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Effects of Continuous Adoption of Artificial Intelligence Technology on the Behavior of Holders' Farmland Quality Protection: The Role of Social Norms and Green Cognition

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Abstract: The continuous adoption of artificial intelligence technology (CAAIT) has fully demonstrated its transformative roles in various fields, and it has effectively improved the economic benefits of agriculture in practical applications. However, sustainable agricultural development can only be achieved if economic and environmental benefits are reconciled. Then, it is necessary to explore whether CAAIT can provide valuable environmental benefits. Therefore, this paper uses AMOS 22.0 and SPSS 25.0 software, a hierarchical regression model, and bootstrapping to analyze the survey data of 522 farmers and finds that: (1) CAAIT is positively correlated with the behavior of holders' farmland quality protection (BHFQP). (2) Social norms (SN) partially mediate the relationship between CAAIT and BHFQP. (3) Green cognition (GC) plays a negative intermediary role in the relationship between CAAIT and SN. (4) GC also moderates the mediating effect of SN in the relationship between CAAIT and BHFQP. This paper attempts to explore whether, how, and when CAAIT can affect BHFQP, providing new empirical research to improve holders' farmland quality protection behavior.

Keywords: artificial intelligence; farmland quality protection; social norms; green cognition

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1. Introduction

Throughout global economic practice, artificial intelligence technology, as a core driving force for a new wave of the industrial revolution, has deeply penetrated all walks of life and unleashed tremendous innovative potential. It was thoroughly applied to the agricultural sector, which effectively improved agricultural production efficiency and product quality and greatly reduced agricultural environmental pollution. Research has shown that the adoption of artificial intelligence technology has an impact on agriculture at the macro, meso, and micro levels [1]. Specifically, at the macro level, the adoption of artificial intelligence technology is conducive to the modernization of agriculture and the protection of the agricultural environment. At the meso level, the adoption of artificial intelligence technology contributes to industries such as agricultural finance, agricultural tourism, agricultural e-commerce, etc. At the microlevel, it also has a positive effect on agricultural enterprises and farmers. In terms of the impact of the continuous adoption of artificial intelligence technology (CAAIT) on holders, relevant discussions have mainly focused on increasing income, disseminating knowledge, and promoting technology [2–4]. Based on this, research on the effect of the adoption of artificial intelligence technology on agriculture covers a wide range of levels, but all levels are in the initial stage, and research results need to be enriched. Compared to the macro and meso levels, correlational research on the microlevel requires more attention from academic circles. Furthermore, the only way artificial intelligence technology can truly play a significant role in the agricultural field is if it is consistently adopted. Additionally, CAAIT is a research topic that needs further exploration of artificial intelligence technology adoption, and its related results are mostly found in the field of behavioral science. Therefore, it remains to be discussed whether CAAIT will have an impact on holders' behavior. This issue cries out for an answer.

As the most important factor in agricultural production, farmland is highly valued for its quality preservation around the world. This is especially important for countries with high population density and limited land resources, as the formulation and strict implementation of farmland quality protection plans are crucial [5]. In addition, as holders are direct participants in agricultural production and the direct users of farmland, their decisions on whether to adopt protective farming practices, how to conduct soil fertilization, the degree of agricultural waste resources, and so on will all impact farmland quality protection outcomes [6,7]. This indicates that the important role of farmers in farmland quality protection cannot be ignored. Previous studies have found that the factors affecting holders' behavior towards farmland quality protection mainly include human capital (age, education level, family labor force, agricultural income, etc.), land capital (farmland management scale, terrain and plot characteristics, soil conditions, etc.), intrinsic psychological factors (technology risk perception, ecological environment perception, policy perception, etc.), and external environmental factors (land system, agricultural technology promotion, policy subsidies, social network relationships, etc.). In the research on the impact of external environmental factors on the behavior of holders' farmland quality protection (BHFQP), it has been found that the promotion of new agricultural technologies can promote the efficient utilization of agricultural resources, improve the ecological environment, and contribute to farmland quality protection [8–10]. As holders are the end-users of new agricultural technologies, their acceptance and adoption of these technologies will directly affect farmland quality protection. Therefore, it is urgent to answer the question of whether CAAIT has the same effect as other existing agricultural technologies and whether it can affect holders' behavior toward farmland quality protection.

Accordingly, this paper attempts to investigate whether (directing effects), how (mediating effects), and when (moderating effects) CAAIT can promote BHFQP. Previous studies have shown that holders live in a social environment, and their decision-making processes are inevitably influenced by social relationships. Social norms (SN) are perceived rules and standards within a group that members adhere to as behavioral norms under shared beliefs. Communication and collaboration between holders during production will inevitably lead to the influence of others' opinions within the village [11]. SN has been extensively discussed in research on holders' behavior, and the continuous adoption of artificial intelligence technologies and the behaviors of holders' farmland quality protection also fall under the topic of research on holders' behavior. However, existing literature has not explored this issue. In addition, cognition is the product of an individual's internal psychological activity, which involves the storage, encoding, reconstruction, concept formation, and issue of judgment of information and emotions during activities. Previous studies have shown that green cognition (GC) is an individual's perception of issues related to the production environment, which plays an important role in the adoption of other technologies [12]. Hence, GC is also likely to have a corresponding function in research on CAAIT, but existing literature has not provided an answer.

To address these gaps, this paper attempts to investigate the following questions: Can CAAIT improve BHFQP? How can social norms mediate the relationship between CAAIT and BHFQP? How can GC moderate the relationship between CAAIT and social norms?

In this study, research data from 522 holders were analyzed using AMOS 22.0 and SPSS 25.0. Based on our findings, this paper contributes to the existing literature in the following aspects:

It expands the research field of CAAIT and the study of consequence variables; demonstrates that the influencing factors of holders' farmland quality protection behavior have both economic and non-economic elements; and unveils the black box and boundary conditions of the influence of CAAIT on BHFQP. Despite the contributions, this paper has its limitations. Due to the lack of a recognized measurement tool for CAAIT, we adopted the measurement method used in other technology adoption studies in the existing literature. Additionally, the study subjects were all from China and cannot fully represent research subjects of other nationalities.

The structure of this paper is as follows: First, a literature review is conducted, and hypotheses are proposed. Then, the research design is explained in terms of sample selection and study procedures. Next, the research data is analyzed, and the corresponding results are reported. Finally, conclusions, contributions, and future research directions are presented.

2. Literature Review and Hypothesis Development

2.1. Literature Review

The adoption of artificial intelligence technology originates from research on technology adoption, which can be analyzed at both the individual and organizational levels. At the individual level, technology adoption refers to the decision-making process by which individuals judge and finally adopt new technology based on their existing cognition [13]. At the organizational level, it refers to the process by which organizations recognize the advantages of new technology and acquire resources to support its adoption [14]. Similarly, the adoption of artificial intelligence technology is discussed from both individual and organizational perspectives. From the individual perspective, the adoption of artificial intelligence technology is further differentiated into initial and continuous adoption [15]. Reviewing the existing literature, a large body of literature has focused on artificial intelligence technology adoption, including organizational adoption intention, organizational actual usage, individual adoption intention, and individual adoption behavior [16,17]. Only a limited amount of research has investigated CAAIT, mainly from the perspective of individual continuous adoption intention. Hence, it is necessary to discuss CAAIT to enrich the research.

The academic community has conducted in-depth research on holders' farmland quality protection behavior, mainly analyzing the status and function of holders in land quality protection, holders' willingness to protect the land quality, the influencing factors of BHFQP, and the performance of their land quality protection behavior [18]. Among them, the influencing factors of BHFQP have received much attention. Research has found that economic factors, individual characteristics, family characteristics, natural attributes of farmland, and institutional and environmental factors can all affect BHFQP [19]. Some scholars believe that holders are rational economic men, and incentives based on economic aspects are the only way to drive them to practice land quality protection behavior. However, some scholars believe that framers' farmland quality protection behavior is due to innate motivation rather than economic factors [20]. Therefore, the factors that influence BHFQP should be complex rather than a single economic or non-economic factor. Therefore, it is essential to analyze the influencing factors of holders' farmland quality protection behavior from multiple perspectives.

The origin of SN can be traced back to the field of sociology, which later expanded to many other fields such as philosophy, law, psychology, economics, etc. Research on SN covers a wide range of topics, mainly focusing on general SN related to the research objects. Some scholars have also paid attention to specific SNs, such as ethnic SNs, regional SNs, and so on [21,22]. In addition, the discussion on SN mainly revolves around their influence on individual decision-making and behavior [23], and some scholars have also analyzed them as intermediate or moderating variables. This indicates that it is feasible to incorporate SN into research models related to individual behavioral variables. Moreover, existing research has demonstrated the correlation between SN and BHFQP. As a deeply ingrained rule and standard, the role of SN needs to be examined in the research topic of CAAIT with transformative functions.

Reviewing existing studies, GC originates from research on individual cognition and refers to an individual's understanding and perception of environmental resources. However, due to different research purposes and perspectives, scholars have not reached a consensus on the definition of GC, and existing research on GC is not very in depth [24]. Most existing literature discusses the GC of different subjects, such as corporate GC, board GC, manager GC, farmer GC, etc. Holders' GC is an extension of holders' cognition, and some scholars have analyzed the dimensions of holders' GC, but more scholars have analyzed its impact on holders' behavior. For example, GC can affect the adoption of green technologies. Therefore, does GC still have a corresponding function in the models of CAAIT research? This remains to be answered.

2.2. Hypothesis Development

2.2.1. Continuous Adoption of Artificial Intelligence Technology and Behavior of Holders' Farmland Quality Protection

Firstly, maximizing profits is the fundamental driving force for holders to engage in agricultural production, and expected returns have an important influence on their production decision-making behavior [25]. CAAIT can effectively increase the expected yield of agricultural products, and holders will actively engage in farmland quality protection to achieve the effect of yield doubling [26]. Therefore, holders' farmland quality protection behavior is the result of their dynamic comparison of costs and benefits after CAAIT. Furthermore, with the upgrading of the consumption structure, the channels for high-quality and high-priced agricultural products in the market are increasing, and the demand for high-quality agricultural products by consumers is continuously increasing [27]. CAAIT will improve holders' expectations for the quality of agricultural products, which is conducive to their pursuit of long-term profit maximization, and will further stimulate holders to actively engage in the behavior of farmland quality protection.

Secondly, the perception of benefits has a significant impact on holders' economic behavior, and the usefulness of CAAIT will lead to the following perceived benefits for holders: CAAIT may improve soil fertility, increase crop yield, and increase planting income [28]; CAAIT may also reduce soil erosion and pollution, effectively improving the production and living environment of holders and ensuring the safety of agricultural products [29]. These positive results of CAAIT are likely to form a perception of benefits in holders' minds. Holders will compare the perceived benefits with their expectations and evaluate the value of CAAIT [30]. As a new and effective technology, the perception of the benefits of artificial intelligence technology generally shows a positive trend for holders. Ultimately, these will lead to positive economic behavior by holders, which may encourage them to consciously engage in the behavior of farmland quality protection.

Thirdly, there exists a special emotional and cognitive connection between global holders and their land, which encompasses their values, property rights, dependencies, and emotional attachment. CAAIT will enhance holders' ecological and economic cognition of their land. For holders, CAAIT will improve land use efficiency and output effectiveness, leading to an increase in property income and strengthening holders' cognition of the land economy [31]. As the farmland system regulates the atmosphere, conserves water sources, maintains soil, and purifies the environment, holders' environmental cognition is becoming clearer. CAAIT can effectively reduce pollution, further enhancing landowners' ecological cognition of their land. CAAIT can influence the land use patterns and behaviors of holders, regardless of whether they have an economic or land interest, and thus affect the protection of farmland quality. Based on this, the following hypothesis is proposed:

Hypothesis 1. *CAAIT has a positive effect on BHFQP.*

2.2.2. Continuous Adoption of Artificial Intelligence Technology and Social Norms

Agriculture has become an important application field for artificial intelligence technology, and more and more framers are adopting artificial intelligence technology to achieve intelligent transformation. In addition, with the improvement of rural information infrastructure such as network broadband, and the widespread use of smartphones based on the development of the Internet, the continuous adoption and effectiveness of artificial intelligence technology have been widely publicized in rural society. Moreover, the artificial intelligence technology used in agricultural production simulates the human intellectual process, enabling computer systems to automatically learn from experience and perform tasks that resemble holders' behavior, which not only improves efficiency but also effectively improves farmland quality, and these positive effects will influence the holders' SN through social media [32]. In this study, SN refers to the norms perceived by holders related to the behavior of farmland quality protection. If important holders in the social network hold positive opinions and attitudes towards CAAIT for farmland quality protection, and recommend other holders use artificial intelligence technology, it will contribute to the formation of a new SN [33]. Specifically, before taking a specific action, holders perceive the common understanding of the surrounding group, and if this group is important to them, especially when the individual does not have enough knowledge to make wise decisions, they are more likely to adopt widely existing social group culture and values, which is more likely to form new group norms [34,35]. In addition, CAAIT involves the perception of the usefulness and ease of use of artificial intelligence technology, which can affect holders' individual attitudes and behavioral intentions. Perceived usefulness refers to holders' belief that CAAIT can reduce their effort and will influence most of the holder groups, making them hold the concept of using artificial intelligence technology for farmland quality protection [36–38]. Perceived ease of use refers to holders' belief that CAAIT can significantly improve their agricultural production performance, which will make most of the holder groups continue to adopt artificial intelligence technology and implement farmland quality protection behaviors. The former affects attitudes, and the latter affects behavior, both of which contribute to the formation of SN related to farmland quality protection. Based on this, the following hypothesis is proposed:

Hypothesis 2. *CAAIT has a positive impact on SN.*

2.2.3. Social Norms and Behavior of Holders' Farmland Quality Protection

SN primarily influences BHFQP through descriptive SN and injunctive SN [36,37]. Descriptive SN refers to the tendency for holders to unconsciously choose to do what most people do [38]. As "ethics-oriented behavior" holds an important position in rural society and is a connected and orderly social network, influential holders who occupy advantageous positions in structural holes in the rural social network will accelerate the spread of information related to farmland quality protection through their behaviors. This descriptive social norm improves the problem of insufficient external motivation for farmers to adopt the behaviors of farmland quality protection. Therefore, when the majority of relatives, friends, neighbors, and other adjacent holders around a holder have already adopted the behaviors of farmland quality protection, it will promote the adoption of farmland quality protection by the holder themselves. Specifically, when holders perceive that the descriptive social norm around them is strong, meaning that other holders in the production process have already adopted the behaviors of farmland quality protection, the holders themselves are likely to unconsciously adopt consistent farmland quality protection behaviors regardless of their attitudes towards farmland quality protection.

Injunctive SN responses to SN reflect the values of group members and emphasize "doing the right thing" [39,40]. It plays a role in external guidance and supervision of the decision-making of holders' production behavior [41] and also creates tangible or intangible pressure on holders to maintain consistency with the group [42]. Due to the long-term predictability and low selectivity of social interactions in rural society, individual holders are labeled negatively if they do not accept the behaviors of farmland quality protection [43], which may result in exclusion and punishment by other holders. Therefore, in this study, injunctive SN refers to the fact that relatives, friends, neighbors, and other adjacent holders believe that the behaviors of farmland quality protection should be adopted, which leads holders to also choose the behaviors of farmland quality protection. During the production process, when other holders around them believe that the behaviors of farmland quality protection should be adopted, holders may be concerned that not implementing such behaviors may affect others' perception of themselves, and even be subjected to unfriendly attitudes or other social sanctions. Holders will consciously or unconsciously change their intentions and behaviors based on the thoughts of those around them until they are consistent with the thoughts of those around them to obtain emotional satisfaction. Based on this, the following hypotheses are proposed:

Hypothesis 3. *SN has a positive effect on BHFQP.*

Hypothesis 4. *SN mediated the effect of CAAIT on BHFQP.*

2.2.4. The Moderated Mediating Effects of Green Cognition

The cognitive theory proposes that individuals make decisions based on cognitions generated by external stimuli, which drive the implementation of individual behavior [44]. Some scholars have applied cognitive theory to the study of green behavior among holders, suggesting that GC refers to the perception and scientific knowledge of resource and environmental issues formed by holders, as well as the psychological experiences when they undertake the obligation to conserve resources and protect the environment. It has been found that GC significantly affects holders' green behavior, as cognitive factors drive the development and implementation of green behavior. As a self-restraint on individual behavior [45], holders with strong GC are more inclined to take on the responsibility of environmental protection through leading by example and demonstration, promoting the coordination of economic and ecological benefits, and gaining self-satisfaction and social recognition [46]. Therefore, it can play a role in regulating the strength of the relationship between CAAIT and BHFQP. Specifically, when holders engage in agricultural production, they gather information from CAAIT and its related benefits, not only in the acquisition and delivery of information resources that are conducted by CAAIT, but also in the construction of environmental information cognition, the reidentification, understanding, and judgment of resource environments, land, and other information. Due to differences in resource endowments, socio-economic status, and information infrastructure, holders' GC exhibits heterogeneity. Holders' GC determines the strength of their green willingness, which affects their green behavior. As a result, the impact of CAAIT on the behavior of land quality protection will also differ due to GC. Based on this, the following hypothesis is proposed:

Hypothesis 5. *GC plays a negative moderating role between CAAIT and SN.*

In the above discussion, this study hypothesizes that SN mediated the positive relationship between CAAIT and holders' farmland quality protection behaviors; GC weakens the positive relationship between CAAIT and SN, and the higher the level of GC, the more it could reduce the impact of CAAIT on SN. Based on these hypotheses, it is further inferred that the higher the level of GC, the weaker the positive effect of CAAIT on BHFQP through SN. That is, the mediating effect of SN is moderated by GC as a moderated mediating effect. Based on this, the following hypothesis is proposed:

Hypothesis 6. *GC weakens the mediating effect of SN on the relationship between CAAIT and BHFQP.*

In summary, this study explores how CAAIT affects BHFQP through SN and the regulatory role of GC in this process. The model of this study is shown in Figure 1.

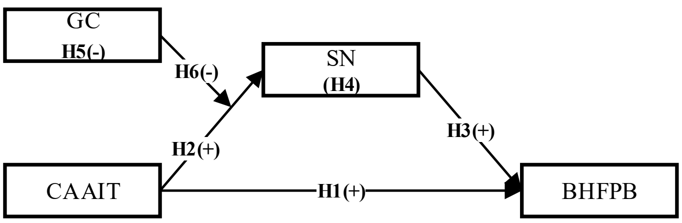

Figure 1. The hypothetical model.

3. Methods

In order to verify the research model, data were collected through a questionnaire survey. This paper first briefly describes the source of the questionnaire and the demographic characteristics of the respondents, and then expounds on the selection of the scale and the definition of variables. In this study, AMOS 22.0 was used for confirmatory factor analysis, and then statistical software, SPSS 25.0, was used for descriptive statistics, correlation analysis, and hierarchical regression. Finally, SPSS PROCESS 4.1 Model 7 is used to test the moderated mediation model.

3.1. Respondents and Procedures

The main purpose of this study is to explore the pre-influencing factors of BHFPB, and at the same time, this study draws attention to the significant influence and role of CAAIT on BHFPB. In addition, because this study involves BHFPB, in the selection of research objects, we chose farmers from different provinces to conduct microsurveys. The data in this article is derived from a survey of 34 investigators who conducted a micro-level investigation of rural households in 25 provinces in China, including Jilin, Anhui, Beijing, Fujian, Guangdong, Guangxi, Guizhou, Henan, Heilongjiang, Hubei, Jiangsu, Jiangxi, Liaoning, Ningxia, Qinghai, Shandong, Shanxi, Shaanxi, Shanghai, Sichuan, Tianjin, Tibet, Xinjiang, Zhejiang, and Chongqing. To avoid measurement bias caused by misunderstanding, the researchers first explained the meaning of concepts such as land quality protection to the respondents and collected data after ensuring that they fully understood. In addition, to ensure that the respondents were indeed rural households that continuously adopt artificial intelligence technologies, a screening question was set up to exclude those who did not meet the requirements. A total of 600 questionnaires were distributed, and after excluding questionnaires with missing information or logical contradictions, 522 valid questionnaires were collected, with a valid response rate of 87%. The main characteristics of the data are as follows: 222 males (42.5%) and 300 females (57.5%). In terms of age, the proportion of respondents aged 29 and below was the largest, with 261 (50%). Other specific demographic characteristics are shown in Table 1.

Table 1. Data characteristics.

		Number of Respondents	Percentage of Respondents
	Total Respondents	522	100
Gender	Male	222	42.5
	Female	300	57.5
Age	29 and below	261	50
	30–39	100	19.2
	40–49	109	20.9
	50–59	44	8.4
	60 and over	8	1.5
Education background	Did not go to school	13	2.5
	Primary school	31	5.9
	Junior high	112	21.5
	Senior high	105	20.1
	College degree or above	261	50
The number of house-holds engaged in agri-cultural labor	One labour forces	60	11.4
	Two labour forces	243	46
	Three labour forces	127	24.1

Table 1. *Cont.*

		Number of Respondents	Percentage of Respondents
The number of house-holds engaged in agri-cultural labor	Four labour forces	53	10
	Five and more	39	8.5
Household annual in-come	30,000 and below	208	39.8
	30,001–50,000	86	16.5
	50,001–100,000	147	28.2
	100,000 and over	81	15.5
The proportion of agri-cultural income	25% and below	88	16.9
	26–50%	186	35.6
	51–75%	103	19.7
	76% and over	145	27.8

3.2. Variable Selection

BHFQP. Improper use of agricultural production factors, especially pesticides and fertilizers, is the main cause of soil pollution in modern agriculture. It is also the reason why many agricultural documents in recent years have repeatedly proposed using organic fertilizers to replace chemical fertilizers and applying pesticides rationally. Therefore, this study focuses on the use of pesticides and fertilizers in BHFQP. Following the approach of previous studies [47], this study sets the use of pesticides as the use of highly toxic, moderately toxic, green pesticides, or no pesticides, assigned values of 1–4, respectively. The use of fertilizers is set as the complete use of chemical fertilizers, the primary use of chemical fertilizers, the mixed use of chemical and organic fertilizers, the primary use of organic fertilizers, or the complete use of organic fertilizers, assigned values of 1–5, respectively. The assigned values of pesticide and fertilizer use are summed up to constitute the holders' farmland quality protection behavior.

CAAIT. From the research on the adoption of artificial intelligence technology, it is found that researchers mostly follow the measurement methods that have been adopted by other technologies when measuring the willingness and behavior of artificial intelligence technology adoption. From the perspective of the frequency of use of the scale, when studying the continuous adoption of individual artificial intelligence technology, scholars often use the three-item scale developed by Bhattacherjee (2001) to measure the individual's continuous adoption intention [48]. Therefore, this study also uses the scale, and the typical questions include "I intend to continue using artificial intelligence technology in agricultural production rather than other methods or tools". All items were measured on a Likert 7-point scale (1 = very disagree; 2 = disagree; 3 = comparative disagreement; 4 = general; 5 = comparative consent; 6 = consent; 7 = very agree).

SN. At present, there are two ways of thinking about the measurement of rural social norms in academic circles. One is to divide social norms into imperative and descriptive social norms, and the second is based on the Chinese context, which is expressed as "what others think should be". The research objects of this study are all from China, so the latter is used to measure social norms [49]. The typical item is "Relatives believe that green production behavior should be adopted". All items were measured on a Likert 7-point scale (1 = very disagree; 2 = disagree; 3 = comparative disagreement; 4 = general; 5 = comparative consent; 6 = consent; 7 = very agree).

GC. The academic community has tried to explore research on green cognition, such as environmental knowledge and environmental impact. Most studies have confirmed the importance of green cognition in farmers' decision-making. This study uses farmers' perceptions of agricultural environmental pollution and agricultural environmental policies to measure green cognitive ability [49,50]. The typical question is "Do you think agricultural environmental pollution is currently severe?". All items were measured on a Likert 7-point scale (1 = very disagree; 2 = disagree; 3 = comparative disagreement; 4 = general; 5 = comparative consent; 6 = consent; 7 = very agree).

Controlled variables. Previous studies have shown that age, gender, education background, number of households engaged in agricultural labor, household annual income, and proportion of agricultural income will affect farmers' cultivated land quality protection behavior. In order to clarify the relationship between independent variables and dependent variables, it is necessary to control the above variables. Based on the basic paradigm of analyzing holders' behavior, this article selects demographic characteristics such as gender, age, and education level, as well as socioeconomic characteristics such as the number of household laborers, household annual income, and the proportion of agricultural income, as control variables.

Therefore, according to the selection and definition of variables, the questionnaire includes five parts: farmers' cultivated land quality protection behavior (2 items), continuous adoption of artificial intelligence technology (3 items), social norms (4 items), green cognition (3 items), and control variables (6 items). The specific items are detailed in Table 2.

Table 2. Variable Definitions.

Type	Variable	Variable Definitions
Dependent variable	BHFPB	Highly toxic chemical pesticides = 1, low-toxic chemical pesticides = 2, green pesticides = 3, no pesticides = 4. (Item: How do you apply pesticides?) Complete use of chemical fertilizers = 1, primary use of chemical fertilizers = 2, mixed use of chemical and organic fertilizers = 3, primary use of organic fertilizers = 4, complete use of organic fertilizers = 5. (Item: How do you apply fertilizer?)
Independent variable	CAAIT	I intend to continue using artificial intelligence technology in agricultural production, rather than other methods or tools. Considering all factors, I hope to continue using artificial intelligence technology frequently in agricultural production in the future. If possible, I will increasingly use artificial intelligence technology in the future.
Mediating variable	SN	Relatives believe that farmland quality should be protected. Village cadres believe that farmland quality should be protected. Large-scale framers believe that farmland quality should be protected. Neighbors believe that farmland quality should be protected.
Moderator variable	GC	Do you think agricultural environmental pollution is severe currently? The improper use of pesticides, fertilizers, and improper disposal of agricultural waste can cause agricultural environmental pollution. Are you familiar with the local agricultural environmental policies?
Controlled variable	Gender Age Education background The number of households engaged in agricultural labor. Household annual income. The proportion of agricultural income.	Male = 1; Female = 0. The actual age of the respondent (years). No education = 1; Primary school = 2; Junior high school = 3; High school = 4; Junior college or above = 5. Number of households engaged in agricultural labor (people). Annual household income (10,000 CNY). The proportion of agricultural income in the total household income.

Note: Continuous adoption of artificial intelligence technology, CAAIT; behavior of holders' farmland quality protection, BHFQP; green cognition, GC; social norms, SN.

4. Data Analysis and Results

4.1. Confirmatory Factor Analysis

This paper conducted a confirmatory factor analysis using AMOS 22.0 software to test the discriminant validity of four variables, namely CAAIT, BHFQP, SN, and GC. Compared to other alternative models, the four-factor model had the best fit for the data. Specifically, the $\chi^2/\mathrm{df} = 3.184$, CFI = 0.971, TLI = 0.954, RMSEA = 0.064, and NFI = 0.959, indicating a high discriminant validity among the four variables.

4.2. Descriptive Statistical Results

Table 3 summarizes and illustrates the mean, standard deviation, and correlation coefficients of each variable. The results show that there is a significant positive correlation between CAAIT and BHFQP (r = 0.260, p < 0.01). Additionally, GC is significantly positively correlated with CAAIT (r = 0.421, p < 0.01) and BHFQP (r = 0.341, p < 0.01). SN is significantly positively correlated with CAAIT (r = 0.540, p < 0.01), BHFQP (r = 0.321, p < 0.01), and GC (r = 0.536, p < 0.01). The significant interdependent relationships between the variables above provide support for the subsequent analyses in this study.

Table 3. Correlation analysis.

	Mean	**SD**	**CAAIT**	**BHFPB**	**GC**		**SN**	
CAAIT	5.324		1.174		1.000			
BHFPB	6.333		1.164		0.260 **	1.000		
GC	4.773		1.082		0.421 **	0.341 **	1.000	
SN	5.435		1.174		0.540 **	0.321 **	0.536 **	1.000

Note: Continuous adoption of artificial intelligence technology, CAAIT; behavior of holders' farmland quality protection, BHFQP; green cognition, GC; social norms, SN; **. At the 0.01 level (two-tailed), the correlation is significant.

4.3. Hypothesis Result Test

Main effect test. This study used hierarchical regression analysis to verify the hypothesis of the main effect. Verification of the main effect. The dependent variable was BHFQP, and the control variables were introduced into the regression equation. Regression analysis was conducted with CAAIT as the independent variable, and the results are shown in Table 4. Figure 2 shows that CAAIT is significantly positively correlated with BHFQP (β = 0.249, p < 0.001). Therefore, Hypothesis 1 is validated.

Table 4. Hierarchical regression analysis results.

	BHFPB				**SN**			
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Gender	0.101 *	0.105 *	0.111 **	0.111 **	−0.032	−0.025	−0.007	−0.011
Age	0.081	0.035	0.019	0.009	0.196 ***	0.098 *	0.073	0.065
Education background	0.159 **	0.111 *	0.111 *	0.098	0.151 **	0.049	−0.019	−0.024
Number of Agricultural labors	0.047	0.037	0.045	0.04	0.008	−0.014	−0.012	−0.006
income	0.041	0.001	0.01	−0.003	0.098	0.013	−0.04	−0.039
Percentage	0.004	0	0.005	3.00E-03	−0.004	−0.011	−0.028	−0.041
CAAIT		0.249 ***		0.111 *		0.526 ***	0.381 ***	0.365 ***
SN			0.318 ***	0.261 ***				
GC							0.388 ***	0.389 ***
int								−0.129 ***
R^2	0.030	0.088	0.127	0.136	0.040	0.299	0.416	0.432
ΔR^2		0.075	0.115	0.122		0.290	0.407	0.422
F	2.655	7.071	10.701	10.065	3.611	31.339	45.709	43.323

Note: Continuous adoption of artificial intelligence technology, CAAIT; behavior of holders' farmland quality protection, BHFQP; green cognition, GC; social norms, SN. "*", "**" and "***" indicate the significance at p < 0.05, p < 0.01 and p < 0.001, respectively.

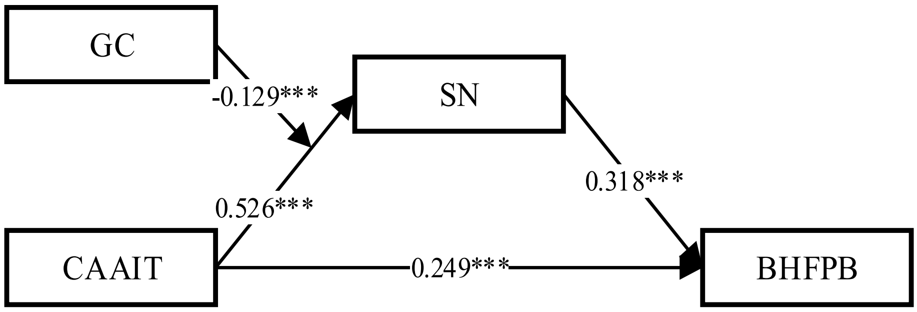

Figure 2. Theoretical model test results. *** represents that it is significant at the 1% level.

Mediation effect test. Based on the support for the main effect, regression analysis was conducted with SN as the dependent variable and CAAIT as the independent variable. Model 6 in Table 4 shows that CAAIT has a significant positive effect on SN (β = 0.526, $p < 0.001$), and thus Hypothesis 2 is validated. Regression analysis was conducted with BHFQP as the dependent variable and CAAIT and SN as the independent variables. Model 4 in Table 4 shows that SN has a significant positive effect on BHFQP (β = 0.261, $p < 0.001$), and compared with Model 2, the regression coefficient of CAAIT on BHFQP decreased from 0.249 to 0.111, indicating that SN partially mediates the effect of CAAIT on BHFQP. Therefore, Hypothesis 3 and Hypothesis 4 are validated.

From the perspective of control variables, women are more inclined to CAAIT to protect the quality of cultivated land. Then, due to the influence of traditional culture, men tend to have the responsibility of raising a family, resulting in less use of CAAIT, which makes the protection of cultivated land quality in agricultural production less effective. Farmers with a higher education background are more inclined to adopt CAAIT to promote the protection of cultivated land quality. On the contrary, farmers with lower educational backgrounds are more inclined to adopt CAAIT less, resulting in less cultivated land quality behavior.

To further examine the mediating role of SN, the Bootstrap method is adopted in this paper for sampling inspection based on the practice of Wen Zhonglin et al. [51], and the results are shown in Table 5. The estimated value of the mediating effect is 0.2464, with a confidence interval of [0.1616, 0.3312], which does not include 0. The direct effect of CAAIT on BHFQP is estimated to be 0.1103, with a confidence interval of [0.0136, 0.2069], which does not include 0. Therefore, Hypothesis 4 is further supported by the data.

Table 5. Mediating effect of SN on CAAIT-BHFQP relation.

	Effect	**SE**	***t***	***p***	**LLCI**	**ULCI**
Total	0.2464	0.0432	5.7091	0	0.1616	0.3312
Direct	0.1103	0.0492	2.241	0.0255	0.0136	0.2069
Indirect	0.1361	0.0368	/	/	0.0687	0.2118

Test of the moderating effect. In order to reduce the influence of multicollinearity, the independent variable (CAAIT) and the adjustment variable (GC) are centralized. Then, construct the product term and put it into the regression equation. As shown in Table 4, the product of CAAIT and GC was significantly negatively correlated with SN (β = −0.129, $p < 0.001$). This result indicates that GC has a marginal moderating effect on the relationship between CAAIT and SN. Therefore, Hypothesis 5 is supported.

To better illustrate the moderating effect of GC on the relationship between CAAIT and SN, this study used the simple slope analysis method to test and draw the moderation effect graph of GC, as shown in Figure 3. For employees with high levels of GC, the negative effect of CAAIT on SN was significant (β = 0.4675, $p < 0.001$). However, for employees with low levels of perceived GC, the negative effect of CAAIT on SN was also significant ($\beta = 0.2622$, $p < 0.001$). Thus, Hypothesis 5 is further supported.

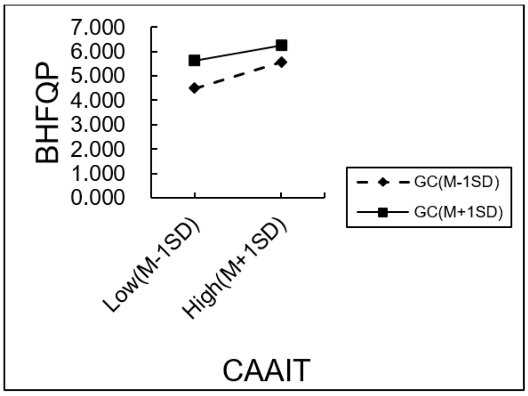

Figure 3. The moderating effect of green cognition on the relationship between continuous adoption of artificial intelligence technology and social norms.

The moderated mediation effect test. Hypothesis 5 proposes that GC negatively moderates the indirect effect of CAAIT through SN on BHFQP. To test this moderated mediation effect, 5000 samples were conducted in this study by bootstrapping to obtain the range of the mediation effect of SN at different levels of the moderator. As shown in Table 6, when employees' GC is low, the indirect effect of CAAIT through SN on BHFQP is 0.1211, with a confidence interval of [0.0535, 0.2004], which does not include 0. When employees' GC is high, the indirect effect is 0.0679, with a confidence interval of [0.0334, 0.1097], which also does not include 0. Therefore, the mediation effect of SN is significantly lower under high GC than under low GC. Furthermore, according to Table 6, the judging criteria index is −0.0246, which has a confidence interval of [−0.0528, −0.0036] and does not include 0, indicating that the moderated mediation effect is significant. Therefore, GC moderates the mediation effect of SN, and Hypothesis 6 is supported.

Table 6. Bootstrap test results of the moderating effect.

	GC	Effect	BootSE	BootLLCI	BootULCI	Index	BootSE	BootLLCI	BootULCI
BHFPB	−1.0818	0.1211	0.0377	0.0535	0.2004	−0.0246	0.0128	−0.0528	−0.0036
	0	0.0945	0.0266	0.0463	0.15				
	1.0818	0.0679	0.0193	0.0334	0.1097				

Note: Behavior of holders' farmland quality protection, BHFQP; green cognition, GC.

5. Discussion

5.1. Discussion of the Empirical Results

This study explored the impact of CAAIT on BHFQP and found that: (1) CAAIT has a positive impact on BHFQP. According to the technology acceptance model, the ease of use of artificial intelligence technology can effectively affect cognition, which in turn affects behavior. Accordingly, CAAIT mainly affects holders' cognition, which improves their economic and ecological cognition of land based on expected benefits, perceived benefits, and land consciousness, leading to spontaneous farmland quality protection by holders. (2) SN mediates the impact of CAAIT on BHFQP. CAAIT has a positive impact on SN, which in turn positively promotes BHFQP. In other words, SN plays a mediating role between CAAIT and BHFQP. This is because the widespread use of artificial intelligence technology, especially its perceived usefulness, will promote the formation of new SNs in rural areas. These new descriptive and prescriptive SNs will create pressure on other holders to engage in more behaviors for farmland quality protection. This conclusion is in line with the theory of rational action, which reflects that people's behavioral intentions are influenced by personal attitudes, and social norms, and directly determine their actual behavior. (3) GC plays a negative moderating role between CAAIT and SN. GC mainly influences holders' behavior from a perceptive perspective, which refers to their perception of resource and environmental issues and scientific knowledge. It motivates holders to take initiative in environmental protection, further weakening the positive relationship between CAAIT and SN. (4) GC weakens the mediating effect of SN between CAAIT and BHFQP. Both GC and SN have cognitive attributes. Therefore, the lower the level of GC, the stronger the positive effect of CAAIT on BHFQP through SN. The negative function of green cognition proves the evaluation process in cognitive evaluation theory, that is, individuals constantly search for information and possible threats in the environment and conduct multiround and continuous evaluations. In other words, the CAAIT makes farmers face the stimulation of new events and have a positive evaluation. However, this process also makes farmers face new challenges brought by artificial intelligence technology, and at the same time, they also need to face the pressure brought by SN, thus entering the re-evaluation stage, and farmers will adjust and control their own response behavior. However, when farmers cannot fully control the stimulus events, that is, they cannot fully predict the artificial intelligence technology, the role of green cognition is no longer the normally expected positive function, but just plays a negative role.

5.2. Theoretical Contribution

This study expanded the research field and outcome variables of CAAIT. While some previous studies have intensively examined the adoption of artificial intelligence technology [52], few have focused on its continuous adoption [53]. Moreover, existing research has only analyzed the factors that influence CAAIT [54,55], while there is a lack of research on its outcome variables. This hinders a comprehensive understanding of the research topic of CAAIT. This study expands the research topic to the field of land issues and discusses the positive effect of CAAIT on BHFQP, which effectively enriches the research on CAAIT.

This study demonstrated that the elements that influence BHFQP include both economic and noneconomic factors. Scholars who adhere to the hypothesis of rational economic man believe that economic factors can drive BHFQP [56,57], while some scholars have also found that non-economic factors can also influence the behavior of holders' farmland quality protection [58,59]. In this study, CAAIT can stimulate holders' economic and noneconomic cognition and, therefore, influence their farmland quality protection behavior. Thus, this study demonstrates and discovers a more inclusive answer: both economic and non-economic factors can influence BHFQP.

This study also revealed the black box and boundary conditions of the effects of CAAIT on BHFQP. A new model was constructed, and the following questions were answered: How does CAAIT affect BHFQP, and under what conditions will the interaction between the two be enhanced? The construction and validation of the research model not only explain the relationship between CAAIT and BHFQP, but also provides a useful supplement to research on SN and GC [60,61].

5.3. Practical Implications

Firstly, agricultural operators should continue to adopt artificial intelligence technology in the field of agriculture. Although artificial intelligence technology has been widely used in agricultural production, such as in intelligent seed breeding and detection, smart soil irrigation, smart planting, crop monitoring, and soil and water management, its effectiveness has not been fully realized. Agricultural business entities should not only strengthen the application of artificial intelligence technology related to agricultural production efficiency, but also increase the application of artificial intelligence technology related to the protection of cultivated land quality, so as to obtain multidimensional cultivated land parameters, analyze the dynamic changes of cultivated land quantity, quality, and ecological evaluation indicators, realize the comprehensive dynamic perception of cultivated land, improve system-accurate identification, and improve the timeliness and accuracy of decision-making.

The government can design “economic + non-economic” policies to drive farmland quality protection behavior by holders. Economic factors can stimulate BHFQP, but the effectiveness of noneconomic factors should not be ignored. Therefore, we should give full play to the role of economic factors in farmers’ cultivated land quality protection behavior in terms of “effective speed” and stimulate farmers’ cultivated land quality protection behavior through financial subsidies such as cultivated land fertility protection subsidies. The financial sector should strengthen work supervision, improve the quality of distribution, and distribute subsidy funds to farmers as soon as possible so that the majority of farmers can share the dividends of subsidy policies. In the aspect of “lasting effect”, we should give full play to the influence of non-economic factors on farmers’ cultivated land quality protection behavior, make full use of the sense of dependence on land formed in the agricultural civilization, and stimulate farmers to take the initiative to protect the quality of cultivated land.

Rural social managers should guide SN in performing their positive functions. SN is contextual. Negative SN has a negative guiding effect on holders’ behavior, but positive SN related to farmland quality protection has a subtle positive guiding effect. Therefore, rural social managers should support the formation and function of positive social norms and spread the positive social norms related to cultivated land quality protection behavior through multilevel, multichannel, and all-round ways, such as hanging publicity slogans, launching publicity vehicles, distributing publicity materials, and other forms, so as to effectively play their positive guiding role in farmers’ behavior.

Media and public welfare organizations should increase propaganda and guidance for GC. GC enables holders to focus not only on economic benefits, but also on their living and production environments. The media and public welfare organizations should strengthen publicity for environmental issues. They can also share environmental protection actions and experiences in rural life through the short video platform and advocate for change from a personal point of view. Through the dissemination and guidance of consciousness, the concept of green cognition is rooted in the hearts of farmers, who encourage each other to infect and finally form a social trend of green environmental protection so that they can choose protective farming techniques that are conducive to ecological construction in agricultural production.

5.4. Limitations and Prospects

This study has both theoretical and practical significance, but it also has limitations. Firstly, the measurement of CAAIT in this study follows the conventional measurement method used in previous studies on the continuous adoption of other technologies. Although it has good reliability and validity, it also has limitations. Secondly, the research sample for this study comes from China. Although the survey targets holders from 25 provinces in China, future research can be expanded to include more countries to broaden the geographical scope of the study.

For future research, firstly, the consequences of the variable profiling of CAAIT can be further explored. Current research on the adoption of artificial intelligence technology is still in its early stages, and there is even less focus on the consequences of continuous adoption and its variables. This inevitably leads to a lack of a comprehensive understanding of CAAIT. Secondly, it is necessary to conduct contextualized research on BHFQP. Due to the significant differences in the specific application scenarios of holders’ farmland quality protection behavior in different geographical environments, the factors influencing BHFQP are not always the same. Therefore, it is necessary to conduct contextualized research on different industries to increase the scientific and practical value of the research results.

6. Conclusions

This study analyzed a sample of 522 holders to explore the effects of CAAIT on BHFQP, the mediating role of SN, and the moderating role of GC. The study found that (1) CAAIT positively affects BHFQP, (2) SN partially mediates the relationship between CAAIT and BHFQP, (3) GC positively moderates the relationship between CAAIT and SN, and (4) GC also moderates the mediating effect of SN on the relationship between CAAIT and BHFQP. Theoretically, this study expands the scope of CAAIT research on the field of land issues, demonstrates that the elements influencing BHFQP can include both economic and noneconomic factors, and reaches a richer and more consistent conclusion that aligns with agricultural production practices. In practice, this study provides practical measures for promoting CAAIT and farmland quality protection from the perspectives of agricultural management entities, the government, rural social managers, the media, and public welfare organizations.

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