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EDITED BY
José M. Martínez-Paz,
University of Murcia, Spain

REVIEWED BY
Esther Folarin,
Covenant University, Nigeria
A. Amarender Reddy,
National Institute of Agricultural Extension Management (MANAGE), India

*CORRESPONDENCE
Fang Long,
17871928200@163.com

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How do agricultural socialization services drive green transition of farmers' grain production under "dual-carbon" targets: an analysis of moderating effects based on factor allocation

Jinzhi Wang and Fang Long*

College of Economics, Hunan Agricultural University, Changsha, Hunan, China

The green production transition represents a significant strategy for promoting organic agriculture and achieving the goal of sustainable development of grain systems. It is an important tool for resource utilization of agricultural waste and reduction of nitrogen and phosphorus emissions. Based on the survey data of grain farmers in Jiangsu Province in 2022, this paper empirically analyzes the impact and mechanism of Agricultural Socialization Services on the green transition of farmers' grain production based on the use of the finite mixture model (FMM) to measure the degree of green transition of farmers' grain production. The study shows that the participation of Agricultural Socialization Services is conducive to the green transition of farmers' grain production, and the more participation of socialization services, the deeper the degree of green transition of farmers' grain production. The mechanism test shows that socialization services promote the green transition of farmers' grain production mainly by regulating Plot Size and Labor Transfer. The extension analysis shows that compared with ordinary farmers, Agricultural Socialization Services play a more obvious role in promoting the Green Transition of Grain Production of new type of agricultural operating entit. This study addresses a theoretical gap in the field of green production under service outsourcing. Therefore, this study is of great significance for the promotion of green development in agriculture and the realisation of the goal of "carbon peak and neutrality".

KEYWORDS

agricultural socialization services, green production transition, resource allocation, organic agriculture, finite mixture models

1 Introduction

The phenomenon of global warming, which is caused by the emission of carbon into the atmosphere, has become a significant global concern, with the potential to pose a serious threat to human development. Agricultural production activities, particularly rice cultivation, represent the primary source of greenhouse gases (GHGs) in addition to industrial production and energy consumption. Recent studies highlight the potential of organic agriculture to mitigate environmental degradation while enhancing economic outcomes for farmers, as evidenced by a Pan-India survey (Reddy et al., 2022). China's long-standing approach to agricultural development, which relies on a significant input of chemical substances to increase food production, has resulted in the over-consumption of resources and the emergence of severe environmental contamination. These developments pose a significant challenge to the realization of the "dual-carbon" objective and the advancement of sustainable agricultural practices (Ren et al., 2022). It is therefore imperative that, while ensuring the stability of agricultural production, effective guidance and incentives are provided to farmers to facilitate a green transition in production, in order to achieve the development of organic agriculture (Wang R. R. et al., 2022).

The transition to green practices in grain production underscores the necessity of moving beyond the conventional approach of "high input, high output, high pollution." This entails a shift from the current operational framework to one that aligns with the principles of green development, leverages advanced production technology, and optimizes the use of resources, while simultaneously enhancing the ecological environment and ensuring the production of high-quality food (Zhang, 2020). As the smallest decision-making unit, the level of green cognition and the production behavior decisions of farmers significantly impact the effectiveness of the green transition in grain production. These decisions are closely linked to farmers' attitudes, perceived benefits, and their readiness for change (Soga et al., 2017). Among these factors, perceived benefits are the primary drivers of farmers' willingness to transform, while their attitudes toward the transition and perceived readiness directly influence their behavior (Sereenonchai and Arunrat, 2023). However, the fundamental national situation of "big country, small farmers" has determined that for an extended period, the ordinary farmer will remain the foundation of grain production in China. Their capital endowment and cognitive level are insufficient to cope with the complex, long-term, and systematic work of green production transition (Boix-Fayos and de Vente, 2023). The majority of Chinese grain farmers continue to adhere to a traditional, rudimentary production model, exhibiting minimal integration of environmentally conscious production elements such as organic fertilizers and bio-pesticides. Additionally, there is a notable absence of resource-intensive production technologies, including water-saving irrigation, soil testing and formula fertilization. Furthermore, the utilization of straw, agricultural film and other waste resources remains insufficient, contributing to a gradual and sluggish pace of green transition in the mode of production.

So, is there a path or model that can promote the green transition of production by farmers who have the will to transform, as well as drive the green transition of the production of farmers who do not have the will to transform through the invisible introduction of green production factors? According to some academics, Agricultural Socialization Services will play a significant role in encouraging farmers to change their way of production to one that is more environmentally friendly (Chen K. et al., 2023). The provision of Agricultural Socialization Services represents a novel organizational approach that can address the scarcity of land flow transition scale operations and facilitate the effective allocation of agricultural production factors. Furthermore, it can facilitate the promotion of organic inputs and advanced production technologies among farmers, enabling them to overcome the traditional constraints of rough management and reduce nitrogen and phosphorus emissions. This is regarded as a crucial strategy for advancing the transition to green production among grain farmers.

Previous studies on Agricultural Socialization Services and the green transition of agriculture primarily concentrate on three areas. The first is theoretical in nature, as demonstrated by Cheng et al. (2022) in the context of "big country, small farmers." It delves deeply into the relationship between socialization services and high-quality agricultural development, highlighting the beneficial effects of socialization services on the modification of the primary agricultural business of grain production and the advancement of grain production techniques. involvement, boosting grain production scale, and enhancing grain production mode all have favorable implications (Zhao et al., 2023). The second is to characterize the level of transition through green total factor productivity and study the relationship between Agricultural Socialization Services and green transition. Most studies believe that socialization services play an important role in promoting agricultural green total factor productivity, and together with the deepening of the degree of participation in socialization services, it will improve agricultural green total factor productivity through the double-wheel drive of agricultural technology efficiency and green agricultural technology change, and realize the transition of farmers' production behavior (Lu et al., 2023; Shi et al., 2024; Wang X. X. et al., 2022). Third, focusing on one or more production behaviors, we analyze the relationship between Agricultural Socialization Services and green transition (Yang et al., 2022). It has been widely recognized that Agricultural Socialization Services have a positive impact on farmers' fertilizer reduction (Ren, 2023; Shi et al., 2023; Yang et al., 2022), adoption of organic fertilizer and soil testing and formulation fertilization technology (Lin et al., 2022; Ren, 2023), pesticide reduction (Li L. et al., 2023; Li and Zhu, 2023), pest and disease specialization Unified Pest Control behavior had significant positive effects (Wang et al., 2023). In addition, (Li et al., 2022), used a finite mixture model, which assumes that a population is composed of several subgroups (or latent classes) with distinct characteristics. By incorporating various behaviors into a unified framework, this model identifies heterogeneous patterns within the data. The study found that fertilizer application and plant protection services significantly promote the green production transition of wheat farmers.

The extant literature on the green production transition in grain farming remains largely theoretical, with limited empirical studies focusing on specific practices, such as the use of organic fertilizers and reduced chemical inputs. Recent studies have highlighted the importance of policy design and implementation in promoting sustainable agricultural practices (Reddy, 2018). There is growing evidence that using organic fertilizers and reducing chemical inputs offer significant environmental and societal benefits. Organic fertilizers improve soil health, enhance soil structure, increase microbial activity, and boost water retention. Organic fertilizers, unlike synthetic ones, also reduce greenhouse gas emissions and air pollution (Muscolo et al., 2020). Reducing chemical inputs promotes sustainable farming, enhancing long-term environmental quality and food security. It also benefits local communities by improving air and water quality (Arunrat et al., 2022). However, the green production transition is a systematic and continuous process, and the adoption of integrated nitrogen and phosphorus reduction technologies and the utilization of agricultural waste resources are also essential components. Given this, this paper uses the survey data of 545 grain farmers in Jiangsu Province, and empirically analyzes the comprehensive effects of socialization agricultural services on the green transition of farmers' grain production, based on the measurement of the degree of green transition of farmers' grain production by using the finite mixture model (FMM); at the same time, it examines the regulating effect of the allocation of factors such as land, technology and labor, etc. Finally, it compares the differences in the transforming effects of socialization services among different production segments and types of farmers, with the aim of providing clues for improving the construction of the agricultural socialization service system and promoting the sustainable advancement of the grain system.

2 Theoretical models and research hypotheses

2.1 Impact of agricultural socialization services on the green transition of farmers' grain production

The transition from traditional methods to green methods in farmers' grain production is referred to as the Green Transition. This process involves upholding the concept of green production, applying green production technology, and achieving resource conservation, environmental protection, and high-quality grain production. The key to this transition lies in the green knowledge and capacity of farmers. Agricultural Socialization Services represent a new organizational form that can scientifically and effectively guide farmers in overcoming the constraints of traditional rough management and transitioning towards green production methods. This is considered an important way to promote the green transition of farmers' production methods (Qing et al., 2023).

We have outlined three key areas where Agricultural Socialization Services have impacts on farmers' green transition of grain production. The aspect of resource allocation comes first. The scale operation of services provided by Agricultural Socialization Services can effectively compensate for the inadequacies of the land flow transition scale operation in the context of the decentralized grain production pattern. In addition to lowering the cost of grain production and improving the efficiency of the allocation of labor, land, machinery, and other inputs, the development of Agricultural Socialization Services can also encourage farmers to manage their arable land in a unified manner, operate their machinery, buy agricultural supplies, and follow other standardized procedures to achieve the Green Transition of Grain Production (Ji et al., 2023; Liu and Li, 2023). The advancement of technology comes in second. The core information collection capabilities of the agricultural socialization service for grain production and management are stronger, and it can directly introduce increased efficiency, reduced pollution, and a greater alignment with market expectations for emerging production technology (Zhang Y. J. et al., 2023). Additionally, it can provide farmers with technical services to help them accept new information and adopt new technologies, thereby realizing the Green Transition of Grain Production (Zhang Y. N. et al., 2023). Factor inputs come in third. Agricultural Socialization Services can not only release surplus agricultural labor through mechanical substitution labor, increase the income of non-farm employment of farmers; can also improve the quality of grain, expand sales channels, realize the increase in the income of grain farmers, play the "crowding out effect" to increase the use of green inputs by farmers, and guide the green transition of farmers' production (Li and Guan, 2023; Mi et al., 2020). Therefore, the first hypothesis presented in this paper is as follows.

H1. Agricultural Socialization Services can promote the farmers' green transition of grain production, and the deeper the participation in socialization services, the more effective the green transition of production will be.

2.2 Impact of agricultural socialization services on the farmers' green transition of grain production from the perspective of production factor allocation

2.2.1 Agricultural socialization services, plot size, and green transition of grain production

Limited and scarce arable land resources are the foundation of grain production. The Green Transition of Grain Production is closely linked to the large-scale operation of agricultural land and its role in resource allocation. Farmers of varying scales of operation differ in capital endowment, cognitive level, and business objectives, which affect their green transition behavior (Li Q. et al., 2023). On the one hand, most of China's smallholder farmers engage in part-time work and lack adequate field management in grain production. This makes it easier for them to compensate for the risk of yield reductions caused by insufficient labor inputs by increasing the use of chemical inputs. The challenges of aging, feminization, and marginalization of production are especially severe for smallholder farmers involved in grain production. The adoption of green inputs and emerging production technologies has been hindered by weakened human capital and technological cognitive barriers, impeding the transition to more sustainable grain production methods (Li and Li, 2023). On the other hand, small farmers may have little incentive to choose environmentally friendly inputs and production technologies due to the low proportion of grain business income in their total household income (Chen and Liu, 2023). However, large-scale households tend to prioritize the cultivation of land power and the goal of long-term yield increase, leading them to choose green production methods. As the scale of operation expands, farmers must pay more for production factor inputs. To control production costs, large-scale households are less likely to over-apply chemical inputs. Therefore, large-scale operations promote the Green Transition of Grain Production.

The impact of Agricultural Socialization Services on the green transition of farmers' grain production may be limited by the scale of cultivated land (Chen et al., 2022). First of all, fragmented land and diversified crop cultivation will impede mechanical operations and make it more difficult to replace labor with machinery when agricultural socialization service organizations provide production services to farmers (Zhang Y. F. et al., 2023). In contrast, relatively concentrated, continuous, and leveled arable land in large areas facilitates the application of agricultural machinery and improves the use of modern production technology and the management level of agricultural socialization service organizations, which is conducive to the transition of grain production into a green industry (Cheng et al., 2023). Secondly, the size of the plot affects farmers' behavior when purchasing socialization services. While machinery can substitute for labor in technology-intensive processes, such as land preparation and harvesting, it has limited substitution in labor-intensive processes. Therefore, labor is still necessary to support operations. Large-scale households face greater labor constraints than small farmers and are more likely to supplement or replace labor by purchasing professional socialization services. This makes it easier to achieve rational use of Chemical Inputs and Green Transition of Grain Production (Tian et al., 2023). Lastly, from the standpoint of the service providers, the size of farming operations and the size of service demand influence the degree of socialization service delivery. Due to the significant fixed costs involved, service providers can only be drawn to provide pertinent services and support the Green Transition of Grain Production when both the commissioned service area and service demand reach a certain scale. In light of this, the second hypothesis put out in this paper is.

H2. The relationship between Agricultural Socialization Services and the green transition of farmers' grain production is moderated by Plot Size. The larger the Plot Size, the greater the role of socialization services in promoting the green transition of production.

2.2.2 Agricultural socialization services, agricultural technology training, and green transition of grain production

The population's level of demand and the structure of grain consumption are continually changing in this new stage of development, which raises the bar for grain production and calls for the development of superior varieties, improved quality, and strong brand identities. Thus, to successfully transition from conventional to green production methods, grain production at this stage requires not only reducing and increasing the efficiency of chemical inputs such as fertilizers and pesticides, and updating green production technologies such as deep plowing and water-saving irrigation, but also integrating advanced concepts and management practices such as soil testing, formula fertilization, physical/biological prevention and control, and resourceful use of waste into the production process (Gao et al., 2023; Ma et al., 2024). Research has demonstrated that inadequate access to agricultural information and technical support are the primary obstacles to achieving green agriculture. Providing Agricultural Technology Training can help correct farmers' cognitive biases, increase their awareness of the benefits of modern agricultural production technology, and facilitate the transition to sustainable and environmentally friendly production practices (Guo and Zhang, 2023). In addition, providing Agricultural Technology Training can enhance farmers' environmental literacy and equip them with the necessary knowledge and skills to address and prevent environmental issues. This can facilitate a shift towards green agricultural production in the long run (Malimi, 2023).

Agricultural socialization service organizations can help farmers overcome information blockages and improve their human capital by providing up-to-date market transaction information, consumer demand preferences, and advanced Agricultural Technology Training. This can help alleviate the imbalance in resource allocation and the uncertainty of technology adoption caused by information asymmetry. Therefore, organizations that provide Agricultural Socialization Services can promote the transition to green production for farmers by utilizing their advantages in specialization and cost-effectiveness (Wang Y. et al., 2022). Additionally, these organizations can indirectly facilitate the transition by providing farmers with valuable market information and professional technical training. A higher level of knowledge about green grain production and a better understanding of the benefits of technology-intensive production link socialization services are possessed by farmers who have received Agricultural Technology Training. This helps to alleviate information asymmetry caused by the speculative behavior of service providers, which in turn reduces the use of chemical inputs by farmers and agricultural socialization service organizations, ultimately leading to a more environmentally friendly grain production process. Accordingly, this paper proposes a third hypothesis.

H3. There is a moderating effect of Agricultural Technology Training between Agricultural Socialization Services and farmers' green transition of grain production. The more farmers receive relevant training, the greater the promotion effect of socialization services on the green transition of production.

2.2.3 Agricultural socialization services, labor transfer, and green transition of grain production

The degree of human capital possessed by grain farmers ultimately determines the Green Transition of Grain Production systems. The Green Transition of Grain Production is severely hampered by the fact that, as a result of the growing disparity between the returns from grain production and other economic activities, farmers have shifted to non-grain and non-agricultural businesses, and their human capital has steadily declined (Yu et al., 2023). On the one hand, the part-time work of grain farmers leads to a shortage of effective supply of labor and other production factors in the process of grain production, and according to the traditional "factor substitution theory", farmers tend to increase the use of chemical inputs to compensate for the shortage of labor factors caused by the loss of grain production. On the other hand, in light of Labor Transfer, the farmers who are left behind operate on a small scale and part-time basis to meet their families' basic grain needs. They are unable to create the economies of scale necessary to offset the high cost of switching to green production methods, and they lack the necessary mechanical operating conditions, which limits the adoption of green technology elements (Lu and Xie, 2018).

The reduction of the labor force and the increase in household income brought about by part-time farming affect farmers' socialization service purchasing behavior through the substitution effect and the income effect, respectively (Qing et al., 2023). On the one hand, the theory of induced technological change holds that rational farmers will choose to replace more expensive and scarce labor factors with capital factors like agricultural machinery and socialization services as rural surplus labor becomes scarcer and more expensive, making up for the labor constraints brought on by part-time farming (Wen et al., 2023). On the other hand, non-farm employment can provide higher income and complement the substitution of 'machinery labor' through Agricultural Socialization Services, thereby alleviating the capital constraint of agricultural production. Therefore, as part-time farming becomes more prevalent, there will be a greater need for socialization services in the grain production industry. When multi-link socialization services are implemented, the advanced production concepts and green production technologies of agricultural socialization service organizations will be maximized and brought into the industry, supporting the green transition of the grain industry. Accordingly, this paper proposes the fourth hypothesis.

H4. The relationship between Agricultural Socialization Services and the green transition in farmers' grain production is moderated by Labor Transfer. The greater the degree of Labor Transfer, the greater the contribution of socialization services to the green transition in production.

In summary, the analytical framework for agricultural socialization services to promote the green transition in farmers' food production is shown in Figure 1.

3 Data, variables, and methods

3.1 Data sources

This paper uses data from the 2022 China Land Economic Survey (CLES) conducted by Nanjing Agricultural University, which gathers household, crop production, and social service purchase data, with new questions on green production technologies like deep plowing and integrated pest management. Although the survey focuses on Jiangsu Province, a key grain-producing area, its findings provide valuable insights into broader agricultural trends in China, though regional variations in climate, agricultural practices, and policies may limit generalizability. The CLES employed a probability proportionate to size (PPS) sampling method across 24 villages in 12 counties and 6 cities, resulting in 1,203 responses. After excluding incomplete questionnaires, 545 valid responses were retained. While the PPS method ensures better representation of larger villages, biases may arise from underrepresentation of remote or economically underdeveloped areas.

The survey relies on self-reported data, which may introduce biases such as social desirability and recall bias, particularly regarding sensitive issues like income and land use. Although measures to ensure anonymity and confidentiality were implemented to reduce these biases, they cannot be entirely eliminated. Given the provincial focus, caution is needed when generalizing the results to the national level. Future research could broaden the geographic scope or employ alternative data collection methods, such as longitudinal studies or objective measures, to improve the robustness of the findings.

3.2 Variables

3.2.1 Variable settings for FMM

Considering the relatively slow adjustment of farmers' inputs to grain production factors in the short term and the fact that the focus of this paper's analysis is on the impact of Agricultural Socialization Services on the Green Transition of Grain Production rather than on the formal aspects of specific production technologies, the classical C-D production function with its concise form and clear economic implications is used. This paper presents a latent category stochastic frontier model based on the basic form of the C-D production function to describe the input-output relationship in the grain production chain of farmers. The specific form of the model is:

$$Y_i = AK_i^{\alpha} L_i^{\beta} e^{\mu} \tag{1}$$

In Equation 1, Y_i represents the annual income per acre of grain for the farmer i; K_i represents the capital input per acre of grain for the farmer i; L_i represents the labor input per acre of grain for the farmer i; A represents the level of integrated technology; and represents the random error term. Equation 2 is transformed into a logarithmic form to obtain:

$$\ln Y_i = \ln A + \alpha \ln K_i + \beta \ln L_i + \mu \tag{2}$$

Based on the research results of Li et al. (2022) and the requirements outlined in the Key Points of Planting Industry in 2023 issued by the Ministry of Agriculture and Rural Development, we selected covariates for the FMM from three aspects: input reduction and efficiency, adoption of green technology, and utilization of waste resources. The seven indicators are Fertilizer Intensity, Organic Fertilizer Rate, Pesticide Intensity, Physical or Biological Control Inputs, the adoption rate of resource-intensive technologies (such as deep plowing and deep-polishing, and water-saving irrigation), the adoption rate of environmentally friendly technologies (such as biopesticides and soil-formula fertilization technologies), and utilization rate of waste resources (such as agricultural film recycled, pesticide packaging recycled, and straw returned to the field adopted). The above indicators are only a few performance characteristics of farmers' green production methods and do not fully represent green production methods. However, by using the relationship between these closely related covariates and outputs, the probability of a farmer's grain production method falling into a green production method can be calculated indirectly. This allows for obtaining proxy variables for the green production transition. Table 1 displays the definitions of the pertinent variables.

3.2.2 Core explanatory variables

The purpose of this paper is to study the impact of Agricultural Socialization Services on the green transformation of farmers' grain production, and to choose "whether to purchase Agricultural Socialization Services in the grain production process" as a measurement indicator to reflect the purchase of Agricultural Socialization Services by farmers. In addition, in the robustness test, the paper uses "the number of purchased socialized service links" and "the cost of adopting socialized services" as core explanatory variables.

TABLE 1 Setting of variables related to FMM.

Variables type	Variables	Descriptions
Grain input-output variables	Grain Output	Average annual income from grain acres (yuan)
	Capital Input	Total capital inputs per acre (yuan)
	Labor Input	Grain acre average labor input (yuan)
Covariates for FMM	Fertilizer Intensity	1 - Total fertilizer use per unit area for grain/Maximum total fertilizer use per unit area in all samples (%)
	Organic Fertilizer Rate	Organic fertilizer application cost per unit grain area/Total fertilizer application cost (%)
	Pesticide Intensity	1 - Pesticide cost per unit area of grain/Maximum pesticide cost per unit area in full sample (%)
	Physical or Biological Control Inputs	Pest and disease control inputs per acre of grain (yuan)
	Rate of adoption of resource-intensive technologies	Percentage adoption of deep tillage and water-saving irrigation technologies (%)
	Rate of adoption of environmentally friendly technologies	Proportion of adoption of biopesticides and soil-formula fertilization technologies (%)
	Rate of utilization of waste resources	Percentage of agricultural film recycled, pesticide packaging recycled, and straw returned to the field adopted (%)

3.2.3 Moderating variables

This paper selects three variables as moderating variables based on the previous theoretical analysis: Plot Size, Agricultural Technology Training, and Labor Transfer. Among them, Plot Size is obtained by dividing the total scale of grain operation of farmers by the number of plots; Agricultural Technology Training is selected as a proxy variable for whether farmers have received training in environmentally friendly related technologies; Labor Transfer is selected as a proxy variable for whether the labor force is engaged in non-agricultural employment as a proxy variable for the mechanism test.

3.2.4 Control variables

Based on the research conducted by Zhang et al. and the current state of grain production, 16 control variables were selected. These variables include characteristics of the household head, household, grain production and operation, and farmers' cognition (Ai et al., 2023). Household head characteristics include gender, age, education level, health status, and Risk Preference. Household characteristics include whether there are cadres, the size of the agricultural labor force, planting specialization, and employment status. Production and operation characteristics include whether agricultural insurance is purchased, the size of the operation, the fertility of the land, irrigation conditions, and subsidies for the planting industry. Farmers' policy awareness mainly refers to their understanding of policies. See Table 2 for specific variables.

3.3 Methods

China's grain production is undergoing a transition from traditional to green methods. While some farmers have already adopted advanced production concepts and technologies, others are still in the process of transitioning. However, a significant proportion of farmers continue to rely on traditional and crude production methods. Previous studies generally agree that farmers' choice of grain production methods is influenced by factors such as resource endowment, external environment, and others. However, it is challenging to measure specific data related to grain production methods, which makes it difficult to scientifically depict the relationship between the various influencing factors and grain production methods. In recent years, the Finite Mixture Model (FMM) has been increasingly applied in economics. This model is capable of modeling unobserved heterogeneity in samples, making it particularly useful for addressing the challenges in representing grain production methods that are difficult to quantify with traditional data. This paper employs the FMM to create an indicator for assessing the likelihood that farmers will choose green production methods. This indicator is then incorporated as an explanatory variable into the econometric model to explore the relationship between *ASS* and the green transformation of farmers' grain production. The aim is to provide empirical insights for both theoretical research and practical decision-making among farmers.

3.3.1 FMM: a means to assess farmers' grain production approaches

The FMM is a powerful tool in econometric modeling, particularly when addressing unobserved heterogeneity. This method enables the segmentation of a population into latent subgroups, each of which may exhibit distinct behaviors or characteristics. FMM is highly adaptable to various types of data and distribution patterns, making it well-suited to capture the heterogeneous growth paths of farmers in the context of grain production. By identifying unobservable heterogeneity in the sample, the model divides the data into several subgroups, assigning each observation to the appropriate subgroup. This capability allows FMM to overcome the limitations of traditional models, which often fail to account for such heterogeneity.

In the context of our study, FMM is particularly advantageous as it helps reveal underlying patterns in farmers' adoption of green production methods. These patterns are not directly observable in the data and are influenced by a range of factors, including resource

TABLE 2 Descriptive statistical summary of the variables.

Variables	Descriptions	Mean	S.D.	Min	Max
Dependent Variables					
Green Transition of Grain Production (*GTGP*)	A posteriori probability of green transition in farmers' grain production calculated by an FMM	0.781	0.316	0	1
Independent Variables					
Agricultural Socialization Services (*ASS*)	Purchase of Agricultural Socialization Services: Yes = 1; No = 0	0.497	0.500	0	1
Moderating Variables					
Plot Size (*PS*)	Divide the total grain operation area of farmers by the number of plots (mu)	3.142	9.576	0.05	147.3
Agricultural Technology Training (*ATT*)	Trained in agricultural technology: Yes = 1; No = 0	0.552	0.498	0	1
Labor Transfer (*LT*)	Percentage of household labor force working outside the home (%)	0.363	0.481	0	1
Controlled Variables					
Gender (*GEN*)	Male = 1; Female = 0	0.840	0.367	0	1
Age (*AGE*)	Actual age (years)	62.29	10.13	30	83
Education (*EDU*)	Years in Education	7.415	3.670	0	17
Health (*HEA*)	Self-assessed health status: Poor health = 1; Great health = 5	4.018	0.994	1	5
Cadre (*CD*)	Cadre = 1, non-cadre = 0	0.191	0.393	0	1
Risk Preference (*RP*)	Risk appetite = 1; risk neutrality = 2; and risk aversion = 3	2.689	0.593	1	3
Agricultural Labor Force Scale (*ALFS*)	Number of agricultural labors in the family (persons)	1.899	0.794	0	5
Crop Specialization (CSL)	Share of household income from grain crops (%)	0.464	0.405	6.01	1
Hired Labor (*HL*)	Yes = 1; No = 0	0.209	0.407	0	1
Crop Insurance (*CI*)	Purchase of plantation insurance: Yes = 1; No = 0	0.431	0.496	0	1
Business Scale (*BS*)	Grain operation size (mu)	34.97	107.0	0.15	1,100
Soil Fertility (*SF*)	Poor = 1; Medium = 2; Good = 3	2.301	0.613	1	3
Irrigation Conditions (*IC*)	Convenient Irrigation: Yes = 1; No = 0	0.811	0.392	0	1
Crop Subsidy (*CS*)	Government planting subsidy (yuan)	3,580	15,526	0	28,560
Policy Awareness (*PA*)	Efforts to promote green production technology: Completely ineffective = 1; Very effective = 5	0.470	1.205	0	6

Note: Risk Preference and soil fertility are transformed into dummy variables for regression in the actual regression.

endowments, external policies, and individual farmer preferences. By applying FMM, we can estimate the probability of farmers transitioning to green production methods based on their unique characteristics and circumstances. This segmentation not only enhances our understanding of farmers' decision-making processes but also enables more precise policy recommendations aimed at promoting sustainable agricultural practices.

In our analysis, we follow the method of Li and Li (2023), who categorize potential sample categories based on the distribution of data. Specifically, we divide the entire sample distribution into multiple sub-probability density functions, allowing for a more nuanced understanding of the factors influencing farmers' choices. This approach is particularly useful in capturing the diversity of factors driving the transition to green grain production.

$$f(\mathrm{Y}|\mathrm{X},\theta) = \sum_{k=1}^{K} \pi_k f(Y|XY,\theta_k) = \pi_1 f_1(X) + \pi_2 f_2(X) + \cdots + \pi_k f_k(X) \tag{3}$$

In Equation 3, $f(\mathrm{Y}|\mathrm{X},\theta_k)$ represents the conditional probability density distribution of sample y when it belongs to potential category k. X is a vector of explanatory variables, and is the parameter to be estimated. π_k denotes the proportion of mixing, and is also referred to as the weight corresponding to each sub-density, and $\sum \pi_k = 1$.

Amidst mounting resource constraints and environmental pollution, Chinese farmers are embracing a green transition. This paper introduces indicators that characterize the green production method as covariates into the FMM to reflect the probability distribution of the input-output relationship in the grain production process. The distribution function of the entire sample can be characterized by the following equation, assuming that the sample farmers can be divided into two potential categories: traditional production and green production:

$$f(Y|X,\theta) = \pi_I f_I(Y|X,\theta_I) + \pi_E f_E(Y|X,\theta_E) \quad (4)$$

The Equation 4 is used to calculate the posterior probability of each sample farmer belonging to the jth category.

$$P(j|X,Y) = \frac{\pi_j f_j(Y|X,\theta_j)}{\pi_I f_I(Y|X,\theta_I) + \pi_E f_E(Y|X,\theta_E)} \quad (5)$$

In the Equation 5, $j = (I,E)$, P_I and P_E represent the *a posteriori* probabilities of sample farmers falling into potential categories. This paper divides grain production methods into two categories: traditional production and green production. Therefore, if the *a posteriori* probability of a sample farmer belonging to the category of green production methods is P, then the *a posteriori* probability of belonging to the category of traditional production methods is 1-P. In fact, since the transition to green production of grain is not a clear-cut technology but a long-term and systematic process, the *a posteriori* probability of a sample farmer falling into the category of green production methods reflects, to some extent the degree of green transition of farmers' grain production.

3.3.2 Basic regression model

To investigate the influence of ASS on the adoption of sustainable practices in farmers' grain production, this paper presents the benchmark model:

$$\ln GTGP_i = \alpha_0 + \theta_1 ASS_i + \theta_2 PS_i + \theta_3 LT_i + \theta_4 ATT_i + \sum_{k=1} \theta_{5k} C_i + \varepsilon_i \quad (6)$$

In Equation 6, $\ln GTGP_i$ is the degree of green transition of farmer's grain production, the size of the *a posteriori* probability that a sample farmer uses a green production method reflects the farmer's degree of $GTGP$; the larger the probability value, the stronger the farmer's degree of $GTGP$; the smaller the probability value, the weaker the farmer's degree of $GTGP$. ASS_i is Agricultural Socialization Services, expressed as whether or not ASS are purchased; PS_i is Plot Size, expressed as the total size of the grain operation divided by the number of arable plots; ATT_i is farm technology training, expressed as the number of times a farm household receives farm technology advice and training in 2021; and LT_i is Labor Transfer, expressed as the number of laborers working outside the household divided by the total number of laborers in the household (Yang and Li, 2023). C_i denotes control variables, including individual characteristics such as gender, age, health, education, and Risk Preference of the ith farm household. Also included are household characteristics such as whether it has a cadre, the size of the agricultural labor force, planting specialization, and whether it employs laborers. Production and operation characteristics such as the size of the operation, whether it has purchased agricultural insurance, soil fertility, irrigation conditions, and subsidies for the planting industry, as well as policy perceptions are also considered. α_0 is the constant term, θ_1, θ_2, θ_3, θ_4 and θ_{5k} is the coefficient that needs to be estimated; and ε_i is the random perturbation term.

3.3.3 Moderated effects model

To analyze how the agricultural socialization service affects farmers' decisions to transition to green production, we construct a model of moderating effects as follows:

$$\ln GTGP_i = \alpha_0 + \theta_1 ASS_i + \theta_2 PS_i + \theta_3 ASS_i \times PS_i + \sum_{k=1} \theta_{4k} C_i + \varepsilon_i \quad (7)$$

$$\ln GTGP_i = \alpha_0 + \theta_1 ASS_i + \theta_2 ATT_i + \theta_3 ASS_i \times ATT_i + \sum_{k=1} \theta_{4k} C_i + \varepsilon_i \quad (8)$$

$$\ln GTGP_i = \alpha_0 + \theta_1 ASS_i + \theta_2 LT_i + \theta_3 ASS_i \times LT_i + \sum_{k=1} \theta_{4k} C_i + \varepsilon_i \quad (9)$$

In Equation 7, $ASS_i \times PS_i$ represents the interaction term between ASS and PS. In Equation 8, $ASS_i \times ATT_i$ represents the interaction term between ASS and ATT. In Equation 9, $ASS_i \times LT_i$ represents the interaction term between ASS and LT. C_i denotes control variables, including individual characteristics such as gender, age, health, education, and Risk Preference of the ith farm household. Also included are household characteristics such as whether it has a cadre, the size of the agricultural labor force, planting specialization, and whether it employs laborers. Production and operation characteristics such as the size of the operation, whether it has purchased agricultural insurance, soil fertility, irrigation conditions, and subsidies for the planting industry, as well as policy perceptions are also considered. α_0 is the constant term, θ_1, θ_2, θ_3 and θ_{4k} is the coefficient that needs to be estimated; and ε_i is the random perturbation term.

4 Results and discussion

4.1 Results of FMM

4.1.1 Calculation of the posterior probability that sample farmers belong to a potential category

4.1.1.1 Determination of the number of farmers' grain production methods

To determine the number of potential categories in the sample, the Bayesian Information Criterion (BIC) index is used, i.e., the number of categories corresponding to the smallest value of the BIC is selected, and the results of model fitting are shown in Table 3. When the number of categories is 2, the value of the BIC is 1,453.524, which is lower than the number of categories of 1 and the number of categories of 3. Therefore, we believe that it is statistically optimal to divide the sample into two major categories, and in this paper, we classify farmers' grain production methods into two categories: traditional production methods and green production methods.

4.1.1.2 This section presents a probability analysis of a sample that may belong to a potential category

The design of the FMM determines the posterior probability that a sample falls into a potential category, which then determines the category to which the sample belongs. China's grain production is shifting from traditional to green methods. The results of the BIC

TABLE 3 Results of potential category tests for grain production practices among sample farmers.

Number of categories	Log-likelihood	Number of parameters	AIC	BIC
1	−888.3093	4	1784.619	1801.822
2	−676.3555	16	1384.711	1453.524
3	−656.9064	27	1367.813	1483.934

TABLE 4 Posterior probability statistic of a sample falling into category A.

Number of categories	Observations	Probability means	Probability standard deviation	Min	Max
P > 0.5	127	0.886	0.155	0.509	1.000
P ≤ 0.5	418	0.087	0.098	0.000	0.498

suggest dividing the samples of the study into two potential categories. If the posterior probability that a sample belongs to category A is P, then the posterior probability that it belongs to category B is 1-P. Thus, the probability analysis of a sample belonging to category A, based on its own probability, is equivalent to that based on category B. The result of the probability analysis remains unchanged. This paper presents the organization of the probability of samples falling into category A, as shown in Table 4. Out of 545 samples, 127 had a posterior probability of P > 0.5, with an average probability of 0.886. The remaining 418 samples had an *a posteriori* probability of P ≤ 0.5, with a mean probability of 0.087. Note that the majority of the samples fell into this group.

4.1.2 Characterizing farmer cultivation by potential category

The paper utilized the sample mean t-test to determine the significance of differences between categories for the seven main indicators of green production methods (see Table 5). The results indicate that, except for the physical/biological control inputs indicator, which did not show significant differences between the two sample categories, the other six indicators showed significant differences, with one group having significantly higher values than the other. Based on the difference in mean values of the indicators that characterize green production methods in the two categories, it can be concluded that the higher the *a posteriori* probability of the sample farmers falling into category A, the more apparent their green production characteristics are. Therefore, this paper concludes that the posterior probability of a sample farmer falling into category A, as measured by the FMM, is highly correlated with the farmer's grain production method. A smaller posterior probability indicates that the farmer is still engaged in traditional production, while a larger posterior probability indicates that the farmer's degree of green production is higher. The posterior probability of falling into the green production method, P, is used as a measure of green production transition in the later analysis.

Group A: Farmers with a higher posterior probability of adopting green production methods, indicating a more pronounced transition towards green production practices.

Group B: Farmers with a lower posterior probability, indicating a continued reliance on traditional production methods with less green production characteristics.

4.2 The impact of agricultural socialization services on green transition of farmers' grain production

4.2.1 Benchmark regression results

Table 6 presents the estimation results of the model without the interaction term. Model 1 shows the results without the introduction of moderating variables, while Models 2-4 show the results with the introduction of *PS*, *ATT*, and LT, respectively. The results of Model 1 regression indicate that the coefficient for socialization services in the green transition of farmers' grain production is 0.364, which is significant at the 1% level (p < 0.01), prior to controlling for *PS*, *ATT*, and LT factors. Therefore, the results suggest that the participation of *ASS* contributes to promoting the green transition of farmers' grain production. This supports hypothesis 1. However, while the study demonstrates a strong correlation, it is important to note that correlation does not imply causation. To explore potential causal mechanisms, we propose several pathways: First, the development of socialization services enhances the specialization of service providers, reducing farmers' learning costs, alleviating human capital constraints, and promoting the adoption of green technologies. Second, socialization services improve resource allocation efficiency, potentially releasing surplus rural labor and encouraging farm households to increase non-farm income, which in turn facilitates investment in green inputs. Third, service providers have greater bargaining power in the production factor market, and their machinery operation services can improve input efficiency, reduce costs, and support the green transition by leveraging cost-saving advantages. While these mechanisms offer potential explanations for the causal effect, further research, such as longitudinal studies or experimental designs, is needed to establish stronger evidence of causality.

After introducing *PS* in Model 2, both *ASS* and *PS* have a significant positive effect on the green transition of farmers' grain production. Specifically, the coefficient for *ASS* is 1.695, which is significant at the 5% level, and the coefficient for *PS* is 1.038, significant at the more stringent 1% level. The results indicate that increasing plot size encourages farmers to transition to more sustainable production methods. There are differences in the business objectives of farmers of different sizes (Zhou et al., 2023). Grain-scale households prioritize controlling total production costs and achieving long-term production goals. This

TABLE 5 Comparison of input indicators for potential farmer categories.

Indicator name	Group A		Group B		A.D.	T-test for sample mean
	Sample	Mean	Sample	Mean		
Fertilizer Intensity	127	0.921	418	0.893	0.028*	1.829
Organic Fertilizer Rate	127	0.606	418	0.102	0.504***	3.136
Pesticide Intensity	127	0.923	418	0.896	0.027*	1.936
Pest Control Inputs	127	100.075	418	80.532	19.542	0.388
Rate of adoption of resource-intensive technologies	127	0.188	418	0.063	0.125***	5.197
Rate of adoption of environmentally friendly technologies	127	0.349	418	0.217	0.133***	4.933
Rate of utilization of waste resources	127	0.289	418	0.157	0.131***	4.937

Note: ***p < 0.01, **p < 0.05, *p < 0.1; standard errors in parentheses.

leads to a lower possibility of excessive application of chemical inputs and a greater inclination towards choosing green production methods. On the other hand, the centralized operation of large areas of contiguous and leveled arable land facilitates the application of agricultural machinery, promoting the rational use of green inputs and the application of emerging technologies, and supporting the *GTGP*.

After introducing *ATT* in Model 3, both *ASS* and *ATT* had a significant positive effect on the green transition of farmers' grain production. Specifically, the coefficient for *ASS* is 1.431, which is significant at the 5% level, and the coefficient for *ATT* is 1.349, significant at the more stringent 1% level. This suggests that receiving *ATT* can promote the green transition of farmers' production. *ATT* can correct farmers' cognitive biases and change their traditional concepts. This can help them realize that emerging agricultural technologies can improve production efficiency, prompting them to actively adopt green production technologies and transition to green production. In addition, *ATT* can promote a transition towards more sustainable grain production in the long term by increasing farmers' awareness of and concern for environmental issues, as well as enhancing their knowledge, skills, and motivation to address current environmental problems and prevent new ones.

After introducing *LT* in Model 4, *ASS* continue to have a significant positive effect on the green transition of farmers' grain production. Specifically, the coefficient for *ASS* is 1.644, which is significant at the 5% level. However, *LT* has a significant negative impact on this green transition, with a coefficient of −1.725, which is significant at the more stringent 1% level. These findings suggest that while *ASS* encourage a greener transition, *LT* may pose a challenge to this process. The *GTGP* depends on the level of human capital of the grain-growing labor force. However, *LT* leads to a gradual reduction and weakening of human capital, which ultimately constrains the formation of green production concepts, the application of emerging technologies, and the *GTGP* methods. Labor migration has resulted in a shortage of available labor for the grain production process. As a result, farmers often resort to increasing chemical inputs to maintain grain production. However, the characteristics of small-scale and part-time operations among left-behind farmers in the context of labor migration do not allow for the formation of a scale of intensification to offset the high cost of green production transition. Additionally, they lack the objective conditions for mechanical operation, which hinders the widespread adoption of green technology elements.

4.2.2 Robustness test

4.2.2.1 Replacement of explanatory variables

To ensure the robustness of the benchmark regression results, this paper includes the green production behavior of farmers as a proxy variable for the *GTGP*. The variable indicates whether the grain production methods of farmers belong to the category of green production. The results are presented in Table 7. The study indicates that *ASS* have a positive impact on farmers' green grain production behavior. This means that socialization services can help farmers transition from traditional to green production methods. The results of the control variables estimation are consistent with the benchmark regression results. Therefore, the benchmark regression results remain valid even after using farmers' green production behavior as a proxy variable for the green transition of farmers' grain production. This indicates that the above conclusions are robust.

4.2.2.2 Replacement of core explanatory variables

To assess the benchmark regression results more thoroughly, this paper replaces the primary explanatory variables of adopting *ASS* with the degree and cost of adoption of socialization services for empirical testing. The results are presented in Table 8. The results of models 1-4 in Table 8 indicate that the adoption of *ASS* promotes the green transition of farmers' grain production at a statistically significant level of 5%. The estimation results of the control variables are consistent with those of the previous paper. The results of models 5-8 in Table 8 indicate that the adoption cost of socialization services significantly promotes the green transition of farmers' grain production at the statistical level of 5%. The estimation results of other variables are also consistent with the benchmark regression. After replacing the core explanatory variables of whether or not to adopt *ASS* with the degree of adoption of *ASS* and the cost of adoption of *ASS*, respectively, we found that the main findings still hold. This means that the benchmark regression results are robust based on the above analysis.

TABLE 6 Estimated results of *ASS* versus *GTGP*.

Variables	Model (1)	Model (2)	Model (3)	Model (4)
ASS	1.489**	1.695**	1.431**	1.644**
	(0.599)	(0.663)	(0.592)	(0.640)
PS		1.038***		
		(0.237)		
ATT			1.349***	
			(0.436)	
LT				−1.725***
				(0.488)
GEN	−0.430	−0.725	−0.286	−0.275
	(0.581)	(0.649)	(0.602)	(0.577)
AGE	−0.282	−0.533	0.105	−0.453
	(1.491)	(1.638)	(1.546)	(1.569)
EDU	0.0352	0.0995	0.119	0.174
	(0.252)	(0.301)	(0.264)	(0.265)
HEA	0.638	0.620	0.900	1.026
	(0.649)	(0.668)	(0.571)	(0.718)
CD	0.273	0.315	0.399	0.424
	(0.620)	(0.627)	(0.605)	(0.577)
RP	−0.0707	−0.164	−0.0879	0.0389
	(0.811)	(0.834)	(0.855)	(0.753)
RA	−0.0301	0.174	−0.0967	−0.218
	(0.528)	(0.586)	(0.557)	(0.520)
ALFS	−0.639	−0.765	−0.489	−0.605
	(0.471)	(0.538)	(0.470)	(0.539)
CSL	0.368***	0.380***	0.352***	0.240**
	(0.0947)	(0.102)	(0.0977)	(0.117)
HL	−0.893	−1.407*	−0.862	−1.222*
	(0.645)	(0.723)	(0.639)	(0.643)
CI	0.535	0.730	0.686*	0.471
	(0.411)	(0.448)	(0.406)	(0.413)
BS	0.0275	−0.0102	0.0271	0.0455
	(0.112)	(0.129)	(0.118)	(0.113)
GSF	0.344	0.402	0.294	0.196
	(0.424)	(0.442)	(0.446)	(0.439)
PSF	−0.656	−0.572	−0.745	−0.590
	(0.648)	(0.717)	(0.633)	(0.688)
IC	0.175	0.294	8.25e-05	0.336
	(0.450)	(0.468)	(0.468)	(0.476)
CS	−0.0698	−0.0729	−0.0735	−0.0606
	(0.0821)	(0.0828)	(0.0816)	(0.0794)
PA	−0.378	−0.724	−0.134	−0.213
	(0.498)	(0.542)	(0.571)	(0.492)
Constant	4.055	5.105	1.297	4.464
	(6.563)	(7.121)	(6.866)	(6.950)
R^2	0.1332	0.2078	0.1751	0.1964
Observations	545	545	545	545

(Continued in next column)

TABLE 6 (*Continued*) Estimated results of *ASS* versus *GTGP*.

Note: ***p < 0.01, **p < 0.05, *p < 0.1; standard errors in parentheses.

4.2.3 Endogeneity test

Given that a farmer's decision to purchase *ASS* during the grain production stage is an autonomous choice, it may lead to self-selection bias and endogeneity problems. To address this issue, this paper employs the propensity score matching (PSM) method to explore the potential endogeneity problems between *ASS* and the green transformation of farmers' grain production. Table 9 presents the PSM estimation results of four different matching methods: 1-1 proximity matching, 1-3 proximity matching, radius matching, and kernel function matching. All methods indicate a significant positive effect of *ASS* on the green transition of farmers' grain production. This means that the adoption of *ASS* can lead to a more environmentally friendly approach to farmers' grain production. In summary, the PSM estimation results are consistent with the previous study, indicating the robustness of the benchmark regression results. This paper aims to assess whether the PSM results can balance the data better through the balance test method. The radius matching method is used as an example for the balance test, and the results are shown in Table 10. The results indicate that after matching, the standardized deviations of most variables are reduced compared to before matching. Additionally, the standardized deviation rate after matching is generally lower than 10%. Furthermore, the t-test results of most variables do not support the hypothesis that there is a systematic difference between the experimental group and the control group. Therefore, the PSM results pass the balance test (He and Huang, 2023).

4.3 Testing the moderating effect of factors allocation

In order to further analyze the path through which *ASS* affect the green transition of farmers' grain production, this paper uses moderated effects analysis, respectively, the three variables of *PS*, *ATT*, and *LT* and their interaction terms with *ASS* are included in the regression model, and the results are shown in Table 11.

Table 11 Model 1 shows the moderating effect of *PS* on the relationship between *ASS* and the green transition path of farmers' grain production. The results indicate that *ASS* have a significant positive effect on this green transition, with a coefficient of 4.673 ($p < 0.01$). *PS* also positively influences the transition, with larger

TABLE 7 Estimated results of *ASS* on farmers' green production behavior.

Variables	Model (5)	Model (6)	Model (7)	Model (8)
ASS	0.915***	0.995***	0.959***	0.967***
	(0.292)	(0.291)	(0.303)	(0.299)
PS		0.814***		
		(0.167)		
ATT			−0.526*	
			(0.278)	
LT				−0.841***
				(0.276)
GEN	0.0410	−0.223	−0.0273	0.0934
	(0.367)	(0.396)	(0.366)	(0.370)
AGE	−0.286	−0.563	−0.404	−0.482
	(0.827)	(0.893)	(0.846)	(0.857)
EDU	0.0278	0.0610	0.00454	0.0799
	(0.176)	(0.190)	(0.175)	(0.180)
HEA	0.316	0.231	0.243	0.488
	(0.398)	(0.395)	(0.424)	(0.406)
CD	0.0262	0.0794	−0.0388	0.0920
	(0.371)	(0.388)	(0.368)	(0.373)
RP	0.873	0.830	0.876	0.996*
	(0.615)	(0.624)	(0.611)	(0.586)
RA	0.0670	0.142	0.0991	−0.00998
	(0.332)	(0.340)	(0.332)	(0.329)
ALFS	−0.404	−0.453	−0.453	−0.380
	(0.329)	(0.341)	(0.333)	(0.343)
CSL	0.169**	0.173**	0.182**	0.0931
	(0.0712)	(0.0725)	(0.0718)	(0.0789)
HL	−0.125	−0.502	−0.140	−0.259
	(0.386)	(0.389)	(0.396)	(0.382)
CI	0.309	0.349	0.279	0.286
	(0.258)	(0.277)	(0.260)	(0.261)
BS	0.110	0.0901	0.109	0.125
	(0.0801)	(0.0855)	(0.0790)	(0.0818)
GSF	−0.152	−0.132	−0.130	−0.244
	(0.264)	(0.279)	(0.260)	(0.269)
PSF	−0.172	−0.105	−0.171	−0.153
	(0.459)	(0.474)	(0.475)	(0.460)
IC	0.440	0.525*	0.504	0.552*
	(0.306)	(0.319)	(0.306)	(0.312)
CS	−0.00303	−0.00683	−0.00334	0.00441
	(0.0435)	(0.0436)	(0.0441)	(0.0429)
PA	−0.242	−0.517	−0.375	−0.176
	(0.351)	(0.375)	(0.363)	(0.352)
Constant	1.738	3.027	2.736	2.304
	(3.717)	(3.958)	(3.862)	(3.840)
R^2	0.0720	0.1321	0.0802	0.0912
Observations	545	545	545	545

(Continued in next column)

TABLE 7 (*Continued*) Estimated results of *ASS* on farmers' green production behavior.

Note: ***p < 0.01, **p < 0.05, *p < 0.1; standard errors in parentheses.

plots showing a greater tendency to adopt green practices, as reflected in a coefficient of 1.906 ($p < 0.01$). Moreover, the interaction term between *PS* and *ASS* is significantly positive (coefficient = 2.793, $p < 0.01$), suggesting that the positive impact of socialization services on the green transition becomes more pronounced as *PS* increases. These findings support Hypothesis 2, highlighting the crucial role of both *ASS* and *PS* in promoting the green transition, with larger plots benefiting more from socialization services. *PS* significantly influences farmers' engagement with socialization services, which in turn affects their production methods. Large-scale households, with more extensive land areas, are more likely to invest in these services to address labor constraints and adopt advanced agricultural technologies, such as machinery and green production techniques. The larger the operation, the more feasible it becomes to integrate these technologies, making green practices both efficient and profitable. This creates a positive feedback loop where service providers are incentivized to offer high-quality services, further promoting the green transition in grain production. In contrast, small farmers with limited resources and smaller plots may struggle to access these services, slowing the adoption of green technologies. However, targeted policies that subsidize socialization services for smallholders can help bridge this gap, fostering broader adoption of sustainable practices across all scales of farming operations.

Table 11 Model 2 shows the moderating effect of *ATT* on the relationship between *ASS* and the path of green transition of farmers' grain production. Specifically, the coefficient for *ASS* is 1.919, which is statistically significant at the 5% significance level, suggesting a positive and substantial impact on the transition to green grain production. Similarly, the coefficient for *ATT* is 1.735, significant at the 1% significance level, indicating a strong and positive effect on the green transition. However, the interaction term between *ATT* and *ASS*, with a coefficient of 1.467, is not statistically significant. This finding suggests that *ATT* does not moderate the relationship between socialization services and the green transition of farmers' grain production. In other words, the positive influences of both socialization services and technology training operate independently, rather than through their interaction (Sui and Gao, 2023). Therefore, Hypothesis 3 has not been supported. The reason for this may be that *ATT* in China is

TABLE 8 Estimated results of the adoption level and cost of *ASS* on *GTGP*.

Variables	Model (9)	Model (10)	Model (11)	Model (12)	Model (13)	Model (14)	Model (15)	Model (16)
Adoption level	1.259**	1.193**	1.208**	1.359**				
	(0.564)	(0.598)	(0.581)	(0.606)				
Adoption cost					0.197**	0.225**	0.199**	0.215**
					(0.0942)	(0.0965)	(0.0957)	(0.0970)
PS		0.932***				1.004***		
		(0.221)				(0.226)		
ATT			1.323***				1.401***	
			(0.437)				(0.431)	
LT				−1.717***				−1.682***
				(0.482)				(0.488)
GEN	−0.473	−0.724	−0.275	−0.312	−0.443	−0.751	−0.240	−0.282
	(0.578)	(0.621)	(0.603)	(0.594)	(0.571)	(0.636)	(0.586)	(0.564)
AGE	−0.285	−0.421	0.0304	−0.367	−0.325	−0.679	−0.0925	−0.673
	(1.302)	(1.322)	(1.318)	(1.491)	(1.355)	(1.422)	(1.409)	(1.670)
EDU	0.0218	0.104	0.101	0.175	0.0282	0.0672	0.109	0.154
	(0.257)	(0.293)	(0.264)	(0.264)	(0.252)	(0.299)	(0.263)	(0.266)
HEA	0.596	0.640	0.849	0.964	0.620	0.644	0.899	1.003
	(0.649)	(0.692)	(0.576)	(0.728)	(0.663)	(0.672)	(0.576)	(0.743)
CD	0.307	0.424	0.422	0.407	0.306	0.407	0.449	0.416
	(0.614)	(0.614)	(0.597)	(0.573)	(0.628)	(0.655)	(0.614)	(0.603)
RP	0.102	0.0175	0.0364	0.118	0.160	0.121	0.128	0.231
	(0.508)	(0.516)	(0.507)	(0.532)	(0.526)	(0.548)	(0.521)	(0.555)
RA	−0.160	−0.271	−0.166	−0.0501	0.0146	−0.130	0.0158	0.153
	(0.838)	(0.853)	(0.876)	(0.776)	(0.827)	(0.851)	(0.881)	(0.778)
ALFS	−0.0798	0.0644	−0.120	−0.287	0.0414	0.231	−0.0251	−0.0977
	(0.519)	(0.553)	(0.541)	(0.506)	(0.522)	(0.563)	(0.550)	(0.535)
CSL	−0.647	−0.752	−0.530	−0.652	−0.608	−0.722	−0.485	−0.593
	(0.456)	(0.499)	(0.445)	(0.552)	(0.441)	(0.494)	(0.436)	(0.523)
HL	0.371***	0.387***	0.356***	0.235*	0.364***	0.383***	0.348***	0.240**
	(0.0987)	(0.105)	(0.102)	(0.122)	(0.0944)	(0.101)	(0.0966)	(0.117)
CI	−1.042	−1.349**	−1.040	−1.307*	−0.587	−1.055*	−0.627	−0.844
	(0.658)	(0.687)	(0.665)	(0.678)	(0.569)	(0.627)	(0.584)	(0.578)
BS	0.591	0.760*	0.732*	0.530	0.530	0.650	0.660*	0.449
	(0.413)	(0.448)	(0.415)	(0.434)	(0.399)	(0.433)	(0.394)	(0.403)
GSF	0.0257	0.000337	0.0294	0.0432	0.0533	0.0136	0.0543	0.0805
	(0.111)	(0.126)	(0.117)	(0.112)	(0.114)	(0.133)	(0.119)	(0.118)
PSF	−0.653	−0.552	−0.719	−0.599	−0.513	−0.474	−0.655	−0.387
	(0.632)	(0.682)	(0.632)	(0.667)	(0.639)	(0.706)	(0.626)	(0.699)

(Continued on following page)

TABLE 8 (*Continued*) Estimated results of the adoption level and cost of *ASS* on *GTGP*.

Variables	Model (9)	Model (10)	Model (11)	Model (12)	Model (13)	Model (14)	Model (15)	Model (16)
IC	0.230	0.370	0.0435	0.416	0.218	0.301	0.0233	0.346
	(0.425)	(0.442)	(0.440)	(0.451)	(0.436)	(0.446)	(0.449)	(0.483)
CS	−0.0875	−0.0775	−0.0865	−0.0792	−0.0722	−0.0763	−0.0765	−0.0650
	(0.0871)	(0.0872)	(0.0842)	(0.0856)	(0.0849)	(0.0847)	(0.0836)	(0.0824)
PA	−0.484	−0.876*	−0.238	−0.273	−0.436	−0.721	−0.176	−0.227
	(0.494)	(0.522)	(0.564)	(0.488)	(0.500)	(0.554)	(0.569)	(0.520)
Constant	4.321	4.752	1.838	4.353	4.215	5.763	2.040	5.358
	(5.875)	(5.892)	(6.006)	(6.665)	(5.968)	(6.197)	(6.256)	(7.258)
R^2	0.1395	0.1999	0.1797	0.2015	0.1127	0.1857	0.1583	0.1732
Observations	545	545	545	545	545	545	545	545

Note: ***p < 0.01, **p < 0.05, *p < 0.1; standard errors in parentheses.

TABLE 9 PSM estimation results for *ASS* in *GTGP*.

	Matching method	Experimental group	Control group	*ATT*	Standard error	T-value
ASS	Near-neighbor matching method N (1)	0.863	0.698	0.166***	0.026	6.290
	Near-neighbor matching method N (3)	0.863	0.696	0.167***	0.041	4.080
	Radius matching method	0.863	0.696	0.167***	0.037	4.520
	Kernel function method (normal)	0.863	0.699	0.164***	0.037	4.460
	Kernel function method (biweight)	0.863	0.696	0.167***	0.038	4.420
	Kernel function method (epan)	0.863	0.698	0.165***	0.038	4.400
	Kernel function method (uniform)	0.863	0.695	0.168***	0.038	4.470
	Kernel function method (tricube)	0.863	0.696	0.167***	0.038	4.440

primarily focused on the individual level. Its aim is to improve the scientific knowledge of grain farmers on new technologies that increase production and ecological environmental protection. This is done to improve their production behavior decisions. However, when *ASS* intervene in grain production, the power of service organizations becomes the main reliance to achieve green production transition. Therefore, the interaction effect between the two is not significant.

Table 11 Model 3 shows the moderating effect of LT on the relationship between ASS and the green transition path of farmers' grain production. The results provide detailed insights into the statistical significance and impact sizes of the key variables. Specifically, the coefficient for *ASS* is 1.194, which is statistically significant at the 10% level. This positive coefficient indicates that *ASS* promote the green transition of farmers' grain production, as hypothesized. In contrast, the coefficient for LT is −1.264, significant at the 5% level, indicating a significant negative effect on the green transition. This finding aligns with the concern that increasing rates of *LT* may hinder the adoption of green production methods by farm households. However, the coefficient of the interaction term between *LT* and *ASS* is 1.830, significant at the 10% level. This positive coefficient suggests that the inclusion of *ASS* can help mitigate the negative effects of LT on the green transition. In other words, *ASS* may act as a catalyst to overcome the obstacles posed by Labor Transfer, facilitating the adoption of green production among farm households. Hypothesis 4 has been confirmed. Due to the continuous transfer of labor from grain growing to other industries, rural surplus labor is becoming scarce. Socialization services can compensate for the lack of labor through mechanical operations. Additionally, increased income from non-farm employment can alleviate the capital constraints of farmers and increase their purchasing behavior for socialization services. Introducing multi-link *ASS* into grain production can maximize the advanced production concepts and green production technologies of socialization service organizations, promoting the *GTGP*. Furthermore, to enhance the practical application of our findings, it is crucial to consider how elements such as *ATT* engage with socialization offerings in realistic scenarios. For instance, socialization service organizations often provide training programs that educate farmers on advanced production concepts and green technologies. These training programs not only improve farmers' skills but also enhance their ability to effectively utilize socialization services. By integrating training with socialization services, farmers are better equipped to adopt green

TABLE 10 Equilibrium test of the martingale matching method.

Variables	Pre-match mean		Post-match mean		Deviation rate		Post-match T-test	
	Experimental group	Control group	Experimental group	Control group	Pre-match	Post-match	T-value	P > t
GEN	0.871	0.810	0.871	0.843	16.600	7.600	0.920	0.357
AGE	0.513	0.580	0.513	0.508	−13.500	1.000	0.110	0.909
EDU	0.550	0.591	0.550	0.568	−8.400	−3.600	−0.420	0.676
HEA	0.428	0.369	0.428	0.414	12.100	2.900	0.330	0.741
CD	0.199	0.182	0.199	0.211	4.300	−2.900	−0.330	0.739
RP	0.085	0.055	0.085	0.055	11.800	11.600	1.350	0.178
RA	0.720	0.788	0.720	0.735	−16.000	−3.700	−0.410	0.680
ALFS	0.760	0.730	0.760	0.765	6.900	−1.200	−0.140	0.888
CSL	0.439	0.416	0.439	0.487	4.700	−9.700	−1.120	0.263
HL	0.351	0.069	0.351	0.312	73.400	10.100	0.950	0.341
CI	0.461	0.401	0.461	0.468	12.100	−1.300	−0.150	0.881
BS	0.173	0.102	0.173	0.129	20.700	13.000	1.450	0.147
GSF	0.391	0.376	0.391	0.366	3.100	5.200	0.610	0.541
PSF	0.103	0.062	0.103	0.085	15.000	6.500	0.710	0.476
IC	0.893	0.730	0.893	0.856	42.500	9.700	1.310	0.192
CS	0.185	0.058	0.185	0.137	39.300	14.700	1.490	0.136
PA	0.236	0.190	0.236	0.264	11.300	−6.700	−0.740	0.462

production methods, thereby accelerating the *GTGP*. Real-world cases demonstrate that farmers who have undergone such training are more likely to adopt multi-link *ASS*, maximizing the benefits of advanced production concepts and green technologies provided by these services. Introducing multi-link *ASS* into grain production can further maximize the advanced production concepts and green production technologies of socialization service organizations, promoting the *GTGP*.

4.4 Heterogeneity analysis

4.4.1 Impact of socialization services on green transition of farmers' grain production

The previous section confirms that the participation of agricultural socialization service organizations can guide the green transition of farmers' grain production. In other words, the more farmers participate in *ASS*, the more enthusiastic they become about the green transition of their grain production. However, it is necessary to examine which segment of *ASS* plays a major role in the process of *GTGP*, as each segment has different preferences for labor, technology, and other production factors. To accurately identify the differences in the promotional effects of *ASS* on the green transition of farmers' grain production in different production segments, this paper divides the six segments of socialization services into labor-intensive socialization services (ploughing, planting, and harvesting) and technology-intensive socialization services (rice transplanting, dousing, and straw returning to the field) based on the demand preferences for production factors in each grain production segment. Table 12 shows that labor-intensive socialization services have a positive effect on the green transition of farmers' grain production at a 5% significance level with a coefficient of 1.632. Additionally, technology-intensive socialization services have a positive effect on the green transition of farmers' grain production at a 10% significance level with a coefficient of 1.103. Both types of services contribute to the green transition, but their impacts vary depending on factors such as the farmer's scale, economic status, and adoption of technology.

The differences in the impact of these two service types are likely due to the varied needs of farmers across different segments. Small-scale farmers tend to prioritize cost-efficiency, and the rising cost of services may limit their willingness to adopt technology-intensive services, which often require higher upfront investments. In contrast, larger farmers, or those with more capital, are more likely to adopt both labor-intensive and technology-intensive services, as they can distribute costs over a larger area of land. For instance, technology-intensive services like rice transplanting and straw return can significantly reduce dependence on chemical fertilizers and improve soil fertility. However, the adoption of such services is often constrained in areas dominated by smallholders due to the higher costs involved.

TABLE 11 The results of mechanism path analysis.

Variables	Model (17)	Model (18)	Model (19)
ASS	4.673***	1.919**	1.194*
	(1.310)	(0.851)	(0.707)
PS	1.906***		
	(0.412)		
ATT		1.735***	
		(0.571)	
LT			−1.264**
			(0.553)
*ASS*PS*	2.793***		
	(0.768)		
*ASS*ATT*		1.467	
		(1.246)	
*ASS *LT*			1.830*
			(0.979)
Control	Y	Y	Y
Constant	4.186	1.039	2.670
	(8.246)	(7.436)	(7.054)
R^2	0.2957	0.1890	0.2112
Observations	512	512	512

Note: ***p < 0.01, **p < 0.05, *p < 0.1; standard errors in parentheses.

TABLE 12 Heterogeneity analysis based on different segments of socialization services.

Variables	Model (20)	Model (21)
Labor-intensive *ASS*	1.632**	
	(0.670)	
Technology-intensive *ASS*		1.103*
		(0.642)
Control	Y	Y
Constant	3.821	2.642
	(7.084)	(6.035)
R^2	0.1439	0.1143

Note: ***p < 0.01, **p < 0.05, *p < 0.1; standard errors in parentheses.

Moreover, tailoring services to meet the specific needs of different farmer segments could further facilitate the green transition. For example, service providers could offer scaled-down or more affordable versions of technology-intensive services for smallholders, or create bundled packages that combine both labor- and technology-intensive services to reduce overall costs. In regions where small farmers predominate, improving the accessibility of these services is crucial for ensuring that the green transition is inclusive and effective.

4.4.2 Impact of agricultural socialization services on the green production transition of farmers of different types

In recent years, China has prioritized the cultivation of new type of agricultural operating entit to promote the high-quality development of the grain industry (Chen Y. J. et al., 2023). These subjects differ from ordinary farmers in their business models, management styles, and development goals, which may impact their choice of grain production methods. Thus, the paper divides the sample farmers into two groups: ordinary farmers and new type of agricultural operating entit. The model test is then conducted separately for each group, and the results are presented in Table 13. The results indicate that *ASS* have a significant positive impact on the green transition of production for both ordinary farmers and new type of agricultural operating entit. This suggests that the inclusion of socialization services can effectively promote the green transition of farmers' grain production. We found that the promotion effect of *ASS* on the green transition of production of new type of agricultural operating entit is more obvious, which indicates that the new type of agricultural operating entit have higher levels of their own quality and knowledge, and higher awareness of green development and environmental responsibility, and are important implementers of the current *GTGP*.

The impact of *ASS* varies by farmer type. For ordinary farmers, services should focus on basic training, infrastructure support, and financial incentives to help them adopt sustainable practices. In contrast, new types of agricultural operating entities, with higher knowledge and management capacity, would benefit more from advanced services like specialized green technology workshops, market information systems, and eco-friendly production techniques. To enhance the effectiveness of the green transition in grain production, the government should tailor services to meet the specific needs of these two groups—basic support for ordinary farmers and advanced services for new agricultural entities. This targeted approach will foster a more effective green transition and contribute to the high-quality development of agriculture.

5 Conclusion and policy recommendations

As the agricultural sector faces increasing pressure to transition towards greener production methods, Agricultural Socialization Services have emerged as a key support mechanism for farmers. This study investigates their impact on the green production transition of grain farmers in Jiangsu Province. The results indicate that Agricultural Socialization Services significantly promote the adoption of green production practices, such as organic fertilizer use and nitrogen and phosphorus reduction technologies. These findings remain robust even after accounting for potential endogeneity using the propensity score matching method. Moreover, the study reveals that Plot Size and part-time farming play a moderating role in the effectiveness of Agricultural Socialization Services in facilitating the green production transition.

TABLE 13 Heterogeneity analysis based on different business types of farm households.

Variables	Ordinary farmers	New type of agricultural operating Entity
ASS	1.620*	1.885**
	(0.922)	(0.870)
Control	Y	Y
Constant	10.921	2.548
	(13.005)	(12.985)
R^2	0.1932	0.3483
Observations	433	112

Note: ***p < 0.01, **p < 0.05, *p < 0.1; standard errors in parentheses.

These findings highlight the importance of tailored Agricultural Socialization Services in supporting the green production transition, particularly for different farm sizes and labor conditions.

To better understand how Agricultural Socialization Services drive the green transition of grain production, we propose a "Theory of Change" that outlines the process flow, identifies bottlenecks, and suggests actionable interventions. ASS promote green transition through resource allocation (efficient use of land, labor, and machinery), technology adoption (disseminating organic fertilizers, soil testing, and water-saving irrigation via training), labor transfer (substituting human labor with machinery), and economic incentives (increased income and reduced costs). However, bottlenecks such as smallholder constraints (financial and cognitive barriers), labor migration (reduced rural labor availability), and inconsistent policy implementation hinder

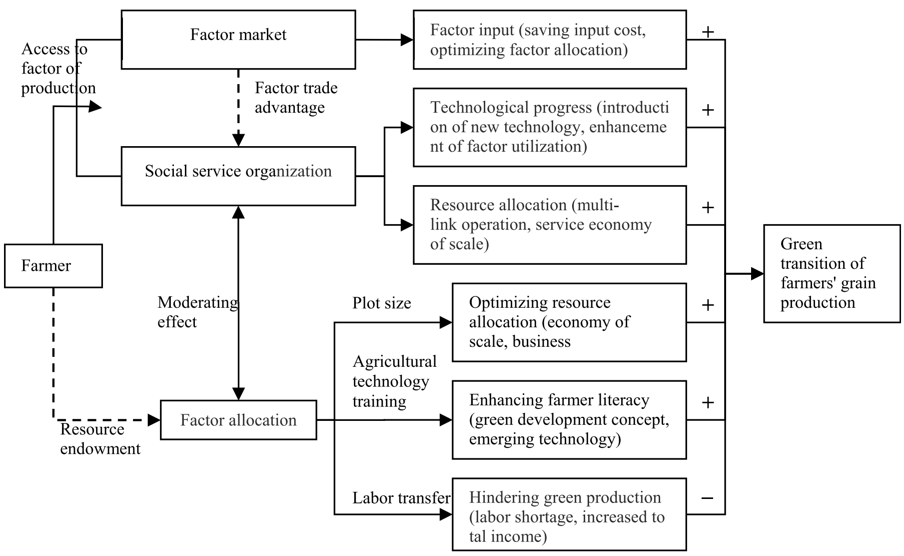

FIGURE 1
Framework diagram of research theory.

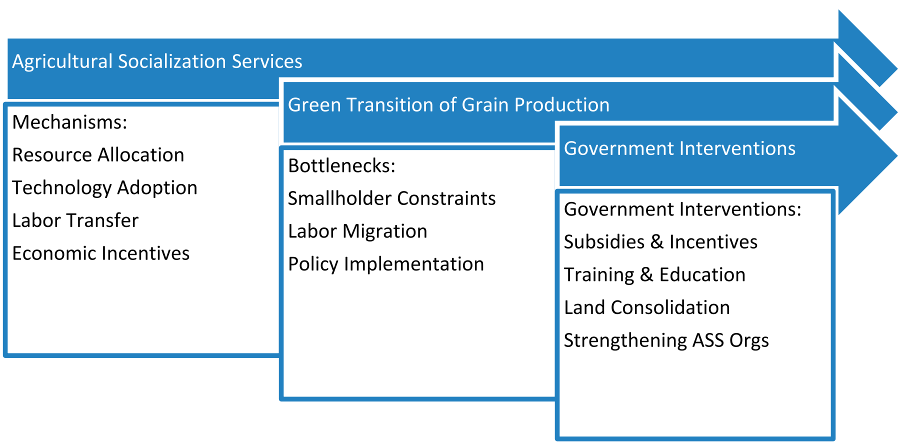

FIGURE 2
Theory of change: how agricultural socialization services drive green transition.

progress. To address these challenges, the government should provide subsidies for green technologies, invest in tailored training programs, promote land consolidation for large-scale farming, and strengthen ASS organizations with financial and technical support to ensure accessible and affordable services, particularly for smallholders.

Figure 2 illustrates the process flow of how ASS influence the green transition of grain production. The diagram shows the key mechanisms (resource allocation, technology adoption, labor transfer, and economic incentives) and identifies the bottlenecks (smallholder constraints, labor migration, and policy implementation). The proposed government interventions are also highlighted to address these challenges.

These findings provide the following insights into the study: (1) To promote the green transformation of grain production, the government should strengthen Agricultural Socialization Services, particularly in regions where green technologies are not yet widely adopted. This can be achieved by offering financial incentives to service providers for adopting green technologies, providing training programs to enhance sustainable agriculture skills, and fostering cooperation between local governments and service agencies to ensure these services reach remote farmers. (2) Tailored support policies should be implemented based on farmers' resource endowments, especially for smallholder farmers. These policies may include financial incentives to reduce barriers to adopting green practices, promoting land transfer and integration with socialized services to support large-scale farming, and offering training and technical assistance to help farmers master sustainable techniques, particularly those that replace chemical inputs. (3) Finally, new agricultural entities, which generally have stronger technical and managerial capacities, should be prioritized as key players in the green transformation. The government can support these entities through tax incentives, low-interest loans, and other policy measures to encourage the adoption of green technologies. Targeted training should also be provided to enhance their management capabilities, and these entities should be encouraged to offer technical support and demonstration projects for smallholder farmers, thus leading the way in green agricultural practices.

This study provides valuable insights into the role of Agricultural Socialization Services in China's green transformation, but several limitations should be addressed in future research. First, the study focuses on Jiangsu Province, which may limit the generalizability of the findings. Future research should include other regions to enable a comparative analysis of Agricultural Socialization Services across diverse agricultural sectors and policy environments. This would help understand how regional contexts influence the effectiveness of these services in promoting green transformation. Second, the lack of longitudinal data limits our understanding of the long-term effects of socialization services on farmers' behaviors. Future studies could use longitudinal data to track these behaviors over time and assess the sustainability of green practices. Finally, this study relies on cross-sectional data, which reveals correlations but cannot establish causality. Experimental or natural experimental designs would provide more insight into the causal mechanisms at play.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

JW: Investigation, Writing–review and editing, Writing–original draft. FL: Investigation, Writing–review and editing, Supervision.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The author(s) declare that no Generative AI was used in the creation of this manuscript.

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