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Influence of Agriculture M(i) Services on Rice Planting Costs on Chinese Family Farms

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ABSTRACT

Through a questionnaire survey on family farms in Chongqing, Shaanxi, Henan, Liaoning, and other provinces and cities, the authors compared and analyzed the factor importance ranking results of three models—multiple linear regression, SNA social network, and multi-layer perceptron neural network—indicating that different research methods have different calculation results. The results are similar and consistent, and the role of agricultural mechanization and informatization services in the three stages of rice planting—harvesting, plowing, and sowing—is significant. The high use of agricultural machinery services during the harvesting, tillage, and sowing stages of rice planting can reduce the cost of rice planting on family farms.

KEYWORDS

Agricultural Mechanization and Informatization Services, Family Farms, Planting Stage, Rice Planting Costs, Stage Effect

INTRODUCTION

Rice is an important food crop in the world and one of China's three main food crops. In China, the rice planting area is large, generally stable at about 450 million mu, accounting for about 20% of the world's total planting area (Collinson, 2014). The yield per unit is significantly higher than that of rice and corn, reaching 6.89 tons per hectare. The yield is basically maintained at 210 million tons, accounting for 36% of the country's total grain output (ChinaReport.com, 2018). Therefore, rice planting is of great significance to ensure the country's food security and farmers' benefits. However, since the beginning of the 21st century, the market competition pressure of the country's agricultural products has been increasing. In order to ensure food security, the Chinese government has adopted a "minimum purchase price policy" to ensure rice output. However, with the rapid increase in agricultural production costs, the domestic rice price is upside down, and its market competitiveness has been severely impacted (Chenglong, 2018; Xiaobin, 2022; Derong et al., 2022; Chuanning, 2022; Huxian, 2022; Maode, 2022). The traditional rice production method, which is

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time-consuming, labor-intensive, and low in production efficiency, is no longer compatible with the reality of the rapid transfer of rural labor and the modernization of agricultural production technology (Meijiayong, 2022; Haoyan et al., 2015; Weiwei, 2022; Xiangfeng et al., 2021). In order to enhance the overall competitive advantage of agricultural products, especially to reduce the production cost of staple food crops, the role of agricultural machinery has gained more attention, and the mechanized production of rice has become the general trend (Jinping et al., 2018). The essence of mechanized rice production is to substitute materialized labor for the living labor process (Wenzhon et al., 2016). Improving the level of mechanization of rice production is an important measure to improve labor productivity, reduce production costs, increase yield, increase revenue, and enhance the comprehensive competitiveness of rice. This article focuses on family farms as the research object, and uses sample observation and quantitative analysis to explore the impact of agricultural services on the cost of rice planting, revealing the strength of the impact of agricultural mechanization services on costs at different stages of rice production. The goal of this research is to be able to contribute to the family farm's rice production process and provide reference for scientific agricultural mechanization service decisions.

Since the promotion of agricultural mechanization, the impact of agricultural machinery on crop production costs has always been a hot issue of concern to the government, academia, and the public. Cong and Jidong (2017) believe that the large-scale application of agricultural machinery in northern provinces and cities has greatly reduced the production cost of major food crops in the northern region, and has significantly improved market price competitiveness. Taking sugarcane as the object, Bei et al. (2019) found that the cost of mechanized sugarcane planting was 688 Yuan less than artificial planting, and the net income per mu was 533 Yuan more. The total cost is 10651.14 Yuan/hm2 less, and the input-output ratio is increased by 218.01% (Yawei et al., 2015). The people of Chai Liping took green onions as the object and found that mechanized planting of green onions can save 20,790 Yuan per hectare in labor costs, which gives full play to the benefits of large-scale operations (Liping et al., 2019). Zhan Xiaomei et al. (2019) summarized years of practical experience data and found that the total mechanized operation time of rapeseed in the hilly and mountainous areas of the south was reduced by 90.8% compared with manual planting, and the operating cost was reduced by 69.1%. Lina (2017) believes that the mechanized production of corn has effectively promoted the improvement of the competitiveness of the country's corn industry. It can be seen that the promotion of agricultural mechanization has greatly improved the efficiency of agricultural production, reduced the cost of crop production and, to a certain extent, achieved an increase in agricultural returns to scale and enhanced the comprehensive competitiveness of agriculture.

Researchers all over the world have valued the mechanization of rice. Research has found that the machine-transplanting technology of rice in Southeast Asian countries, such as Japan, South Korea, and Thailand, has the characteristics of high yield and stable production, low labor intensity, and high requirements for seedling raising technology. While the machine-transplanting technology of rice in the United States, Australia, New Zealand, and other countries have high operational efficiency and labor. The main characteristics embody in low strength, simple operating tools, high output, and suitability for large-scale operation (Ruiyin et al., 2008). Domestically, the technical and economic analysis of three rice planting schemes by Jianqing et al. (2012), including mechanical planting, mechanical direct seeding, and mechanical planting, found that mechanical planting rice has the highest unit planting cost, and mechanical direct seeding rice has the lowest unit planting cost. Wenzhong et al. (2018) established a "machine substitution" estimation model for rice production, and found empirically that from 1992 to 2016, the cumulative net labor cost of rice mechanization development in Zhejiang Province was 75.07 billion Yuan; cumulative labor input was reduced by 43,753,400. Zhu Dongping's (2016) investigation into the full-process mechanization of rice production in Fuyang found that the full-process mechanization of rice production technology can reduce the labor intensity of farmers and effectively mobilize farmers' enthusiasm for growing grain, which is essential to ensure stable rice production, high yield, cost-saving, and efficiency. Tingping (2015) analyzed the mechanization of rice planting in Guangdong Province and found that when mechanized operations are used, the efficiency of general non-retail rice planting operations is 60% higher and the income level is about 30% higher. Huizhe (2013) compared the rice no-tillage machine inserting with the tiller-inserting machine and found that the former has a better effect on increasing production, the cost of mechanical operations has been greatly reduced, and the economic benefit of output is higher. In summary, mechanized rice production has achieved remarkable results. However, compared with other countries, production is affected by the level of education of farmers, the degree of machinery ownership, the degree of land fragmentation, the area of family operations, profit orientation, government funds, and technology investment, etc. (Haoyan et al., 2015). The overall level of rice seedlings is not high, and in the process of raising seedlings, transplanting seedlings, fertilizing and drying, as well as the whole production process, there is an inverted U-shaped relationship between the planting area and the use of mechanized services by farmers (Lin, 2017), which has led to the mechanization of rice in the country. The relatively high cost squeezes out the profit space of rice farming, which may reduce the income of farmers (Guilin, 2016). Therefore, in-depth management of land fragmentation, vigorously improving agricultural machinery operating conditions, and establishing agricultural machinery cooperative organizations will help farmers invest in high-power agricultural machinery (Chaoyang, 2018) and promote the mechanized production of rice.

Mechanization (M(i)) and is always a close unit and cannot be separated. The mechanization processes include in modern society. For example, the agricultural drones and other agricultural machine's operation systems or platforms require mobile phones. Based on existing literature reports, although a large number of empirical studies have confirmed that agricultural M(i) has a significant positive effect on crop production, cost-saving, and efficiency, after analyzing the limiting factors of rice M(i), the questions that remain are, "How does agricultural M(i) affect the rice production process and cost?" What is its mechanism of action during different stages of rice production? There are few related literature reports, and this is of great value for in-depth understanding and promotion of the level of mechanized rice production.

IMPACT OF AGRICULTURAL M(I) SERVICES ON THE COSTS OF RICE BASED ON REGRESSION MODELS

This study extensively discusses agricultural M(i) services. Additionally, it studies different agricultural M(i) services in different planting stages. Thus, in the questionnaire design, from the perspective of different rice planting stages, agricultural M(i) services have different degrees of influence in their six stages and use the Richter scale 7-sub-scale to measure the importance of cost reduction of the six rice planting stages (Table 1).

For this study, the authors selected a total of 176 observation samples of rice growers from the questionnaire surveys of family farms in Chongqing, Shaanxi, Henan, Liaoning, and other provinces and cities. From the 176 questionnaires visited, participants answered the different stages of agricultural M(i) services (Tillage stage V1, sowing stage V2, plant protection stage V3, irrigation and drainage stage V4, fertilization stage V5, harvest stage V6), and the extent of the impact on the cost of rice on family farms in China. An Excel table was used to organize the data, and data transposition was performed. The data was then organized and imported into statistical analysis software. A correlation test was performed using Pearson correlation coefficient (Pearson's r), and the two-tailed test option was selected, resulting in the agricultural M(i) service for the six different stages of rice planting, and the relationship between each (Table 2).

Table 2 shows the correlation between the importance of agricultural M(i) services at different stages of rice planting. For example, it can be concluded that the Pearson correlation coefficient between the cultivation stage V1 and the rice cost V7 is 0.813, and the associated probability is less than 0.05, which has passed the significance test. It shows that the farmers interviewed in the cultivation stage believe that the importance of agricultural M(i) services is strongly related to the harvest stage, and tends to be the same. The table show that all passed the significance test with a

Table 1. Basic Characteristics of Varieties

Variety	Stage	Meaning
V1	Cultivation Stage	Agricultural M(i) services to reduce the influence of agricultural cost in the rice cultivation stage
V2	Sowing Stage	Agricultural M(i) services to reduce the influence of agricultural cost in the rice sowing stage
V3	Plant Protection Stage	Agricultural M(i) services to reduce the influence of agricultural cost in the plant protection stage
V4	Irrigation Stage	Agricultural M(i) services to reduce the influence of agricultural cost in the irrigation stage
V5	Fertilization Stage	Agricultural M(i) services to reduce the influence of agricultural cost in the fertilization stage
V6	Harvest Stage	Agricultural M(i) services to reduce the influence of agricultural cost in the harvest stage
V7	Total Cost	Agricultural M(i) services to reduce the influence of the total agricultural cost

Note: Investigation questionnaires use “Mechanization” referred to as “M(i)” for its implanting information system naturally.

Table 2. Rice Planting Cost-Related Coefficient Matrix

Correlation								
		V1	V2	V3	V4	V5	V6	V7
V1	Pearson correlation factor	1	.554**	.455**	.529**	.551**	.804**	.813**
	Significance level (Two tails)		.000	.000	.000	.000	.000	.000
V2	Pearson correlation factor	.554**	1	.857**	.875**	.796**	.562**	.761**
	Significance level (Two tails)	.000		.000	.000	.000	.000	.000
V3	Pearson correlation factor	.455**	.857**	1	.774**	.816**	.487**	.662**
	Significance level (Two tails)	.000	.000		.000	.000	.000	.000
V4	Pearson correlation factor	.529**	.875**	.774**	1	.709**	.518**	.737**
	Significance level (Two tails)	.000	.000	.000		.000	.000	.000
V5	Pearson correlation factor	.551**	.796**	.816**	.709**	1	.509**	.672**
	Significance level (Two tails)	.000	.000	.000	.000		.000	.000
V6	Pearson correlation factor	.804**	.562**	.487**	.518**	.509**	1	.829**
	Significance level (Two tails)	.000	.000	.000	.000	.000		.000
V7	Pearson correlation factor	.813**	.761**	.662**	.737**	.672**	.829**	1
	Significance level (Two tails)	.000	.000	.000	.000	.000	.000	

Note: * * The correlation was significant at the 0.01 level (double tail).

significance level (Two tails) of zero. It can be concluded the correlation between the variables is significant, which is suitable for regression model analysis.

Table 3 shows the linear regression analysis results of the importance and cost of agricultural M(i) services at different stages of rice planting. In the table, one can see an adjusted R2 coefficient of 0.99, indicating that the agricultural M(i) services levels of the four planting stages of tillage V1, sowing V2, drainage and irrigation V4, and harvesting V6 can explain 99% of the change in rice costs. The standard error of the predicted value of the dependent variable is 0.533, and the Durbin–

Table 3. Fitness of Rice Cost

Model Summary[c,d]					
Model	R	R^{2b}	Adjusted R^2	Estimation error	Dubin -Watson Factor
1	.995[a]	.991	.990	.533	2.150

a. Forecast: V6, V2, V4, V1

b. For regression through the origin (no intercept model), the R square measures the proportion of factor variable variability of the origin of the regression interpretation. This cannot be compared to the R square of the model containing the intercept.

c. Dependent variable: V7

d. Linear regression via the origin

Watson statistic is 2.15, indicating that the residual sequence is not correlated. The overall fit of the regression model is relatively good.

Table 4 shows the significance test results of the importance of agricultural M(i) services at different planting stages to the cost of rice. According to the data in the table, the importance of agricultural M(i) services in the cultivation stage V1, the sowing stage V2, the drainage and irrigation stage V4, and the harvest stage V6, have a positive effect on the cost of rice. The significance level of sig<0.05 indicates that V1, V2, V4, and V6 all have a significant impact on rice cost V7.

According to Table 4, one can also obtain the following regression equation model.

Regression model of non-standardized coefficients:

$$Y = 0.293X_1 + 0.173X_2 + 0.173X_3 + 0.364X_4 \tag{1}$$

(0.049)(0.050)(0.050)(0.048)

Regression model after standardized coefficients:

$$Y = 0.298X_1 + 0.165X_2 + 0.171X_3 + 0.372X_4 \tag{2}$$

The regression equation after the standardized coefficient shows that M(i)of the harvest stage V6 has the greatest impact on the cost of planting, with a coefficient of 0.372. This is followed by the M(i) of the cultivation stage V1 on the cost of planting, with a coefficient of 0.298, and then the sowing

Table 4. Rice Cost Regression Coefficient

Coefficient [a, b]						
Model		Nonstandard Coefficient		Standardization Coefficient	t	Sig.
		B	Standard error	Beta		
1	V1	.293	.049	.298	5.972	.000
	V2	.173	.050	.165	3.431	.001
	V4	.173	.050	.171	3.485	.001
	V6	.364	.048	.372	7.522	.000

a. Dependent variable: V7

b. Linear regression via the origin

stage V2, with a coefficient of 0.171. The drainage and irrigation stage V4, had a coefficient of 0.165. Mechanized services in these four stages all have an impact on the importance of rice planting M(i).

ANALYSIS OF THE IMPACT OF AGRICULTURAL M(I) SERVICES ON THE COST OF RICE FAMILY FARMS BASED ON EXPLORATORY FACTORS

An exploratory factor analysis was performed on the importance of agricultural M(i) services in the six stages of rice planting under the conditions of cost: tillage stage V1, sowing stage V2, plant protection stage V3, irrigation and drainage stage V4, fertilization stage V5, and harvest stage V6. A correlation analysis was done based on the collected and sorted data, and resulted in the correlation coefficient scale shown in Tables 5 through 7.

Table 5 shows that the correlation coefficient between the six factors of agricultural M(i) services in the cultivation stage V1, the sowing stage V2, the plant protection stage V3, the irrigation and irrigation stage V4, the fertilization stage V5, and the harvest stage V6 is relatively large, and the associated probabilities are all at the value of zero. Thus, the correlation between factors was significant and factor analysis could be done.

KMO and Bartlett sphericity tests were performed on the data between the six factors of cultivation (stage V1, sowing stage V2, drainage and irrigation stage V4, fertilization stage V5, and harvest stage V6). As shown in Table 5, the KMO value obtained was 0.825, which was greater than 0.7. Bartlett's sphericity test obtained a variance value of 956.349; the associated probability was zero, and the significance level was high, which further showed that it was suitable for factor analysis.

Table 5. Rice Cost Correlation Coefficient Matrix

Related Coefficient Matrix							
		V1	**V2**	**V3**	**V4**	**V5**	**V6**
Correlation Coefficient	V1	1.000	.554	.455	.529	.551	.804
	V2	.554	1.000	.857	.875	.796	.562
	V3	.455	.857	1.000	.774	.816	.487
	V4	.529	.875	.774	1.000	.709	.518
	V5	.551	.796	.816	.709	1.000	.509
	V6	.804	.562	.487	.518	.509	1.000
Significance (unilateral)	V1		.000	.000	.000	.000	.000
	V2	.000		.000	.000	.000	.000
	V3	.000	.000		.000	.000	.000
	V4	.000	.000	.000		.000	.000
	V5	.000	.000	.000	.000		.000
	V6	.000	.000	.000	.000	.000	

Table 6. KMO and Bartlett's Test Significance Test

The Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.825
Bartlett Sphericity Test	Approx. Chi-Square	956.349
	df	15
	Sig.	.000

Table 7. Main Factor Extraction

Total Variance Interpretation						
Component	Initial Characteristic Value			The Sum of the Extracted Load Square Total		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.288	71.474	71.474	4.288	71.474	71.474
2	.939	15.653	87.127			
3	.313	5.220	92.347			
4	.219	3.651	95.998			
5	.140	2.340	98.338			
6	.100	1.662	100.000			

Note: Extraction method: the main component analysis.

In Table 7, the common factor was extracted by using the largest eigenvalue. The eigenvalue of common factor 1 is 4.288, and the variance explanation rate is 71.474%. The eigenvalue of common factor 2 was 0.939, and the eigenvalue of common factor 3 was 0.313. The feature value of factor 4 was 0.219, and the feature value of common factor 5 was 0.140. The feature value of common factor 6 was 0.100, and the values were all less than one. According to the principle that the common factor needs to be greater than one, the common factor extracted was the common factor one. The authors also observed the factor loading, as shown in Table 8.

From the perspective of factor loading, the load rate of the importance of agricultural M(i) services in the cultivation stage V1 on the cost was 0.748, and the load rate of the importance of agricultural M(i) services in the planting stage V2 on the cost was 0.928. The load value was the highest. The load rates of the irrigation and irrigation stages V4, fertilization stage V5, and harvest stage V6 were 0.879, 0.880, 0.874, and 0.746, respectively. Their load rates were relatively high, and their common factor was the impact of agricultural M(i) services level on cost. Therefore, this unique common factor can be named "agricultural M(i) services level and rice cost."

ANALYSIS OF THE IMPACT OF AGRICULTURAL M(I) SERVICES ON THE COST OF RICE FAMILY FARMS BASED ON TWO NETWORK MODELS

Analysis of the Six Planting Stages of the "Cost of Rice" Based on the SNA Model

The social network analysis (SNA) model, is a common social network analysis paradigm that mainly describes the distance between various related factors or related stages and the relationship between clan and other aspects. In this article, the authors used UCINET 6 to complete the visual processing of social network phase correlation, visual processing of branch blocks, centrality analysis of each phase, phase block cluster analysis, and phase block density analysis.

In order to analyze the correlation between "rice cost" in the cultivation stage V1, the sowing stage V2, the plant protection stage V3, the drainage and irrigation stage V4, the fertilization stage

Table 8. Factor Load Level

Composition Matrix								
Component Matrix	Component	1	V1	V2	V3	V4	V5	V6
			0.748	0.928	0.879	0.88	0.874	0.746

a. 1 Components Extracted

V5, and the harvest stage V6, the authors first conducted a correlation analysis on the collected 127 samples using SPSS software to perform the Pearson correlation coefficient test.

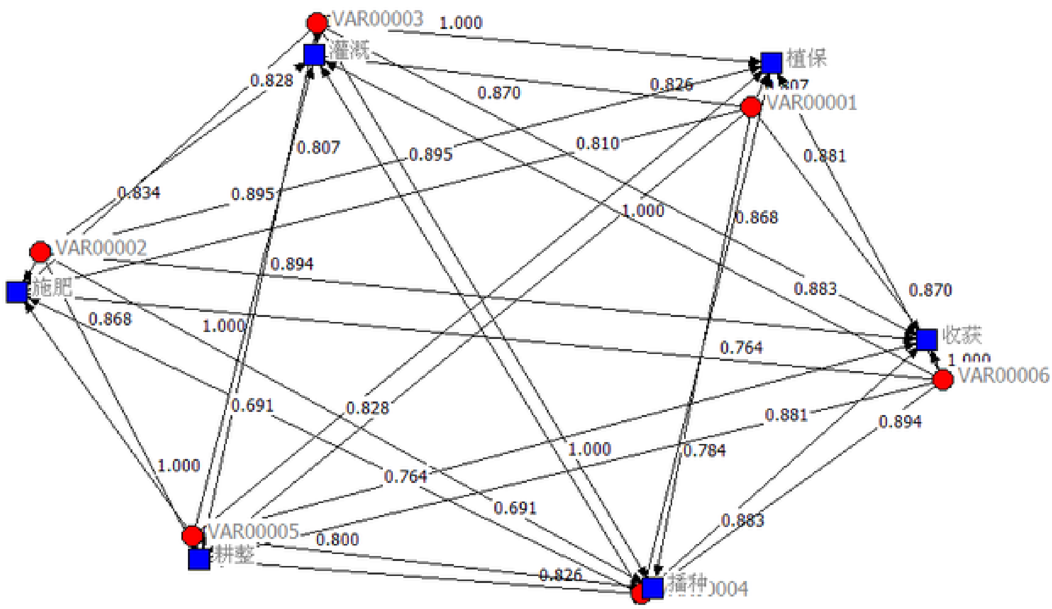
It can be seen from Table 9 that the correlation coefficients of Pearson Correlation at each planting stage of rice are mostly above 0.8, and some of the lower correlation coefficients also passed the two-tailed association probability test, indicating that this affects the "cost of rice's" six farming stages. The whole stage V1, sowing stage V2, plant protection stage V3, irrigation and drainage stage V4, fertilization stage V5, and the harvest stage V6 are closely related and can be analyzed using the SNA model.

The authors chose SNA UCINET 6 software for data entry, and then used NETDRAW for visualization processing and obtained the diagram shown in Figure 1.

Table 9. Rice Cost Correlation Coefficient Matrix

Correlations							
		VAR00001	**VAR00002**	**VAR00003**	**VAR00004**	**VAR00005**	**VAR00006**
VAR00001	Pearson correlation coefficient	1	.868	.807	.826	.810	.881
	Significance level (Two tails)		.000	.000	.000	.000	.000
VAR00002	Pearson correlation coefficient	.868	1	.895	.834	.800	.894
	Significance level (Two tails)	.000		.000	.000	.000	.000
VAR00003	Pearson correlation coefficient	.807	.895	1	.784	.828	.870
	Significance level (Two tails)	.000	.000		.000	.000	.000
VAR00004	Pearson correlation coefficient	.826	.834	.784	1	.691	.883
	Significance level (Two tails)	.000	.000	.000		.000	.000
VAR00005	Pearson correlation coefficient	.810	.800	.828	.691	1	.764
	Significance level (Two tails)	.000	.000	.000	.000		.000
VAR00006	Pearson correlation coefficient	.881	.894	.870	.883	.764	1
	Significance level (Two tails)	.000	.000	.000	.000	.000	

Figure 1. MDS Exhibition With Double Nodes



From the MDS LAYOUT diagram, it can be seen that there is a strong correlation between tillage, sowing, plant protection, irrigation and drainage, fertilization, and harvesting. The correlation coefficients are 0.868, 0.807, 0.826, .881, 0.870, etc., indicating their impact on the region. The cost of rice has a similar effect.

On this basis, the authors further analyzed the centrality of analysis-centrality measures, using OutDegree and InDegree to characterize the results in the Table 10 data.

From the degree and centrality measurements shown in Table 10, it can be seen that the out-point OutDegree had the highest centrality at the harvesting stage V6, with a value of 4.292, and the in-point OutDegree had the highest centrality at the harvesting stage V6, with a value of 4.292. Therefore, relating to rice cost, the high degree of influence is the harvesting stage V6. In other words, the cost of agricultural M(i) services in the harvesting stage has the greatest impact on the cost of the entire planting stage.

To further analyze the interdependence among the six stages of rice farming, the authors used, the block diagram analysis-partition diagram, resulting in the following relationship connection diagram, relationship connection matrix, and density matrix shown in Figure 2 and Table 11.

Table 10. Centrality Analysis of the Planting Phase

Order	Stage Variable	1	2	3	4
		OutDegree	InDegree	NrmOutDeg	NrmInDeg
6	VAR00006	4.292	4.292	95.911	95.911
2	VAR00002	4.291	4.291	95.888	95.888
1	VAR00001	4.192	4.192	93.676	93.676
3	VAR00003	4.184	4.184	93.497	93.497
4	VAR00004	4.018	4.018	89.788	89.788
5	VAR00005	3.893	3.893	86.994	86.994

Figure 2. Trees Shapes of Division Cluster

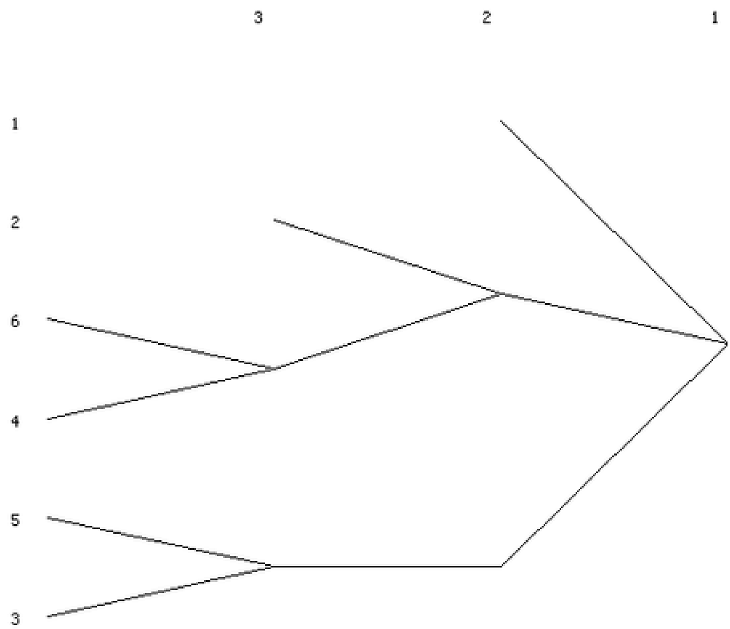


Table 11. Block Matrix of Planting Stage

Order	Stage Variable	5	3	1	2	4	6
5	VAR00005	1.000	0.828	0.810	0.800	0.691	0.764
3	VAR00003	0.828	1.000	0.807	0.895	0.784	0.870
1	VAR00001	0.810	0.807	1.000	0.868	0.826	0.881
2	VAR00002	0.800	0.895	0.868	1.000	0.834	0.894
4	VAR00004	0.691	0.784	0.826	0.834	1.000	0.883
6	VAR00006	0.764	0.870	0.881	0.894	0.883	1.000

From Table 11, it can be seen that rice agricultural M(i) services cost is the relationship connection graph and the relationship connection matrix, which can be divided into four blocks. The first block is the plant protection stage V3, the fertilization stage V5, and the second block is irrigation and drainage. Stage V4, is the harvest stage V6, the third block is the sowing stage V2, and the fourth block is the tillage stage V1. The maximum value of the block is 0.895, and the minimum value is 0.691.

It can be seen from Table 12 that, among the four blocks, the maximum value is 0.868, which is the density coefficient between the second block and the third block, indicating that the relationship between the two blocks is strong. The minimum value is 0.777, which is the density coefficient between the first block and the fourth block, indicating that the relationship between these two blocks is weak.

Relationship Network Analysis of the Six Planting Stages of the "Cost of Rice" Based on the Multi-Layer Perceptron Neural Network Model

The multilayer perceptron network (MLP) model can be used to detect the nonlinear and complex relationship between the input layer and the output layer, in order to more intuitively understand the

Table 12. Planting Block Density Matrix

	1	2	3	4
1	0.828	0.808	0.847	0.777
2	0.808	/	0.868	0.854
3	0.847	0.868	/	0.864
4	0.777	0.854	0.864	0.883

six cultivation stages that affect the "cost of rice." Stages V1 through V6 have a complex influence on the total cost V7. The authors selected 127 data from Chongqing, Shaanxi, Henan, Liaoning, and other provinces and cities for the model analysis.

It can be seen from Tables 13 and 14 that a total of 127 samples were selected, one of which was eliminated during the calculation process, the number of model training samples was 87, the test support samples were 39, and the effective rate was 100%. Training was terminated until the error could not be further reduced. The relative error of the training sample was 0.054, and the total error was 2.330; the relative error of the detection support sample was 0.193, the total error was 1.929, thus the training effect generally meets the expected requirements.

As can be seen from the scatter plot of predicted and actual values in Figure 3, the scatter plot is basically distributed around the 45-degree straight line of the predicted value of the dependent variable VAR0007, indicating that the predicted value and the actual value fit well. It can be seen from Figure 4, Residual Error Estimation Distribution, that most of the scattered points are distributed around 0 mean, and the upper and lower sides are basically symmetrical, which meets the requirement that the residuals meet the requirements of close to normal distribution.

Table 13. Data Selection

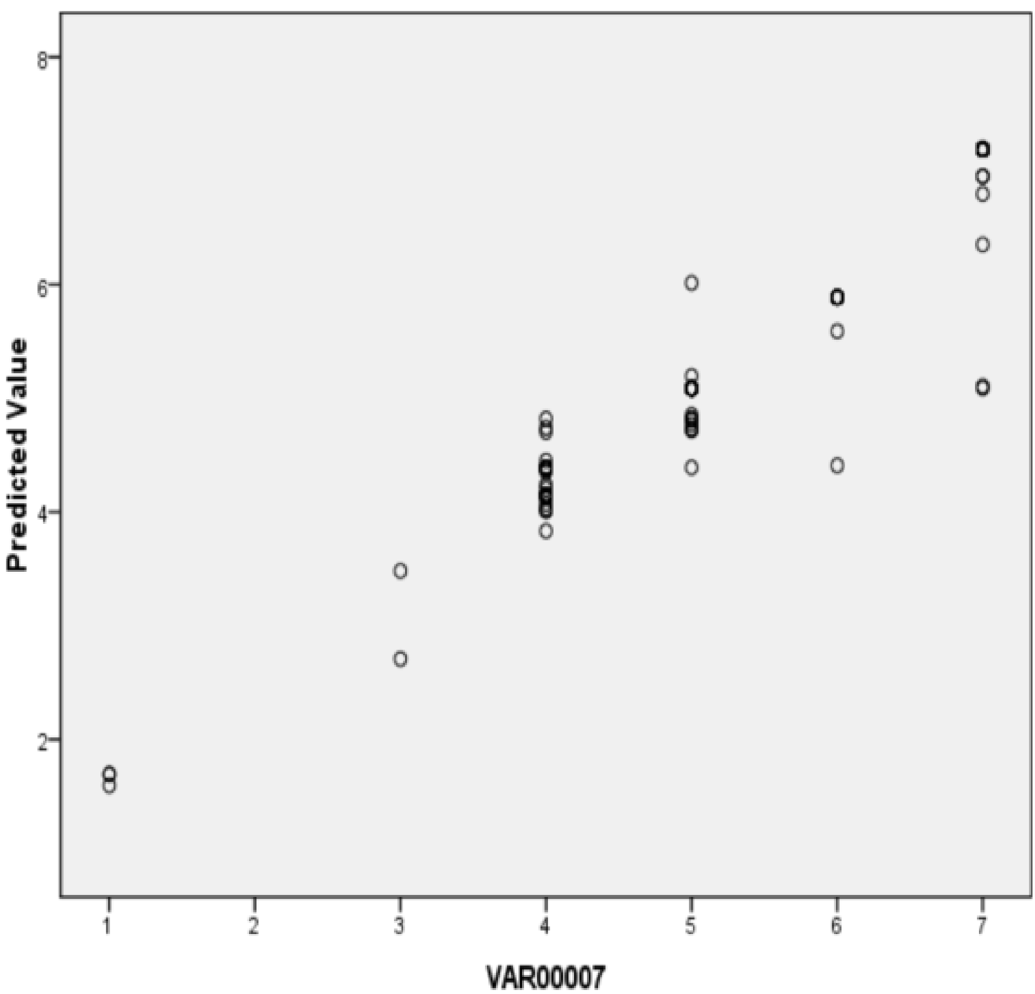
Individual Case Observation Summary			
		N	Percentage
Sample:	Training	87	69.0%
	Test	39	31.0%
Effective		126	100.0%
Exclusion		1	
Total		127	

Table 14. Model Description

Model Summary		
Training	Error square sum	2.330
	Relative error	.054
	Training time	0:00:00.016
Test	Error square sum	1.929
	Relative error	.193

Dependent variable: VAR00007
Note: Error calculation is based on the test samples.

Figure 3. Scatter Plot of Predicted and Actual Values

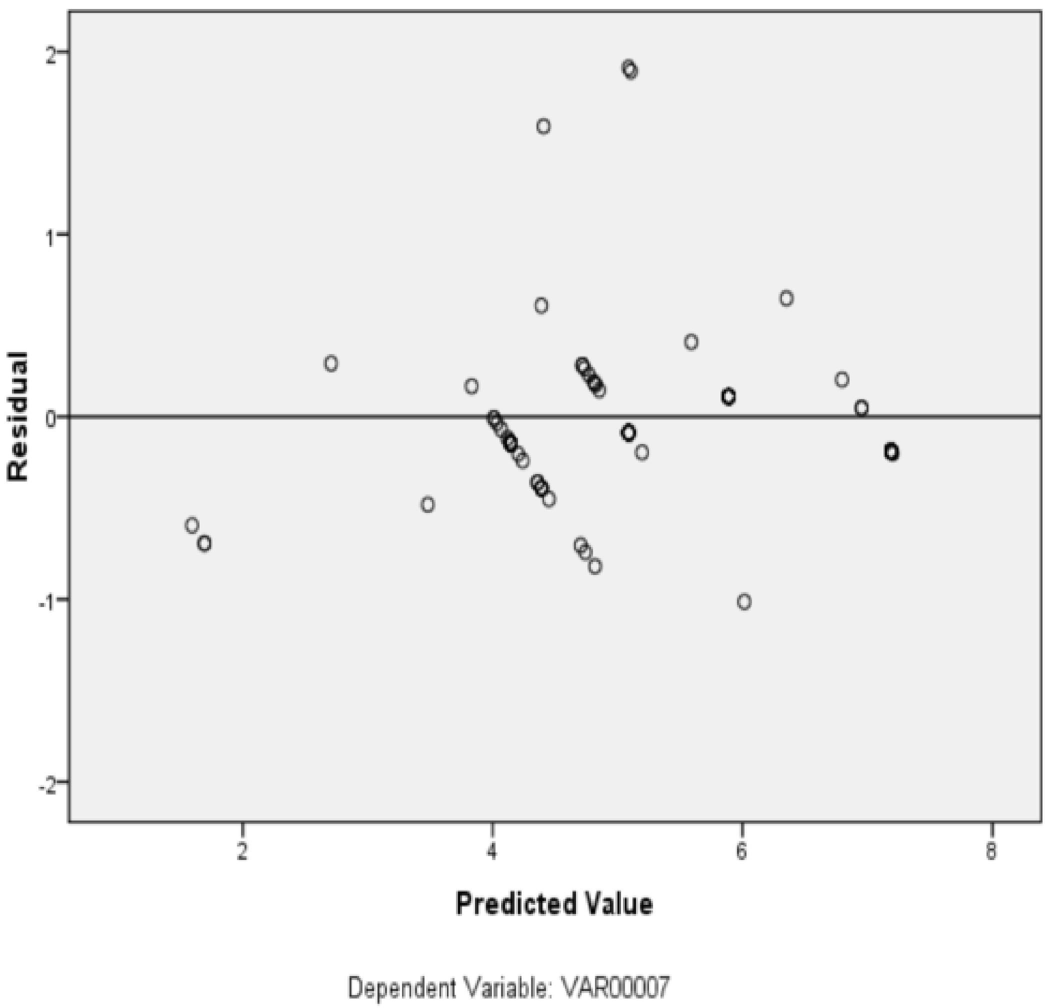


From the above two scatter plots, it can be seen that the model meets the requirements of the multilayer perceptron neural network model MLP. The following graphics and data in Figure 4 can be used as analysis arguments.

The non-linear and complex relationship diagram of the multilayer perceptron network (MLP) of the six planting stages of the “cost of rice” shows that the model contains a hidden layer (Hidden-Layer). There are four units in the layer (Units), as well as an input layer (Input-Layer) and an output layer (Output-Layer). There are a large number of lines mapped from the input layer to the hidden layer. The gray lines represent the positive weight relationships, and the blue lines represent the negative weight relationships. Similarly, the mapping from the hidden layer to the output layer is the same. There are two blue lines representing negative weight relationships, and three gray lines representing positive weight relationships.

Table 15, shows the parameter estimation between the input layer, the output layer, and the hidden layer, and it can be seen that the training sample is divided into six groups of variables and an error term (Bias). Each variable group contains seven neural units. Forty-three neurons are mapped to five neural units in the hidden layer, and there are a total of 172 mapped weight values, of which 66 are

Figure 4. Residual Error Estimation Distribution



negative weight values and 106 are positive weight values. There are four neurons from the hidden layer to the output layer, and there is an error (Bias) neuron, of which the negative weight value is two, which are -0.461 and -0.126, and the positive weight value is three, which is 0.949 and 0.919, 0.228. Therefore, one can arbitrarily pass a neuron input weight value, pass the hidden layer weight value, and obtain an output-layer weight value. Different mappings include positive values, negative values, and various non-linear paths that blend positive and negative values.

It can be seen from Table 16 and Figure 5 that the importance of the independent variables is ranked: (1) VAR00001 in the cultivation stage, with a coefficient of 0.320, and the importance after standardized treatment was 100%; (2) VAR00006 in the harvest stage, with a coefficient of 0.320, and after standardized treatment, the importance was 62.5%; (3) VAR00002 at the sowing stage, the coefficient was 0.187, and the importance after standardized treatment was 58.4%; (4) the importance of VAR00003 at the plant protection stage, the coefficient was 0.100, and the importance after standardized treatment was 31.1%; (5) VAR00004 in the irrigation stage, the coefficient is 0.096, and the importance after standardized treatment was 30.1%; (6) VAR00005 in the fertilization stage, the coefficient was 0.096, and the importance after standardization was 30.1%.

Table 15. Parameter Estimation Between the Input, Output, and Implied Layers

Predictor		Predicted				
		Hidden Layer 1				Output Layer
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	VAR00007
Input-Layer	(Bias)	.227	-.756	.246	.096	
	[VAR00001=1.00]	-.569	.105	.010	.424	
	[VAR00001=3.00]	-.199	-.024	-.247	.419	
	[VAR00001=4.00]	.439	.090	-.320	-.359	
	[VAR00001=5.00]	.248	-.188	.147	.090	
	[VAR00001=6.00]	.502	.012	.287	-.065	
	[VAR00001=7.00]	.182	.828	.035	.102	
	[VAR00002=1.00]	-.225	-.374	-.251	.495	
	[VAR00002=3.00]	-.334	-.410	.192	-.104	
	[VAR00002=4.00]	.153	-.603	-.336	.198	
	[VAR00002=5.00]	.093	-.260	.014	.347	
	[VAR00002=6.00]	-.226	.251	-.295	.101	
	[VAR00002=7.00]	.296	.472	-.018	-.343	
	[VAR00003=1.00]	-.349	-.257	.206	-.004	
	[VAR00003=3.00]	.252	-.311	.358	.028	
	[VAR00003=4.00]	-.241	-.466	-.231	-.410	
	[VAR00003=5.00]	.534	.377	-.354	-.328	
	[VAR00003=6.00]	.420	.180	-.469	-.107	
	[VAR00003=7.00]	.206	-.098	.177	.327	
	[VAR00004=1.00]	-.658	-.633	-.207	.339	
	[VAR00004=3.00]	-.186	.115	.433	-.007	
	[VAR00004=4.00]	.270	-.169	-.289	.383	
	[VAR00004=5.00]	.450	-.314	.277	.020	
	[VAR00004=6.00]	.475	.289	-.447	.238	
	[VAR00004=7.00]	-.080	.645	-.181	-.017	
	[VAR00005=1.00]	.239	-.428	.452	-.176	
	[VAR00005=3.00]	.352	-.182	.460	.148	
	[VAR00005=4.00]	.295	.414	-.081	-.313	
	[VAR00005=5.00]	-.344	.096	.093	.069	
	[VAR00005=6.00]	-.423	.290	.245	.473	
	[VAR00005=7.00]	.161	.479	.278	-.242	
	[VAR00006=1.00]	-.214	-.342	-.359	.265	
	[VAR00006=3.00]	-.611	-.175	-.472	-.072	
	[VAR00006=4.00]	-.080	-.197	.087	.025	
	[VAR00006=5.00]	.335	.197	.330	-.445	
	[VAR00006=6.00]	-.362	.377	.319	.047	
	[VAR00006=7.00]	.221	.423	-.273	-.434	
Hidden-Layer 1	(Bias)					-.461
	H(1:1)					.949
	H(1:2)					.919
	H(1:3)					.228
	H(1:4)					-.126

Table 16. Measure of the Importance of Independent Variables

Importance of Independent Variables		
	Importance	Standardization Importance
VAR00001	.320	100.0%
VAR00002	.187	58.4%
VAR00003	.100	31.1%
VAR00004	.096	30.1%
VAR00005	.096	30.1%
VAR00006	.200	62.5%

COMPARATIVE ANALYSIS OF FACTOR RANKING OF VARIOUS RESEARCH METHODS

Since the characteristics of each research method are different, the calculation results of each research method may be different. The authors further analyzed the calculation results of three methods: multiple linear regression, the SNA social network, and the multilayer neural network, as shown in Table 17.

Table 15, regarding the phased impact of agricultural M(i) services on rice planting costs, shows that the multiple linear regression calculations are most importantly at the harvest stage V6. The SNA social network calculation results are also at the harvest stage V6, and the layer-sensing neural network is the cultivation stage V1. However overall, the first three results calculated by the three methods are the same, namely the harvest stage V6, the cultivation stage V1, and the sowing stage V2, indicating that agricultural M(i) services are effective in rice planting strongly. The three stages that have the greatest impact on cost are the experimental results confirmed by research methods, original data, and test data.

CONCLUSION

Based on previous studies, this paper analyzes the effect of agricultural M(i)on the cost of rice planting at different stages by decomposing rice planting stages.

Firstly, the authors obtained the total cost of agricultural M(i) services as the dependent variable through the multiple linear regression model, and the linear equation, with the cost of different planting stages, as the independent variable to analyze the importance of M(i) services at different stages.

Secondly, the social network (SNA) model was used to analyze the relationship between the impact of agricultural M(i) services on the cost of rice planting at different stages, and the results similar to the multiple linear regression model were obtained through visualization processing, centralization analysis, and density coefficient.

Thirdly, they used the multilayer perceptron neural network model to analyze the six planting stages of the "cost of rice," and obtained a weight chart of the nonlinear complex mapping relationship between the input layer, the hidden layer, and the output layer.

Finally, the authors compared and analyzed the factor importance ranking results by three different models: the multiple linear regression, the SNA social network, and the multi-layer perceptron neural network, which explained that different research methods have different calculation results, but their factor ranking calculation results in convergence at most. That same show "the harvest stage V6, the cultivation stage V1, and the sowing stage V2" are very important cost influences by agricultural M(i) services.

Figure 5. Non-Linear and Complex Relationship Diagram Between MLP Multiple Factors

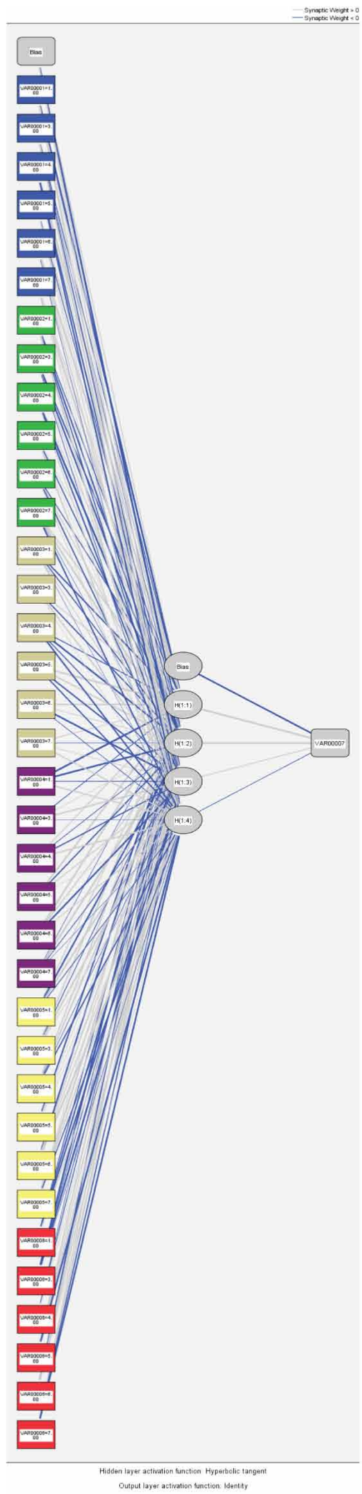


Figure 6. Bar Graph of the Importance of Independent Variables

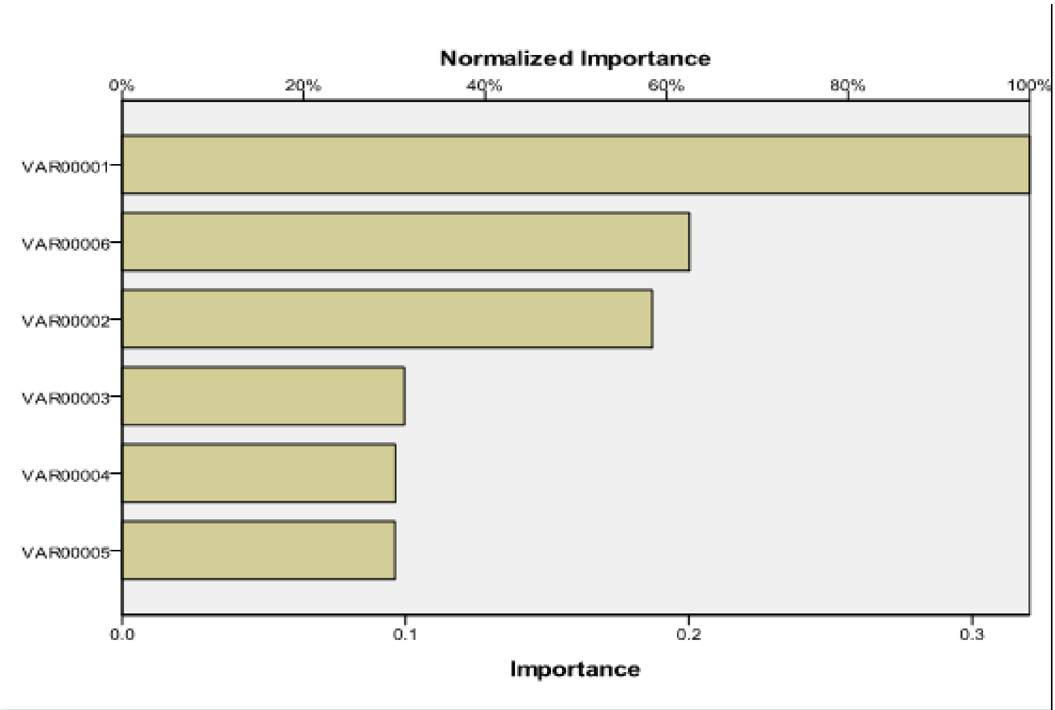


Table 17. Factor Ranking of Various Research Methods

Importance	Multivariate Linear Regression	SNA(Social Network Service)	Multilayer Perceptual Neural Network
1	Harvest Phase V6	Harvest Phase V6	Tillage Stage V1
2	Tillage Stage V1	Seed Stage V2	Harvest Phase V6
3	Seed Stage V2	Tillage Stage V1	Seed Stage V2
4	Drainage and Irrigation Stage: V4	Plant Protection Stage: V3	Plant Protection Stage: V3
5	/	Irrigation Stage V4	Irrigation Stage V4
6	/	Fertilization Stage V5	Fertilization Stage V5

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