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ORIGINAL ARTICLE

An empirical exploration into the determinants of rice farmers' decisions to adopt low-carbon agricultural technologies in Hubei Province, China

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Abstract
Agricultural greenhouse gas emission is a well-known contributor to anthropogenic climate change. It is imperative to encourage farmers to adopt low-carbon agricultural technologies (LATs). In this paper, the Delphi method was used to select nine LATs with good carbon emission reduction effects among all possible technologies adopted in the agricultural production process. Moreover, based on the survey data of 1114 farmers in Hubei province of China, we identified the potential determinants of rice farmers' decisions to adopt LATs and obtained the hierarchical structure of these determinants by employing the multivariate probit model, ordered probit model, and interpretative structural model. Results showed that there were strong complementary relationships between the nine LATs, and most rice farmers (83.48%) adopted three or fewer LATs simultaneously. It was also found that rice farmers' decisions to adopt LATs were mainly influenced by four types of factors, namely individual characteristics, family resource endowments, production managerial factors, and external environmental factors, with production managerial factors exerting the most significant effect. Specifically, for rice farmers who joined agricultural cooperatives, who thought the agricultural machinery costs were acceptable, and who had paddy fields with a higher concentration degree, the probability of the adoption of three or more LATs would increase by 18.05%, 3.81%, and 0.11%, respectively (21.97% in total). In addition, the key determinants of rice farmers' decisions to adopt three or more LATs were divided into three levels, i.e., surface factors, middle-level factors, and deep factors. To promote LATs, policymakers should offer targeted incentives, such as agricultural machinery purchase subsidies, technical guidance, and agricultural cooperative services.

Keywords Rice farmer · Low-carbon agricultural technology · Multivariate probit model · Ordered probit model · Interpretative structural model

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1 Introduction

Climate change is one of the most serious environmental problems facing human society, which has posed severe challenges to carbon sequestration and energy conservation. Agricultural greenhouse gas (GHG) emission is a well-known contributor to anthropogenic climate change. On the one hand, rice cultivation is the key to food security; on the other hand, it is one of the major sources of GHG emission, especially CH_4 emission. Over recent years, the Chinese government has initiated several agricultural programs to ensure food security and environmental sustainability (Liu et al. 2019). For instance, the Ministry of Agriculture and Rural Affairs is leading the promotion of low-carbon agricultural technologies (LATs) to reduce agricultural carbon emissions and improve the quality of agricultural products. However, in many rural areas of China, the adoption of such technologies is slow (Luo et al. 2014, 2016).

LATs are characterized by low energy consumption, low pollution, and low GHG emission. CH_4 and N_2O are the major GHG from rice planting, and effective low-carbon technologies for rice cultivation are needed to mitigate the negative effects of carbon emissions. Many field experiments have proved that integrated pest management (Mukherjee and Arora 2011), conservation tillage (Alvarez et al. 1995; Mehra et al. 2018), irrigation management (Javadi et al. 2019), and rice-fish culture can effectively reduce agricultural GHG emissions during rice cultivation. Although extensive research on LATs has been conducted (Zhao and Zhou 2021), a widely recognized definition of LATs has not yet been made. The Delphi method has been extensively used to evaluate technologies or measures (Xiong et al. 2021). In this paper, we invited twenty experts in agronomy and crop science from the Huazhong Agricultural University to evaluate the carbon emission reduction effects of eighteen rice production technologies through two rounds of questionnaires. According to scoring results, nine of them were included, namely no or minimum tillage, intermittent irrigation, soil testing and formulated fertilizer, straw returning, integrated pest management, water-saving and drought-resistant rice, controlled-release fertilizer, planting green manure, and rice field culture.

Although these LATs have great potential in carbon emission reduction, their adoption remains slow (Luo et al. 2014, 2016). In fact, agricultural producers find it difficult to use LATs (Goyal and Netessine 2007; Smollo et al. 2017). The key to raising the adoption rate of LATs lies in finding out the influencing factors of farmers' decision-making behaviors. First, individual characteristics, such as gender (Karami and Mansoorabadi 2008), age (Jirarud et al. 2016), and educational level (Moges and Taye 2017), affected farmers' willingness to adopt new technologies to different degrees. Second, family attributes, such as agricultural income (Li et al. 2021a, b, c), risks (Sattler and Nagel 2010; Espinosagoded et al. 2010), and migrant workers (Li et al. 2021a, b, c), had a great effect on the adoption rate of a technology. Third, external factors, such as technical experience exchange (Niu et al. 2022), training (Huang et al. 2012), and technical guide (Huang et al. 2021), influenced farmers' adoption behaviors. Based on the theory of planned behavior, the psychological factors that affect farmers' intentions and behaviors (Jiang et al. 2018), especially their perceptions of climate change (Li et al. 2021a, b, c), have been identified. To sum up, many researchers have studied the determinants of farmers' adoption behaviors of a single new technology and made suggestions on how to boost the adoption rate, which provided an important reference for this paper. However, there are still some questions to be further explored. What is the influence mechanism of farmers' decisions to simultaneously adopt several LATs (i.e., joint adoption behavior)? Is there a hierarchy relationship between the influencing factors of farmers' joint adoption behaviors? Further exploration in these aspects will contribute to a better understanding of farmers' low-carbon production decisions and can provide targeted policy implications to improve the adoption rate of LATs and mitigate agricultural carbon emissions.

Based on household-level data from rural areas in Hubei Province, China, this paper attempted to enrich the knowledge in this field from the following aspects: (1) considering farmers' adoption of a single LAT would be influenced by their adoption of other LATs, farmers' joint adoption behaviors were empirically analyzed with the nine LATs introduced; (2) a hierarchical structure of the influencing factors of farmers' joint adoption behaviors was further explored, and they were divided into surface factors, middle-level factors, and deep factors accordingly. In this paper, multivariate probit model (MVP), ordered probit model (OPM), and interpretative structural model (ISM) were employed to reveal the interrelationships between the nine LATs, to identify the determinants (i.e., individual characteristics, family resource endowments, production managerial factors, and external environmental factors) of rice farmers' adoption intensity of LATs, and to further analyze the hierarchy structure of these significant determinants of rice farmers' decisions to adopt three or more LATs. It is expected that this research could provide scientific evidence for policymakers in developing countries and regions to formulate targeted policies that can promote the adoption of LATs and mitigate agricultural carbon emissions.

2 Data and methods

2.1 Data collection and sample

The study was launched in the middle reaches of the Yangtze River, Hubei Province of Central China (Fig. 1). The climatic and topographical conditions in this district make it one of the main rice-producing regions in China. There are three main rice production areas in Hubei Province: (1) the foothills of single-season japonica rice-producing areas in middle and northern Hubei Province, called as area 1; (2) the Jianghan Plain and the quality single and double season japonica rice-producing areas in eastern Hubei Province, called as area 2; and (3) the quality japonica rice-producing areas in northeastern Hubei Province, called as area 3. We randomly selected two to five cities or counties from each

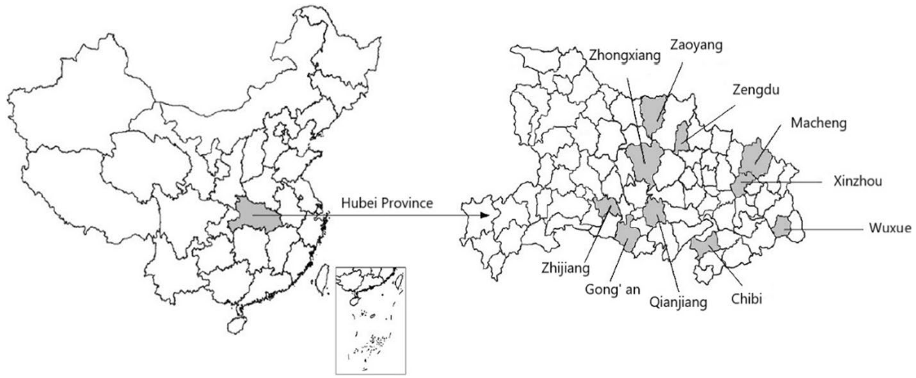

Fig. 1 Survey areas

production area (five cities or counties in area 2 were selected due to its larger area), and then four to five villages were randomly chosen from each county or city. We randomly visited 25–30 farmers in each village. Face-to-face questionnaire investigation was conducted among rice farmers in Zaoyang, Zhongxiang, and Zengdu, which belong to area 1; Zhijiang, Gong'an, Qianjiang, Chibi, and Wuxue, which belong to area 2; and Macheng and Xinzhou, which belong to area 3.

Based on the pre-survey, some interview questions were revised. A structured questionnaire was designed for this study, and it mainly consists of four parts: (1) individual characteristics, such as gender, age, educational level, and farming experience; (2) family resource endowments, such as per-capita paddy field area, agricultural labor, agricultural income proportion, and migrant workers; (3) production managerial factors, such as concentration degree of paddy field, land transfer, agricultural machinery cost, and participation in agricultural cooperatives; and (4) external environmental factors, such as technical experience exchange, training and technical guide, and supply of low-carbon agricultural materials.

Face-to-face interviews were overseen by three doctoral students and seven postgraduates with abundant rural research experience. They were professionally trained before the formal survey. The random sampling strategy was adopted, and 1200 questionnaires were sent out. A total of 1114 effective questionnaires were obtained after eliminating those with incomplete and inconsistent essential information.

2.2 LAT selection

The Delphi method was used, and twenty experts in ecological agriculture from the College of Plant Science and Technology of Huazhong Agricultural University were invited to complete the questionnaire and score 18 rice production technologies according to their carbon emission reduction effects anonymously and individually. The evaluation score was set as "−1," "0," "1," and "2," respectively, representing the increase, no increase/decrease, decrease, and large decrease of GHG emissions. After two rounds of questionnaires, 14 out of 18 technologies were scored "1" or "2" for 15 times or more, indicating that at least 15 out of 20 experts believed that they had significant carbon emission reduction effects and can be regarded as LATs. Then two LATs were eliminated, given that rice farmers were unfamiliar with the professional terms necessary for their application. After combining the remaining twelve technologies, nine LATs were finally determined for rice cultivation in this study. The specific description of the nine LATs is shown in Table 1.

2.3 Model selection

2.3.1 MVP and OPM

MVP is designed to regress a vector of correlated quantal variables on a mixture of continuous and discrete predictors, and it can be widely used in biological, economic, or psycho-sociological research (Lesaffre and Molenberghs 1991). In the actual farming process, rice farmers often simultaneously adopt multiple LATs for rice cultivation. Considering the complementary relationships among the nine LATs, MVP was employed to hold the intrinsic relevance of multiple technologies and to analyze the determinants of rice farmers' decisions to adopt LATs (Gao et al. 2017). Moreover, the number of LATs that rice

Table 1 Description of the nine LATs

Name	Definition	Literature support
No or minimum tillage	Less tillage and no tillage	It is a potential climate change mitigation strategy (Mei et al. 2018)
Intermittent irrigation	Drying the field many times	It can decrease CH_4 emissions from paddy fields (Dong et al. 2017), improve root activities, and cut the cost of field management and water-saving work (Li et al. 2011; Mi et al. 2021)
Soil testing and formulated fertilizer	Fertilizing through soil testing and fertilizer field trials or mixed usage of organic and chemical fertilizers	It can reduce GHG emissions (Liu et al. 2019)
Straw returning	Piling up crushed straw directly in the field	It has the lowest net carbon emissions (Cheng et al. 2015), and the energy utilization of rice straws is economically viable and efficient (Sun et al. 2017)
Integrated pest management	Mixed application of biological and chemical pesticides	It can decrease the reliance on harmful chemical pesticides (Cuyno et al. 2001), and the average dosage of organic manure, urea, nitrogen, phosphorus, and potassium used by farmers will be significantly less than before (Souleymane and Karim 2018)
Water-saving and drought-resistant rice	Seeds with high nitrogen efficiency and low permeability	It has a higher yield potential under irrigation and an acceptable grain quality and can reduce water consumption; it also reduces CH_4 emissions from paddy fields in flood periods (Luo 2010)
Controlled-release fertilizer	Slowly releasing fertilizers or less fertilizer	It can reduce carbon emissions caused by excessive fertilizer application (Tani et al. 2015) and provide a safer, more economical, and more efficient way of administering nutrients (Cole et al. 2016)
Planting green manure	Planting legumes and astragalus	It can achieve the dual goals of resource conservation (i.e., cutting down the number of chemical fertilizers) and environmental protection (i.e., controlling soil pollution and carbon emissions) (Li et al. 2020)
Rice field culture	Rice-duck or rice-shrimp culture	It could effectively avoid damages by decreasing the number of pests, pathogens, and weeds in paddy fields (Yu et al. 2008) and coordinate GHG emission reduction and agricultural income growth (Liu et al. 2015)

farmers adopted, as a count variable, could be used as the adoption intensity (Teklewold et al. 2013). On this basis, OPM was used to distinguish the differences in the determinants of rice farmers' decisions to adopt a single LAT and to adopt many LATs (Zeng et al. 2019), because this model is appropriate for the evaluation of the correlation between the ordinal dependent variable and the relevant independent variables. In this study, rice farmers' decisions to adopt LATs (Y_i) can be described based on the following formulas:

$$Y_i^* = \alpha_i + \beta_i X_i + \varepsilon_i, i = 1, 2, \dots 9 \tag{1}$$

$$Y_i = \begin{cases} 1, \text{if } Y_i^* > 0 \\ 0, \text{otherwise} \end{cases} \tag{2}$$

In the above formulas, *i* represents one of the nine LATs, namely no or minimum tillage (S), intermittent irrigation (I), soil testing and formulated fertilizer (F), straw returning (R), integrated pest management (P), water-saving and drought-resistant rice (D), controlled-release fertilizer (C), planting green manure (M), and rice field culture (G);Y_i^* is a potential variable that cannot be observed; X_i denotes the core explanatory variable; α_i is a constant, and β_i is the corresponding estimated coefficient; and ε_i denotes random errors; because rice farmers may adopt multiple LATs,ε_i will obey a multivariate normal distribution, and ε_i ~ MVN (0, D), with its mean being zero and the covariance being D. The covariance matrix D is shown in Formula 3:

$$D = \begin{bmatrix} 1 & T_{SI} & T_{SF} & T_{SR} & T_{SP} & T_{SD} & T_{SC} & T_{SM} & T_{SG} \\ T_{IS} & 1 & T_{IF} & T_{IR} & T_{IP} & T_{ID} & T_{IC} & T_{IM} & T_{IG} \\ T_{FS} & T_{FI} & 1 & T_{FR} & T_{FP} & T_{FD} & T_{FC} & T_{FM} & T_{FG} \\ T_{RS} & T_{RI} & T_{RF} & 1 & T_{RP} & T_{RD} & T_{RC} & T_{RM} & T_{RG} \\ T_{PS} & T_{PI} & T_{PF} & T_{PR} & 1 & T_{PD} & T_{PC} & T_{PM} & T_{PG} \\ T_{DS} & T_{DI} & T_{DF} & T_{DR} & T_{DP} & 1 & T_{DC} & T_{DM} & T_{DG} \\ T_{CS} & T_{CI} & T_{CF} & T_{CR} & T_{CP} & T_{CD} & 1 & T_{CM} & T_{CG} \\ T_{MS} & T_{MI} & T_{MF} & T_{MR} & T_{MP} & T_{MD} & T_{MC} & 1 & T_{MG} \\ T_{GS} & T_{GI} & T_{GF} & T_{GR} & T_{GP} & T_{GD} & T_{GC} & T_{GM} & 1 \end{bmatrix} \tag{3}$$

In Formula 3, the elements on the off-diagonal lines represent certain unobservable interrelationships between the equations of random disturbances of the nine LATs. The non-zero values of the elements on the off-diagonal lines indicate the potential correlations between the disturbance terms of the equations. If the value on the off-diagonal line is significantly greater than zero, the two LATs have a complementary relationship. Conversely, if the value on the off-diagonal line is smaller than zero, the two LATs have a substitution relationship. Thus, MVP can be used for a more accurate estimation of the interrelationships between the nine LATs, and OPM can be used to further explore the determinants of rice farmers' adoption intensity of these technologies.

2.3.2 ISM

ISM is a technique for the analysis of entities and their interrelationships in systems (Wang et al. 2017). It can be employed to explore the hierarchical structure of the determinants of rice farmers' decisions to adopt LATs. According to ISM, S_i ($i = 1, 2 \dots k$) denotes the significant determinants, and k denotes the number of significant determinants. Thus, the adjacency matrix R can be determined by the following formula:

$$R_{ij} = \begin{cases} 1, \ S_i \ had \ an \ impact \ on \ S_j \\ 0, S_i \ had \ no \ impact \ on \ S_j \end{cases} i = 1{,}2 \ldots k; j = 1{,}2 \ldots k \quad (4)$$

Then, the reachability matrix B can be calculated by the following formula:

$$\mathrm{B} = (\mathrm{R} + \mathrm{I})^{\lambda+1} = (\mathrm{R} + \mathrm{I})^{\lambda} \neq (\mathrm{R} + \mathrm{I})^{\lambda-1} \neq \cdots \neq (\mathrm{R} + \mathrm{I})^{2} \neq (\mathrm{R} + \mathrm{I}) \quad (5)$$

In the above formula, matrix I is an identity matrix ($2 \leq \lambda \leq k$), and Boolean arithmetic is used in the matrix power operation. The factors in each layer can be determined by the following formula:

$$L = \{S_i | P(S_i) \cap Q(S_i) = P(S_i)\} \ i = 1, 2 \ldots k \quad (6)$$

$P(S_i)$ is a reachable set representing the set of all factors that can be reached from the factor S_i, namely the set of elements corresponding to all columns with a matrix element of 1 in the S_i row. $Q(S_i)$ is an antecedent set representing the set of all factors that can reach the factor S_i, namely the set of elements corresponding to all rows where the matrix element in the S_i column is 1. According to the element order of L_i, a reordered reachable matrix B can be written, where the corresponding elements of each unit matrix are at the same level. Finally, the directed edges are used to connect the adjacent levels and factors at the same level to establish a hierarchical structure of the factors that affect rice farmers' decisions to adopt LATs. Matlab can be used to complete the above steps.

2.4 Variable selection

The present research was conducted with the farmer behavior theory and behavioral economics as the theoretical basis. As an economic man, a farmer will choose to engage in modern agricultural production without hesitation when he believes that increasing modern production factors can contribute to higher agricultural output and income (Schultz 1964; Noltze et al. 2012). Popkin (1979) put forward the term "rational peasant" based on Schultz's rational smallholder theory, holding the view that farmers conform to the assumption of "rational economic man" and their decisions are completely rational. Behavioral economics focuses on the analysis of economic behaviors and phenomena from the perspective of psychology (Mullainathan and Thaler 2001). Unlike classical economics, which assumes the presence of a rational economic man, behavioral economics holds that irrational behaviors may influence people's economic decisions. Dominated by different goals and values, psychological endurance, status, preferences, interactions between decision-making behaviors, and dependence on the environment, individuals will make different decisions. Based on the two theories, we selected four types of factors (a total of nineteen variables) as the influencing factors of farmers' adoption behavior of LATs. The theoretical framework is as follows (Fig. 2).

2.4.1 Individual characteristics

According to Karami and Mansoorabadi (2008), female farmers' attitudes were more positive toward agricultural sustainability, and Wang et al. (2018) found that males had a higher willingness to engage in pollution control and management activities. Hence, we argue that

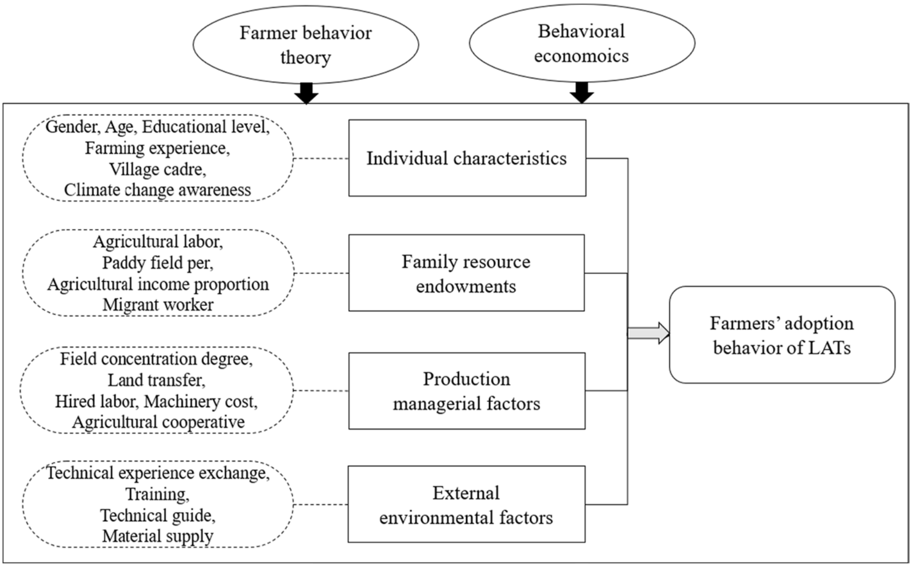

Fig. 2 Theoretical framework

the impact of gender on farmers' LATs adoption behavior is unclear. Generally, the adoption rate of green technologies is higher in a younger population with a higher educational level and more farming experience. The farmer with a special identity, such as a village cadre (Li et al. 2020), may be more willing to adopt green technologies to play an exemplary role. Therefore, the impact of special identities is expected to be positive. Climate change awareness also affects agricultural production activities (Karki et al. 2020; Trinh et al. 2018), and its impact is expected to be positive.

2.4.2 Family resource endowments

There is a negative relationship between the amount of labor input and agricultural production efficiency (Guo et al. 2022), and thus we expect the influence of labor input to be negative. Considering the impact of population on paddy field area, the relationship between per capita paddy field and technology adoption can be more accurately represented. As to agricultural income proportion, some scholars believed that farmers with a lower proportion of agricultural income preferred green production (Li et al. 2021a, b, c), while other scholars held the opposite view (Xue et al. 2021). Accordingly, we argue that the impact of agricultural income proportion on farmers' adoption behavior of LATs is unclear. The number of migrant workers directly affects agricultural labor, with a larger number of migrant workers leading to less agricultural labor and a lower adoption rate of LATs (Li et al. 2021a, b, c).

2.4.3 Production managerial factors

Generally, a high field concentration degree of paddy fields improves the willingness of farmers to adopt green technologies for productivity improvement. Thus, we expect the influence of field concentration degree to be positive. As to land transfer, Mao et al. (2021)

thought that land transfer has an inhibiting effect on farmers' green production behavior, while the view of Xie and Huang (2021) was the opposite. Hence, we argue that the expected impact of land transfers on farmers' adoption behavior of LATs is unclear. Households with more hired laborers are more likely to adopt green technologies (Pfeffer 1992). Machinery cost accounts for a large proportion of agricultural costs. With the rise of machinery costs, farmers' production costs will surely rise, and therefore their willingness to adopt green production will decrease (Li et al. 2020). Agricultural cooperatives provide materials, subsidies, technologies, and other resource elements to farmers, and we expect that they exert a positive impact on the adoption of green technologies.

2.4.4 External environmental factors

Technical experience exchange (Niu et al. 2022), training (Huang et al. 2012), and technical guide (Huang et al. 2021) are important determinants directly affecting farmers' green production behaviors. If there is a supply of low-carbon agricultural materials, farmers' willingness to participate in green production will increase. Accordingly, the effect of low-carbon agricultural material supply is expected to be positive.

The specific variables and definitions are shown in Table 2.

3 Results

3.1 Descriptive statistics

Stata 15.1 was used to conduct the descriptive statistical analysis of rice farmers' demographic and socioeconomic characteristics. The results are shown in Table 3. Among the surveyed rice farmers, there were 781 males and 333 females. Most respondents were aged above 40, and 39.77% were aged 50–60. As for educational level, more than half of respondents received only primary or junior high school education, 13.73% attended high or vocational school, and only 1.62% went to universities. The farming experience of respondents was mostly 31–40 years, with the average being over 20 years. Nearly one-third of respondents took up non-agricultural economic activities. The number of migrant workers in the household of respondents was smaller than 2 (83.57%), and the number of agricultural laborers was generally 1–2 (88.15%). In addition, the minority of respondents were village cadres (14.45%).

Table 4 reveals that rice farmers' adoption rates of LATs were generally low, mostly ranging from 10 to 35%. Among the nine LATs, the adoption rate of straw returning was the highest, reaching 84.74%, while that of rice field culture was the lowest, being only 5.21%. The adoption rates of integrated pest management (33.66%) and intermittent irrigation (30.79%) were the second highest and third highest, respectively. Rice farmers' adoption rate of other LATs was comparatively lower, mainly 10–20%.

3.2 Results of MVP

According to the regression results in Tables 5 and 6, rice farmers in different areas showed different preferences for LATs. Area 3 was taken as the control group. In area 1, rice farmers preferred to adopt straw returning and were less willing to adopt no or minimum tillage, soil testing and formulated fertilizer, planting green manure, and rice field culture. Rice

Table 2 Four types of potential factors of rice farmers' decisions to adopt LATs

Variable	Definition	Expected sign
Individual characteristics		
Gender	Gender of the surveyed farmer	±
Age	Age of the surveyed farmer	–
Educational level	Educational level of the surveyed farmer	+
Farming experience	Farming experience of the surveyed farmer	+
Village cadre	Whether the surveyed farmer is a village cadre	+
Climate change awareness	Farmers' awareness level of climate change	+
Family resource endowments		
Agricultural labor	Number of agricultural laborers in the household	–
Paddy field per	Per-capita paddy field area in the household	+
Agricultural income proportion	Proportion of agricultural income in the household	±
Migrant worker	Number of migrant workers in the household	–
Production managerial factors		
Field concentration degree	Concentration degree of paddy fields	+
Land transfer	Whether there is a system of land transfer	±
Hired labor	Number of laborers employed in agricultural production	+
Machinery cost	Level of agricultural machinery purchase costs	–
Agricultural cooperative	Whether the surveyed farmer participates in an agricultural cooperative	+
External environmental factors		
Technical experience exchange	Whether there is an exchange of technical experience among farmers	+
Training	Whether the surveyed farmer receives technical training	+
Technical guide	Whether the local government provides technical guidance	+
Material supply	Whether there is a supply of low-carbon agricultural materials	+

Table 3 Demographic and socioeconomic characteristics of the surveyed farmers

Variable	Item	Frequency	Percentage	Variable	Item	Frequency	Percentage
Gender	Male	781	70.11%	Village cadre	Yes	161	14.45%
	Female	333	29.89%		No	953	85.55%
Age	≤30	7	0.63%	Educational level	Illiterate	101	9.07%
	31–40	50	4.49%		Primary	425	38.15%
	41–50	287	25.76%		Junior high	717	37.43%
	51–60	443	39.77%		High/vocation	153	13.73%
	≥61	327	29.35%		College/above	18	1.62%
Migrant worker	≤2	931	83.57%	Farming experience	0–20	138	12.39%
	3–5	173	15.53%		21–30	263	23.61%
	≥6	10	0.90%		31–40	381	34.20%
Agricultural labor	≤2	982	88.15%		41–50	254	22.80%
	≥3	132	11.85%		≥51	78	7.00%

Table 4 Rice farmers' adoption rate of the nine LATs

LAT	Number	Percentage
No or minimum tillage (S)	117	10.50%
Intermittent irrigation (I)	343	30.79%
Soil testing and formulated fertilizer (F)	197	17.68%
Straw returning (R)	944	84.74%
Integrated pest management (P)	375	33.66%
Water-saving and drought-resistant rice (D)	116	10.41%
Controlled-release fertilizer (C)	152	13.64%
Planting green manure (M)	194	17.41%
Rice field culture (G)	58	5.21%

farmers in area 2 were more likely to adopt straw returning, integrated pest management, and controlled-release fertilizer and less likely to adopt planting green manure. Compared with rice farmers in area 3, rice farmers in areas 1 and 2 were more willing to adopt straw returning while showing a more negative attitude toward planting green manure.

As we hypothesized, rice farmers' individual characteristics, family resource endowments, production managerial factors, and external environmental factors significantly affected their decisions to adopt LATs to varying degrees, and the signs were the same as expected. The specific effects are as follows:

(1) Rice farmers' individual characteristics significantly impacted their adoption of LATs. Male farmers were more willing to use new LATs (except straw returning) than females. Younger farmers were more likely to be attracted by green technologies and were willing to adopt LATs, especially soil testing and formulated fertilizer, integrated pest management, controlled-release fertilizer, and rice field culture. What is more, rice farmers with a higher education level tended to adopt integrated pest management and soil testing and formulated fertilizer with higher requirements and would engage in more economic activities than those with lower educational levels. Rice farmers that are more experienced showed less interest in no or minimum tillage, straw returning,

Table 5 Results of MVP regression

Variable	S	I	F		R		P		D	C	M	G
Area 1	−0.664*** (0.196)	−0.046 (0.125)	−0.287* (0.153)		0.953*** (0.159)		0.078 (0.136)		0.158 (0.168)	0.106 (0.191)	−0.936*** (0.156)	−0.658*** (0.232)
Area 2	0.091 (0.144)	−0.152 (0.112)	−0.107 (0.137)		0.385*** (0.120)		0.539*** (0.122)		−0.076 (0.157)	0.418** (0.168)	−0.370*** (0.124)	−0.220 (0.202)
Individual characteristics												
Gender	0.064 (0.127)	0.314*** (0.100)	0.301** (0.121)		−0.203* (0.119)		0.208** (0.102)		0.124 (0.124)	0.327** (0.137)	0.276** (0.121)	0.078 (0.172)
Age	0.014 (0.009)	−0.002 (0.007)	−0.018** (0.009)		0.013 (0.009)		−0.012* (0.007)		−0.018 (0.012)	−0.027*** (0.009)	0.015* (0.008)	−0.021** (0.012)
Educational level	−0.012 (0.019)	−0.024 (0.014)	0.035** (0.016)		0.017 (0.017)		0.038*** (0.014)		−0.013 (0.019)	0.006 (0.018)	0.004 (0.016)	−0.052** (0.024)
Farming experience	−0.014** (0.006)	−0.002 (0.005)	0.003 (0.007)		−0.015** (0.007)		−0.001 (0.005)		0.009 (0.009)	−0.002 (0.006)	−0.011** (0.006)	−0.009 (0.009)
Village cadre	−0.490*** (0.179)	−0.113 (0.124)	0.212 (0.133)		−0.001 (0.150)		−0.114 (0.125)		0.289** (0.146)	0.106 (0.146)	0.221* (0.134)	−0.001 (0.202)
Climate change awareness	0.056 (0.062)	0.130*** (0.047)	0.049 (0.053)		−0.005 (0.053)		0.024 (0.047)		0.036 (0.059)	0.029 (0.059)	0.149*** (0.056)	0.165* (0.0092)
Family resource endowments												
Agricultural labor	0.066 (0.076)	0.021 (0.058)		−0.009 (0.067)		−0.052 (0.063)		0.043 (0.053)	0.077 (0.076)	0.103 (0.075)	0.012 (0.059)	0.163* (0.089)
Paddy field per	−0.003 (0.021)	−0.004 (0.004)		0.006 (0.004)		0.009 (0.011)		0.002 (0.006)	−0.003 (0.006)	0.004 (0.005)	−0.002 (0.008)	−0.001 (0.006)
Agricultural income proportion	0.146 (0.183)	−0.048 (0.147)		0.218 (0.166)		0.156 (0.173)		0.241 (0.146)	0.506*** (0.186)	0.409** (0.188)	0.016 (0.173)	0.318 (0.228)
Migrant worker	0.038 (0.044)	−0.075** (0.037)		−0.124*** (0.045)		0.032 (0.041)		−0.005 (0.037)	0.066 (0.047)	0.034 (0.049)	0.018 (0.040)	0.079 (0.052)
Production managerial factors												
Field concentration degree	0.008*** (0.003)	0.003 (0.003)		0.000 (0.003)		−0.005 (0.003)		0.008 (0.008)	0.004 (0.003)	−0.003 (0.003)	−0.037** (0.017)	0.069*** (0.015)

Table 5 (continued)

Variable	S	I	F	R	P	D	C	M	G
Land transfer	0.001	0.200**	−0.137	−0.171	0.038	−0.179	0.144	0.279***	0.407***
	(0.121)	(0.092)	(0.112)	(0.112)	(0.095)	(0.123)	(0.113)	(0.106)	(0.141)
Hired labor	−0.213	−0.108	−0.048	0.442***	−0.035	0.197	−0.168	−0.075	−0.011
	(0.147)	(0.103)	(0.117)	(0.149)	(0.101)	(0.121)	(0.123)	(0.122)	(0.179)
Machinery cost	0.066	−0.118**	−0.022	−0.108*	−0.109**	−0.068	−0.142**	−0.047	0.019
	(0.063)	(0.052)	(0.060)	(0.061)	(0.053)	(0.066)	(0.068)	(0.060)	(0.080)
Agricultural cooperative	0.233	0.468***	0.497***	0.666**	0.051	0.443**	0.137	0.235	0.677***
	(0.226)	(0.175)	(0.182)	(0.288)	(0.181)	(0.196)	(0.212)	(0.201)	(0.237)
External environmental factors									
Technical experience exchange	0.133**	−0.017	0.079*	0.0821*	0.224***	0.098*	0.079	0.075*	0.064
	(0.055)	(0.039)	(0.047)	(0.044)	(0.041)	(0.051)	(0.052)	(0.043)	(0.069)
Training	−0.028	0.123***	0.188***	0.104*	0.002	0.064	0.084	0.103**	0.078
	(0.060)	(0.045)	(0.049)	(0.057)	(0.045)	(0.053)	(0.056)	(0.050)	(0.077)
Technical guide	0.237***	0.095***	0.118***	−0.016	0.061*	−0.021	0.185***	−0.021	0.012
	(0.040)	(0.033)	(0.039)	(0.040)	(0.033)	(0.040)	(0.044)	(0.037)	(0.060)
Material supply	0.315**	0.167	−0.167	0.212	0.261**	−0.267*	−0.213	−0.264**	0.005
	(0.152)	(0.121)	(0.135)	(0.134)	(0.127)	(0.141)	(0.151)	(0.128)	(0.205)
Wald chi^2	1370.620								
Prob > chi^2	0.000								

*, **, and *** represent 10%, 5%, and 1% confidence levels, respectively; area 3 is the control group

Table 6 Results of covariance matrix by MVP

LATs	S	I	F	R	P	D	C	M
S								
I	0.057							
	(0.058)							
F	0.087**	0.058						
	(0.004)	(0.054)						
R	−0.018	−0.074*	0.027					
	(0.560)	(0.014)	(0.375)					
P	0.134**	0.019	0.218**	0.022				
	(0.000)	(0.534)	(0.000)	(0.457)				
D	−0.002	0.072*	0.173**	0.063*	0.037			
	(0.953)	(0.017)	(0.000)	(0.036)	(0.217)			
C	0.111**	0.154**	0.241**	0.001	0.204**	0.139**		
	(0.0002)	(0.000)	(0.000)	(0.962)	(0.000)	(0.000)		
M	0.059*	0.083**	0.054	−0.042	0.024	0.060*	0.121**	
	(0.050)	(0.005)	(0.072)	(0.160)	(0.433)	(0.044)	(0.000)	
G	0.065*	0.168**	0.029	0.021	0.107**	0.052	0.142**	0.127**
	(0.031)	(0.000)	(0.333)	(0.488)	(0.000)	(0.081)	(0.000)	(0.000)

S, I, F, R, P, D, C, M, and G are the abbreviations of the nine LATs. * and ** represent 10% and 5% confidence levels, respectively

and planting green manure, possibly because they were restricted by traditional farming practices and habits. Additionally, farmers with the identity of village cadre were more willing to accept new technologies, such as planting green manure and water-saving and drought-resistant rice. Farmers sensitive to climate change tend to adopt intermittent irrigation, planting green manure and rice field culture.

(2) Family resource endowments had an influence on rice farmers' LAT adoption behaviors. Specifically, the number of agricultural laborers in the household positively impacted rice farmers' adoption of rice field culture, possibly because more agricultural laborers could ensure sufficient support for fish, shrimp, or duck farming in paddy fields. High incomes stimulated rice farmers to apply controlled-release fertilizer and water-saving and drought-resistant rice. In addition, families with more migrant workers were unwilling to invest too much time and energy in intermittent irrigation or soil testing and formulated fertilizer.

(3) Production managerial factors also significantly affected rice farmers' adoption behaviors. When the concentration degree of paddy fields was high, rice farmers preferred technologies that could be used in large areas, such as no or minimum tillage and rice field culture. In addition, land transfers significantly impacted rice farmers' adoption of intermittent irrigation, planting green manure, and rice field culture. The efficiency of land resource allocation should be improved so that rice farmers who engaged in land transfers could adopt more LATs. The number of hired laborers in agricultural production had a positive impact on rice farmers' adoption of straw returning. As agricultural machinery costs decreased, rice farmers would become more willing to adopt LATs. In addition, joining agricultural cooperatives would encourage rice farmers to adopt more LATs because they could obtain more helpful information and technical

know-how regarding LATs there, and when confronted with a technical challenge, they would get out of trouble with the help of skilled farmers in agricultural cooperatives.

(4) External environmental factors significantly impacted rice farmers' adoption behaviors. Technical experience exchange, training, and technical guidance, through which rice farmers could obtain technical know-how and develop self-confidence, would improve their willingness to adopt LATs, especially no or minimum tillage, intermittent irrigation, straw returning, integrated pest management, soil testing, and formulated fertilizer. Moreover, with sufficient low-carbon agricultural material supply, rice farmers were more likely to adopt no or minimum tillage and integrated pest management.

The covariance matrix is shown in Table 6. All covariance passed the significance test at the 5% confidence level, showing twenty positive effects and one negative effect. It is indicated that rice farmers' adoption of a single LAT was influenced by their adoption of other LATs. The interrelationships between the nine LATs were mostly complementary, such as no or minimum tillage vs. soil testing and formulated fertilizer, rice field culture vs. intermittent irrigation, and soil testing and formulated fertilizer vs. integrated pest management. One possible cause might be that several LATs need to be adopted simultaneously during rice cultivation to achieve GHG emission reduction. However, intermittent irrigation and straw returning showed a substitution relationship, suggesting that most rice farmers who adopted straw returning would not apply intermittent irrigation. The reason might be that the benefits brought by straw returning and intermittent irrigation are similar. Specifically, straw returning can increase the microbial content in the soil and effectively enhance soil fertility; intermittent irrigation could maintain total nitrogen and organic matter in the soil. Considering the agricultural laborer and complex operation required by these two technologies, rice farmers may prefer to choose only one of them to improve soil quality and reduce GHG emissions.

3.3 Results of OPM

Based on the above analysis, OPM was used to further identify the determinants of rice farmers' adoption intensity of LATs (i.e., the number of LATs that they adopted) and to estimate the marginal effects. The variation in the number of LATs adopted by rice farmers and the estimation results of OPM are shown in Tables 7 and 8. According to statistical analysis results of the survey data in Table 7, most rice farmers (83.48%)

Table 7 Rice farmers' adoption intensity of LATs

Number of LATs	Number of rice farmers	% of total
0	45	4.04%
1	329	29.53%
2	362	32.50%
3	194	17.41%
4	105	9.43%
5	49	4.40%
6	14	1.26%
7	11	0.99%
8	4	0.36%
9	1	0.09%

Table 8 Results of OPM regression

Variable	Result	Marginal effect									
		dy/dx ($n=0$)	dy/dx ($n=1$)	dy/dx ($n=2$)	dy/dx (n = 3)	dy/dx ($n=4$)	dy/dx ($n=5$)	dy/dx ($n=6$)	dy/dx ($n=7$)	dy/dx ($n=8$)	dy/dx ($n=9$)
Area 1	−0.066 (0.103)	0.0053 (0.0081)	0.0157 (0.0244)	−0.0002 (0.0006)	−0.0070 (0.0109)	−0.0064 (0.0099)	−0.0041 (0.0064)	−0.0014 (0.0023)	−0.0012 (0.0019)	−0.0004 (0.0007)	−0.0002 (0.0003)
Area 2	0.209** (0.093)	−0.0166** (0.0078)	−0.0494** (0.0219)	0.0007 (0.0017)	0.0220** (0.0099)	0.0202** (0.0092)	0.0129** (0.0061)	0.0046** (0.0023)	0.0037** (0.0019)	0.0014 (0.0009)	0.0006 (0.0006)
Individual characteristics											
Gender	0.314*** (0.078)	−0.0251*** (0.0065)	−0.0744*** (0.0186)	0.0010 (0.0025)	0.0332*** (0.0083)	0.0304*** (0.0079)	0.0194*** (0.0055)	0.0069*** (0.0025)	0.0056*** (0.0019)	0.0021* (0.0012)	0.0009 (0.0008)
Age	−0.006 (0.005)	0.0005 (0.0004)	0.0014 (0.0013)	−0.0000 (0.0000)	−0.0006 (0.0006)	−0.0006 (0.0005)	−0.0004 (0.0003)	−0.0001 (0.0001)	−0.0001 (0.0001)	−0.0000 (0.0000)	−0.0000 (0.0000)
Educational level	0.003 (0.011)	−0.0003 (0.0009)	−0.0008 (0.0026)	0.0000 (0.0000)	0.0004 (0.0012)	0.0003 (0.0011)	0.0002 (0.0007)	0.0001 (0.0002)	0.0001 (0.0002)	0.0000 (0.0001)	0.0000 (0.0000)
Farming experience	−0.010*** (0.004)	0.0008** (0.0003)	0.0024*** (0.0009)	−0.0000 (0.0001)	−0.0011*** (0.0004)	−0.0010*** (0.0004)	−0.0006*** (0.0002)	−0.0002** (0.0001)	−0.0002** (0.0001)	−0.0001 (0.0000)	−0.0000 (0.0000)
Village cadre	0.075 (0.099)	−0.0060 (0.0080)	−0.0178 (0.0235)	0.0002 (0.0007)	0.0079 (0.0105)	0.0073 (0.0096)	0.0046 (0.0062)	0.0016 (0.0022)	0.0013 (0.0018)	0.0005 (0.0007)	0.0002 (0.0003)
Climate change awareness	0.115*** (0.038)	−0.0092*** (0.0031)	−0.0272*** (0.0089)	0.0004 (0.0009)	0.0121*** (0.0041)	0.0111*** (0.0037)	0.0071*** (0.0024)	0.0025** (0.0010)	0.0021** (0.0009)	0.0008* (0.0005)	0.0003 (0.0003)
Family resource endowments											
Agricultural labor	0.053 (0.048)	−0.0042 (0.0038)	−0.0124 (0.0114)	0.0002 (0.0004)	0.0055 (0.0051)	0.0051 (0.0047)	0.0032 (0.0030)	0.0011 (0.0011)	0.0009 (0.0009)	0.0004 (0.0004)	0.0002 (0.0002)
Paddy field per	0.003 (0.003)	−0.0002 (0.0002)	−0.0007 (0.0007)	0.0000 (0.0000)	0.0003 (0.0003)	0.0003 (0.0003)	0.0002 (0.0002)	0.0001 (0.0001)	0.0001 (0.0001)	0.0000 (0.0000)	0.0000 (0.0000)
Agricultural income proportion	0.264** (0.122)	−0.0211** (0.0098)	−0.0626** (0.0292)	0.0008 (0.0022)	0.0279** (0.0129)	0.0255** (0.0120)	0.0163** (0.0077)	0.0058* (0.0031)	0.0047* (0.0025)	0.0018 (0.0012)	0.0008 (0.0008)
Migrant worker	−0.016 (0.030)	0.0013 (0.0024)	0.0038 (0.0071)	−0.0001 (0.0002)	−0.0017 (0.0032)	−0.0016 (0.0029)	−0.0010 (0.0019)	−0.0004 (0.0007)	−0.0003 (0.0005)	−0.0001 (0.0002)	−0.0000 (0.0001)
Production managerial factors											
Field concentration degree	0.003** (0.002)	−0.0003* (0.0001)	−0.0008* (0.0004)	0.0000 (0.0000)	0.0004* (0.0002)	0.0003* (0.0002)	0.0002* (0.0001)	0.0001* (0.0000)	0.0001* (0.0000)	0.0000* (0.0000)	0.0000 (0.0000)

Table 8 (continued)

Variable	Result	Marginal effect									
		dy/dx ($n=0$)	dy/dx ($n=1$)	dy/dx ($n=2$)	dy/dx (n = 3)	dy/dx ($n=4$)	dy/dx ($n=5$)	dy/dx ($n=6$)	dy/dx ($n=7$)	dy/dx ($n=8$)	dy/dx ($n=9$)
Land transfer	0.106 (0.073)	−0.0085 (0.0059)	−0.0251 (0.0172)	0.0003 (0.0009)	0.0112 (0.0077)	0.0103 (0.0071)	0.0066 (0.0046)	0.0023 (0.0017)	0.0019 (0.0014)	0.0007 (0.0006)	0.0003 (0.0003)
Hired labor	−0.003 (0.079)	0.0002 (0.0063)	0.0006 (0.0188)	−0.0000 (0.0003)	−0.0003 (0.0084)	−0.0003 (0.0077)	−0.0002 (0.0049)	−0.0001 (0.0017)	−0.0000 (0.0014)	−0.0000 (0.0005)	−0.0000 (0.0002)
Machinery cost	−0.125*** (0.041)	0.0100*** (0.0035)	0.0297*** (0.0097)	−0.0004 (0.0010)	−0.0133*** (0.0044)	−0.0121*** (0.0041)	−0.0078*** (0.0027)	−0.0027** (0.0011)	−0.0022** (0.0009)	−0.0008 (0.0005)	−0.0004 (0.0003)
Agricultural cooperative	0.582*** (0.152)	−0.0464*** (0.0134)	−0.1377*** (0.0361)	0.0018 (0.0048)	0.0614*** (0.0164)	0.0562** (0.0151)	0.0359*** (0.0100)	0.0127*** (0.0046)	0.0104** (0.0042)	0.0039** (0.0022)	0.0017 (0.0014)
External environmental factors											
Technical experience exchange	0.162*** (0.031)	−0.0129*** (0.0028)	−0.0384*** (0.0072)	0.0005 (0.0013)	0.0171*** (0.0033)	0.0157*** (0.0032)	0.0100*** (0.0023)	0.0035*** (0.0011)	0.0029*** (0.0009)	0.0011* (0.0006)	0.0005 (0.0004)
Training	0.141*** (0.039)	−0.0112*** (0.0034)	−0.0333*** (0.0092)	0.0004 (0.0011)	0.0149*** (0.0042)	0.0136*** (0.0039)	0.0087*** (0.0025)	0.0031*** (0.0011)	0.0025** (0.0010)	0.0010* (0.0006)	0.0004 (0.0004)
Technical guide	0.110*** (0.027)	−0.0088*** (0.0024)	−0.0260*** (0.0063)	0.0003 (0.0009)	0.0116*** (0.0029)	0.0106*** (0.0027)	0.0068*** (0.0019)	0.0024*** (0.0008)	0.0020*** (0.0007)	0.0007* (0.0004)	0.0003 (0.0003)
Material supply	0.017 (0.096)	−0.0013 (0.0076)	−0.0039 (0.0226)	0.0001 (0.0003)	0.0018 (0.0101)	0.0016 (0.0092)	0.0010 (0.0059)	0.0004 (0.0021)	0.0003 (0.0017)	0.0001 (0.0007)	0.0000 (0.0003)
Wald chi^2 (22)	320.490										
Prob > chi^2	0.000										
Pseudo R^2	0.084										

*, **, and *** represent 10%, 5%, and 1% confidence levels, respectively. Area 3 is the control group. The marginal effects of some variables are very small (approximately equal to 0.0000 after rounding), but their significance levels have been indicated above. To calculate the marginal effects of each variable accurately, the data of marginal effect are rounded up and rounded down to four decimal places in this table

adopted three or fewer LATs simultaneously. Seventy-nine rice farmers (7.09%) applied five or more LATs, and four of these farmers simultaneously applied eight LATs and only one adopted all LATs at the same time.

In Table 8, it can be observed that Wald chi^2(22) = 320.490 ($p \geq 0.000$), suggesting the joint test of all slope coefficients equaling zero was rejected. According to column 2, the coefficients of gender, climate change awareness, agricultural cooperative, technical experience exchange, training, and technical guide were all positive at 1% significance level, indicating that these factors could strengthen rice farmers' adoption intensity of LATs with other conditions unchanged. However, rice farmers' farming experience and the machinery cost showed a negative effect on their adoption intensity at 1% significance level, possibly because they were trapped by traditional farming practices and habits, and the high machinery cost might reduce their enthusiasm for adopting LATs. The coefficients of agricultural income proportion and paddy field concentration degree on rice farmers' adoption intensity were both positive at 5% confidence level, indicating the same beneficial influence. Compared with rice farmers in area 3, rice farmers in area 2 preferred simultaneous adoption of three or more LATs. As for the marginal effects, it could be observed that when $n \leq 1$, the signs of marginal effect coefficients were opposite to those of the estimation results in column 2; when $n = 2$, the signs of marginal effect coefficients changed, but there was no statistical significance; when $n \geq 3$, the signs of these coefficients were consistent with those of the results in column 2, and the statistical significance was found at the same confidence level. It was shown that the influence of these determinants on rice farmers who adopted one LAT or did not adopt LAT was quite different from that on farmers who adopted three or more LATs. In practice, farmers' adoption of three or more LATs indicates that they have more trust in these new technologies and are willing to make a contribution to protecting the environment by using LATs in the process of rice cultivation. In addition, farmers' adoption behaviors of three or more LATs would always have a better carbon emission reduction effect than adopting only one LAT. Therefore, the hierarchical structure of these significant determinants affecting rice farmers' decisions to adopt three or more LATs was further analyzed.

Based on the results of marginal effects, the probability of rice farmers' decisions to adopt three or more LATs was discussed. Specifically, for rice farmers in area 2, the probability of the adoption of three or more LATs would increase by 6.34%. For farmers who were male, who had less farming experience, and who were concerned about climate change, the probability of the adoption of three or more LATs would go up by 9.76%, 0.31%, and 3.57%, respectively (13.64% in total), indicating that individual characteristics had a significant influence on rice farmers' adoption intensity. For farmers who had a higher agricultural income proportion, the probability of the adoption of three or more LATs would increase by 8.02%, meaning that family resource endowments also affected rice farmers' adoption intensity. For rice farmers who joined agricultural cooperatives, who thought the agricultural machinery costs were acceptable, and who had paddy fields with a higher concentration degree, the probability of the adoption of three or more LATs rose by 18.05%, 3.81%, and 0.11%, respectively (21.97% in total), indicating that production managerial factors played a crucial role in rice farmers' adoption intensity. For rice farmers who participated in technical experience exchange and received training and technical guidance about LATs, the probability of the adoption of three or more LATs would increase by 5.03%, 4.38%, and 3.41%, respectively (12.82% in total), suggesting that the external environmental factors also had a significantly positive impact on rice farmers' adoption intensity.

3.4 Results of ISM

In this study, ISM was introduced to further analyze the hierarchical structure of the determinants of rice farmers' decisions to adopt LATs. According to the results of OPM regression, ten determinants (except area dummy variables) that significantly influenced rice farmers' adoption of three or more LATs were selected to build ISM, including gender, farming experience, climate change awareness, agricultural income proportion, field concentration degree, machinery cost, agricultural cooperative, technical experience exchange, training, and technical guide. After establishing the logical matrix, adjacency matrix, and reachable matrix in turn, the hierarchical structure of the ten determinants was obtained (Fig. 3).

As shown in Fig. 3, gender (+9.76%), farming experience (−0.31%), agricultural income proportion (+8.02%), and field concentration degree (+0.11%) were surface factors. Agricultural cooperative (+18.05%), technical experience exchange (+5.03%), climate change awareness (+3.57%), and training (+4.38%) were middle-level factors, with agricultural cooperative being determined by the other three factors, indicating that agricultural cooperative was an intermediary between rice farmers and LATs. In agricultural cooperatives, farmers can obtain more knowledge about climate change and engage in frequent technical experience exchange and training, which would motivate them to adopt more LATs. Machinery cost (−3.81%) and technical guide (+3.41%) were deep factors. Before deciding to adopt a specific technology, rice farmers would compare its benefits and costs, and they were more willing to adopt technologies with less machinery cost. In addition, if farmers were provided with technical guidance, which would equip them with agricultural skills, they would be more willing to adopt more LATs.

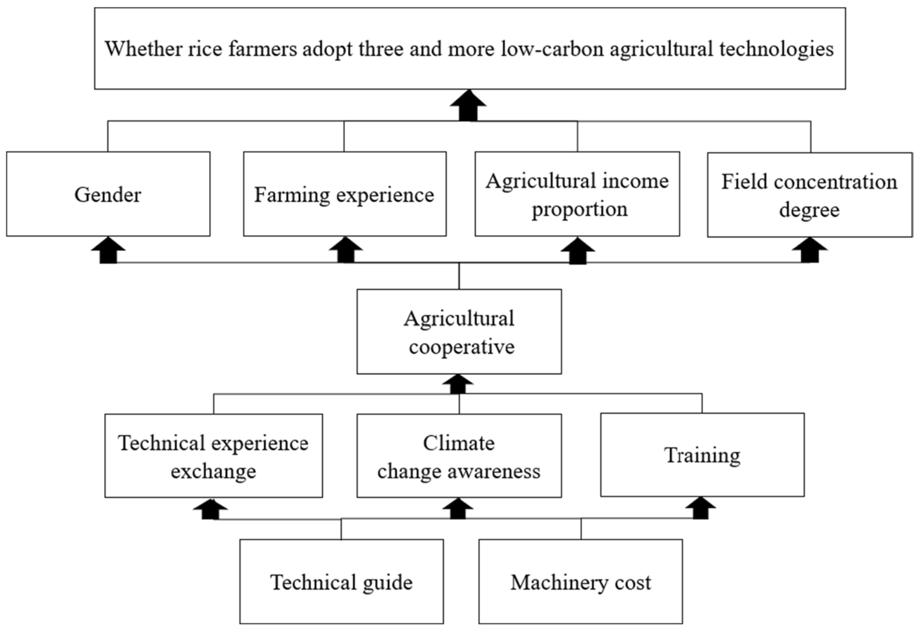

Fig. 3 Hierarchical structure of the determinants of rice farmers' decisions to adopt three or more LATs

4 Discussion, conclusions, and policy recommendations

4.1 Discussion and conclusions

In this study, the Delphi method was used to select nine LATs with good carbon emission reduction effects among all possible technologies adopted in the agricultural production process. Based on the survey data of 1114 farmers in Hubei province, China, the influence of individual characteristics, family resource endowments, production managerial factors, and external environmental factors on rice farmers' decisions to adopt LATs was analyzed with MVP, OPM, and ISM. Three main findings are stated as follows.

First, the nine LATs have a complementary relationship or substitution relationship. Specifically, rice field culture vs. intermittent irrigation, soil testing, and formulated fertilizer vs. integrated pest management had a complementary relationship; intermittent irrigation vs. straw returning had a substitution relationship. The finding that the nine LATs had a complementary or substitution relation is partially consistent with the conclusion in previous studies (Luo et al. 2014). However, the relationship between specific technologies varies in different studies. In the present study, no or minimum tillage and controlled-release fertilizer were complementary but were substitutional in the paper of Luo et al. (2016). The reason may be that in the research of Luo et al. (2016), farmers widely use no or minimum tillage, considering the high cost and variable nutrient release rates of controlled-release fertilizer; but in the present paper, the adoption rates of the two technologies were relatively low (about 10–14%), and some high-income farmers could bear the cost of adopting them at the same time. Zeng et al. (2019) found a strong substitution relationship between some technologies, which were strongly complementary in the present paper. The difference can be attributed to not only the technical preference of farmers and the actual farming situation but also the type of the selected technology.

Second, based on the estimation results of MVP and OPM, rice farmers' decisions to adopt LATs were mainly influenced by four types of factors, namely individual characteristics, family resource endowments, production managerial factors, and external environmental factors, with production managerial factors exerting the most significant effect. Specifically, for rice farmers who joined agricultural cooperatives, who thought the agricultural machinery costs were acceptable, and who had paddy fields with a higher concentration degree, the probability of the adoption of three or more LATs would increase by 18.05%, 3.81%, and 0.11%, respectively (21.97% in total). Among all factors, agricultural cooperative exerts the most significant positive effect on rice farmers' adoption intensity, and this result is consistent with the conclusion drawn from previous research (Ma et al. 2018). Moreover, technical guide has a positive effect on farmers' adoption of LATs, and this finding was the same as the conclusion drawn from the previous research (Huang et al. 2021), which showed that technical guidance could effectively reduce pesticide overuse.

Third, there exists a hierarchical structure of the determinants of rice farmers' decisions to adopt three or more LATs. Specifically, the key influencing elements for rice farmers' adoption intensity were divided into three layers: surface factors (gender, farming experience, agricultural income proportion, and field concentration degree), middle-level factors (agricultural cooperative, technical experience exchange, climate change awareness, and training, with the first factor dominated by the others), and deep factors (machinery cost and technical guide). Cost is one of the most important factors affecting farmers' production decisions, which is consistent with the conclusion drawn by Luo et al. (2016). However, in the study of Zhang et al. (2020), labor force, age, land type, etc., were underlying factors of farmers' willingness to adopt technologies. The inconsistency was attributed to the different variables selected in the two articles.

4.2 Policy recommendations

According to the above findings, policymakers can develop effective approaches to improve rice farmers' willingness to adopt LATs for climate change mitigation. As a result of the strong complementary relationship between the nine LATs, policymakers and implementers should consider the relevance of one LAT to others when designing and initiating strategies to promote LATs in rural areas. More specifically, efforts should be made to encourage rice farmers to adopt complementary LATs, which could improve their enthusiasm for low-carbon agricultural production. Given that individual characteristics, production managerial factors, and external environmental factors have a greater impact on rice farmers' adoption behaviors, it is suggested that agricultural cooperative services, professional technical guide, and lectures concerning climate change should be provided, and effective compensation measures should be taken to encourage rice farmers to adopt more LATs. As machinery cost and technical guidance are the most fundamental factors, local governments can reduce production costs by offering agricultural machinery purchase subsidies and providing more technical guidance to improve rice farmers' technical know-how about LATs to ease their concerns over the risks and strengthen their confidence in low-carbon production.

5 Limitations and further research

Despite the comprehensiveness of this study, some limitations should be noted, which may cast light on future research. First, this study was conducted with a cross-sectional data of the surveyed rice farmers because the promotion of LATs for rice cultivation is still in the primary stage, making it slightly inferior to research based on long-term panel data. In the follow-up study, fixed observation points in rice-producing areas can be set to track rice farmers' initial purchase of low-carbon agricultural materials, medium-term management of paddy fields, and later rice straw returning. The obtained information can be used to analyze their continuous adoption of LATs. Second, actual policy experiments on rice farmers are expected to be conducted in the natural environment to evaluate the implementation effects of specific incentives such as training, technical guidance, and subsidies.

Abbreviations GHG: Greenhouse gas; MVP: Multivariate probit model; OPM: Ordered probit model; ISM: Interpretative structural model; S: No or minimum tillage; I: Intermittent irrigation; F: Soil testing and formulated fertilizer; R: Straw returning; P: Integrated pest management; D: Water-saving and drought-resistant rice; C: Controlled-release fertilizer; M: Planting green manure; G: Rice field culture

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Author contribution All authors made a substantial and intellectual contribution to the work and approved it for publication. Linli Jiang designed this study and performed the data collection and analysis. Nan Chen contributed significantly to the material and manuscript preparation. Yun Tian contributed to revising the manuscript critically for important intellectual content. Yun Luo put forward valuable ideas and participated in writing the manuscript.

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Data availability All data generated or analyzed during the study are included in this article. Any other details that support the findings of this study are available upon reasonable request from the corresponding author. The data are not publicly available since they contain information that could compromise research participant privacy.

Declarations

Ethical statement The study involving human participants were reviewed and approved by the National Natural Science Foundation of China (Project number: 72003051) and the Ministry of Education of Humanities and Social Science of China (Project number: 19YJC790048). Oral informed consent was obtained from every farmer and expert to participate in the survey.

Competing interests The authors declare no competing interests.

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