Scientific Journal of Agricultural Sciences 4 (2): 24-33, 2022
Print (ISSN 2535-1796) / Online (ISSN 2535-180X) DOI: 10.21608/sjas.2022.143316.1236

Quantifying the Determinants of Improved Wheat Variety Adoption in Egypt: Binary Response Models

Dina Emam[1] and *Victor Shaker[2]

[1]Department of Rural Sociology and Agricultural Extension, Faculty of Agriculture, Cairo University, Egypt.
[2]Department of Agricultural Economics Faculty of Agriculture, Cairo University, Egypt.
*Corresponding Email: victor.shaker@agr.cu.edu.eg

Received on: 7-6-2022 **Accepted on: 1-8-2022**

ABSTRACT

Wheat, the most vital strategic crop in Egypt, has been dramatically subject to international economic and political fluctuations because Egypt is the world's largest wheat importer. Despite the efforts exerted to release early maturing and high-yielding varieties as a substitute for horizontal expansion, their diffusion remains slow in some rural areas. No prior studies have quantified the drivers of improved wheat varieties adoption, considering Egyptian small-scale farmers. In this work, logit and probit models are applied using primary data gathered from 143 wheat-growing farmers in Moshtohor village, Al Qalyubia Governorate, in 2021. Although the logistic model fits the data better, both models yield similar results. The findings confirm that education, farm size, extension service accessibility, credit accessibility, and off-farm income positively affect the adoption decision; however, it is negatively affected by the farmer's age. In particular, extension service accessibility and credit accessibility appear to be the most influential factors within the Egyptian context. Policymakers should put in place effective extension programs, make credit easier to get, promote private sector investment in input acquisition and distribution, encourage young farmers to join in exploring new technology and best practices, and preserve the key traits of wheat cultivars that farmers and consumers want. Future work will refine the model by extending the survey nationwide and including other explanatory variables.

KEYWORDS: Innovation adoption; Wheat, Small-scale farmers; Binary models; Egyptian economy.

1. INTRODUCTION

Technology adoption is simply the decision to select, acquire, and use innovation. However, diffusion is how it spreads. Understanding the driving factors of choice is essential for economists, producers, and creators of these technologies (Hall & Khan, 2003).

Egypt's wheat production in 2022/23 (July–June) is forecasted to reach 9.8 million tonnes, up by 8.9 percent compared to 9 tonnes in 2021/22. The rise is attributed to an increase in the total area harvested, which is expected to rise to 3.64 million feddans from 3.33 million feddans last year. Before the planting season, the government established its wheat purchase prices, and the government intends to increase wheat harvested areas by about one million Feddans in the coming three years (Wally & Akingbe, 2022).

Wheat consumption is predicted to be 20 million tonnes in 2022/23, a 2.43 percent decline from the 2021/22 forecast of 20.5 million tonnes. The decrease is due to a 2.6 percent decrease in consumption of Food, Seed, and Industrial usage (FSI). This drop is due to a rise in European and white flatbread (non-subsidized) prices and baked items such as cakes, biscuits, wafers, croissants, and pastries, among other things.

Wheat imports totaled 62.6 million tonnes during the preceding five years, with 59.7 percent coming from Russia and 22.3 percent from Ukraine (82 percent combined), both key suppliers to the Egyptian market. In 2021, private sector imports accounted for 60% of overall imports, while government imports accounted for 40%. During the last five years, the private sector has emerged as a prominent participant in Egypt's wheat market, increasing market share year after year.

Given the challenges of the horizontal expansion strategy, efforts are being made to create breeding and cultivation techniques (Abdelmageed et al., 2019). Before planting, the Ministry of Agriculture and Land Reclamation (MALR) established a wheat varietal policy that considers each geographical area's climate, water, and land resources. This includes nine varieties in the Delta, thirty in Middle Egypt, and seventeen in

Upper Egypt (Wally & Akingbe, 2022). The Agricultural Research Center (ARC) successfully developed new wheat varieties, including Sakha 95, Beni Suef 7, and Misr 3. The new varieties were supplied to farmers ahead of the planting season, generally in November.

Over the last six years, the use of early maturing as well as high yielding seed varieties, increasing the number of certified seeds distributed to farmers, ideal sowing time, laser leveling techniques, and boosting the area of wheat raised bed cultivation to more than 1.24 million feddans have all made significant contributions to substantial vertical expansion (Wally & Akingbe, 2022). Despite the superiority of the new varieties of wheat, small-scale farmers are still slow to make adoption decisions (Selim & Eltarabily,2022). International relations' risk and uncertainty have further accentuated the problem.

Egypt's extension organization is aged and deteriorating. The extension employees are unspecialized and unsatisfied with their jobs. Some impediments to extension work are connected to centralization, authority delegation, institutional work, funding, training opportunities, and the link with scientific research institutions (Mansour et al.,2002).

While the official agricultural policy has long given subsidized access to agricultural finance, most farmers have been unable to get formal loans. Reforms implemented in 2016 may boost the number of farmers who may obtain loans, although the impact of these reforms is unknown (Kassim et al., 2018). The tendency of rural families to pursue non-farm activities in their survival among their strategies for survival and diversifying their income sources (Dontsop-Nguezet et al., 2016).

In their paper of 1985, Feder et al. argue that farmers' adoption behavior, particularly in low-income countries, is impacted by a complex collection of socio-economic, demographic, technical, institutional, and biophysical factors. The drivers of adoption are previously unstudied in the Egyptian context.

A challenging problem that arises in this domain is that the introduction of improved wheat varieties has met with partial success, as proved by rates of adoption. It is expected that removing the barriers to rapid adoption could further increase average farm incomes.

Hence, the present work aims to investigate the significant factors relevant to the adoption decisions made by small-scale Egyptian farmers. Therefore, 143 wheat-growing farmers from Moshtohor village were surveyed using a sampling procedure in 2021. The main downside of the current work is that the surveyed farmers are geographically concentrated.

This paper is organized as follows: The first section presents the literature review. The second section introduces the methodology, and the results are discussed in the third section. Finally, the conclusion is drawn in the fourth section.

2. LITERATURE REVIEW

Rogers (1962) defines the adoption process as "the mental process an individual passes from first hearing about an innovation to final adoption." Agricultural technology refers to equipment, farming techniques, genetic material, and agricultural inputs developed to make agriculture more effective. The seminal work provided by Feder et al. (1985) established many classical adoption theories.

Empirical approaches to the analysis of technology adoption include binary response models: Tobit, Propensity Score methods, and Principal Component Matching, in addition to descriptive statistics, are the most widely applied models in the literature on the adoption of new agricultural technologies.

Much work on the factors influencing adoption in developing countries has been carried out and can be reviewed in Table (1).

Table 1. Definition of variables and their prior expectations.

Variables	Description	Value	Expected signs
Age	Age of the farmer	Years	+/-
Education	Number of schooling years	Years	+
Farm size	Area of farming	Feddans	+/-
Extension service	If the farmer has access to extension service.	1 =Yes 0 =No	+
Credit accessibility	If the farmer has access to credit.	1 =Yes 0 =No	+
Off-farm income	If the farmer engages in off-farm activities.	1 =Yes 0 =No	+/-

Source: authors' compilation.

The results are highly consistent with the adoption theory. To date, most studies have dealt with the situation in many developing countries and the adoption of various agricultural technologies. Therefore, the present study focuses on the status of wheat-growing farmers to fill the gap in the Egyptian setting.

3. METHODOLOGY

As the present work questions the driving factors of adoption, Moshtohor Village, in Al Qalyubia Governorate, was chosen as a model representing the status of small-scale farmers in Egypt. A multistage sampling approach was used to sample the wheat growers in the designated area in 2021. One hundred forty-three wheat-growing farmers were selected as the total sample size for this study after omitting the incomplete responses and outliers. Sixty-six farmers are classified as adopters, whereas 77 farmers are non-adopters. The coronavirus pandemic outbreak was the biggest challenge surrounding data collection.

Following the literature on agricultural technology adoption, several variables were chosen as explanatory variables, namely: age, farm size, education, access to extension service, and credit accessibility. The survey data was analyzed using Stata12.

Categorical models with dependent variables coded as "0" and "1" are called two-ended or dummy dependent variable models. Logit and probit models are commonly used to estimate the relationship between response and explanatory variables. They also belong to the generalized linear models (GLM) family. As the response variable is binary, the normal least squares method (OLS) cannot be used in estimation; however, the maximum probability estimate is the alternative. (İşçi Güneri & Durmuş,2020). To better understand the individual steps of the chosen methodology, Figure (1) provides the conceptual flowchart.

A general linear regression model is expressed in Equation (1), where y_i is a regressand and x_i is a regressor.

$$y_i=\alpha+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_k x_k+\varepsilon_i \qquad (1)$$

In the above model, α constant term and β are regression coefficients. If the regressand is continuous, the traditional OLS can be employed to estimate this model. However, logit or probit regression methods can be used when it is discrete.

3.1. Logit model

The logit model can be utilized to model the probability of an event with two responses. The dependent variable y_i takes "0" and "1"; therefore, it is called the binary logit model. Equation (2) expresses the probability when the response variable is "1."

$$P_i = E(y=1|x_i) = \frac{1}{1+e^{-(\alpha+\beta x_i)}} = \frac{1}{1+e^{-z_i}} \qquad (2)$$

In this model, P_i represents information about the argument x_i, while the first individual signifies the probability of making a specific choice. As OLS cannot directly predict α and β parameters, the logit function can be estimated using Equation (3).

$$1-P_i = 1-\frac{1}{1+e^{-(\alpha+\beta x_i)}} = 1-\frac{1}{1+e^{-z_i}} \qquad (3)$$

If Equations (2) and (3) are proportional, Equation four is obtained.

$$\frac{p_i}{1-p_i} = e^{Z_i} \qquad (4)$$

It is also the odds or odds ratio (OR). The natural logarithm of this model in the "e" base can be represented as Equation 5.

$$L_i = \ln\left(\frac{P_i}{1-P_i}\right) = Z_i = \alpha + \beta X_i \qquad (5)$$

The parameters in the L_i function can be estimated by the maximum likelihood model (ML) instead of the OLS method. The coefficients in such models cannot be interpreted as the effect of changing the independent variables on the expected value of the response variable. Consequently, OR values or marginal effects must be calculated.

3.2. Probit Model

The weakness of the linear probability model comes from the fact that the predicted probability values are not in the range between "0" and "1". However, the probit model is considered one of the models used to solve this problem, keeping the probabilities between "0" and "1". As the dependent variable y_i is binary, P_i is expressed in Equation (6).

$$P_i=E(y=1|x_i) =\phi(x_i\beta) \qquad (6)$$

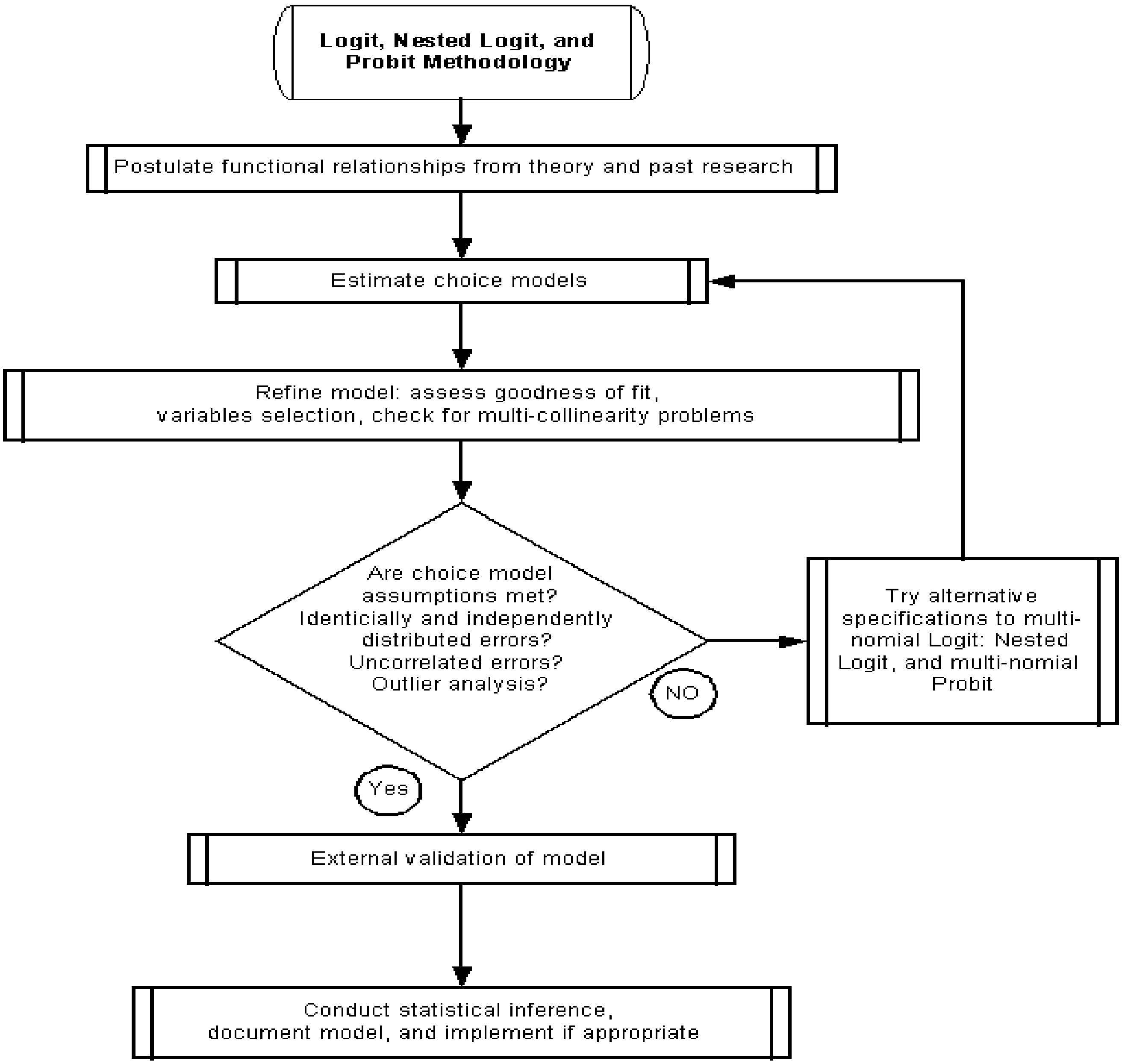

Figure 1. Logit and Probit Methodology

Source: Washington et al. (2002).

Where ϕ refers to the cumulative distribution function and β maximum likelihood coefficients of the standard normal distribution.

If adopted as a model with a latent variable, the probit probability model based on the normal cumulative distribution function can be expressed by Equation (7).

$$y_{i^*}=I_i=\alpha+\beta x_i \qquad (7)$$

Where x_i is observable, but y_{i^*} is not observable. Considering that y_i has a threshold value that cannot be observed (y_{i^*}), it can be said that if y_i exceeds the value y_{i^*}, the event will occur, and if it does not, the event will not occur (Equation (8)).

$$y_i=\begin{cases}1 & y_i^* > 0 \\ 0 & otherwise\end{cases} \qquad (8)$$

In case y_i* is less than or equal to y_i, calculated from standardized cumulative distribution functions under the assumption of normality. If ϕ(Z) cumulative normal distribution function is defined as ϕ(Z)=P(Z≤z) for the normal standard variable Z. Then, Z here is a standardized normal variable, i.e., N (0,1). Thus, the model can be expressed by Equation (9).

$$F^{-1}(P_i)=F^{-1}(I_i)=\alpha+\beta x_i \quad (9)$$

In this model, $F-1$ is the inverse of the normal cumulative distribution function. The parameter estimates must be modified to obtain estimates of the marginal effects, interpreted as the change in predicted probability due to changes in the explanatory variables (Greene, 2003).

Although logit and probit models generally give similar results, many researchers choose the logit over the probit due to its comparative mathematical simplicity.

3.3. Diagnostic tests

There are many ways to calculate R^2. However, there is no consensus on which one is the best. Specifically, the one proposed by McFadden (1974) is often the reported method in statistical software. On the other hand, Pearson's chi-squared test can evaluate how likely any difference observed between the sets arose by chance.

The Hosmer and Lemeshow test is another commonly used goodness-of-fit test in which the predicted and observed frequency should match closely. That is, the more closely they match, the better the fit. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are applied to compare models; the model that always gives the lowest values is preferred.

The linear predicted value "hat" and linear predicted value squared "hatsq" test whether all the relevant predictors are included in the model and if the linear combination is sufficient. Accordingly, if "hat" is statistically significant, the model is well specified. However, if "hatsq" is significant, the model is not correctly specified.

Multicollinearity appears in the model when there is a strong interrelationship among the variables. The variance Inflation Factor (VIF) can be estimated to measure the strength of the interrelationships. Most research papers regard a VIF greater than 10 as a sign of multicollinearity; however, some are more conservative.

4. RESULTS AND DISCUSSION

The survey data support the aim of the present work to determine the relevant factors influencing the adoption of the improved wheat varieties. Having been developed by ARC, the common varieties in the research area are Benisuif 5, Giza171, Misr1, Misr2, and Sids14. Some of which are high in productivity, resistant to disease, and tolerant of various environmental stresses (Table (2)).

Table 2. Improved wheat varieties cultivated in Moshtohor village.

Variety	Resistant to rusts	Resistant to water deficit	Early maturing	High yield	Heat tolerant
Sids 14	√		√		
Benisuif 5				√	√
Misr 1	√	√		√	√
Misr 2	√				√
Giza171	√		√		

Source: Survey data 2021.

4.1. Demographic and socioeconomic characteristics

One hundred forty-three farmers were surveyed after being selected through sampling procedures in 2021. Sixty-six farmers are classified as adopters, whereas 77 farmers are non-adopters. The characteristics of the sampled farmers can be summarized as presented in Table (3).

On average, the adopters are younger (48 years) than non-adopters (55 years), having less farming experience (17 and 22 years for adopters and non-adopters, respectively). However, the adopters have more years of education (12 years) than non-adopters (8 years). The farm size is larger for adopters (1.43 feddan) than non-adopters (1.10 feddan). Likewise, the wheat area is larger for adopters (0.96 feddan) than non-adopters (0.83 feddan). The t-test shows that all differences between the two groups' means are statistically significant at a 5 percent significance level.

Table 3. Basic Characteristics of farmers in Moshtohor village.

Characteristic	Unit	Adopters (n = 66)		Non-adopters (n = 77)		T-TEST
		Mean	S.D.	Mean	S.D.	
Age	Year	48.21	7.82	55.35	7.54	5.55**
Farming experience	Year	16.88	9.10	22.38	11.53	3.18**
Education level	Year	12.42	2.16	8.06	3.95	-8.33**
Farm size	Feddan	1.43	0.84	1.10	0.63	-2.61**
Wheat area	Feddan	0.96	0.43	0.83	0.31	-2.10**
Family labor	Person	9.00	2.95	9.00	2.78	0.31 (NS)
Hired labor	Person	5.00	3.14	4.00	2.37	-2.45**
Livestock units	Unit	3.76	5.44	3.62	4.99	-0.15(NS)

** denotes a 5% significance level.
Source: Authors' calculations.

Furthermore, the household labor is the same for both groups (9 persons); they are slightly different regarding hired labor (5 and 4 persons for adopters and non-adopters, respectively). Adopters and non-adopters, on average, own the same units of livestock (4 units). Educational status, off-farm income, extension service accessibility, and credit accessibility, on the other hand, are compared in (Table (4)).

Table 4. Classifications of farmers in Moshtohor village.

Variables	Adopters (n = 66)		Non-adopters (n = 77)		χ2
	No.	%	No.	%	
Education					
Illiterate	0	0.00	12	15.58	11.22 **
Literate	66	100.00	65	84.42	
Off-farm income					
No	8	12.12	54	70.13	48.69**
Yes	58	87.88	23	29.87	
Extension service accessibility					
No	6	9.09	65	84.42	80.66**
Yes	60	90.91	12	15.58	
Credit accessibility					
No	5	7.58	61	79.22	73.40**
Yes	61	92.42	16	20.78	

** denotes a 5 percent significance level.
Source: Authors' calculations

The findings indicate that all adapters (100%) are literate compared to non-adopters (84%). More adopters (88%) earn off-farm income than non-adopters (23%). Also, more adopters (91%) have access to extension service than non-adopters (16%). Similarly, more adopters (92%) have access to credit compared to non-adopters (21%). Based on the chi-squared statistic (χ^2), the differences between the two groups are statistically significant.

To sum up, the overall direction of the results shows that the adopters have stronger characteristics than non-adopters. This result is consistent with most of the literature investigated.

4.2. Logit and Probit Analysis

The two binary models were applied to estimate the impacts of the selected explanatory variables on adoption decisions. The findings reveal that all the regressors are statistically significant. On the other hand, it is necessary to assess model fit and diagnose potential problems before using the models to make any statistical inference. In this regard, the results confirm the validity of both models for statistical inference; however, the logit model proves to be better based on model selection criteria (Table (5)). Since the coefficients obtained in both models cannot

Table 5. logit and Probit model estimates.

Adoption	**Logit Model**			**Probit Model**		
	Coef.	**Std. Err.**	**P>|z|**	**Coef.**	**Std. Err.**	**P>|z|**
Age	-0.16	0.06	0.01	-0.08	0.03	0.02
Education	0.81	0.23	0.00	0.42	0.12	0.00
Farm size	1.89	0.66	0.00	1.01	0.35	0.00
Extension service	2.50	0.89	0.01	1.33	0.49	0.01
Credit accessibility	2.17	0.91	0.02	1.13	0.49	0.02
Off-farm income	2.06	0.95	0.03	1.06	0.48	0.03
Constant	-7.10	3.42	0.04	-3.72	1.81	0.04
N	143			143		
Log-Lik In,t Only	-98.697			-98.697		
Log-Lik Full Model	-20.388			-20.655		
D(136)	40.776			41.309		
LR(6)	156.617			156.084		
Prob > LR	0.000			0.000		
McFadden's R^2	0.793			0.791		
McFadden's Adj R^2	0.723			0.720		
Maximum Likelihood R^2	0.666			0.664		
Cragg & Uhler's R^2	0.889			0.887		
McKelvey and Zavoina's R^2	0.915			0.905		
Efron's R^2	0.837			0.833		
Variance of y*	38.616			10.530		
Variance of error	3.290			1.000		
Count R^2	0.951			0.951		
Adj Count R^2	0.894			0.894		
AIC	0.383			0.387		
AIC*n	54.776			55.309		
BIC	-634.171			-633.637		
BIC'	-126.840			-126.307		
Pearson chi2(133) (Prob > chi2)	126.01 (0.65)			119.47(0.79)		
Hosmer-Lemeshow chi2(133) (Prob > chi2)	126.01(0.65)			119.47 (0.79)		
Specification Error						
_hat (P>|z|)	1.08 (0.000)			1.10 (0.00)		
_hatsq (P>|z|)	0.05(0.151)			0.10 (0.05)		
Multicollinearity (Mean VIF)	2.12			2.12		

Source: Authors' calculations.

be interpreted directly, the marginal effects were calculated in Table (6).

The two models’ outcomes are almost identical and can be respectively compared, considering other variables remain constant.

Age: a farmer’s age impacts adoption negatively as younger farmers are more likely to adopt new technologies. Accordingly, a 1-year increase in farmer’s age is expected to decrease the probability of adoption by 0.03 in both models.

Education: better-educated farmers are better technology adopters. Therefore, it is possible to increase the probability of adoption by 0.16 and 0.15, respectively, due to increasing the years of education by one year.

Farm size: being unable to allocate pieces of their lands to try improved wheat varieties, farmers with smaller farm sizes are not likely to adopt them. Consequently, a 1-feddan increase in the farm size is likely to increase the probability of adoption by 0.37 and 0.36, respectively.

Extension service: receiving advisory service is vital in farmers' adoption decisions. Accordingly, the probability of adoption is expected to rise by 0.46 and 0.45, respectively, for farmers having access compared to those with no access.

Table 6. Marginal effect for logit and Probit models

Adoption	Logit Model			Probit Model		
	dy/dx	Std. Err.	P>|z|	dy/dx	Std. Err.	P>|z|
Age	-0.03	0.01	0.01	-0.03	0.01	0.02
Education	0.16	0.04	0.00	0.15	0.04	0.00
Farm size	0.37	0.13	0.01	0.36	0.12	0.00
Extension service *	0.46	0.16	0.00	0.45	0.15	0.01
Credit accessibility*	0.39	0.15	0.01	0.38	0.15	0.02
Off-farm income*	0.37	0.16	0.02	0.35	0.15	0.03

(*) denotes discrete change of dummy variable.
Source: Calculated from Table (5).

Credit accessibility: credit facilitation service enables most smallholder farmers to purchase inputs of the improved wheat varieties. As a result, the probability of adoption is expected to increase by 0.39 and 0.38, respectively, for farmers having access compared to those with no access.

Off-farm income: participating in off-farm activities would increase the family's income. Hence, farmers would easily adopt new technology. Hence, the probability of adoption is expected to increase by 0.37 and 0.35, respectively, for farmers participating in off-farm activities compared to those who do not.

These results tie well with previous studies; however, the present work suggests that extension service accessibility and credit accessibility are the most influential factors within the Egyptian setting.

5. CONCLUSION

The results are significant factors impacting the adoption decisions made by wheat-growing farmers in Moshtohor village. This paper contributes to filling the gap in Egyptian literature regarding innovation adoption by small-scale farmers. The logit and probit analysis findings indicate that education status, farm size, extension service accessibility, credit accessibility, and off-farm income positively affect the adoption decision; however, the adoption decision is negatively affected by farmers' age. Interestingly, access to extension service and credit has proven to be the most prominent factors in decision-making.

These outcomes may contribute to designing policies and programs to enhance agricultural productivity. Policymakers should implement effective extension programs, facilitate credit accessibility, and support private sector investment in input acquisition and distribution. Young farmers need to be encouraged to join in exploring new technology and best practices. More emphasis should be placed on preserving the key traits of wheat cultivars that farmers and consumers want.

The main shortcoming of the present research is that it exclusively focuses on geographically concentrated farmers. Future work will refine the model by extending the survey nationwide and including other explanatory variables.

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الملخص العربي

قياس العوامل المحددة لتبنى أصناف القمح المحسنة في مصر: منهجية نماذج الاستجابة الثنائية

دينا إمام[1] و فيكتور شاكر[2]

[1]قسم الاجتماع الريفي والإرشاد الزراعي، كلية الزراعة، جامعة القاهرة ، مصر
[2]قسم الاقتصاد الزراعي، كلية الزراعة، جامعة القاهرة ، مصر

بالرغم من الجهود المبذولة للنهوض بالزراعة المصرية من خلال إدخال التكنولوجيا الحديثة المتمثلة في استنباط أصناف وسلالات عالية الإنتاجية؛ إلا أن تبنى تلك المستحدثات قد اتسم بالتباطؤ الشديد من قبَلَ غالبية صغار المزارعين. بناءً على ذلك، تهدف الدراسة الحالية إلى الوقوف على أهم العوامل المحددة للتبني؛ بغية استقراء الوضع الراهن لصغار المزارعين في ظل الظروف المصرية. ولتحقيق الهدف البحثي، تم اتباع أسلوب المعاينة في اختيار ١٤٣ مزارع من صغار مزارعي محصول القمح بقرية مشتهر، التابعة لمركز طوخ بمحافظة الدقهلية، وذلك خلال موسم زراعة القمح لعام ٢٠٢١. ولقد تم اختيار محصول القمح؛ نظراً لما يمثله من أهمية إستراتيجية وغذائية كبيرة، حيث تعد مصر أكبر مستورد للقمح في العالم. ولقد تم استخدام نموذجين من النماذج ثنائية الاستجابة (Binary Response Model): نموذج الانحدار اللوجستي (Logit Model) ونموذج الاحتمالية الخطية (Probit Model)؛ لدراسة أثر المتغيرات موضع الدراسة على قرار المزارعين بتبني الأصناف المحسنة من القمح من عدمه.

في هذا الإطار، أشارت النتائج إلى الحالة التعليمية، وحجم المزرعة، وتوافر الخدمات الارشادية، إلى جانب اتاحة الفرص الائتمانية والمشاركة في الأنشطة غير الزراعية تعد من العوامل المؤثرة بشكل إيجابي على قرارات المزارعين. أما العمر للمرحلة فإنها تؤثر سلباً على قرار التبني؛ فكلما تقدم عمر المزارع كان أكثر عزوفاً عن تبنى الأصناف المحسنة. وبصفة خاصة، أوضحت النتائج أن توافر الخدمات الارشادية وإتاحة الفرص الائتمانية يعدا من أبرز العوامل المحددة للتبني.

والجدير بالذكر أن النتائج المتحصل عليها من هذه الدراسة تتطابق مع نتائج الدراسات السابقة في حالة الدول النامية؛ ولذلك تساهم الدراسة الحالية بفاعلية في سد الفجوة القائمة في الدراسات السابقة فيما يتعلق بتبني المستحدثات الزراعية في ظل الظروف المصرية. بالرغم من ذلك، فإن الاقتصار على دراسة حالة المزارعين في نطاق جغرافي معين يعد من أهم محددات الدراسة.

في ضوء النتائج المتحصل عليها، يتعين على صناع السياسات البدء في وضع برامج إرشادية فعالة، وتذليل العقبات التي تواجه الائتمان الزراعي، إلى جانب دعم استثمارات القطاع الخاص في مجال توفير وتوزيع المستلزمات الإنتاجية. من ناحية أخرى، توصى الدراسة بضرورة تشجيع شباب المزارعين على استكشاف التقنيات الحديثة وأفضل الممارسات، كما توصى بالحفاظ على الخصائص الأساسية لأصناف القمح التي يريدها المزارعون ويرغبها المستهلكون. فيما يتعلق بالدراسات المستقبلية، تقترح الدراسة ضرورة توسيع النطاق الجغرافي للعينة، بالإضافة إلى أدخال متغيرات تفسيرية أخرى.

الكلمات الدالة: تبنى المستحدثات، محصول القمح، صغار المزارعين، نماذج الاستجابة الثنائية، الاقتصاد المصري.