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Farmers' social networks' effects on the sustainable production of fresh apples in China's Shaanxi province

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Introduction: Recently, the public and policymakers have acquired knowledge of the detrimental effects of pesticide use in agriculture. These include the threat to the health of chemical applicators and the threat that pesticide residues pose to the safety of food. The present study focuses on the farmers' social networks from a new perspective, along with the farmers' concurrent agricultural business and their impact on the farmer's safe production behavior.

Methodology: The Endogenous Switching Probit Regression model and Binary Probit Group Regression model were employed for the empirical analysis of survey data collected from 585 households in the Xianyang, Yan'an, and Weinan districts of Shaanxi province, China.

Results and Discussion: The results revealed that farmers' social networks can greatly affect farmers' safe production behavior. Additionally, we noted that the farmers' social networks may play a positive role in promoting the farmers' safe production behaviors of both concurrent agricultural business and non-concurrent agricultural business farmers. Moreover, their correlation coefficients were found significant at a confidence level of 5%. Our findings suggest that the government needs to construct social networks among farmers by setting up a communication platform and promoting the acquaintance of safe production through reciprocal culture.

KEYWORDS

concurrent agricultural business, endogenous switching probit regression model, pesticide, safe production, social networks, binary probit group regression model

Abbreviations: ATT, average treatment effect on treated; ATU, average treatment effects on the untreated; CAB, concurrent agricultural business; EFA, exploratory factor analysis; ESP, endogenous switching probit; IPM, integrated pest management; KMO, kaiser-meyer-olkin; LR, likelihood ratio; MRL, maximum residual limit; NBSC, national bureau of statistics of China; SPBr, safe production behavio; SPSS, statistical package for the social sciences; USDA, United States department of agriculture; WHO, world health organization.

1 Introduction

In China, the agriculture sector is playing a significant role in economic and social development. Agriculture accounts for 7.3% of the country's GDP in 2021 and is considered the backbone of the booming Chinese economy (Statistical Year Book, 2021). Two-thirds of China's population lives in rural areas, and their livelihood relies heavily upon agriculture (Koondhar et al., 2021a). China is the largest apple producer, consumer, and exporter in the world, followed by the United States and EU (USDA. China, 2020). According to the National Bureau of Statistics of China, fresh apple output was around 45.9 million tons in 2021, with an increase of 4% from 2020. In China, Shaanxi province ranked 1st in producing fresh apple fruit with 11.85 million tons of production in 2020, followed by Shandong with 9.5 million tons, Shanxi with 4.3 million tons, Gansu with 3.86 million tons, and Henan with 4.1 million tons (Statistical Year Book, 2021). Agricultural productivity has improved remarkably in the past decades in China, but this development has also resulted in severe environmental and ecological problems (Ju et al., 2009; Fan et al., 2011; Khan et al., 2020; Balsalobre-Lorente et al., 2022), such as excessive usage of pesticides, which seems to be much higher in cash crops than in cereal crops, causing food safety issues. (Bushway and Fan, 1998; Fan et al., 2011; Aziz et al., 2020).

The economic and living standards of Chinese people have improved in the last two decades, but environmental limits have also risen with development (Wu and Xu, 2009; Koondhar et al., 2021b). Pesticides are widely used by farmers in most agricultural sectors to reduce losses and increase yields and quality. These pesticides play a key role in the supply chain of agricultural products to consumers and ensure high profitability for farmers (Oerke and Dehne, 2004; Hou and Wu, 2010; Khan et al., 2020; Khan et al., 2022). Although due to excessive use and demand, common people's exposure to pesticides is instigated by pesticide residues in air, drinking water, and food is chronic and hazardous (Van Amerongen, 1992; Damalas and Eleftherohorinos, 2011; Liu et al., 2012; Piwowar, 2021). WHO (World Health Organization) has stated that approximately 600 million pesticide poisoning cases occur per annum, causing 420,000 deaths around the world (WHO, 2020).

To reduce the adverse effects of these chemicals, it is necessary to investigate the farmer's awareness of pesticide residues and their application practices (Cooper and Hall, 1993; Bhandari, 2014; Bagheri et al., 2018; Ren and Jiang, 2022). Zhongze and Qingjiang (Zhongze and Qingjiang, 2007) stated that 75% of farmers had little knowledge about pesticides residues, while 25% of farmers were even unfamiliar in nine regions of China. Similarly Puyun, Ping (Puyun et al., 2007) also investigated the excessive use of pesticides by farmers for controlling vegetable pests and using these chemicals to cover their losses without knowing their hazardous effects. (Zhang et al., 2004) empirically explored the influencing factors of farmers' safe production adoption behavior of pesticides. It was observed that farmers' adoption behavior of pesticides depends on the relationship with food processing firms and different farmers' cooperative communities. Moreover, Ci-yuan (Ci-yuan, 2005) qualitatively analyzed the farmers' safe production behavior (SPB) and adaptation problems in China and observed that the main obstacles in the pesticide application were low effectiveness and high prices.

Furthermore, in 2005, 2010, 2015, and 2017, the *per capita* net income of rural residents in China was 34.85.%, 38.76%, 40.27%, and 40.93%, respectively (NSBC. National, 2019), indicating that the percentage of farmers' concurrent agricultural business (CAB) is deepening every year. However, with the growing number of CAB workers, agricultural food production confronts another problem. From the perspective of risk constraints, agricultural production is very susceptible to extreme weather or natural disasters, and the quality of agricultural products is also affected by the production behavior of the farmers (Chen Yishan and Ji, 2017; Ali et al., 2021; Khan et al., 2021). Globalization also plays good role in awareness of energy and environmental-related challenges everywhere because of the expanding idea of global information and shared knowledge (Liu et al., 2023). Nowadays, researchers emphasize the need to explore the relationship between CAB and agricultural production from various perspectives (Mailfert, 2007; Ali et al., 2020). In the off-farm, CAB farmers who work in cities return to their farms during the growing season. However, this practice may lead to a decline in grain yields and quality as well as trigger food safety concerns (Jiang Changyun, 2015; Wang et al., 2021). The CAB employment situation significantly increased the amount of pesticide application per unit of wheat, rice, and corn (Chen Yishan and Ji, 2017).

This study employed integrated pest management technology (IPM) as an example to investigate the farmers' SPB. IPM technology refers to the use of all applicable technologies and methods in a specific environment to reduce population dynamics of pests and diseases in a way that is suitable for local soil, climate, and economic conditions (Yu, 2009; Niassy et al., 2022). Social networks have always had a significant impact on how farmers learn and make decisions (Rogers and Kincaid, 1981). A number of studies have highlighted the importance of interpersonal networks formed through discussion groups, farmer-to-farmer linkages, and peer-to-peer advice networks in facilitating learning (Baumgart-Getz et al., 2012; Muange et al., 2014; Ren et al., 2022). The measurement of social networks is quite different in academia, such as how Geng Yuning (Geng and Lu, 2017) and others measured social networks from two dimensions: a homogenous network and a heterogeneous network. Zhihai (Zhihai, 2018) divided social networks into clan networks based on kinship, career, and networks of friends on the basis of geographical boundaries. Granovetter (1977); Haihua (2016); Li Bowei (2017) divided social networks into strong relationship networks and weak relationship networks. Looking back into the literature, this study focuses on the perspective of the human network, including farmers' production, planting, and sales links, combined with the existing scholars' research on the rural social network, trying to break the traditional social network division and analysis mode. Therefore, the present study divided social networks into three dimensions, including clan social network, production social network, and market social network. The Clan Social network of farmers is based upon their relationship with neighbors and relatives which can have influence on their decision making and information gain (Isaac et al., 2007). The production social network is based upon the links of farmers with seed suppliers, fertilizers and other pesticides suppliers. They can provide recent information regarding the usage of agrochemicals and advance technologies regarding sustainable production (Dolinska and d'Aquino, 2016). The market social network of farmers can be based upon the market sales links and

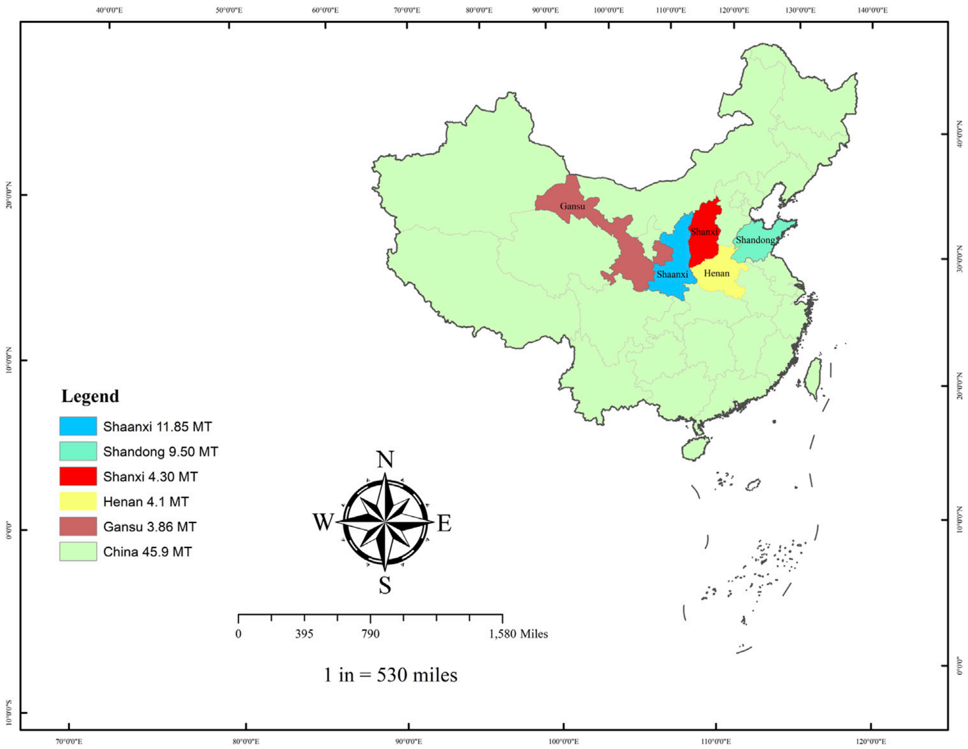

FIGURE 1
Major Apple producing provinces of China, (2020). MT represents metric ton.

the information sharing among those links regarding the quality, price, and endurance of the product produced. This type of network can also have potential impact upon the farmers knowledge and can also provide market feedback of the produced goods (Nyantakyi-Frimpong et al., 2019).

Moreover, In the year 2020, Shaanxi's apple production reached 11.85 million tons, an increase of 4.8% over the previous year (Figure 1), accounting for about a quarter of China's total fresh apple production (Statistical Year Book, 2021). Therefore, we selected Shaanxi Province for our research survey. The major apple counties by production quantity were selected as the sample area, i.e., from Xianyang district; Mihara, Suihua, and Xun counties were selected, from Yan'an district; Huangling, Luochuan, and Yichuan counties were selected, and from Weinan district; Baishui county was selected.

Following the research question of this study: what is the impact of farmer's social network on the sustainable production of fresh apples in China's Shaanxi province? We aimed to estimate these (1) identify the key factors and characteristics of farmers' social networks in Shaanxi province, (2), analyze the influence of social networks on the adoption of sustainable apple production practices among farmers, (3), assess the impact of social networks on the economic and environmental sustainability of apple production in the region, and (4) provide recommendations for policymakers and stakeholders on how to leverage social networks to promote sustainable apple production practices among farmers in Shaanxi province. Moreover, we explore and empirically analyze the impact of farmers' concurrent agricultural business (CAB) and social networks on farmers' safe production behavior (SPB), using IPM technology as a reference in the major apple orchards of Shaanxi province. By examining the role of social networks in promoting sustainable apple production practices, this study aims to contribute to a better understanding of how social networks can be leveraged to promote sustainable agriculture in China and beyond.

2 Materials and methods

2.1 Background of the study area

Shaanxi is a province of the People's Republic of China located in the middle part of the country. Due to its central position in China's interior, the province is landlocked and shares borders with eight other provincial areas of China. It borders the autonomous region of Inner Mongolia to the north, the Ningxia autonomous region to the northwest, Gansu to the west, Sichuan to the southwest, Chongqing municipality to the south, Hubei to the southeast, Henan to the east, and Shanxi to the northeast (Figure 2). The provincial territory includes portions of the Loess Plateau in the middle reaches of the Yellow River, as well as the Qinling Mountains, which stretch across the southern part of the province. The Loess Plateau in the north has an elevation of 800–1,300 m and covers roughly 45 percent of the province's total area. The Central Shaanxi Plain in the middle of the province has an average elevation of about 520 m. The Central Shaanxi Plain in the middle of the province has an average elevation of about 520 m. The Qinling and Daba mountainous

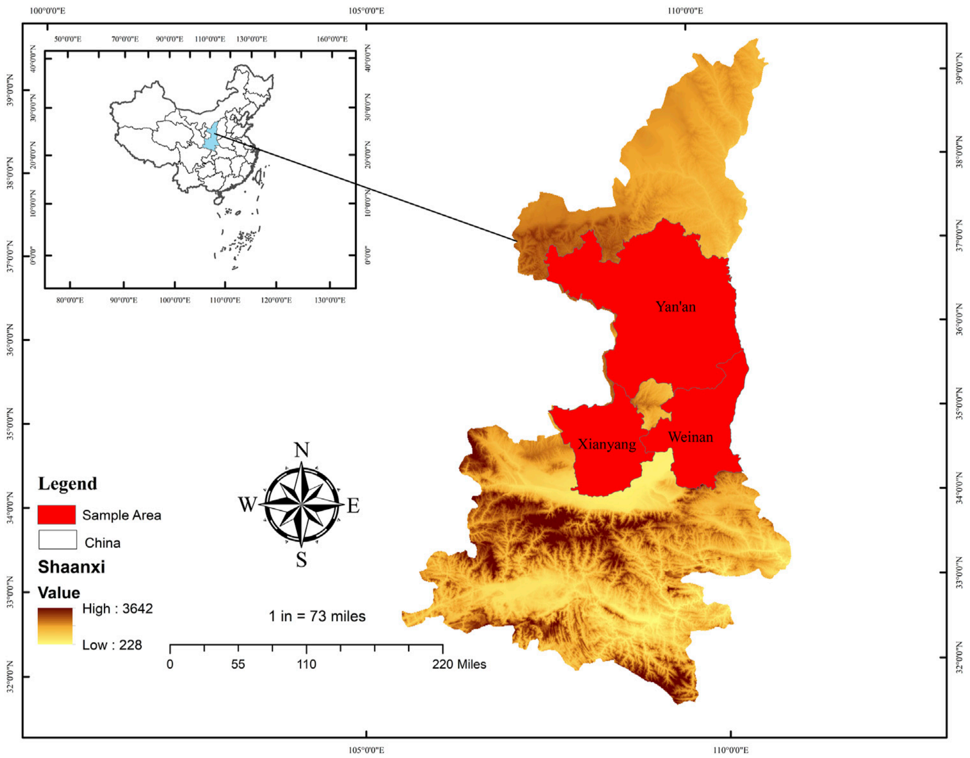

FIGURE 2
Map of the sampled area.

areas in the south include the Hanjiang River Valley, and they cover approximately 36% of the province's total area. The northern part of Shaanxi is cold in the winter and very hot in the summer, with dry winters and springs. The southern portion generally receives more rain. The average temperature annually is roughly between 9°C and 16°C, with January temperatures ranging from −11°C to 3.5°C and July temperatures ranging from 21°C to 28°C.

2.2 Selection of sample

The study utilized a stratified sampling technique to ensure that the obtained samples were representative of the target population. This technique involves dividing the population into subgroups or strata based on relevant characteristics such as age, gender, income, or geographic location. Then, a sample is selected from each subgroup using a random sampling method. This helps to ensure that each subgroup is well represented in the final sample.

In this study, the first stage of the sampling procedure involved randomly selecting 3 to 4 villages in each county. This ensured that the sample included farmers from different geographic locations, which is important for the study's validity. In the second stage, farmer households were investigated, and non-base members of the village and neighboring village farmers were included as a control group. This ensured that the sample included a diverse range of farmers, including those who were not part of the agricultural base being studied. The use of a control group is also crucial for ensuring the validity of the study's findings.

Finally, in the third stage, farmer interviews were conducted at the agricultural base, and random household surveys were conducted in each village. The use of structured questionnaires during face-to-face interviews ensured that detailed information was collected from the participants.

Overall, the study included 586 farmers from 23 villages, and 585 valid questionnaires were collected, representing a response rate of 99.83%. The sample size and structure distribution are shown in Supplementary Table S1. By using a stratified sampling technique and a three-stage sampling procedure, the study was able to obtain a representative sample of the target population and ensure the validity of its findings.

3 Data analysis

3.1 Variable description

This study uses CAB and social networks as independent variables, while farmers' SPB as a dependent variable (Figure 3). According to the proportion of non-agricultural revenue to the overall income earned by farmers, part-time farmers are categorized into concurrent agricultural business households. Specifically, The Rural Development Institute of the Chinese Academy of Social Sciences (2019) distinguishes between two types of concurrent agricultural businesses (CABs): CAB I refers to farmers whose non-agricultural incomes account for 5%–50% of household income, while CAB II refers to farmers whose non-agricultural

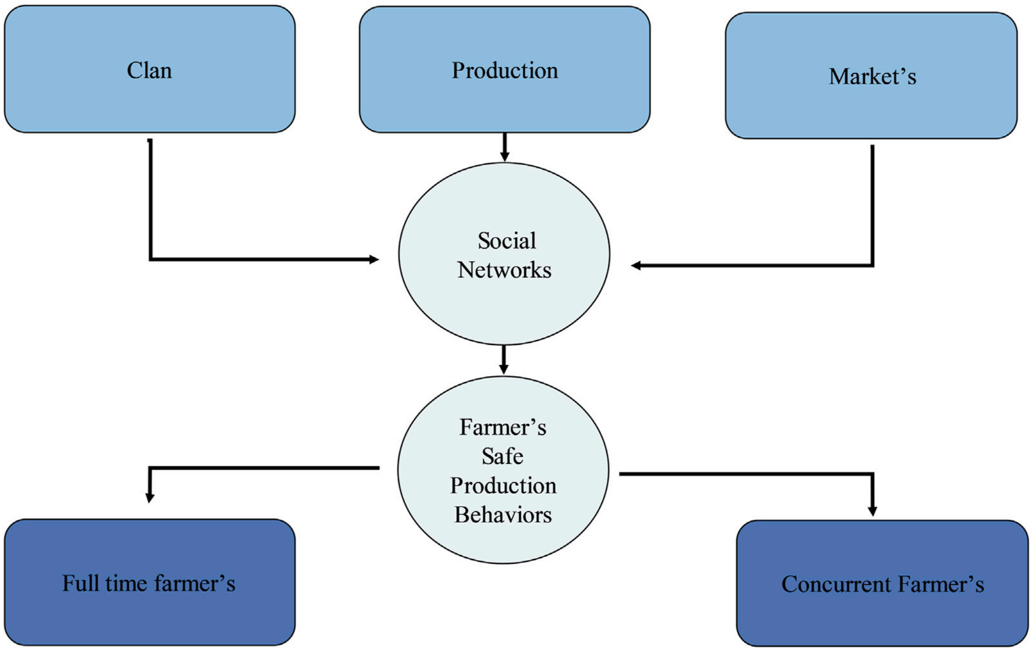

FIGURE 3
The conceptual model of the research.

income accounts for 50%–95% of household income. We considered CAB I and CAB II as a single independent variable, named "concurrent agricultural business (CAB)."

Furthermore, social networks were divided into three dimensions, namely, clan social networks, production social networks, and market social networks. For dimensionality reduction, we performed exploratory factor analysis (EFA) on the social network variables. The KMO test value of the sample is 0.736, and the chi-square of the Bartlett spherical test is 1403.724 (sig = 0. 000), indicating that the sample data is suitable for factor analysis. (See Supplementary Table S2).

3.2 Control variables

Our research study presented control variables from the following aspects: First, the individual characteristics of farmers, including age, education level, risk preference, and farmers' cognitive status. Second, the characteristics of households including family farming labor, planting scale and number of plots. Third, environmental characteristics such as township distance and road conditions. The definition of each variable and descriptive statistics is given in Table 1.

3.3 Model (I) endogenous switching probit model

The endogenous switching probit (ESP) model was used to analyze the relationship between CAB farmers' SPB and non-CAB farmers' SPB. According to the rational assumption, when the expected utility of using IPM is greater than 0, farmers will adopt IPM; otherwise, they will not adopt IPM. However, it is impossible to assess the impact of IPM technology on farmers because of the subjectivity of the evaluation process. Here, assuming that Y_i^* is the utility of IPM technology adopted by farmers, if $Y_i^* > 0$, then $Y_i = 1$, otherwise $Y_i = 0$, the IPM technology adoption model is as follows:

$$Y_i^* = X_i\alpha + CBA_i\eta + \varepsilon_i, Y_i = 1\, if\, Y_i^* > 0 \quad (1)$$

Here, Y_i^* is considered as the possibility to adopt IPM technology, whereas X_i includes the vector of farmer's individual character, cognitive character, family planting character, and environment character. CB_i is whether farmer participates in the Concurrent Agricultural Business, η are parameters to be estimated, and ε_i is an error term, but the household carries on the farmers' CAB and cannot be regarded as the exogenous variable. On the other hand, as a rational individual, the farmer's CAB behavior is often the result of self-selection in pursuit of optimization. Moreover, there are unobservable variables that affect whether the farmers carry out CAB and the farmers' SPB. Therefore, using a probit model to estimate the effect of the farmer's CAB on the farmer's SPB.

We have constructed a two-stage estimation model using the Endogenous Switching Probit (ESP) framework. In the first stage, we applied the Selection Equation estimation probit model to analyze farmers' participation in the (CAB). In the second stage, we focused on (SPB) and its impact on their CAB involvement. We fitted the endogenous transformation model using the entire sample and made counterfactual inferences based on the model's results. We

TABLE 1 Variable definition and descriptive statistical analysis results.

Variable name		Variable meaning	Mean	Standard deviation
IPM technology adoption		Adopted IPM = 1; no = 0	0.37	0.48
Individual characteristics of farmers	Age	Actual age/year of the household	51.61	10.01
	Education level	1 = No school; 2 = Primary school; 3 = Junior high school; 4 = High school/ secondary school; 5 = College and above	2.85	0.81
	Risk preference	Head of household risk preference: risk averse = 1, risk neutral = 2; risk preference = 3 (0–3 points = 1; 3–6 points = 2; 6–9 points = 3)	2.06	0.83
	Cognitive level	Your recognition of "pesticide residues are harmful to health" 1 = completely disagree; 2 = basic disagreement; 3 = general; 4 = basic identity; 5 = complete identity	4.32	1.12
		Your recognition of "spraying pesticides on the environment" 1 = completely disagree; 2 = basic disagreement; 3 = general; 4 = basic identity; 5 = complete identity	3.78	1.47
		Your recognition of "spraying pesticides affecting human health" 1 = completely disagree; 2 = basic disagreement; 3 = general; 4 = basic identity; 5 = full identity	4.28	1.11
Farmer family characteristics	Family farming labor	Number of members engaged in apple cultivation in the family	2.17	0.79
	Planting scale	Apple Orchard Area/Hectare	0.679	5.68
	Degree of land fragmentation	Number of apple planting plots	2.85	1.27
Environmental characteristics	Township distance	The distance from the family to the nearest township	10.79	8.28
	Road condition	Recent roads in towns and counties: dirt road = 1; gravel road = 2; asphalt road = 3; cement road = 4	3.32	1.04

then categorized two sets of farmers from the sample into two SPB models: one for CAB farmers and the other for non-CAB farmers.

We conducted an analysis on the relationship between farmers' CAB and SPB, and further explored how rural employment and social networks influence farmers' SPB. To examine the relationship between variables, we treated Integrated Pest Management (IPM) technology as a binary variable and used a binary probit group regression model. Additionally, to understand the role of social networks, we introduced the degree of CAB among farmers and investigated its interactions with social networks. This allowed us to investigate the mechanisms through which social networks regulate farmers' SPB (Dhakal and Escalante, 2022). The Endogenous Switching Probit (ESP) framework was used to build a two-stage estimation model. In the first stage, the Selection Equation estimation probit model was applied to investigate the farmer's participation in the CAB. However, in the second stage, the model was focused on farmers' SPB and its effect on farmers' CAB (Ma and Abdulai, 2016). The entire sample was utilized to fit the endogenous transformation model, and counterfactual inference was interpreted based on the model's fitting result. We grouped two sample sets of farmers into two SPB models: CAB and non-CAB farmers, which are as follows:

$$\begin{aligned} CBA_i^* &= Z_i\gamma + \mu_i, CBA_i = 1\, if\, CBA_i^* > 0 \\ Y_{i1}^* &= X_i^{'}\beta_{i1} + CBA_i\eta + \varepsilon_{i1}, Y_{i1} = 1\, if\, Y_{i1}^* > 0\ \&\ CBA_i = 1 \\ Y_{i0}^* &= X_i^{'}\beta_{i0} + CBA_i\eta + \varepsilon_{i0}, Y_{i0} = 1\, if\, Y_{i0}^* > 0\ \&\ CBA_i = 0 \end{aligned} \quad (2)$$

Farmers with concurrent agriculture businesses were classified as follows: $CBA_i = 1$ otherwise $CBA_i = 0$。 Y_{i1} with Y_{i0} separate SPB of CAB and non-CAB farmers; the vector $X_i^{'}$ is an explanatory variable, μ_i、 ε_{i0} with ε_{i1} is the meddling item immediately. μ_i、 ε_{i0} with ε_{i1} subject to zero mean and joint normal distribution assumptions, the correlation matrix is presented as follow:

$$\Omega = \begin{bmatrix} 1 & \rho_0 & \rho_{10} \\ & 1 & \rho_1 \\ & & 1 \end{bmatrix} \quad (3)$$

ρ_1 Express μ_i、 ε_{i0} Relevance, ρ_0 Express μ_i with ε_{i1} Relevance, ρ_{10} Express ε_{i0} with ε_{i1} relevance, and ρ_{10} cannot be calculated because Y_{i1} with Y_{i0} cannot be observed simultaneously, and ε_{i0} with ε_{i1} the joint distribution is not known. The selection equation and the resulting equation were simultaneously estimated using the full information maximum likelihood method (FIML) in the ESP model. In order to control the selectivity bias caused by unobservable variables in the ESP estimation process, ρ_1 with ρ_0 was automatically generated and included in the SPB model of the apple farmers who had a CAB.

In addition, using the estimated ESP model, we examine the average processing effect of the CAB behavior on the farmer's SPB model, including the average treatment effects (ATT) and the control group's average treatment effects on the untreated group (ATU). Notably, we reduced the selectivity bias caused by the observed and unobserved heterogeneity by using ESP and obtained a more accurate average processing effect.

In particular, ATT compares the probabilities of SPB model adoption by farmers engaging in CAB and those engaging in non-CAB behavior, while ATU contrasts the probabilities of production

TABLE 2 ATT and ATU estimated results.

	ATT	ATU
Model I.a	−0.31***	−0.26***
Model I.b	−0.38***	−0.21***

behavior models employed by CAB and non-CAB farmer households. The calculations for ATT and ATU are as follows:

$$ATT = \frac{1}{N_1}\sum_{i=1}^{N_1}\left[\Pr(Y_1 = 1 \mid I = 1, X = x) - \Pr(Y_0 = 1 \mid I = 1, X = x)\right] = \frac{1}{N_1}\sum_{i=1}^{N_1}\left[\frac{\phi(\alpha X_1, \eta I, \rho_1) - \phi(\alpha X_0, \eta I, \rho_0)}{F(\eta I)}\right] \tag{4}$$

$$ATU = \frac{1}{N_0}\sum_{i=1}^{N_0}\left[\Pr(Y_1 = 1 \mid I = 0, X = x) - \Pr(Y_0 = 1 \mid I = 0, X = x)\right] = \frac{1}{N_0}\sum_{i=1}^{N_0}\left[\frac{\phi(\alpha X_1, \eta I, \rho_1) - \phi(\alpha X_0, \eta I, \rho_0)}{F(-\eta I)}\right] \tag{5}$$

among them, N_1 with N_0 the number of apple growers representing both CAB and non-CAB farmers; $\Pr(Y_1 = 1 \mid I = 1, X = x)$ with $\Pr(Y_0 = 1 \mid I = 1, X = x)$ predicts the probability of adoption of IPM technology in farms with non-CAB and CAB farmers, and $\Pr(Y_1 = 1 \mid I = 0, X = x)$ with $\Pr(Y_0 = 1 \mid I = 0, X = x)$ predicts the probability of adoption of IPM technology in the counterfactual situation of two groups of farmers; ϕ is a cumulative binary normal distribution function; F is the cumulative normal distribution function.

3.4 Model (II): binary probit grouping regression model

In this section, after analyzing the relationship between farmers' CAB and SPB, we further explored the degree of rural employees' occupation and the impact of social networks on farmers' SPB. The IPM technology is a typical two-category variable, the binary probit group regression model, in which we use to analyze the correlation between variables and introduce the degree of CAB of farmers (non-agricultural income/total income) and interactions with social networks to further explore the regulatory mechanisms of social networks (Wang et al., 2018). The models related to the degree of rural CAB and the impact of social networks on farmers' SPB are as follows:

$$\begin{aligned} T_i^* &= \alpha_0 + \alpha_1 X_i + \varepsilon_i \\ T_i^* &= \alpha_0 + \alpha_1 X_i + \alpha_2 CBA_{ik} + \varepsilon_i \\ T_i^* &= \alpha_0 + \alpha_1 X_i + \alpha_2 CBA_{ik} + \alpha_3 SN_{it} \\ &\quad + \alpha_4 SN_{ip} + \alpha_5 SN_{im} + \varepsilon_i \\ T_i^* &= \alpha_0 + \alpha_1 X_i + \alpha_2 CBA_{ik} + \alpha_3 SN_{it} + \alpha_4 SN_{ip} \\ &\quad + \alpha_5 SN_{im} + \alpha \sum CBA_{ik} * SN_{in}(n = t, m, p) + \varepsilon_i \end{aligned} \tag{6}$$

$$T_{\mathrm{i}} = \begin{cases} 1\ if\ T_{\mathrm{i}}^* > 0 \\ 0\ if\ T_i^* \le 0 \end{cases} \tag{7}$$

In Eq. 6, T_i^* represents the choice of implementing of IPM; vector X_i represents the relevant control variables that influence the decision-making of farmers SPB, including the individual characteristics, cognitive characteristics, family characteristics and environmental characteristics of the farmers; CBA_{ik} represents the degree of concurrent agricultural business of a farmer; SN_{it} represent clan social network of farmers; SN_{ip} represent production social network of farmers; SN_{im} represents market social network of farmers; $\sum CBA_{ik}{}^*SN_{in}$ represents an interaction between the type of social network of the farmer and the type of the farmer's CAB; α_i represents parameters to be evaluated; ε_i is random error term; T_{i} indicates the actual adoption results of the farmers.

4 Results

The relationship between farmers' CAB and social networks on apple farmers' SPB was systematically evaluated employing Stata15.0 software, ArcGIS, and Excel throughout the manuscript. The regression results are shown in Tables 2, 3.

Understanding farmers' social networks plays a role in their decision-making. Social networks are included in the farmer's decision-making equation, and the influence of social networks on the SPB of farmers was examined. According to the scores and its contribution rates of each factor, the equation of social network indicators is given:

$SN = (20.49 \times SN_m + 19.45 \times SN_p + 16.21 \times SN_t)/56.15$ ρ_0 Significantly confirms that the selectivity bias is caused by unobservable variables. Therefore, solving the problem of selectivity bias and unobservable variables is the premise of the consistency and unbiased estimation of the influence of farmers' CAB on SPB. Models I and II, which exhibit correlation coefficient between the error equations of the selection equation and the result equation of the non-CAB farmers, indicates the existence of ρ_0 positive selectivity bias, demonstrating that farmers with a lower probability of SPB are more likely to work for CAB. In Table 3, the correlation coefficient was combined with a significant (LR) Likelihood Ratio test to reject the null hypothesis that the farmers' CAB selection equation is not related to the farmers' SPB result equation. This shows that the ESP model is more accurate than the general Logit and Probit model estimates.

4.1 Switch model: concurrent agricultural business (CAB)

The results obtained from Model I.a and Model I.b provide valuable insights into the relationship between household age and farmers' CAB (Table 2). Both models demonstrate a negative correlation, indicating that as individuals grow older within a household, they tend to exhibit less inclination towards engaging

TABLE 3 Binary probit grouping regression model.

Main independent variable	Model II.a	Model II.b	Model II.c	Model II.d
	Coefficient	Coefficient	Coefficient	Coefficient
Farmers CAB level		−0.0301 (0.49)**	−0.0216 (0.49)*	−0.0204 (0.04)*
Clan social network			0.0109 (0.05)	0.0080 (0.09)
Production social network			0.0952 (0.05)*	0.1481 (0.09)*
Market social network			0.1243 (0.05)**	0.1883 (0.09)**
Interaction effect				
Farmers CAB level × Clan social network				0.0132 (0.03)
Farmers CAB level × Production social network				0.1658*
Farmers CAB level × Market social network				0.4963 (0.05)**
Control variable				
Age	−0.0081 (0.00)	−0.0086 (0.00)	−0.0084 (0.00)	−0.0081 (0.00)
Education level	0.1445 (0.07)**	0.1238 (0.07)**	0.1270 (0.07)**	0.1260 (0.06)*
Risk preference	0.1648 (0.06)**	0.1625 (0.64)**	0.1484 (0.06)**	0.1655 (0.05)
Cognitive level				
Pesticide residues are harmful to health	−0.0293 (0.05)	−0.0388 (0.05)	−0.0329 (0.05)	−0.0203 (0.05)
Spraying pesticides pollutes the environment	0.00878 (0.04)	0.0041 (0.04)	0.0066 (0.04)	0.0009 (0.04)
Spraying pesticides affects human health	0.0632 (0.05)	0.0571 (0.05)	0.0672 (0.05)	0.0717 (0.06)
Family farming labor	−0.0047 (0.07)	−0.099 (0.07)	0.0155 (0.07)	0.0098 (0.07)
Planting scale	0.0261 (0.01)**	0.0252 (0.01)**	0.0236 (0.01)**	0.0329 (0.03)**
Degree of land fragmentation	0.0248 (0.04)	0.0341 (0.04)	0.0303 (0.04)	0.0398 (0.04)
Township distance	0.0079 (0.00)	0.0068 (0.00)	0.0061 (0.00)	0.0052 (0.00)
Road condition	−0.6702 (0.10)*	−0.1850 (0.10)*	−0.1654 (0.10)	−0.1795 (0.11)
Log likelihood	−364.76685	−363.3521	−362.4910	−361.0260
Prob> χ	0	0	0	0
Pseudo R^2	0.0508	0.0574	0.0666	0.0804
ΔR^2		0.0066	0.0092	0.0138

Note: *, **, *** indicates that the significance test is passed at the level of 10%, 5%, and 1%, respectively.

in CAB. This suggests that younger farmers may be more proactive in participating in cooperative activities compared to their older counterparts.

Furthermore, the study identifies several factors that positively influence farmers' CAB. Education level, risk appetite, and awareness of safety in production all contribute to the likelihood of farmers engaging in CAB. Notably, the education level, risk preference, and understanding of the environmental impact of pesticide use are statistically significant at a 5% level of significance. This implies that the number of years of education completed by farmers plays a role in shaping their attitudes towards CAB behavior. Farmers with higher levels of education are more likely to embrace CAB as they perceive it as a means to increase their income.

CAB is considered a routine activity among farmers, and it is particularly prevalent among individuals with a strong preference for cooperative actions. This finding suggests that farmers who possess a greater inclination towards engaging in cooperative behaviors are more likely to participate in CAB.

Additionally, the switching model analysis reveals interesting insights. In Model I.a, the presence of social networks has a significant positive impact on farmers' CAB behavior, with a confidence level of 5%. Conversely, in Model I.b, the clan social network exhibits the most substantial positive influence on farmers' SPB, as indicated by a coefficient of 0.567. This suggests that farmers who are part of a clan social network are more likely to engage in SPB. Moreover, both the production social network (coefficient of 0.302) and the market social network (coefficient of 0.415) significantly contribute to farmers' SPB.

4.2 Outcome model: farmers' safe production behavior

The study finds that social networks have a positive influence on the SPB of both CAB and non-CAB farmers. In Model 1.a, the correlation coefficients indicate that there is a moderate positive relationship between social networks and SPB for both groups of farmers. The coefficient of 0.318 suggests that there is a significant association between social networks and SPB among CAB farmers, while the coefficient of 0.567 indicates a stronger correlation among non-CAB farmers. This implies that social networks play a more prominent role in influencing SPB among non-CAB farmers.

The stronger impact of social networks on non-CAB farmers may be attributed to the fact that agricultural income serves as their

TABLE 4 Estimated results of the Switch model and Outcome model.

Variable	Switch model Model I.a	Outcome model I.a		Switch model Model I.b	Outcome model I.b	
		CAB	Non-CAB		CAB	Non-CAB
Age	−0.252***	−0.01**	−0.022***	−0.244***	−0.013*	−0.021***
Educational level	0.350***	0.267***	0.220***	0.396***	0.242***	0.220***
Risk type	0.199***	0.266***	0.234***	0.298***	0.035***	0.205***
Pesticide residues are harmful to health	0.080	0.092	0.028	0.091	0.098	0.039
Spraying pesticides pollutes the environment	0.093**	0.063	0.046	0.122*	0.017*	0.471
Spraying pesticides affects people's health	0.030	0.004	0.008	0.243	0.009	0.009
Social network*	0.560**	0.318**	0.567***			
Clan social network				0.567**	0.028	0.012**
Production social network				0.302**	0.09*	0.132**
Market social network				0.415***	0.168*	0.301***
Family farming labor		−0.080	0.072		−0.091	0.078
Planting scale		0.022*	0.009		0.034*	0.009
Degree of land fragmentation		0.048	0.011		0.053	0.014
Township distance		0.004	0.002		0.006	0.001
Road condition		−0.131	−0.151*		−1.521	−0.154
ρ_1		0.750			0.610	
ρ_0			0.930**			0.716**
Log Likelihood	−675.41068			−676.82486		
LR test of indep.eqns.(rho1 = rho0 = 0)	chi2 (2) = 3.03			chi2 (2) = 5.74		
	Prob > chi2 = 0.0028			Prob > chi2 = 0.0496		
Number of samples	585			585		

primary source of livelihood. As a result, these farmers have developed well-established social networks that contribute to the adoption and implementation of sustainable production practices. On the other hand, CAB farmers, who operate under a contractual agreement, may have limited control over their production decisions and may face more constraints in accessing and utilizing social networks.

Model I.b further explores the influence of social networks on farmers' SPB and suggests that social networks can help mitigate the negative impact on SPB. This implies that social networks can act as a mechanism for farmers to overcome barriers and challenges in adopting sustainable practices, thereby improving their SPB.

To obtain more reliable estimates of the impact of CAB on farmers' SPB, the study addresses the issue of selectivity bias by excluding observable and unobservable variables that may have influenced the selection of CAB. By doing so, the study provides on the Treated ATT and on the Untreated (ATU) estimates that better reflect the true impact (Table 3).

The results in Model I.a show that the implementation of CAB reduced the likelihood of CAB farmers adopting SPB techniques by 31.0%. Similarly, Model I.b indicates a reduction of 38% in the probability of CAB farmers using SPB methods. This suggests that the presence of CAB has a significant negative effect on the adoption of sustainable practices among farmers. However, Model Ib demonstrates a relatively lower reduction in the probability, indicating that the influence of CAB on reducing SPB adoption is slightly less pronounced.

4.3 Binary probit grouping regression model results

According to the estimated results, the probability ratio function and the goodness of fit estimation indicate that the model has a strong overall fitting effect, as shown in Table 4. Upon analyzing the changes, it becomes evident that the model has improved both the goodness of fit and the interpretative level. The coefficient of the farmers' CAB level was found to be significantly negative. This means that an increase in the use of CAB by farmers has a detrimental impact on their SPB, and the coefficient suggests that this effect may be associated with the degree of CAB usage. Model II.b-d reveals that the influence of the clan social network on SPB is positive but not statistically significant. However, it was observed that the impact of the production social network and market social network on SPB was significant and market-oriented.

In the binary probit grouping regression model, several variables were added in sequence, including control variables, the farmers' CAB variable, the social network variable, the interaction of the social network variables, and the farmers' CAB degree variable. In order to address collinearity issues, an interactive term between the social network variables and the farmers' CAB variable was constructed. The social network variables and the farmers' CAB variables were standardized separately. The coefficient of interaction between the clan social network and the degree of farmers' CAB was positive (0.0132), but it was not statistically significant. This indicates that the clan social network has a negative influence on the farmers' SPB. However, by decelerating the regulation, the negative impact of CAB can be mitigated, although this effect is not immediately apparent. Similarly, the interaction term of farmers' CAB and production social network has a positive influence on the farmers' SPB (0.1658*) at a 10% significant level. The interaction term of farmers' CAB and market social network also has a positive influence on the farmers' SPB (0.4963**) at a 5% significant level. These findings suggest that the social networks in these two dimensions are decreasing and negatively affecting farmers' SPB. Furthermore, it was observed that the type of regulation can not only reduce the negative impact of farmers' CAB but also the impact of the market social network, and this effect is more pronounced.

Among the control variables, individual characteristics of the farmers such as education level and risk preference of the head of the household have a positive impact on the farmers' SPB at 10% and 5% levels of significance, respectively. This implies that higher education levels increase the probability of implementing SPB. For example, for each year of education attained by the head of the household, the probability of implementing SPB increases by 11.92%. Similarly, risk-neutral farmers have a 14.37% higher probability of implementing SPB compared to risk-averse farmers. The age of the head of the household was found to be non-significant, possibly because the average age of the sample farmers was 52 years old, and the majority of them (73.5%) were older than 45 years old. The farmers' cognitive variables were also found to be insignificant, which may be due to a gap between farmers' perceptions and their actual behaviors, as well as the limited conversion of farmers' awareness of environmental health into the adoption of integrated pest management (IPM) technology.

Household characteristics and the planting scale variables were found to be significant at a 5% level of significance, indicating that larger-scale farmers are more likely to implement SPB. This is because certain pest control methods, such as insect repellent lamps, insect boards, and insect sex hormones, can be quite expensive. Therefore, compared to small-scale apple farmers, larger-scale farmers have lower marginal costs and a higher probability of adopting IPM technology. On the other hand, the degree of fragmentation of land and the number of family laborers has no significant effect on the dependent variable. The coefficient of family agricultural labor is negative, which contradicts empirical evidence. One possible explanation is that more household agricultural labor may result in an increased family burden, causing them to perceive IPM technology as highly risky. Therefore, families with more family farming labor may be more inclined to adopt new technologies with higher risks. The coefficient of land fragmentation is positive, indicating that the more plots of land farmers have, the more likely they are to adopt IPM technology. This finding is contrary to empirical conclusions, and one possible explanation is that the higher the level of fragmentation, the lower the loss of farmers. Environmental characteristics and road condition are significant at the 10% level, while the distance to the township is non-significant. This suggests that the distance to the township may not be an important factor affecting farmers' adoption of IPM technology.

5 Discussion

First, social networks can promote farmers' SPB (Stave et al., 2007), and also play a positive role in promoting the SPB of both the CAB farmer and the non-CAB farmer. However, the current survey showed that social networks significantly affect non-CAB farmers. Agriculture is the only source of income for non-CAB farmers, and their complex social network is always focused on agricultural production. Their dissemination of information is related to the production of crops, thus promoting their SPB (Jarosz, 2000).

Second, the social networks of farmers have a positive impact on the SPB of both CAB and non-CAB farmers. Based on the research, only the production social network and the market social network have a significant impact on the SPB of CAB farmers, whereas the clan social network has a non-significant impact. One possible reason might be that farmers in rural areas tend to be deprived of information asymmetry and rely more on their personal relationships when acquiring technical information. However, studies have shown that with the social transformation and economic development, the rural society has also undergone major changes, gradually transitioning to civil society, and the role of social networks based on kinship has also weakened (Yang Rudai and Zhu, 2011). Although clan social network can provide heterogeneous information and resources for farmers and enrich their knowledge, it is also more difficult to obtain substantial help, thus having no significant impact on the application of safe production (Peng and Yang, 2021). These results are consistent with Zhu and Liu (Zhu and Liu, 2018). The clan social network plays an important role in the influence of rural CAB behavior. It could be because of the social network constructed by the farmers. The clan social network can transmit the CAB information that is different from the other two dimensions. Further, when a rural household in a certain area has CAB behavior, it will accept the condition that the geographical relationship will be used as a link to drive the CAB behavior of the farmers nearby, "pro-band, neighbors, and friends" (Junqi, 2010).

However, research indicates that with social transformation and economic development, rural society has also experienced substantial improvements, gradually transitioning to civil society, and the function of kinship-based social networks has diminished (Yang Rudai and Zhu, 2011). The current local society is still a face-to-face community organization with strong homogeneity in China. When challenged by the information impact brought by agricultural "new technology" or "new concept", this type of network relationship homogeneity could weaken the information acquisition and adoption, and the homogenous relationship network may not be effective for farmers (Matuschke and Qaim, 2009; Ma Xingdong and Huo, 2018). Regarding the strengthening of farmers' SPB, the production social network is a key aspect of the farmers' social networks. The reason for this is that farmers' decisions to use chemical fertilizers and pesticides are heavily influenced by the agricultural material merchants who act as an intermediary between the suppliers and demanders of agricultural resources. In the process of interaction between sellers and farmers, each participant could establish various formal and informal relationships. This includes exchanging information on agricultural materials, the choice of pesticides and fertilizers, resolving conflicts, and visiting experimental fields. Additionally, a multi-level, complex social network, namely, the rural agricultural social network, should be established (Zhang, 2014). Furthermore, this kind of interaction will improve the level of trust between farmers and agricultural product sellers. Farmers are more likely to learn more about safe production technology from agricultural salespersons and are more likely to obtain higher quality agricultural materials, which reduce their safe production costs. Therefore, the production social network could have a positive influence on farmers' safe production behavior (Conley and Christopher, 2001).

The impact of the market social network "rational small farmers" aims to maximize profits (Schultz, 1964). Therefore, farmers may take the initiative to pay attention to the price and information of agricultural products in the market, as well as consumers' attitudes towards the consumption of agricultural products, which could directly affect the production decisions of the farmers. In a relatively closed social network environment in rural areas, it is only the purchaser that can directly connect to the agricultural market and obtain agricultural information. Therefore, the social network formed by farmers and purchasers can often provide farmers with more agricultural market price information, mainstream agricultural production technology information in the market, and consumer attitudes. Therefore, the market social network could influence the mindset of farmers' SPB in a positive manner. These results confirmed the findings of Isaac, Erickson (Isaac et al., 2007), who reported that farmers' social networks help to promote farmers' knowledge and decision-making relying on the information gained by local sources.

Third, production social network and market-based social network can alleviate the negative impact of farmers' CAB on their SPB. The coefficient of interaction between the clan social network and the farmer's degree of CAB is positive (0.0132), but not significant. This suggests that the clan social network plays a slowing adjustment role in the negative impact of farmers' CAB on the SPB of farmers. The reason is that the CAB is the product of the particularity (periodicity and seasonality) of agricultural production under specific conditions (Ofolsha et al., 2022). The role can not only reduce the negative impact of the farmers' CAB, but the mitigation effect is also not obvious (Conley and Christopher, 2001). Several studies suggested that farmers social networks based on kinship and friends have strong and significant impact upon the farmers decision making and technology adoption (Gyau et al., 2016; Tesfaye et al., 2020). While in our study we found it non-significant because there are also several studies who found that this impact also depends upon the interaction level with kins and friends as well depends upon the size of the social network. If the social network of a farmer based on kinship and friends is larger can have more significant impact upon the farmers choices of adopting new technologies and decision making (Negi et al., 2020; Ofolsha et al., 2022). The interaction between farmers' CAB and production social network and the interaction between farmers' CAB and market social network are significantly positive. Acquiring new information from a number of sources suggests that a wide social network is likely to impact exposure to the characteristics of new agricultural techniques and hence improve the possibility that smallholder farmers will decide to participate in collective action. Additionally, knowledge obtained from market and extension agents is considered as a strong network link when it comes to collective action, increasing the chance of involvement decisions in sustainable production (Mekonnen et al., 2018; Gupta et al., 2020).

As the number of farmers' CAB increases and the comparative advantage of agriculture declines, the farmer's CAB behavior is due to farmers' using a non-agricultural rational choice of income and agricultural income (Shang Xin, 2010). Driven by the motive of maximizing profits, rational individual farmers can invest their own capital elements (including labor, land, and other elements) in areas with greater income, while farmers' CAB behavior is the optimal allocation of farmers' labor resources within the family. With the decision of farmers to make a choice of CAB behavior, it means that farmers may choose to "ignore" the agricultural production field with a relatively small income, which leads to their lack of attention to SPB in the production process. However, when a farmer's CAB behavior occurs, his social networks can be expanded. As social networks grow, the above-mentioned impact mechanism for social networks should also grow to help farmers with their SPB.

6 Conclusion

Visualizing farmers' social networks illuminates some of the supports and constraints that directly impact on the farmers' SPB, both the CAB and non-CAB farmers. Their correlation coefficients are significant. The impact of CAB farmers is more obvious. For non-CAB farmers, their agricultural income is their only source of income. Therefore, the multifaceted social network formed is focusing on agricultural production, and its members' information sharing and dissemination are related to agricultural production, thereby promoting their SPB.

Second, according to the dimensions of the social network, the clan social network, production social network, and market social network have a positive impact on the SPB of CAB and non-CAB farmers, but only production and market social networks promote the SPB of CAB farmers and are significant, while the clan social network only has a small impact. The production and sales of agricultural products are the most important links in their industrial chain. Hence, these two networks affect farmers' SPB.

Third, production social network and market social network can alleviate the negative impact of farmers' CAB on their SPB. The clan social network can reduce the negative impact brought by the farmers' CAB, but this slowing effect is not obvious. The interaction coefficients of production and market social networks and the degree of farmers' CAB are significantly positive, indicating that the social networks of these two dimensions play a mitigation adjustment role in the negative impact of the farmers' CAB on the SPB of farmers. Therefore, they can reduce the negative impact brought by the farmers' CAB, and the impact of the market social network is even more pronounced.

Based on our results, we recommend that the relationship between farmer yield and pesticide prices along with quality and quantity consumption effects can be measured upon farmers' safe production and the concluded social networks can be utilized for further research.

6.1 Policy implications

The study's conclusions have significant policy ramifications for encouraging farmers in Shaanxi province to use sustainable production methods for apples, and in order to solve the problem of agricultural product safety in the apple industry under the background of an increasing trend of farmers' CAB, we propose the following suggestions:

Based on the research conclusion of this study, first, in the process of helping farmers to carry out safe production, the government needs to take full account of the reality of local farmers' CAB and promote some small-scale innovative agricultural technology training by inviting experts from some research institutes to give lectures in the local area about safe production. This approach is expected to change farmer's attitude toward apple production and enhance awareness of safe production practices.

Second, supporting the building of farmer-to-farmer extension programs or other forms of social capital among farmers, such as farmers' cooperatives, is one possible policy option. These policies could be implemented by providing financial and technical support to farmer's organizations and by creating incentives for farmers to participate in social as well as farmer to farmer extension program.

Third, another policy consequence is to use social networks to encourage the adoption of sustainable apple producing methods. This might be accomplished by identifying important players in the social networks of farmers and giving them the knowledge and tools, they need to encourage other farmers to adopt sustainable practices. Such regulations might be put into effect via specialized outreach and education initiatives that are catered to the individual requirements of various farming communities.

Fourth, because farmers can have a more comprehensive and scientific understanding of SPB through exchanges with different types of subjects among social network members, the government should actively promote exchanges between farmers and the outside world. For example, by providing a platform for farmers to communicate with outside agricultural distributors, farmers will have more opportunities to choose agricultural materials at appropriate prices and guarantee quality, thus reducing the cost of safe production to a certain extent and promoting the SPB of farmers.

Overall, these regulations are anticipated to have a number of results, including an increase in the use of environmentally and economically sustainable apple production methods, better apple production sustainability, and higher social capital among farmers. These measures might help create a more resilient and sustainable agricultural system in the Shaanxi province by encouraging sustainable farming practices and fostering social networks among farmers.

6.2 Research limitations

The study only chooses one technology for sustainable apple production, i.e., Integrated Pest Management while the usage of organic and inorganic fertilizers was neglected. Furthermore, there are 28 major apple producing counties in Shaanxi province while the study was conducted only in 8 counties.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

Data Curation and methodology were performed by ZK and JZ. JZ, UA, SK, and AK did formal analysis and software. ZK wrote the original draft. Review and editing were performed by ZK and MK. Supervision by LT. All authors contributed to the article and approved the submitted version.

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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.

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2023.1177028/full#supplementary-material

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