0.001	0.517
Regional dummies	Chongzhou_dummy	0.028	0.472	0.004	0.952	1.029
	Pidu_dummy	−0.297	0.451	0.435	0.510	0.743
	_cons	7.407 ***	2.434	9.260	0.002	1647.114

Note: *, **, *** indicate significant at the level of 10%, 5%, and 1%, respectively.

4.1.1. Analysis of Individual Force's Influencing Factors on Farmers' Willingness

The empirical findings align with Hypothesis 1, suggesting that Individual Force significantly impacts farmers' willingness to pay for homestead usage. As indicated in Table 4, the variable "age X1" exhibits significance at the 10% level. The regression coefficient bears a negative sign, implying a lesser inclination towards Paid Homestead Use as the household head's age increases. This observation can be attributed to two potential factors. Firstly, older household heads, who are more deeply ingrained with the concept of private homestead ownership, are accustomed to using their ancestral home without any charge and may find it challenging to adapt to the sudden notion of paid use. Secondly, as the household head ages, their labour capacity diminishes, often leading to a single source of income. The ensuing economic pressures deter them from affording Paid Homestead Use.

The variable representing "confidence in urban foothold X3" is significant at the 5% level, with a negative coefficient. This suggests that farmers with a higher level of urban foothold confidence demonstrate a reduced willingness to pay for Homestead Use. This may be because farmers who are confident in establishing a city life spend less time in rural areas, and therefore, find the Paid Use of Residential Land an additional financial burden with few perceived benefits.

Lastly, "the clarity of the village collective housing land system X6" is significant at the 5 per cent level, and it shows a positive coefficient. This suggests that a clearer understanding of the system increases farmers' propensity to support paid use. This could be because a clearer village collective system fosters more trust in the village collective organization and comfort with the new policy, thereby indicating a higher willingness to pay for use.

4.1.2. Analysis of Regional Force's Influencing Factors on Farmers' Willingness

The empirical findings lend support to Hypothesis 2, positing that Regional Force significantly impacts farmers' willingness to pay for Homestead Use. Specifically, the variable "number of migrant workers X9" under the purview of Regional Force demonstrates significance at the 5% level. The negative coefficient suggests that an increase in the household's migrant worker population corresponds to a diminished willingness to pay for Homestead Use. This could be attributed to fewer people remaining at home to utilize the homestead as the number of migrant workers increases. Consequently, the cost-effectiveness of paying the over-occupation fee for residential land decreases for farmers who utilize less residential land, affecting their willingness to pay. The variable "village−township distance X13" is significant at the 1% level, with a positive coefficient, implying that farmers' willingness to pay for Homestead Use increases as the distance from the village to the township expands. Prior studies suggest that villagers in more remote rural areas are more dependent on land, preferring Paid Homestead Use over Paid Homestead Withdrawal [32].

The variable "degree of infrastructure improvement X14" is significant at the 1% level. Its positive coefficient indicates that farmers are more inclined to support Paid Homestead Use as the village's infrastructure conditions improve. This is likely because improved infrastructure enhances satisfaction with homestead residence, thus increasing farmers' willingness to continue to pay for Homestead Use.

4.1.3. Analysis of Cultural Force's Influencing Factors on Farmers' Willingness

The empirical findings align with Hypothesis 3, positing that Cultural Force significantly impacts farmers' willingness to use homestead land with compensation. The variables "Empathy X15", "Policy Identity X20", and "Collective Pride X21" all demonstrate significance at the 1% level and bear negative regression coefficients. This suggests that farmers with greater empathy for disadvantaged village groups are less likely to support Paid Homestead Use. This may stem from farmers' concern about the increasing economic burden on disadvantaged groups with the promotion of the system of Paid Homestead Use, especially when they show strong empathy for the disadvantaged groups or place themselves in the disadvantaged group's position.

Farmers exhibiting a strong sense of collective pride demonstrate a reduced willingness to pay for Homestead Use. Research suggests that households with a pronounced sense of collective pride often already benefit more from the village's collective Residence Reform (superior village infrastructure, increased income from collective economic organizations, housing upgrades, etc.). There are two potential explanations for this: Firstly, the possible economic expenses associated with Paid Homestead Use may lead farmers with a strong sense of collective pride to realize the potential economic losses they face in living in their own village. Secondly, they may anticipate that the introduction of the Paid Homestead Use System will not enhance their marginal welfare.

Interestingly, farmers with a strong sense of policy acceptance exhibit a lower willingness to pay for Homestead Use. An existing study, exemplified by specific cases, has identified a phenomenon of institutional path dependence for farmers, manifested as an affinity for established institutional arrangements and a concern for potential economic losses that may result from changes to new systems [33]. Hence, this phenomenon could possibly be explained by the notion that farmers with a strong sense of policy identity may identify more with the previous institutional arrangement. Therefore, the introduction of the Paid Homestead Use System, which disrupts the inertia of the old system, may be met with resistance.

4.1.4. Analysis of Insignificance of Regional Dummy Variables

The coefficients of the regional dummy variables are not significant, indicating that, after controlling for the impact of all other variables, the region itself does not exert a significant influence on the dependent variables under study. This may be because the intra-regional differences (captured by other explanatory variables) are more important than the inter-regional differences. However, this does not necessarily mean that regional factors are unimportant, as they might still play a role indirectly through their influence on other variables included in the model. Future research could explore this further, possibly by examining how regional factors interact with other variables or by using different measures or definitions of 'region'.

4.2. Heterogeneity Analysis

Given that Paid Homestead Use entails monetary expenditure, a farming household's income could potentially influence their willingness to pay for such use. Consequently, this study categorizes farming households into high-income, middle-income, and low-income groups based on their annual household income. We then conduct a Segmented Regression Analysis to explore the heterogeneity across different income levels. The outcomes of this heterogeneity analysis are presented in Table 5 below.

Table 5. Results of heterogeneity analysis of farmer's willingness to Paid Use of Residential Land.

Dimensionality	Variable	Entirety	Low-Income Group	Middle-Income Group	High-Income Group
Individual force	Age X1	−0.357 *	−0.403	−0.877 **	−0.210
	Educational level X2	−0.179	−0.292	−0.397	0.076
	Urban foothold confidence X3	−0.430 **	−1.229 *	−0.566	−0.011
	Non-farm employment intention X4	0.168	0.635	−0.402	1.892 **
	Homestead system understanding degree X5	0.295	−0.372	0.556	0.584 *
	Clarity of village collective housing land system X6	0.424 **	2.390 ***	−0.244	0.134
	Village collective "homestead reform" publicity power X7	0.062	−0.124	0.027	0.098
Regional force	Whether there are village cadres at home X8	0.095	0.893	0.131	−0.363
	Number of migrant workers X9	−0.326 **	−0.680 **	−0.262	−0.224
	Gender of household head X10	−0.261	−0.985	0.408	−0.935
	Whether the homestead is over-occupied X11	0.031	−0.119	0.577	−0.536
	Per capita homestead area X12	−0.005	−0.009	−0.009	0.007
	Village−township distance X13	0.165 ***	0.314 *	0.287 **	0.126
	The degree of infrastructure improvement X14	0.921 ***	0.877 *	1.852 ***	0.897 **
Cultural force	Empathy X15	−0.564 ***	−1.232 **	−0.257	−0.812 **
	Homestead property function perception X16	0.348	1.449 **	0.007	0.216
	Homestead security function perception X17	−0.361	−1.915 **	−0.404	0.119
	Land complex X18	−0.266	0.670	−1.048	0.857
	Herd mentality X19	0.697	0.576	0.244	0.942
	Policy identity X20	−0.568 ***	−0.912 **	−0.579 *	−0.387
	Collective pride X21	−0.666 ***	−0.896 *	−0.673 *	−0.985 **
_cons		6.984 ***	15.819 **	7.299	3.966
N		450	144	164	142
Chi-square value		100.856 ***	57.611 ***	49.712 ***	40.598 ***
Logarithmic likelihood value		301.055	65.508	99.823	88.429

Note: *, **, *** indicate significant at the level of 10%, 5%, and 1%, respectively.

The regression outcomes reveal that certain explanatory variables within the three primary dimensions exert heterogeneous effects on farming households across different income groups.

Within the Individual Force dimension, age significantly and negatively influences only the middle-income farmers, while it does not bear a substantial impact on the low- and high-income groups. This suggests that age variation more significantly affects the willingness for Paid Homestead Use within the middle-income bracket. Confidence in urban location exerts a significant negative influence on the low-income group, yet it does not impact the middle- and high-income groups. This further signifies that the fee for paid use of the over-occupied portion of the homestead is insignificant for the middle- and high-income brackets, but constitutes an "extra expense" for low-income farmers confident in urban living and working. Moreover, the clarity of the village collective residence system significantly affects the low-income group's willingness to pay for use. High-income farmers' willingness to pay for land use significantly increases with their readiness to take up non-farm employment and their understanding of the land use system.

Within the Regional Force dimension, the number of migrant workers significantly inhibits low-income farmers' willingness to pay for land use but does not significantly impact the middle- and high-income groups. This further confirms that low-income farmers are more concerned about the "cost-effectiveness" of paid use. Village−township distance has a significant positive effect on the willingness of low- and middle-income farmers, but not on high-income farmers. This may be attributed to low- and middle-income households' greater land-dependency [34], leading them to prefer Homestead Paid Use over Homestead Withdrawal. The degree of village infrastructure improvement significantly influences the willingness for paid use across high, middle, and low-income groups, with the effect being most pronounced in the middle-income group.

Within the Cultural Force dimension, empathy significantly inhibits the willingness for paid use among both high and low-income farmer groups. Other influencing factors, such as policy identity, align with the benchmark regression results and will not be elaborated on further. However, it is noteworthy that the low-income farming households' perception of the multifunctional value of the homestead significantly impacts their willingness to pay for use. Specifically, the stronger the low-income farming households perceive the property function of the homestead, the stronger their willingness for paid use; conversely, the stronger their perception of the homestead's security function, the weaker their willingness for paid use. This is predominantly because farmers who acknowledge the importance of the homestead's security function rely more on rural residences to fulfill their housing needs. Consequently, the burden of the fee for paid use weighs heavier on them, leading to their tendency to oppose paid use, and the converse holds true as well.

5. Analysis of the Superiority and Interpretability of Random Forests in Machine Learning

5.1. Superiority and Performance Evaluation of Random Forest in Machine Learning Algorithms

All variables under the Distributed Cognition theoretical framework and the nine variables that demonstrated significance in the Logistic Regression were incorporated into various Machine Learning Models for further validation and analysis. These models included the Classical Decision Tree (D-Tree), the Conditional Inference Tree (C-Tree), Random Forest (R-Forest), and Support Vector Machine (SVM) models. Parametric metrics were employed to evaluate the performance of classifiers.

Table 6 reveals that Random Forest surpasses the other classifiers in performance, both when including all variables and when including only the significant variables. Moreover, compared with other classification methods, Random Forest also exhibits a distinct advantage in measuring variable importance. Therefore, Random Forest was ultimately selected as the machine learning model for this study.

Table 6. Performance evaluation results of different machine learning algorithms.

Unit; %	(1) Inclusion of All Variables				(2) Inclusion of Significant Variables			
	D-Tree	C-Tree	R-Forest	SVM	D-Tree	C-Tree	R-Forest	SVM
Sensitivity	97	97	97	100	99	99	96	98
Specificity	17	0	22	6	22	22	78	44
Precision	88	86	89	87	95	95	98	96
Accuracy	86	84	87	87	94	94	95	95

Note: Sensitivity represents the probability that positive observations can be successfully predicted, also known as Recall; Specificity refers to the probability of a specific negative observation being successfully predicted. Precision indicates the percentage of observations predicted correctly among those predicted to be positive. Accuracy represents the proportion of observations that have been correctly classified.

5.2. Random Forest-Based Variable Importance Analysis and Model Robustness Validation

Random Forest (R-Forest) is an Ensemble Supervised Learning method that uses decision trees as its fundamental unit. For each observation, R-Forest employs all the generated decision trees for classification, predicting the category of the observation by invoking the "majority rule" principle.

As illustrated in Figure 4, the top 11 variables in terms of importance encompass all the significant variables from the Logistic Regression when all variables are considered. This further substantiates the robustness of the logistic model results. Given that the predictive effect of Random Forest, particularly its specificity performance, in case (II) surpasses that in case (I), the results from (II) are used as the foundation for ranking variable importance. Additionally, each of the three forces contains three significant variables from the Logistic Regression. By aggregating the importance scores of the significant variables within each dimension, it is determined that the order of importance within the three force dimensions follows: Individual Force > Regional Force > Cultural Force.

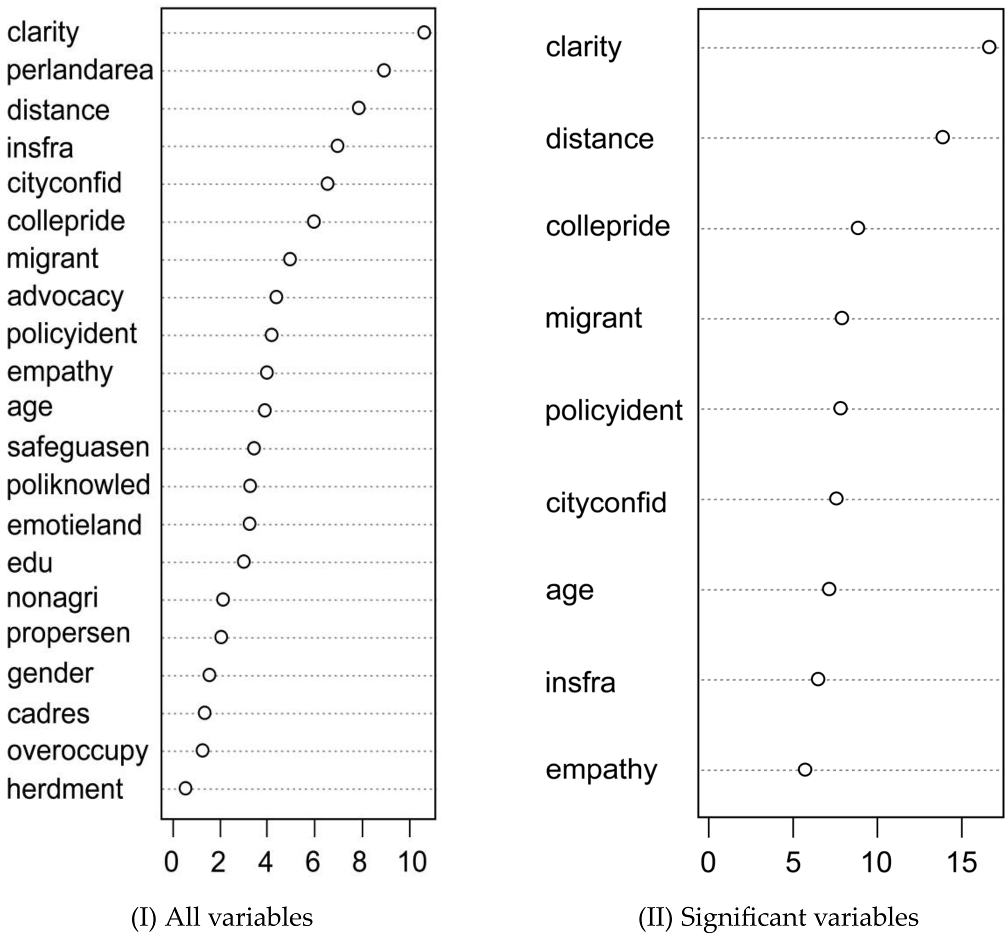

Figure 4. Importance rankings of Random Forest variables.

5.3. Interpretation and Characterisation of Tree Models Based on SHAP Values

SHAP, grounded in the game-theoretically optimal Shapley value, is notably effective for calculating SHAP for tree-based models such as Random Forest and the Gradient Boosting Tree. Consequently, in this study, we employ the swarm plot of the interpretable model SHAP to complement the Random Forest model results with local features based on the Logistic Regression analysis conducted earlier. As depicted in Figure 5, each coloured point represents a specific sample, and the colour signifies the sample's eigenvalue. The horizontal coordinate reflects the SHAP value of the feature item, and through the distribution of the coloured dots, we can observe the influence of each feature on the target variable.

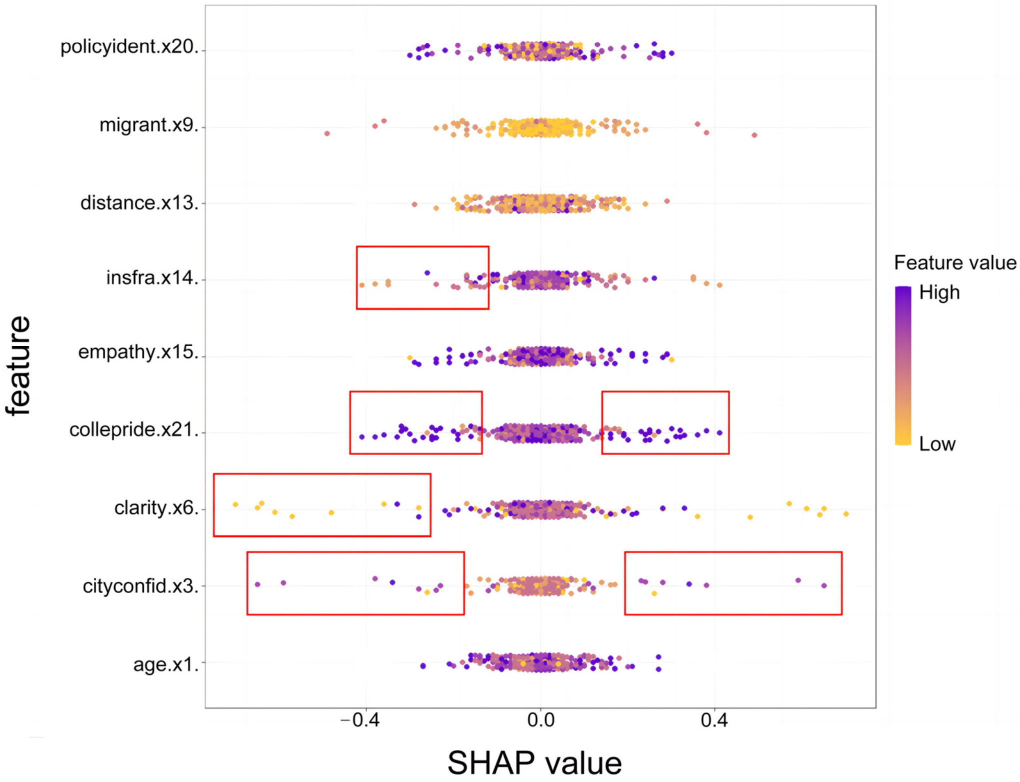

Figure 5. SHAP Swarm Map. Red boxes highlight areas of particular interest discussed in the text.

When the SHAP value for the infrastructure improvement feature is between [−0.4, −0.1], the distribution largely consists of orange dots, indicating low infrastructure improvement. This suggests that farmers in villages with inadequate infrastructure conditions tend to oppose the Paid Use of Homesteads.

The SHAP value of the collective pride characteristic is primarily scattered with dark purple dots at both ends, suggesting a larger variance in willingness among farmers with strong collective pride (dark purple) compared to those with weak collective pride (orange). Furthermore, a weak willingness to pay for Homestead Land Use (negative SHAP value) is predominantly found among farmers with strong collective pride (dark purple).

The left end of the SHAP value for the clarity of the homestead system feature is primarily populated with orange dots, indicating that the weak willingness for Paid Homestead Use is mainly among the farmer group with a low degree of clarity regarding the Homestead System.

For the confidence in the city feature, dark purple dots are distributed at both ends of the SHAP value, while the orange dots are more concentrated near the 0 value. This suggests a polarisation in the willingness of farmers with sufficient confidence in urban living (dark purple) to engage in Paid Homestead Use.

6. Results

Drawing upon the Distributed Cognitive Theory, this study utilizes 450 micro research data sets from rural areas in three counties and cities (districts) in the Sichuan Province. We employ multiple Supervised Machine Learning models in conjunction with field interviews to analyse factors influencing the cognition and willingness of farmers in underdeveloped areas regarding the Paid Use of Homesteads. The findings reveal that: (1) 83.6% of the surveyed farmers are willing to participate in the Paid Use of Homesteads, with 51.3% preferring to pay the usage fee via an online platform, as most farmers envisage utilizing the funds acquired from the Paid Use of Homesteads for village infrastructure construction or public welfare. (2) Individual Force, Regional Force, and Cultural Force significantly influence farmers' willingness to pay for Homestead Use. The order of importance is as follows: Individual Force > Regional Force > Cultural Force. Specifically, "confidence in urban living" within Individual Force, "the number of migrant workers" in Regional Force, and "empathy for disadvantaged groups", "policy identity", and "collective pride" within Cultural Force all significantly and negatively impact farmers' willingness to pay for Homestead Use. Conversely, "clarity of the Village Collective Homestead System" within Individual Force and "the degree of village infrastructure improvement" within Regional Force significantly and positively impact farmers' willingness to pay for Homestead Use. (3) The "three forces" exert heterogeneous effects on the willingness to pay for Homestead Use among different income groups. (4) The ranking of variable importance in the Random Forest model verifies the robustness of the Logistic results. When significant variables from the Logistic Regression replace all variables in the Random Forest model, the overall predictive performance of the model improves considerably (specifically, the model's specificity performance is significantly superior to that of the logistic model). (5) Results from the explanatory model SHAP reveal that farmers residing in villages with underdeveloped infrastructures and a low level of clarity regarding the Homestead System tend to be against the Paid Use of Homesteads. Conversely, the willingness to pay for Homestead Use among farmers with a strong sense of confidence in urban living and collective pride exhibits polarization.

7. Discussion and Policy Implication

Based on the study findings, the following policy recommendations are proposed:

(1) Pilot regions should establish diverse payment channels and expedite the development of online payment facilitation platforms. More than half of the farmers in the surveyed area, particularly the younger demographic, express a preference for conducting payments through online platforms. However, in practice, several pilot areas have not yet established online payment platforms.

(2) To mitigate resistance to the Reform of Paid Use of Homesteads, the primary focus should be on the farmers themselves, followed by the geographical resource endowment. By combining the results of the Logistic Significance and Random Forest variable importance scores, the significance of the "three forces" can be ranked as follows: Individual Force > Regional Force > Cultural Force. Therefore, rather than attempting to alter the geographical resource endowment or constraints, policies that prioritize changes within the farmers themselves (such as enhancing their abilities, inclinations, and environmental knowledge) will yield more effective results in reducing resistance to Paid Use Reform.

Regarding the dimension of Individual Force, the grassroots publicity of the new policy on the Paid Use of Residential Land should be intensified to break down the old perceptions held by farm households.

In terms of the Regional Force dimension, greater attention should be devoted to the development of rural public service infrastructure, and a portion of the funds can be sourced from the fees collected for Paid Use of Residential Land by the Village Collectives. On the one hand, the empirical results show that the extent of infrastructure improvement in the village influences the willingness of farmers at all income levels to pay for the Use of Residential Land; on the other hand, research interviews indicate that a considerable number of farmers expressed a demand for improved village infrastructure.

(3) Categorizing and implementing policies targeting farmers of varying income levels to mitigate resistance towards the Reform of Rural Homestead System is crucial. For instance, middle- and high-income farmers should be educated about the benefits of the Paid Use of Homesteads System as well as the limitations of associated fees. This approach aims to alleviate their concerns regarding the new round of Homestead Reform. In the pilot regions where the Reform on Paid Use of Residential Land has been implemented, it is important to popularize the policy of fee assistance for disadvantaged groups, allowing

low-income farming groups to fulfill specific criteria to defer, reduce, or even exempt their payment.

(4) Enhancing the comprehensibility and clarity of the Residential Land Use policy publicized by the Village Collectives is essential. An analysis of the SHAP hive chart indicates that the reluctance to pay for land use primarily stems from a lack of understanding regarding the Homestead System; therefore, improving farmers' awareness and understanding of the land policy will greatly facilitate the smooth implementation of the reform.

In conclusion, the policy recommendations highlighted above are intended to tackle the existing reluctance and barriers encountered during the implementation of the Paid Use of Residential Land Reform. Through the enhancement of payment channels, fostering a deeper understanding of the system among farmers, and ensuring policy inclusiveness and adaptability to different income groups, the intended reform can potentially see greater acceptance and success.

This study delivers a comprehensive analysis of factors impacting farmers' willingness to pay for Homestead Use, addressing gaps in the existing literature. Prior quantitative studies on the topic have been limited to traditional Logistic Regression analyses, focusing solely on four variable categories: family characteristics, policies and market environment, selected variables of paid exit and use for rural homestead, and reform cognition [32,35]. Our research broadens this scope and innovates in terms of methodology.

We employed quantitative analysis and multiple Supervised Machine Learning models, going beyond current theoretical explorations on Paid Retention of Homestead Land. This approach enables us to tackle issues often overlooked in traditional econometric models. We have constructed a more comprehensive decision-making framework, which highlights the significant roles of individual, regional, and cultural factors in the decision-making process. We also confirmed the heterogeneous effects of household income on the willingness to pay for Homestead Use, emphasizing the need for policy interventions that consider the diverse economic conditions in rural areas. In conclusion, our study not only enhances the understanding of factors influencing farmers' willingness to pay for Homestead Use but also suggests targeted policy interventions based on these findings. The study stands out in its innovative use of diverse methodologies and broadened scope of variable selection.

However, it must be acknowledged that this study still has its limitations. Firstly, the factors influencing the willingness of farmers to use their Homestead Land for a fee range beyond the 21 selected. Variables such as Purpose of Homestead Land Use, arable land planting area, productivity, distance from Homestead to Arable Land, policy subsidies, and community pressures may also significantly impact willingness but were not included in this study. Future research should incorporate these additional variables to enrich and refine the analysis. Secondly, the difficulty encountered by farmers in expressing their payment willingness during surveys, where most responses were uncertain, indicates limitations in data acquisition and the need for improved methodologies. Understanding the economic endurance and payment willingness of farmers is crucial to the reform's optimization. Therefore, future studies should aim at developing more sophisticated methods to capture this critical information.

Through these measures, we aim to contribute to the ongoing discourse and enhance the robustness of future research. The acknowledgement of these limitations is not to undermine the findings of the current study but to pave the way for a more nuanced understanding of impeding factors and the design of future investigative strategies.

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References

1. Kong, X.; Liu, Y.; Jiang, P.; Tian, Y.; Zou, Y. A Novel Framework for Rural Homestead Land Transfer under Collective Ownership in China. *Land Use Policy* **2018**, *78*, 138–146. [CrossRef]
2. Liu, S.; Xiao, W.; Ye, Y.; He, T.; Luo, H. Rural Residential Land Expansion and Its Impacts on Cultivated Land in China between 1990 and 2020. *Land Use Policy* **2023**, *132*, 106816. [CrossRef]
3. Tao, Z.; Guanghui, J.; Wenqiu, M.; Guangyong, L.; Yanbo, Q.; Yingying, T.; Qinglei, Z.; Yaya, T. Dying Villages to Prosperous Villages: A Perspective from Revitalization of Idle Rural Residential Land (IRRL). *J. Rural Stud.* **2021**, *84*, 45–54. [CrossRef]
4. Zhou, T.; Jiang, G.; Ma, W.; Zhang, R.; Yang, Y.; Tian, Y.; Zhao, Q. Revitalization of Idle Rural Residential Land: Coordinating the Potential Supply for Land Consolidation with the Demand for Rural Revitalization. *Habitat Int.* **2023**, *138*, 102867. [CrossRef]
5. Sargeson, S. Subduing "The Rural House-Building Craze": Attitudes Towards Housing Construction and Land Use Controls in Four Zhejiang Villages. *China Q.* **2002**, *172*, 927–955. [CrossRef]
6. Long, H.; Li, Y.; Liu, Y.; Woods, M.; Zou, J. Accelerated Restructuring in Rural China Fueled by 'Increasing vs. Decreasing Balance' Land-Use Policy for Dealing with Hollowed Villages. *Land Use Policy* **2012**, *29*, 11–22. [CrossRef]
7. Wang, Y.; Xie, Y. Economic Analysis and Path Construction of Market-Oriented Compensated Use of Rural Residential Land. *Rural Econ.* **2022**, *02*, 53–61.
8. Zhang, Y.; Zhao, P.; Liu, H. Research on the Differential Implementation Effects and Causes of Compensated Use of Residential Land: A Stakeholder Perspective. *Agric. Econ. Issues* **2021**, *02*, 14–25. [CrossRef]
9. Yue, Y. The Real Logic and Verification of Compensated Use Reform for Rural Residential Land. *Rural Econ.* **2021**, *08*, 46–53.
10. Xia, Z. Exploration of Compensated Use of Residential Land under the Background of Land System Reform. *J. Beijing Univ. Technol. (Soc. Sci. Ed.)* **2018**, *18*, 14–20.
11. Yang, Y. Exploration and Construction of Compensated Use System for Residential Land in China. *Nankai J. (Philos. Lit. Soc. Sci. Ed.)* **2016**, *04*, 70–80.
12. Davis, R.A. A Cognitive-Behavioral Model of Pathological Internet Use. *Comput. Hum. Behav.* **2001**, *17*, 187–195. [CrossRef]
13. Vasiliou, C.; Ioannou, A.; Zaphiris, P. Understanding Collaborative Learning Activities in an Information Ecology: A Distributed Cognition Account. *Comput. Hum. Behav.* **2014**, *41*, 544–553. [CrossRef]
14. Hatch, T.; Gardner, H. Finding Cognition in the Classroom: An Expanded View of Human Intelligence. *Distrib. Cogn. Psychol. Educ. Consid.* **1993**, 164–187.
15. Wang, X.-J. Theory of the Multiregional Neocortex: Large-Scale Neural Dynamics and Distributed Cognition. *Annu. Rev. Neurosci.* **2022**, *45*, 533–560. [CrossRef]
16. Zaina, L.A.M.; Sharp, H.; Barroca, L. UX Information in the Daily Work of an Agile Team: A Distributed Cognition Analysis. *Int. J. Hum. Comput. Stud.* **2021**, *147*, 102574. [CrossRef]
17. Hazlehurst, B.; Gorman, P.N.; McMullen, C.K. Distributed Cognition: An Alternative Model of Cognition for Medical Informatics. *Int. J. Med. Inform.* **2008**, *77*, 226–234. [CrossRef]
18. Hollan, J.; Hutchins, E.; Kirsh, D. Distributed Cognition: Toward a New Foundation for Human-Computer Interaction Research. *ACM Trans. Comput.-Hum. Interact.* **2000**, *7*, 174–196. [CrossRef]
19. Rogers, Y.; Ellis, J. Distributed Cognition: An Alternative Framework for Analysing and Explaining Collaborative Working. 1994, 9, 119–128. *J. Inf. Technol.* **1994**, *9*, 119–128. [CrossRef]
20. Tao, Z.; Guanghui, J.; Guangyong, L.; Dingyang, Z.; Yanbo, Q. Neglected Idle Rural Residential Land (IRRL) in Metropolitan Suburbs: Spatial Differentiation and Influencing Factors. *J. Rural Stud.* **2020**, *78*, 163–175. [CrossRef]
21. Yu, J.; Li, J.; Lo, K.; Huang, S. Withdrawal Intention of Farmers from Vacant Rural Homesteads and Its Influencing Mechanism in Northeast China: A Case Study of Jilin Province. *Chin. Geogr. Sci.* **2023**, *33*, 634–648. [CrossRef]
22. Meuwissen, M.P.M.; Feindt, P.H.; Spiegel, A.; Termeer, C.J.A.M.; Mathijs, E.; Mey, Y.d.; Finger, R.; Balmann, A.; Wauters, E.; Urquhart, J.; et al. A Framework to Assess the Resilience of Farming Systems. *Agric. Syst.* **2019**, *176*, 102656. [CrossRef]
23. Eckel, C.C.; Grossman, P.J. Sex Differences and Statistical Stereotyping in Attitudes toward Financial Risk. *Evol. Hum. Behav.* **2002**, *23*, 281–295. [CrossRef]

24. Zhang, Y.; Torre, A.; Ehrlich, M. The Impact of Chinese Government Promoted Homestead Transfer on Labor Migration and Household's Well-Being: A Study in Three Rural Areas. *J. Asian Econ.* **2023**, *86*, 101616. [CrossRef]
25. Su, K.; Hu, B.; Shi, K.; Zhang, Z.; Yang, Q. The Structural and Functional Evolution of Rural Homesteads in Mountainous Areas: A Case Study of Sujiaying Village in Yunnan Province, China. *Land Use Policy* **2019**, *88*, 104100. [CrossRef]
26. Liu, R.; Jiang, J.; Yu, C.; Rodenbiker, J.; Jiang, Y. The Endowment Effect Accompanying Villagers' Withdrawal from Rural Homesteads: Field Evidence from Chengdu, China. *Land Use Policy* **2021**, *101*, 105107. [CrossRef]
27. Guo, B.; Yuan, L.; Lu, M. Analysis of Influencing Factors of Farmers' Homestead Revitalization Intention from the Perspective of Social Capital. *Land* **2023**, *12*, 812. [CrossRef]
28. Wang, Y.; Wang, Z.; Huang, F.; Wang, Z.; Zhao, Y.; Shuai, J.; Shuai, C. Modeling Behavioral Factors Influencing Farmers' Willingness to Adopt Rooftop Solar Photovoltaic: Empirical Evidence from Rural China. *J. Clean. Prod.* **2023**, *424*, 138874. [CrossRef]
29. Yang, C.; Chen, R.; Zhong, S.; Liu, W.; Xin, G. How Social Solidarity Affects the Outcomes of Rural Residential Land Consolidation: Evidence from Yujiang County, South China. *Land Use Policy* **2023**, *130*, 106662. [CrossRef]
30. Chapman, M.; Satterfield, T.; Chan, K.M.A. When Value Conflicts Are Barriers: Can Relational Values Help Explain Farmer Participation in Conservation Incentive Programs? *Land Use Policy* **2019**, *82*, 464–475. [CrossRef]
31. Fernández-Delgado, M.; Cernadas, E.; Barro, S.; Amorim, D. Do We Need Hundreds of Classifiers to Solve Real World Classification Problems? *J. Mach. Learn. Res.* **2014**, *15*, 3133–3181.
32. Zhang, Y.; Li, M.; Song, K.; Liu, W.; Zheng, A. Analysis of Factors Influencing Compensated Exit and Use of Rural Residential Land. *Econ. Geogr.* **2023**, 1–11. Available online: http://kns.cnki.net/kcms/detail/43.1126.k.20230525.1939.002.html (accessed on 1 February 2024).
33. Hongsheng, C.; Xingping, W. Exploring the Relationship between Rural Village Characteristics and Chinese Return Migrants' Participation in Farming: Path Dependence in Rural Employment. *Cities* **2019**, *88*, 136–143. [CrossRef]
34. Gao, J.; Cai, Y.; Wen, Q.; Liu, Y.; Chen, J. Future Matters: Unpacking Villagers' Willingness to Withdraw from Rural Homesteads in China. *Appl. Geogr.* **2023**, *158*, 103049. [CrossRef]
35. Hu, Y.; Wu, X.; Wang, C.; Yu, Y.; Dong, W.; Xu, X. Exploring Factors Influencing Farmers' Decisions on Paid Exit and Use of Homesteads-An Empirical Study Based on Traditional Agricultural Areas in Yicheng City. *China Land Sci.* **2018**, *32*, 22–29.