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The Impact of Agricultural Mechanization on Agricultural Green Total Factor Productivity and its Promotion Prospect

-- Based on the Survey Data of Six Cities in Northern Anhui

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Abstract: From the perspective of rural revitalization, efforts to improve agricultural green total factor productivity is the key to achieve high-quality and efficient development of agricultural economy, and also an important starting point for building a modern agricultural power and Promoting Rural Revitalization Strategy. Based on the survey data of six cities in Northern Anhui, combined with the needs of green sustainable agricultural development and ecological civilization construction, SEM model and decision tree model were established to analyze the factors affecting the improvement of agricultural green total factor productivity, and explore the prospect and attitude of residents in six cities in Northern Anhui to the improvement of agricultural green total factor productivity. Finally, the paper puts forward targeted policy suggestions from six aspects of policy support, resource integration, technology transformation, public participation, environmental protection and market guidance, aiming to explore the feasible path for improving agricultural green total factor productivity in the six cities in Northern Anhui.

Keywords: Agricultural mechanization; Agricultural green total factor productivity; Six cities in Northern Anhui; Promotion path.

1. Introduction

In the context of the implementation of the Rural Revitalization Strategy, efforts to improve agricultural green total factor productivity is the key to the revitalization of the agricultural industry, and it is also an important starting point to realize the construction of a powerful agricultural modernization country and promote the high-quality development of agriculture[1]. In recent years, with the introduction of China's "14th five year plan" and the formulation of the long-term goal of 2035, the construction of a powerful country with agricultural modernization has become an important part of the national strategy. In October 2022, the report of the 20th National Congress of the Communist Party of China first proposed to accelerate the construction of an agricultural power. In February 2023, the No. 1 document of the Central Committee focused on comprehensively promoting the theme of Rural Revitalization and anchored the goal of building an agricultural power. In February 2024, the No. 1 document of the Central Committee proposed to adhere to and strengthen the party's comprehensive leadership over the work of "agriculture, rural areas and farmers", once again anchored the strategic goal of building an agricultural power, and raised the task of building an agricultural power to an unprecedented height. Nowadays, with the continuous progress of science and technology, agricultural mechanization has become an important support for building an agricultural power and the key to the high-quality development of agriculture. Since the implementation of the Agricultural Mechanization Promotion Law in 2004, China's agricultural mechanization has entered a period of rapid development [2].

It is worth noting that with the acceleration of urbanization, more and more young rural labor force choose to leave the countryside, leading to the aging of rural population. In this context, the traditional mode of agricultural production has been impacted to a certain extent, "elderly agriculture" has become one of the important factors hindering the improvement of agricultural production efficiency and agricultural development, "who will farm the land", "where will the grain come from" and other practical issues have gradually become the focus of the government. According to the data of the National Bureau of statistics, the total investment in China's primary industry from January to November 2023 was 964.7 billion yuan, with agricultural investment accounting for 2.1% of the total investment in the whole industry, and the statistical investment decreased by 0.2% year on year. Under this unfavorable situation, the traditional agriculture that only depends on production "relying on the harvest of heaven", labor relying on manpower, and unsustainable development is no longer feasible. It is necessary to seek a more efficient, high-yield, environment-friendly, green and sustainable agricultural development model. Therefore, analyzing the factors affecting the improvement of agricultural green total factor productivity, exploring the prospect and attitude of residents towards the improvement of agricultural green total factor productivity, and summarizing a set of innovative improvement paths suitable for the six cities in Northern Anhui and even similar agricultural regions have important research value for promoting rural revitalization, maintaining food security, protecting the ecological environment, and answering the practical problems of "who will grow grain" and "where will grain come from" in the new era.

2. Literature Review

As the key factor to improve agricultural productivity and promote agricultural modernization, agricultural mechanization has always been the core issue in the field of agricultural economy. Domestic literature has conducted a large number of studies on the international differences of agricultural total factor productivity from different angles. In terms of measuring methods of agricultural total factor productivity, Zhaozhe[3] used SBM-DDF model to measure agricultural green total factor productivity, and used GML index and threshold regression model to explore the impact of agricultural green total factor productivity on urban-rural income gap. Wangchaohui et al [4] comprehensively used DEA Malmquist, spatial autocorrelation method and spatial lag model to analyze the spatial differentiation pattern of rural labor non-agricultural transfer, and discussed the impact of agricultural total factor productivity on rural labor non-agricultural transfer and its spatial effect. In terms of exploring the influencing factors of agricultural total factor productivity, Lishimei et al [5] believed that the impact of rural labor transfer on the eastern, central and western regions was heterogeneous, which hindered the improvement of agricultural total factor productivity. Dengxiaolan and others [6] believe that the degree of agricultural mechanization has a positive role in promoting agricultural total factor productivity.

According to the existing domestic studies, the academic circle has made a more in-depth analysis of the impact of agricultural mechanization and rural labor transfer on agricultural total factor productivity [7], but there are still shortcomings: first, the existing studies have mostly analyzed the impact mechanism of agricultural mechanization and agricultural total factor productivity in theory, or obtained relevant panel data from the macro level for empirical test, It is easy to ignore the actual problems and real situations at the micro level. Second, there are few studies on the impact path of Agricultural Mechanization on the improvement of agricultural total factor productivity. The impact mechanism of Agricultural Mechanization on agricultural total factor productivity and the improvement path of agricultural total factor productivity are still worth further discussion. Therefore, based on the survey data of the six cities in Northern Anhui, this study analyzes the factors affecting the improvement of agricultural green total factor productivity by establishing SEM model and decision tree model, and explores the prospect and attitude of residents in the six cities in Northern Anhui on the improvement of agricultural green total factor productivity, so as to explore the feasible path for the improvement of agricultural green total factor productivity in the six cities in Northern Anhui To realize the high-quality development of agriculture and rural areas, this paper puts forward targeted policy suggestions and reference basis.

3. Data and Methods

3.1. Data sources

The data used in this study are from the social practice survey conducted by the team in six cities in Northern Anhui in January 2024. In order to select a small number of representative research areas, this survey used the PPS sampling method to conduct a questionnaire survey on the residents of six cities in Northern Anhui. By consulting the statistical yearbook of Anhui Province in 2023, the population distribution of six cities in Northern Anhui was investigated, and four rounds of stratified sampling were conducted according to the proportion of permanent residents in the six cities.

In the survey sample, men accounted for 52.74%, indicating that the respondents were mainly men; 34.25% of the respondents were aged from 18 to 30, indicating that the respondents were mainly young and middle-aged; 36.99% of the respondents had a higher education level than the respondents in the table; The monthly income of 5001-10000 yuan accounted for 30.14%, indicating that the respondents were mainly middle-income groups. Overall, the survey sample shows the basic characteristics of male dominated, moderate age, high education level and medium monthly income level.

3.2. Model establishment

3.2.1. SEM model

SEM model, namely structural equation model, is a framework model for constructing, evaluating and quantifying the direct and indirect effects in causal network, including two basic models: measurement model and structural model. The measurement model represents the covariant relationship between potential variables and observation variables, and can be regarded as a regression model, regression from observation variables to potential variables. The equation can be expressed as:

$$y_i = \Lambda w_i + \varepsilon_i, i = 1,2,\dots,n \quad (1)$$

Where, y_i is the observation variable of$\times 1$and Λ is the factor matrix of $p \times q$ corresponding to the observation vector; w_i is the factor score vector of $p \times 1$.

The structural model part represents the structural relationship between potential variables. It can also be used as a regression model to regress the linear terms of several endogenous and exogenous potential variables from endogenous potential variables. Expressed by equation:

$$\eta_i = \pi\eta_i + \Gamma\xi_i + \delta_i, i = 1,2,\dots,n \quad (2)$$

Where, η_i and ξ_i are potential variables of $q_1 \times 1$ and $q_2 \times 1$ respectively; π and Γ denote unknown correlation parameter matrix.

Due to the unmeasurable nature of the latent variable, this paper uses several measurable variables to measure the latent variable. Among them, the cognitive situation includes three variables: the low level of agricultural mechanization, the unreasonable allocation of resources, and the low level of agricultural technology training and popularization; The external environment includes three variables: insufficient agricultural policy support, small and scattered agricultural planting scale, and environmental pollution and ecological destruction; Science and technology include two variables: backward infrastructure and backward agricultural production technology; Agricultural structure includes two variables: single agricultural planting structure and lack of agricultural funds. The variables contained in potential variables are shown in Table 1. According to the Likert scale, the following scale with variable values of 1-5 is designed.

Finally, the proposed model is verified and analyzed.

Table 1. Observation variables corresponding to latent variables

Latent variable	Variable symbol	Observational factors
Cognitive situation	a_1	Low level of agricultural mechanization
	a_2	Improper resource allocation
	a_3	Agricultural technical training and popularization strength is not high
Exotic environment	a_4	Insufficient agricultural policy support
	a_5	Agricultural cultivation scale is small and scattered
	a_6	Environmental pollution and ecological destruction
Technology	a_7	The infrastructure is backward
	a_8	Agricultural production technology is backward
Agricultural structure	a_9	Agricultural planting structure is single
	a_{10}	Lack of agricultural funds

For this purpose, this paper establishes the following assumptions:

H_1: The external environment has a significant and positive impact on cognitive situations.

H_2: Tcience and technology have a significant positive impact on cognitive conditions.

H_3: Agricultural structure has a significant and positive impact on cognitive conditions.

3.2.2. Decision tree model

Decision treeis a non-parametric effective supervised learning method, which can summarize decision rules from a series of characteristic and labeled data, and present these rules with the structure of the dendrogram to solve the classification and regression problems. Python The Sklearn library for machine learning provides two kinds of algorithms: information entropy and Gini coefficient.

$$Entropy(t) = -\sum_{i=0}^{c-1} p(i|t)\log_2 p(i|t) \quad (3)$$

$$Gini(t) = 1 - \sum_{i=0}^{c-1} p(i|t)^2 \quad (4)$$

Where, t represents a given node, i represents the arbitrary classification of the label, and p (i | t) represents the proportion of the label classification i on the node t. When using information entropy, sklearn actually calculates the information gain based on information entropy, that is, the difference between the information entropy of the parent node and the information entropy of the child node.

In order to make the decision tree better generalization, this paper is pruning the decision tree. The pruning strategy has a great influence on the decision tree, and the correct pruning strategy is the core of optimizing the decision tree algorithm. According to the question "The prospect of agricultural mechanization to improve agricultural green total factor productivity in six cities in northern Anhui", four options are designed, as shown in Table 2:

Table 2. Five options for the prospect and attitude design of agricultural green total factor productivity

Option	Content
Option1	Very optimistic, in line with the green development trend
Option2	More optimistic, but there is room for progress
Option3	Not too optimistic, more restrictive factors
Option4	Not optimistic and not concerned

Questionnaire respondents to the five options is divided into four levels, 1 points, 2 points, 3 points and 4 points, as the respondents of agricultural mechanization of agricultural green total factor productivity prospects of positive quantitative attitude, the higher the score shows that its outlook towards agricultural mechanization and the more positive. This paper encodes the relevant element data, as shown in Table 3:

4. Results and Analysis

4.1. Analysis of the factors affecting the increase of agricultural green total factor productivity

Using SPSS software, according to the symbol of the structural equation model path diagram rules, draw the path diagram of the model, the first potential variable in the model of the coefficient of the measurement index is 1, exogenous potential variables, endogenous potential variables of measuring error coefficient is 1.

According to the model path coefficient table (Table4): Based on the external environment-> cognitive situation of the paired term, the significance P-value is 0.001 which shows significance at the level, the null hypothesis is rejected, so this path is valid, and the coefficient of influence is 0.879. Based on the matching science and technology-> cognitive situation, the significance P value is 0.003, and the level is significant, the null hypothesis is rejected, so this path is valid and its influence coefficient is 0.425. Based on the paired agricultural structure-> cognitive situation, the significance P-value is 0.091 without significance at the level, the null hypothesis cannot be rejected, and this path is invalid.

Table 3. Data encoding

Variable	Code
Sex	Male-1, female-2
Age	Under 18 years-1; 18-30-2; 31-40-3; 41-50-4; 51-60-5; over 60-6
Education level	Primary school and below-1; middle school-2; high school (including technical secondary school, vocational high school, technical school) -3; junior college-4; undergraduate-5; master's degree and above-6
Monthly income level	Under 3000 yuan-1; 3000-5000-2; 5001-10000-3; 10001-50000-4; over 50000-5
full-time equivalence	full-time equivalence-1; other-0
Commercial / service industry general worker	Commercial / Service industry worker-1; other-0
Enterprise managers	Enterprise managers-1; other-0
Agricultural workers	Agricultural workers-1; other-0
Cadres / staff of the government and public institutions	Cadres / staff of government and public institutions-1; other-0
Ordinary worker	Ordinary worker-1; other-0
Self-employed / contractor	Self-employed / contractor-1; other-0
Freelancer	Freelancer-1; other-0
Retirement	Retirement-1; Other-0
Domicile	Fuyang-1; Bozhou-2; Huaibei-3; Suzhou-4; Bengbu-5; Huainan-6
Years of work in agriculture	1 year-1; 1-3 years-2; 4-6 years-3; 7-9 years-4; 10-15-5; 16-20-6; 20 years-7
Mechanical quantity	No purchase-1; 1-2-2; 3-5-3; 6-10-4; 11-15-5; 16 over-6

Table 4. Table of model path coefficient

Subactive variables	Explicit variables	Non-standardized coefficients	Standardization coefficient	standard error	Z	P
exotic environment	Cognitive situation	0.575	0.879	0.173	3.328	0.001***
technology	Cognitive situation	0.346	0.425	0.116	2.978	0.003***
agricultural structure	Cognitive situation	-0.232	-0.319	0.137	-1.692	0.091*
Note: ***, ** and* represent the significance levels of 1%, 5% and 10%, respectively						

Combined with the SEM model of the operation results and path coefficient, the following conclusion: the external environment and science and technology have significant positive influence on cognitive understanding, the path coefficient is 0.879, that the improvement of the external environment will promote the cognitive understanding of respondents, if the government to strengthen guidance, actively promote the policy, is beneficial to promote respondents to agricultural green total factor productivity and related policies; Science and technology has a significant positive impact on the degree of cognition, and its path coefficient is 0.425, indicating that to further enhance the respondents' awareness of green agricultural total factor productivity and related policies, it is necessary to actively introduce new production technologies and replace advanced infrastructure.

4.2. Analysis of the prospect and attitude of agricultural green total factor productivity increase

On the basis of Python machine learning, this paper introduces the decision tree to study the relationship between the respondents' attitude towards the improvement of agricultural green total factor productivity in the six cities of northern Anhui and the relationship between gender, age, education level, monthly income level, occupation, residence, working years and number of machinery.

On the feature selection, this paper adopts the information gain criterion, takes the feature with the largest information gain as the node feature of the decision tree, and constructs the subnodes according to the different values of the feature. Call this method recursively to construct decision trees on subnodes until all features have small information gain or no features can be selected. The decision tree model was constructed based on the ID3 algorithm and used to classify the prospect and attitude of agricultural green total factor productivity in six cities in northern Anhui. To optimize the accuracy of the model, the model with the maximum depth is 3-20, and the training procedure is shown in Figure 2.

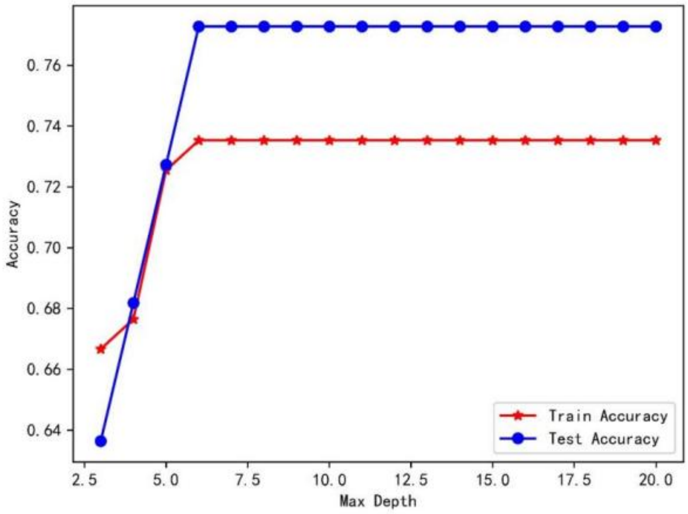

Figure 1. Accuracy of the different maximum depth of the decision tree

It can be observed from Figure 2 that the accuracy of the model also improves as the maximum depth of the decision tree increases. The accuracy of the test set peaks when the maximum depth reaches 6. However, when the maximum depth exceeds 6, the accuracy of the training set already stabilizes, but the accuracy of the test set begins to decrease. Therefore, we chose the decision tree model with a maximum depth of 6. By observing the confusion matrix of the prospect attitude, it is found that the number of samples is the most, the least number of samples is observed, and the accuracy of the classification model is relatively high, and the number of samples is very small, which shows that the decision tree model constructed in this paper has high classification accuracy.

The importance of each feature is understood from Figure 3. Through the information gain calculation of ID3 algorithm, this paper finds that the residence of X14 is the feature with the largest information gain, so it is selected as the node feature.

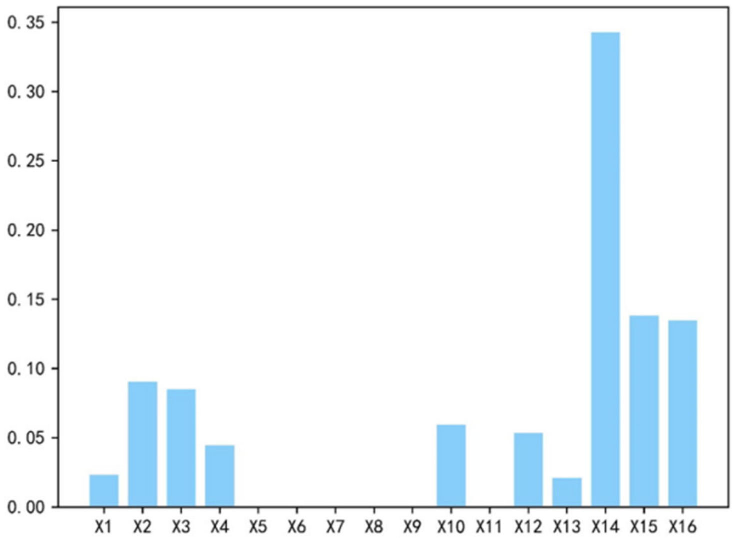

Figure 2. Importance of each indicator

Including: X1 for gender, X2 for age, X3 for education, X4 for monthly income level, X5 for students, X6 for business / service ordinary worker, X7 for enterprise managers, X8 for agricultural workers, X9 for the government, institution cadres / staff, X10 for ordinary workers, X11 for self-employed / contractor, X12 for freelance, X13 for retirement, X14 for residence, X15 for working fixed number of year, X16 for mechanical quantity.

As can be seen from Figure 2, five factors: residence (X14), working years in the agricultural field (X15), machinery quantity (X16), gender (X2) and education level (X3) play a major role in the respondents' attitude to the improvement of agricultural green total factor productivity in the six cities in northern Anhui. Among them, the prospect and attitude to the improvement of agricultural green total factor productivity in the six cities in northern Anhui is relatively high and related to its living area and education level, followed by its working years and number of machinery. This shows that the local residents of the six cities in northern Anhui and the residents with high working years in the agricultural field have a deeper understanding of agricultural mechanization, and the more optimistic about the prospect of agricultural green total factor productivity improvement in the six cities in northern Anhui.

5. Conclusions and Suggestions

5.1. Conclusions

The research shows that the external environment and science and technology have a significant positive impact on the cognition degree of agricultural green total factor productivity. According to the path coefficient analysis, the improvement of external environment can improve the cognition of agricultural green total factor productivity, so the government should strengthen guidance and improve residents 'understanding of agricultural green total factor productivity and related policies; science and technology have a significant positive impact on improving the cognition of agricultural green total factor productivity, so the government should actively introduce new production technology and improve infrastructure to further enhance residents' cognition of agricultural green total factor productivity.

The characteristics of residents themselves are an important factor affecting the prospect and attitude of agricultural green total factor productivity. The five factors of gender, residence, education level, working years and number of machinery play a major role in the residents' attitude towards the improvement of agricultural green total factor productivity in the six cities in northern Anhui. Among them, the prospect and attitude of agricultural green total factor productivity of the six cities in northern Anhui has a higher connection with its residence area and education level, which is followed by its working years and the number of machinery. It shows that the local residents of the six cities in northern Anhui and the residents with high working years in the agricultural field have a deeper understanding of agricultural mechanization, and the more optimistic the attitude towards the improvement of agricultural green total factor productivity in the six cities in northern Anhui.

5.2. Suggestions

(1) Policy support to accelerate the process of agricultural mechanization. In order to make agricultural mechanization play a key role in improving agricultural production efficiency, protecting the environment and promoting sustainable agricultural development, agricultural mechanization related policies combined with agricultural green development should be formulated, and agricultural mechanization should be taken as an important means to promote agricultural modernization and improve agricultural production efficiency. At the same time, we will strengthen the implementation of agricultural subsidies, encourage farmers and enterprises to adopt these technologies through policy subsidies and tax incentives, and introduce incentive policies for agricultural mechanization to reduce the economic burden that farmers may face in the process of mechanized operations. Finally, the government should formulate a long-term development plan for agricultural mechanization to ensure that agricultural mechanization develops in the right direction, which is of great significance for ensuring the sustainable agricultural development and national food security.

(2) Resource integration and optimize the efficiency of resource allocation. In order to further improve the efficiency of agricultural production, the primary task is to promote the large-scale land management and land transfer work, so as to help improve the utilization rate of land and the efficiency of agricultural machinery operation, and lay a good foundation for the subsequent resource sharing. Secondly, cross-regional and cross-industry cooperation should be encouraged, such as the establishment of agricultural machinery cooperatives or agricultural and enterprise cooperation associations, so as to achieve the efficient sharing of resources. By establishing agricultural machinery sharing platform, the use cost of agricultural machinery can be reduced and the utilization efficiency of resources can be further improved. At the same time, to optimize the efficiency of resource allocation, the agricultural sector should build agricultural informatization platform, with the platform of big data and cloud computing and other advanced technology, effectively promote the development of agricultural mechanization, make the allocation of resources more intelligent, ensure that agricultural machinery in the best time and place, improve the overall operation efficiency.

(3) Develop and transform, and vigorously popularize smart agriculture. In order to strengthen the infrastructure construction of smart agriculture, farmers or enterprises where conditions permit can use remote monitoring and information collection systems to help monitor farmland conditions in real time and collect crop growth data, so as to promote the development of smart agriculture. Secondly, the integration of artificial intelligence technology, Internet, Internet of Things and other information technologies into the process of agricultural mechanization can help us manage farmland more effectively and improve agricultural production efficiency. At the same time, the use of intelligent agricultural machinery and precision agricultural technologies, such as spraying with drones and intelligent irrigation systems, should also be promoted to improve the efficiency of agricultural production. In addition, in order to better help farmers use smart agricultural technology and improve their agricultural production efficiency, it is necessary to build an agricultural mechanization service system at the government level, provide farmers with agricultural machinery training and technical guidance for farmers, and improve their operational skills.

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