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Determinants of green energy adoption for sustainable agriculture development in district Swabi, Khyber Pakhtunkhwa, Pakistan

Arshad Ullah Jadoon, Yan Yunxian* and Liu Chao

School of Economics and Management, Jilin Agricultural University, Changchun, China

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Tamer Mansour,
National Research Centre, Egypt

*CORRESPONDENCE
Yan Yunxian
jlauyyx@126.com

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The main objective of the present study is to analyze the determinants of the adoption of green energy products in farming by farmers of the district Swabi, Khyber Pakhtunkhwa. A sample size of 460 was determined by using the Cochran formula. Data were collected using a structured questionnaire through non-probability sampling methods, including convenience and snowball sampling techniques. Data has been analyzed using simple descriptive statistics and Robit regression. The key results indicate that the use of green energy products declines when farmers are uncomfortable using them, are illiterate, or are completely unaware of these technologies. The use of green energy products has shown an increasing effect with higher income, greater farming experience, greater family support during peak seasons, and higher awareness of green energy products among the farmers. Following the study, the government is required to provide agriculture-specific education and training. Incentives and support from the government for installation, maintenance, upgradation, and expansion can significantly lower the barriers to adopting green energy.

KEYWORDS
farmers' behavior, green energy adoption, renewable energy technologies, Robit regression, sustainable agriculture

1 Introduction

Pakistan has an agrarian economy, and agricultural production is highly dependent on the natural environment. The natural environment and agricultural productivity have a bidirectional causality. Researchers (Chel and Kaushik, 2011) have found that most agricultural machines use fossil fuels, thereby increasing greenhouse gas emissions and contributing to climate change. Moreover, the agriculture sector affects the environment through water pollution, soil, land, and landscape degradation, as well as greenhouse gas emissions from energy use (Novelli, 2018). These adverse effects of traditional farming can be mitigated by adopting sustainable agriculture practices.

The concept of sustainable agriculture practice is both ambitious and ambiguous. Agriculture practices must fulfill the following five attributes. First, it shall conserve resources, including land, water, plants, and genetic resources. Second, it shall have the property of being environmentally non-degradable. Third, it shall be most appropriate in terms of technology. Fourth, it shall be most viable economically, and fifth, it shall be socially acceptable and equitable (Lee, 2005).

As (Dönmez et al., 2024) articulated that sustainable agriculture is primarily related to fulfilling human nutritional needs while preserving the quality of the environment and ensuring economically viable farming practices. The core principles of sustainable agriculture are the conservation of resources, the resilience of economic activities, the promotion of social equity, and the enhancement of competitiveness in the markets. In other words, it is about employing highly innovative farming techniques or practices that are environmentally beneficial, economically viable, and equitable for society as a whole. In principle, these innovations shall address the adverse impacts of climate change, water scarcity, and soil quality degradation. However, Bathaei and Štreimikienė (2023) defined sustainable agriculture as ensuring the availability of food and energy supply in the future while protecting natural resources.

Researchers (Khan et al., 2016) highlighted that Pakistan ranked 16th in terms of vulnerability to climate change, even though it is ranked 135th in global greenhouse gas emissions. It is because of climate change that Pakistan is facing frequent spells of floods and droughts, which are adversely affecting the country's primary sector, i.e., the agriculture sector (Fahad and Wang, 2020). According to the estimates (Hussain et al., 2020), the costs associated with climate change in Pakistan are seven to 16 billion dollars annually. Pakistan is looking to adopt sustainable agriculture practices to minimize the impact of climate change.

There are increasing environmental problems due to practices in the agricultural production sector (Asiedu-Ayeh et al., 2022). Researchers (Wang et al., 2023) have found that almost one-third of global energy consumption occurs in the agriculture sector, which accounts for one-third of total greenhouse gas emissions. Energy is required for pumping water for irrigation, running farm machinery for sowing, removing weeds, spraying chemicals, fertilization, harvesting, transporting raw materials and finished products, refrigerating, drying, and processing agricultural products (Majeed et al., 2023).

In the context of the above discussion and scenario, the present study investigates the key determinants of farmers' adoption of green energy in 4 Tehsils of District Swabi, namely Lahore, Razar, Swabi, and Topi, for sustainable agriculture practices. The study also examines the key barriers and motivations for adopting green energy for farming in the same district, as well as farmers' perceptions of government policies and financial incentives. The study will provide proper incentives for policymakers to achieve high rates of green energy to support agricultural sustainability. The present study contributes to the literature by presenting a case study in the district of Swabi, one of the top agricultural-producing districts, which utilizes Robit regression to analyze survey data on the adoption of green energy products for farming.

2 Review of literature

In the literature on the adoption of green energy products by farmers for farming purposes, farmers' intentions are derived from various theories, including diffusion of innovation, technology acceptance model, post-materialist theory, social learning theory, theory of planned behavior, and theory of economic and social risk factors. The theory of diffusion of innovation states that farmers are likely to adopt green energy if neighboring farmers have adopted it (He et al., 2022; Silk et al., 2014; Wang et al., 2020). The technology acceptance model predicts that the usefulness of green energy products, such as cost savings or increasing revenue by preserving agricultural products, can significantly increase adoption rates among farmers, as highlighted by researchers (Dash and Choudhury, 2021; Gao et al., 2022; Wu et al., 2024; Yazdanpanah et al., 2022).

The theory of post-materialism predicts that farmers' adoption of green energy products increases with an increase in education and level of income. Educated and financially well-off farmers can use the latest technologies. Researchers (Yang et al., 2025) confirmed this behavior of the farmers. The theory of social learning explains that the social network of the farmers can significantly enhance adoption intention, based on the report (D. Liu et al., 2023) in China. Conversely, theories of planned behavior, economic and social risks describe that adoption intentions are farmers' specific internal behaviors along with economic advantages relative to their social risks. The discussion can be found in Ataei et al. (2021) and Mouloudj et al. (2023).

In the context of theoretical models, the most recent and relevant research studies are summarized and presented to highlight the available literature related to the recent study.

Researchers (Zeng et al., 2022) investigated the consumer desire to adopt green technologies in five districts of Khyber Pakhtunkhwa, Pakistan. They collected data from 330 households and concluded that factors that positively affect households' willingness to adopt green technologies are environmental concern, awareness of green technologies, openness to experience, and the benefits of green energy technologies. In contrast, the associated costs of adopting green technologies and their level of discomfort adversely affect the consumer's intentions to adopt green energy technologies. In the case of Bangladesh, Mondal and Hasan (2025) reported that subjective and mitigating norms played a significant role in adoption intention by the farmers. Similarly, Cozzi et al. (2025), Torfei Monfared et al. (2025) and Yin et al. (2024) concluded that norms played a vital role in the adoption intentions of farmers in Italy, Iran, and China, respectively.

One of the sources of green energy is solar energy. In a country like Pakistan, the grid energy supply is short of its market demand and expensive. Thus, it is crucial for farmers to install an off-grid solar system for irrigation purposes. In this connection, (Khan et al., 2024) investigated the impact of installing a solar system for irrigation on the income level of the 1,080 farmers in Pakistan. They used logit and propensity score matching models and concluded that there is a positive correlation between adopting solarization and farmers' income.

Researchers (Asiedu-Ayeh et al., 2022) investigated the behavioral factors that inspire the rice farmers of Ghana to adopt green technologies for agricultural production. They employed the index method of probabilistic linguistic preference. They concluded that knowledge, cost and benefits, norms (i.e., descriptive), moral and environmental concern, and injunctive norms are the main factors that promote the adoption of green technologies in Ghana. Conversely, Swedish farmers highlighted the role of state-level funding and support for adopting green energy, as described by Hahn et al. (2025).

Furthermore, researchers (Wang et al., 2023) collected data from 801 farmers in China and examined the adoption of renewable energy on farms and technical efficiency. They concluded that the level of education, size of the farm, financial support from the government, perceptions such as usefulness, effectiveness in terms of costs, and availability of information all play a vital role in the adoption of green energy in China. Similar to the study (Gul et al., 2025), another report (Wang et al., 2023) also concluded that education, gender of the farmer, innovative ability, interest in use, access to credit and diversification of farm's land positively affected the farmers intentions to adopt solar energy in Sindh Province of Pakistan. Conversely, researchers (Yang et al., 2025) reported that the social network of Chinese farmers significantly affected the adoption intention of green energy. In China (Li et al., 2023), it was confirmed that social networks affect adoption intentions.

Furthermore, researchers (D'souza et al., 1993) investigated the determinants of farmers' intention for the adoption of sustainable agriculture practices. They used survey data from West Virginia in 1990. They concluded that farmer awareness and knowledge played a key role in developing intentions to use sustainable practices for agricultural purposes. In a more advanced experiment carried out by the Gathala et al. (2020), it was concluded that improved agricultural methods resulted in a 10% increase in crop yield, a reduction in emissions by up to 17, and 50% decrease in labor.

The study (Bathaei and Štreimikienė, 2023) highlighted that a total of 84 indicators had been used for sustainable agriculture based on the review of 420 papers from SCOPUS. These indicators can be classified into various dimensions. They are related to the social setup, environmental concerns, economic concerns, institutional concerns, and technological dimension.

Researchers (Moerkerken et al., 2023) performed an empirical study to examine the perception and response of farmers in the adoption of solar energy for agricultural production in the Netherlands. They conducted surveys in 2015, 2018, and 2020, and applied panel data regression models; they concluded that willingness to reduce greenhouse gas emissions had increased to 82% in 2020 from 35% in 2015. The three major determinants highlighted are behavioral intention, farmers' perceptions of the usefulness of solar energy, and farmers' innovativeness. Researchers (Yu et al., 2025) stated that if farmers had provided helpful information about the technologies, they would have adopted the technologies.

Conversely, the study (Bozorgparvar et al., 2018) examined the intentions of livestock producers in Iran to adopt green energy. They selected a random sample of 140 respondents. They concluded that farmers' attitudes, behavioral control, moral and subjective norms were the most significant drivers of the farmers' intentions to use green energy on their farms.

The study (Elahi et al., 2022) focused on the farmers' intention and willingness to install photovoltaic water pumps in the province of Punjab, Pakistan. They collected data from 1,200 farmers through a well-structured questionnaire. They concluded that farmers' attitude towards the protection of the environment, lack of access to a supply of electricity, and the relative benefits of solarization played a positive role in adopting solar energy for water pumps; however, installation costs played a negative role. Moreover, they found that education, household income, and the lack of grid electricity increased the probability of willingness to pay extra for green energy. In a similar study, Kumar et al. (2020) concluded that perception related to benefits, computability, and incentives by the government played a positive role in solarization of water pumps for agricultural purposes.

Moreover, researchers (Novelli, 2018) analyzed the determinants of eco-friendly choices by the farmers in Italy, using the data of the 2010 agriculture census. They reported that farm size, type of farming, and location of the farmer played a significant role in adopting the eco-friendly choices for agriculture. Among the personal characteristics, they highlighted age as a key factor in the adoption of eco-friendly decisions.

The review of the literature shows that the published papers significantly contribute to the literature as per the knowledge of the researchers. No study has analyzed farmers' adoption intentions for green energy products in the district of Swabi, Khyber Pakhtunkhwa, using Robit regression as the analytical tool. The Robit regression is superior to logit and probit regressions, which are commonly used in the literature. Robit regression, a link function for logit regression that mitigates the problem of outliers and hence reports more consistent estimates of the coefficients. It is in that context that the present study contributes to research and can enhance the understanding of policymakers to improve the adoption of green energy for sustainable agriculture and the environment.

3 Methodology

The most popular models for the analysis of the data when the dependent variable is a binary response variable are the logit and probit models. These models are estimated using maximum likelihood estimators, and the estimated results are sensitive to the outliers in the data (Liu, 2004; Roy, 2012). However, researchers (Liu, 2004; Newson and Falcaro, 2023) pointed out that Robit regression is the simplest robust alternative for handling outliers in binary outcome data. The Robit regression model uses the Student t-distribution instead of the popular normal distribution. The heavier tails of the t-distribution ensure that outliers do not influence the model outcomes, and inference based on it is consistent because of the consistent power of the model that has been used for the analysis in this study.

The generalized case of the Robit model, as presented by Roy (2012), is outlined here. Let $Y = (Y_1, Y_2, Y_3 \ldots .Y_n)$ be the vector of n binary variables which are random and independent of each other, with $F_v.(.)$ representing the CDF of the student t distribution. The degree of freedom, v, is known and fixed such that $P(Y_i = 1) = F_v\left(x_i^T \beta\right)$. In this function, the vector of covariates associated with Y_i is represented by $x_i^{'}s, i = 1, 2, \ldots .n$ and β is the vector of unknown coefficients of the regression model. Both $x_i^{'}s$ and β are the vectors of $p \times 1$ dimensions.

The joint mass probability function (pmf) of Y is given by Equation 1 as below.

$$p(y|\beta) = \prod_{i=1}^{n} \left(F_v\left(x_i^T \beta\right)\right)^{y_i} \left(1 - F_v\left(x_i^T \beta\right)\right)^{1-y_i} \tag{1}$$

Robit models are a special class of generalized linear models (GLMs). The coefficients obtained by the robit models are similar to GLM with binomial or Bernoulli variance function and a robit link function, also known as t link function with $v\ d.f$. It is defined, as shown by Newson and Falcaro (2023), by substituting an inverse of the cumulative students' t distribution function in place of the inverse cumulative standard normal distribution in the link function of the probit model. It can be written as Equation 2,

$$\eta(\mu) = F_{t(v)}^{-1}(\mu) \tag{2}$$

Where, $\eta(\mu)$ is the link function from the conditional mean μ, $F_{t(v)}(.)$ is the cumulative number of students' t distribution function with $d.f$ defined by v and $F_{t(v)}^{-1}(.)$ is its inverse function. It can be differentiated twice, with the first and second derivatives given in Equations 3 and 4.

$$\frac{d\mu}{d\eta} = f_{t(\nu)}(\eta) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\nu\pi}\,\left(\frac{\nu}{2}\right)}\left(1+\frac{\eta^2}{\nu}\right)^{-\frac{\nu+1}{2}} \quad (3)$$

Where the density function for t distribution is given by $f_{t(\nu)}(.)$ with the $d.f.$ is given by ν. If Equation 3 is further differentiated with respect to μ and if μ is given by $\left(1+\frac{\eta^2}{\nu}\right)$, the second derivative is obtained, after applying the chain rule, as shown in Equation 4.

$$\frac{d^2\mu}{d\eta^2} = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\nu\pi}\left(\frac{\nu}{2}\right)}\frac{2\eta}{\nu}\frac{\nu+1}{2}\left(1+\frac{\eta^2}{\nu}\right)^{-\frac{\nu+3}{2}} \quad (4)$$

Finally, Equations 2–4 define those variables that are needed to fit the Robit model by the GLMs. Moreover, there is a hard and fast rule for the specification of $d.f.$ However, it is shown by Newson and Falcaro (2023) that the use of fewer $d.f.$ can generate coefficients less influenced by outliers in the data.

In the present case, the dependent variable is GE_i which represents whether the farmer is using green energy products for agriculture or not. It is coded as a binary variable with 1 if the farmer uses green energy products and 0 otherwise. Conversely, the study also uses a group of covariates that are associated with GE_i. These covariates are related to the demographic nature of the farmer, awareness and knowledge of the farmer about the green energy products, perception and attitude of the farmer towards green energy, and government and institutional support available to the farmers. These covariates are used to analyze the adoption of green energy products by the farmers. As there are many covariates, it is prudent to use them across groups to explain farmers' adoption of green energy. These covariates are given in Table 1.

There is no data on the exact number of farmers in the district of Swabi; the statistical population of the farmers is unknown. Various techniques can be used to determine sample size if the size of the statistical population is unknown. In the present case, the most popular technique of Cochran (1977) has been used for such a purpose, which is given in Equation 5 as follows:

$$n = \frac{Z^2 pq}{e^2} \quad (5)$$

Where, Z means $Z-$score, p is the estimated proportion of the population with the desired quality of adopting green energy products, $q = 1-p$ and e is the marginal error. In the present case, $p = 0.5, q = .50, e = 0.05$ and $Z = 1.96$ corresponds to a 95% confidence interval. Substituting these values into Equation 5 gives an approximate sample size of 384.16; however, the study has interviewed a total of 460 farmers in the district of Swabi. After conducting the final survey, only 400 questionnaires were complete and usable for the empirical analysis, which indicates an almost 87% response rate.

There is a total of 4 Tehsils in the District Swabi, namely Lahore, Razar, Swabi, and Topi. The sample size is equally divided among the four Tehsils, that is, 460 farmers have been interviewed through a structured questionnaire, from each of the four Tehsils. Out of 460 questionnaires, only 400 are complete and used for analysis. Out of 400 questionnaires, 112 respondents are from Lahore, 88 respondents are Razar, 104 from Swabi and finally 96 from Topi Tehsil. Data is analyzed using descriptive techniques as well as Robit regression models.

4 Results and discussion

The analysis of the survey data has been carried out using descriptive statistics and regression analysis. The descriptive statistics include

TABLE 1 Description and list of variables.

S. No	Variable	Label	Level of measurement
1	GE_i	Use of green energy products	It is a dummy variable with 1 = Yes, Zero otherwise
2	$GECL_i$	Use of green energy causes discomfort	Yes = 1, and zero otherwise
3	edu_s_i	education of the respondent (coded)	A seven-scale coding scheme has been used to code the education of the farmer
4	y_pm_i	Log of income (per month) of the farmer	It is measured in Pakistani rupees
5	exp_s_i	experience of the farmer (coded)	A six-scale coding scheme has been used to code the experience of the farmer
6	$aware_i$	Awareness of green energy	A five-scale coding scheme has been used to code the awareness level of the farmer
7	$barriers_i$	Barriers to adopting green energy	It is a dummy variable with 1 = Yes, Zero otherwise
8	$s\_f\_family_i$	Support of family members in farming	It is a dummy variable with 1 = Yes, Zero otherwise
9	$benefits\_t_i$	Types of benefits obtained using green energy	A six-scale coding scheme has been used to code the benefits obtained by the farmer from the use of green energy
10	$support\_s_i$	The type of support needed for installing green energy	A six-scale coding scheme has been used to code the support needed for the farmer for the use of green energy

The scale of measurement is mentioned against each variable available in the questionnaire.

measures of central tendency, standard deviation, maximum, and minimum values of the variables. It also includes one-way and two-way frequency tables. These analyses provide a helpful overall insight into the data.

The average schooling of the sample respondents is almost 7 years of education, which is less than middle school education. Interestingly, the average monthly income is Rs 84,186. It seems to be a bit higher with such a low level of education of the sample respondent. On the other hand, Table 2 shows that the average experience of the farmer is not greater than 8 years of farming experience.

Table 3 is constructed to reveal the type of green energy used by the farmers (Table 4). It shows that most farmers use solar energy as a green energy product. It is available to farmers as well. Table 5 indicates that most farmers are slightly aware of green energy products. The total of 70 and 66 respondents is very mindful and highly aware of the green energy products, respectively. It shows that awareness about green energy products can play a better role in preserving the environment. The government can initiate awareness programs to highlight the true potential of solar energy to farmers.

Table 6 indicates that 320 farmers, out of a total of 400, are using green energy products, and the remaining 80 farmers are not using green energy products. Among the 320 farmers who use green energy products, 252 are uncomfortable with their use. Table 2 indicates that most of the farmers have an average age of approximately 37 years (see Table 6). Table 6 presents the mean, standard deviation, minimum, and maximum of the variables that are quantitatively measured.

Table 7 illustrates the sources of knowledge of green energy. Most of the farmers, about 237, learned about green energy from friends, family, and fellow farmers. It may be because of the very low education level of the respondents. The government can initiate special learning programs for the farmers to enable them to explore the true potential of green energy. Table 8 indicates that 186 farmers, out of 400, cannot operate a green energy product by themselves, whereas 214 can operate. Out of 214 farmers who can operate green energy products, the majority of the farmers are at low and beginner levels of skill. It advances the need for the government to initiate skill enhancement education for the farmers so that they can efficiently operate the green energy products.

Table 3 indicates that the majority of the farmers are not supported by the government or NGO for installing or using green energy products. It means that they have done it by themselves. Most farmers are seeking support to expand their generations, acquire technical know-how, and maintain their installed capacity, along with tax incentives. It highlights the scope for government intervention in this field. The critical area of intervention is the technical know-how and enabling farmers to operate the green energy products by themselves.

The above descriptive statistics are complemented by the regression output given in Tables 9 and 10. The regression results in Table 9

TABLE 2 Descriptive statistics of selected numeric variables.

Variable	Obs	Mean	Std. Dev.	Min	Max
Age of the farmers in years (age_i)	400	37.185	8.237	20	54
Education in years (edu_i)	400	7.32	5.227	0	16
No of family members supporting farming (n_family_i)	400	5.678	2.662	1	12
Income per month (i_I_i)	400	84,186.5	41,188.267	30,000	200,000
Income per year (inc_i)	400	1,010,238	494,259.2	360,000	2,400,000
Experience in farming in years ($\exp_i$)	400	9.607	3.67	1	28
Size of land (in acres) (s_agr_i)	400	8.23	4.369	3	28
Log of income (per month) (y_pm_i)	400	11.222	0.49	10.309	12.206
Log of income (per year) (y_pa_i)	400	13.707	0.49	12.794	14.691

Source: Authors' calculations using STATA 18.0 from the survey data.

TABLE 3 Types and sources of support for adopting green energy by the farmers.

The type of support needed for installing green energy	Source of support for installing green energy		
	No, not supported by the government or an NGO	Yes, supported by the government or an NGO	Total
Expanding generation	51	17	68
Acquiring technical know-how	54	16	70
Maintenance	64	12	76
Low-interest loan	38	12	50
Training programs	42	20	62
Tax-related incentives	56	18	74
Total	305	95	400

Source: Authors' calculations using STATA 18.0 from the survey data.

TABLE 4 Type of green energy used by the farmer across the dimension of whether it is available or not.

Types of green energy in farming	Availability of green energy		
	No	Yes	Total
Solar energy	57	246	303
Biogas energy	2	20	22
Solar and biogas	4	16	20
Fossil fuel energy	8	47	55
Total	71	329	400

Source: Authors' calculations using STATA 18.0 from the survey data.

TABLE 5 Awareness of the respondent of green energy.

Awareness of green energy	Freq.	Percent	*Cum.*
Not at all aware	78	19.50	19.50
Slightly aware	131	32.75	52.25
Moderately aware	55	13.75	66.00
Very aware	70	17.50	83.50
Extremely aware	66	16.50	100.00
Total	400	100.00	

Source: Authors' calculations using STATA 18.0 from the survey data.

TABLE 6 Summary of the use of green energy across the discomfort level in its use.

Use of green energy products	Green energy discomfort		
	No	Yes	Total
No	22	58	80
Yes	68	252	320
Total	90	310	400

Source: Authors' calculations using STATA 18.0 from the survey data.

TABLE 7 Sources of learning of the respondent.

Learning sources of green energy	Freq.	Percent	*Cum.*
Friends, family, and fellow farmers	237	59.25	59.25
Government awareness programs	26	6.50	65.75
NGO awareness programs	33	8.25	74.00
Print, Electronic, and social media	102	25.50	99.50
Others	2	0.50	100.00
Total	400	100.00	

Source: Authors' calculations using STATA 18.0 from the survey data.

TABLE 8 Knowledge of operating green energy and skills level.

Rate the skills of green energy	Knowledge of operating green energy		
	No, I cannot operate green energy products by myself	Yes, I can operate green energy products by myself	Total
No skills at all	186	0	186
Low/beginner	0	66	66
Developing	0	56	56
Intermediate	0	37	37
Proficient	0	33	33
Expert/advanced	0	21	21
Expert/master	0	1	1
Total	186	214	400

Source: Authors' calculations using STATA 18.0 from the survey data.

represent the odds ratios of the coefficients, whereas Table 10 contains the coefficients of marginal effects of each explanatory variable on the dependent variable. In the economic theory, the coefficients of Table 10 make more sense than the coefficients of Table 9. Table 9 is reported because the marginal effects, in Table 10, are computed from the odds ratio of Table 9.

Table 9 represents the coefficients (in terms of log odds ratios) of the robit regression given in Equations 1 through 4. A total of four different versions of the model has been computed with different specifications with to the number of explanatory variables. These log odds ratios range from $-\infty$ to ∞. The coefficients of Table 9 need to be converted into log odd ratios → odd ratios → probabilities. In the present case, we are not interested in the probabilities of occurrence. We are interested in the effects of different explanatory variables on the intention decisions of the farmers. It can be achieved by computing marginal effects from Table 9. These coefficients are easy to interpret, indicating statistical significance and the sign of the effects.

There is a total of nine explanatory variables, as listed in Table 10. The first coefficient in all four models is that of the use of green energy discomfort (GECL), which is defined as Yes equals 1 and 0 if otherwise. In the regression output, the sign is negative, which means that the use of green energy products decreases if it is not comfortable. Conversely, the use of green energy products increases if it is comfortable for farmers to use them in farming. In all four regression models, the coefficient of "GECL" is statistically significant. It indicates that user-friendly green energy products can increase the overall use of green energy in farming, consistent with the study (Cozzi et al., 2025; da Conceição Lussanje et al., 2025; Karbo et al., 2025; Zeng et al., 2022). They also reported that the ease of use of green technologies enables farmers, in Ghana, to adopt them quickly. The study (Giua et al., 2022) highlighted that the likelihood of technology adoption depends on its complexity.

Table 10 presents the coefficients of the variable edu_s_i—education of the farmers—which is constructed to transform years of schooling into a 7-point Likert variable (see Table 1). The marginal effects of edu_s_i, in all four models, are negative and statistically significant. It can be interpreted as per the level of education as the bottom category is illiterate versus primary, middle and secondary, intermediate, graduation, post-graduation and higher than post-graduation of education. Interestingly, the sign of the coefficients indicates that the probability of use of green energy products reduces as the level of education of the farmer rises. It may be because the level of the farmers' education represents the general education, not agriculture-specific education. In the sample of the farmers, the average year of

TABLE 9 Estimated output of the regression model (odd ratios).

Use of green energy products	(1) Use of green energy products	(2) Use of green energy products	(3) Use of green energy products	(4) Use of green energy products
$GECL_i$	−4.469*** (−4.02)	−4.746*** (−4.00)	−5.160*** (−3.51)	−5.647*** (−3.31)
edu_s_i	−1.340 (−1.73)	−1.388 (−1.88)	−1.590 (−1.85)	−1.843* (−2.14)
y_pm_i	22.06*** (4.13)	23.03*** (3.99)	24.89*** (3.58)	27.51*** (3.78)
exp_s_i	0.0941 (0.19)	0.0780 (0.25)	0.200 (0.65)	0.0404 (0.14)
$aware_i$	−0.540* (−2.02)	−0.624* (−2.07)	−0.800* (−2.14)	−0.771* (−2.17)
$barriers_i$	0.685 (0.12)	0.0816 (0.08)	0.129 (0.15)	0.245 (0.31)
$s\_f\_family_i$		1.403 (1.70)	1.694 (1.90)	1.887 (1.66)
$benefits\_t_i$			−0.616* (−2.30)	−0.572* (−2.19)
$support\_s_i$				0.310 (1.70)
Constant	−230.3*** (−4.23)	−240.8*** (−4.00)	−259.4*** (−3.60)	−288.0*** (−3.81)
Observations	400	400	400	400

t statistics in parentheses. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.
Source: Authors' calculations using STATA 18.0 from the survey data.

TABLE 10 Coefficients of marginal effects of Robit regression.

Variables	(1)	(2)	(3)	(4)
$GECL_i$	−0.209*** (0.0301)	−0.214*** (0.0228)	−0.211*** (0.0229)	−0.203*** (0.0300)
edu_s_i	−0.0627* (0.0316)	−0.0627* (0.0251)	−0.0649** (0.0237)	−0.0661*** (0.0184)
y_pm_i	1.032*** (0.108)	1.040*** (0.0915)	1.017*** (0.0795)	0.987*** (0.0786)
exp_s_i	0.00440 (0.0229)	0.00352 (0.0140)	0.00816 (0.0121)	0.00145 (0.0106)
$aware_i$	−0.0253* (0.00989)	−0.0282** (0.00941)	−0.0327*** (0.00875)	−0.0277*** (0.00674)
$barriers_i$	0.0321 (0.275)	0.00369 (0.0450)	0.00529 (0.0353)	0.00880 (0.0281)
$s\_f\_family_i$		0.0633 (0.0347)	0.0692* (0.0312)	0.0677 (0.0387)
$benefits\_t_i$			−0.0252** (0.00795)	−0.0205** (0.00718)
$support\_s_i$				0.0111* (0.00532)
N	400	400	400	400

Standard errors in parentheses and the (*) are defined as per *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. Estimates are based on Table 11.

schooling is almost 7 years of the schooling which is too low. Most of the farmers, in the sample, are illiterate, which may be the reason that education does not play its role here.

The impact of the log of estimated per-month income of the farmers on the use of green energy products, in the sample of district Swabi, is also shown in Table 10. Its marginal effect is positive and statistically significant across all four models. It shows that a rise in the income of the farmer is directly enhancing the use of green energy products. The result highlights that high initial costs of installing green energy products are a major barrier, suggesting that an increase in the number of farmers can be accompanied by greater use of these products. It can also lead to improvement in the natural environment. Conversely, Czyżewski et al. (2025b) described how training and workshops, apart from education, can enable farmers to adopt organic farming. In the present, the education variable is not specifically education in farming practices, rather it is a general education, which may be because of that reason that it is not enabling farmers to adopt green energy products.

The experience of the farmers (exp_s_i) also matters in farming. It is believed that experienced farmers can maximize the gains from farming through wise decisions based on their experience of farming. In the present study, the experience of the farmer is coded on a 6-point Likert scale measurement (see Table 1). In Table 11, the coefficient is positive, implying that the use of green energy products by the farmers increases as the level of experience of the farmers increases. A recent study (Borychowski et al., 2025) have discussed the role of farmers' experience in adopting green energy. They found it logical, but also concluded that it is a problem of overconfidence bias.

TABLE 11 Diagnostic tests of Robit regression.

Model/test	Number of obs	Wald chi² (d.f)	Prob > chi²	Log pseudo-likelihood
Model (1)	400	22.611754 (6)	0.00093751	−91.192109
Model (2)	400	20.36748 (7)	0.0048283	−89.822216
Model (3)	400	17.978017 (8)	0.0213919	−88.134168
Model (4)	400	18.792972 (9)	0.0270119	−86.226394

Degree of freedom in parentheses.
Source: Author calculation using Stata 18.

The level of awareness ($aware_i$) of the farmers can also play its role while deciding whether to use green energy products or not. In the present study, the level of awareness is measured on a 5-point scale. The base category of awareness is 'not aware at all', and the final category is 'extremely aware'. Its signs of the coefficients of awareness are negative and statistically significant. It means that the use of green energy products decreases if farmer awareness rises. In a sample of 400 farmers, more than 50% were either not aware or slightly aware of the use of green energy products (Karbo et al., 2025). Additionally, the study reported that farmers' misconceptions about green energy products are a key barrier to their adoption.

The study also estimates the marginal effect of barriers to adopting green energy products (barriers$_i$) on the use of green energy products. It is dummy variables with "Yes = 1" and zero otherwise. The marginal effect of barriers$_i$is positive and vice versa. It shows that barriers observed have lowered the use of green energy products by the farmers. However, the coefficient is statistically insignificant in all four specifications but still highlights the role of barriers observed by the farmers.

In the subsequent analysis, the variables $s\_f\_family_i$, $benefits\_t_i$, $support\_s_i$ are also gradually introduced to the regression models. Models (2)–(4) show the marginal effects of support of family members, in peak seasons ($s\_f\_family_i$) is positive in all three specifications and statistically significant in model (3). The base category is 'no support in the peak seasons.' It can be interpreted that support of family members in the peak seasons increases the probability of use of green energy products by the farmers, and the same is termed as intergenerational support by Czyżewski et al. (2025a). In rural areas, farming is mostly done by the family members as a whole in peak seasons. In this context, a farmer without family support during the peak farming season can significantly reduce the likelihood of the farmer's decision to use green energy products.

The marginal effects of types of benefits ($benefits\_t_i$) of green energy products on the farmers' decision of whether to use green energy products or not. It is also given in models (3) and (4) in Table 11. The base category of benefit of green energy product is the 'reduction of energy bills and others include an increase in crop yields, protection of the environment, government incentives, and others. The sign of the coefficients of $benefits\_t_i$ is negative and statistically significant. It indicates that the marginal effect of benefit types decreases, for the farmers, as benefits move from crop yields, protection of the environment, government incentives to reduction in energy bills. Alternatively, a reduction in the energy bill is a crucial incentive in deciding whether to use a green energy product.

Lastly, the marginal effects of types of support needed in installing green energy products ($support\_s_i$) on the farmers' use of green energy products are also estimated in Table 11. The types of support include expanding generation, acquiring technical know-how, maintenance, low-interest loans, training programs, and tax-related incentives. The marginal effects of the $support\_s_i$ It is positive and statistically significant. It indicates that these types of support enhance the use of green energy products by the farmers. The study of (A. Khan et al., 2025) also concludes that critical support to the farmers such as incentives, guidance and financial support, plays a vital role in increasing the adoption rate.

Table 11 shows diagnostic tests associated with Robit Regression. There are two tests, i.e., the Wald test and the Log pseudo-likelihood test. The Wald test indicates that explanatory variables, in all four models, significantly improve the fit of the models. The log likelihood test is a type of measure of goodness of fit in the Robit Regression. It represents the best fit as much as the most negative value of the tests. These tests are accompanied by the correlation matrix of the explanatory variables from Robit regression in Table 12 and Figures 1–4.

The correlation coefficients can be explained conventionally. For instance, the correlation coefficient between barriers and the log of per-month income is 0.08. There is a positive but weak correlation. Conversely, the correlation coefficient between awareness and education is 0.83, and between benefits and awareness is 0.63, among others.

The average marginal effects of each model are computed based on the average predicted change in the outcome probability across the entire dataset and the list of explanatory variables when the predictor changes by one unit. These average marginal effects help to translate the latent scale coefficients obtained from the Robit regression into intuitive probabilities and plot them into a 95% confidence interval, making them easier to understand and communicate. The plots of average marginal effects provide a clear visualization of varying effects of explanatory variables on the dependent variables across the different regions, that is, positive and negative regions. Robit regression uses a link function derived from the t-distribution, and marginal effects derived from Robit regression are not constant. These marginal effects depend on the values of the predictors and the density of the t-distribution at various points.

Figures 1–4 depict that the average marginal effects corresponding to the variable GECL are negative, but their magnitude decreases at

TABLE 12 Correlation matrix of coefficients of Robit regressions.

e(V)	$GECL_i$	edu_s_i	y_pm_i	exp_s_i	$aware_i$	$barrier\_s_i$	s_family	benefits	$support_i$	_cons
$GECL_i$	1.00									
edu_s_i	0.78	1.00								
y_pm_i	−0.93	−0.80	1.00							
exp_s_i	−0.01	−0.26	−0.00	1.00						
$aware_i$	0.74	0.83	−0.77	−0.36	1.00					
$barriers_i$	0.04	−0.22	0.08	0.42	−0.13	1.00				
$s\_f\_family_i$	−0.53	−0.30	0.47	−0.40	−0.28	−0.57	1.00			
$benefits\_t_i$	0.55	0.40	−0.59	−0.02	0.63	−0.02	−0.35	1.00		
$support\_{si}$	−0.56	−0.48	0.61	−0.29	−0.33	0.10	0.27	−0.30	1.00	
_cons	0.93	0.80	−1.00	0.01	0.76	−0.08	−0.47	0.58	−0.62	1.00

Source: Authors' calculation using STATA 18.

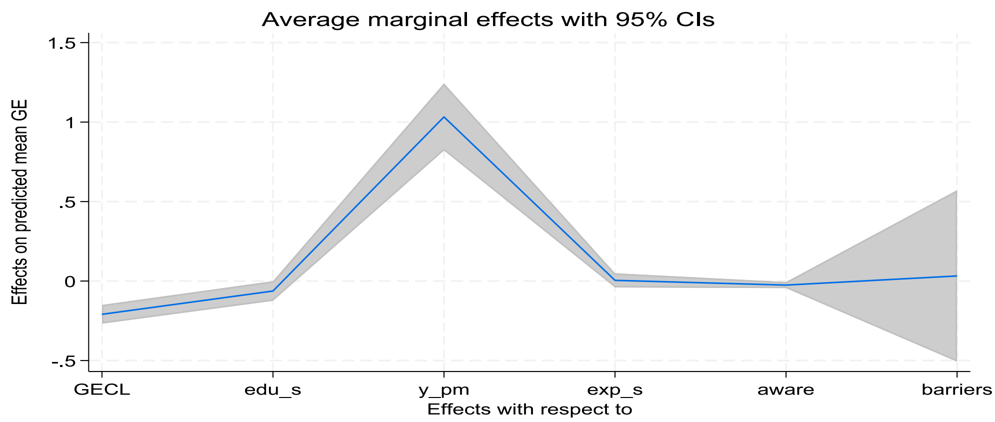

FIGURE 1
Average marginal effects with 95% confidence interval of model (1). Source: Authors' calculation using Stata 18.0.

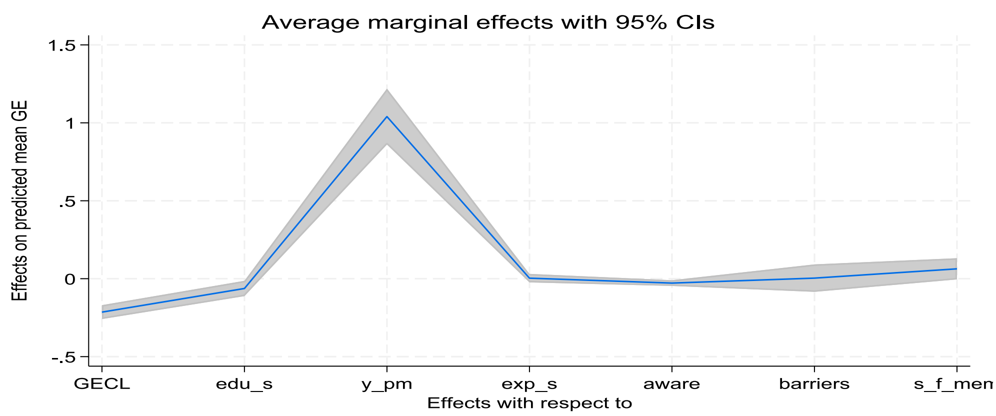

FIGURE 2
Average marginal effects with 95% confidence interval of model (2). Source: Authors' calculation using Stata 18.0.

high values. Similarly, the marginal effects of the education variable are negative at smaller values and become positive at larger values. The impact of the log of estimated income (per month) is also positive and consistent, whether values are small or large. The remaining variables can also be explained in a similar way.

5 Conclusions and recommendations

The present study was conducted to investigate the determinants of the use of green energy products by farmers of District Swabi of Khyber Pakhtunkhwa. A structured questionnaire is distributed

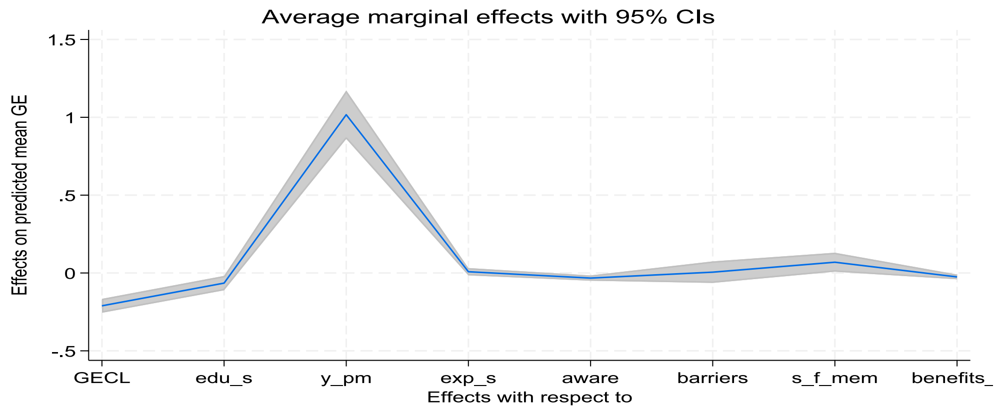

FIGURE 3
Average marginal effects with 95% confidence interval of Model (3). Source: Authors' calculation using Stata 18.0.

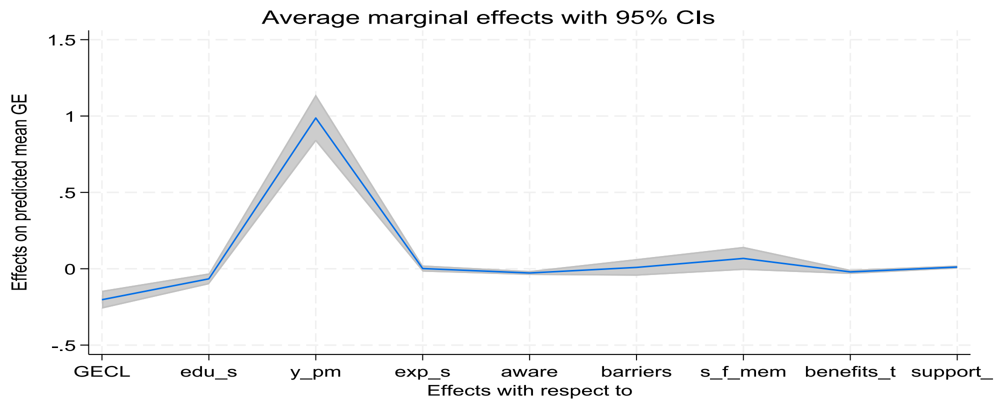

FIGURE 4
Average marginal effects with 95% confidence interval of Model (4). Source: Authors' calculation using Stata 18.0.

among a sample size of 460 farmers. Out of 460, only 400 questionnaires were completed and used for analysis. The key results, along with policy suggestions and scope for further research, are summarized here.

Data analysis revealed that 320 out of 400 farmers use green energy products. Among the 320 farmers, 252 are uncomfortable with its use, and 68 are comfortable. The study indicates that most of the farmers have an average age of approximately 37 years. The average schooling is 7 years in the sample. Moreover, most farmers are using solar energy for farming, but the majority are either unaware of or only slightly aware of green energy products. The farmers learned about solar energy from family, friends, and relatives, and they considered it essential for farming because it reduces their energy bills.

The Robit regression analysis indicates that the use of green energy products decreases, based on marginal effects, when farmers are not illiterate and are not aware of green energy products. On the other hand, the marginal effect of the log of per month, types of support, and farming experience of the farmers enhances the farmers' use of green energy products. Similarly, the study also confirmed that the use of green energy products by the farmers decreased if the farmers had seen barriers to adopting it and a lack of support from family members during peak seasons.

Based on the research findings, it is suggested that the government may introduce agriculture and the use of green energy specific education or training programs to the farmers so that the environment is protected and the cost of production is reduced through the use of green energy products. The study also suggests that the government may implement special programs to provide support to farmers in the installation, maintenance, expansion, and upgradation of green energy products so that barriers to adopting green energy are significantly lowered in the sample area of the study. Future research may extend the present study by including more districts or regions or using longitudinal and experimental research designs to examine the farmers' intentions for adopting green energy. Further research may focus on behavioral, psychological factors, and technical know-how that influence farmers' decisions. Furthermore, research may also incorporate gender, social inclusion and government interventions that could provide more comprehensive insights for policy formulation and sustainable energy transitions in agriculture.

Data availability statement

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

Author contributions

AJ: Formal analysis, Visualization, Data curation, Resources, Validation, Project administration, Software, Writing – review & editing, Methodology, Funding acquisition, Supervision, Conceptualization, Writing – original draft, Investigation. YY: Visualization, Writing – original draft, Methodology, Supervision, Writing – review & editing. LC: Software, Methodology, Data curation, Writing – review & editing, Formal analysis, Funding acquisition.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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