From conventional to smart: Farmers' preferences under alternative policy scenarios

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Abstract

This study investigates the impact of ex-ante policy scenarios on conventional farmers' intentions to adopt smart farming applications and identifies influential factors. Through survey data collected from 117 conventional farmers, three scenarios (no support, cash support, credit support) were presented to determine their intention to adopt smart farming. The findings reveal that financial support significantly boosts farmers' intention to adopt these technologies. Additionally, farm income, knowledge, and inheritor positively influence adoption, while education and age hinder it. To promote the adoption of smart farming systems, we recommend providing educational programs to increase farmers' knowledge and offering financial benefits to offset the costs of purchasing and installing the systems. Our findings are relevant for developing countries, such as Türkiye, that are transitioning to smart farming and can inform policies that facilitate the adoption of smart farming systems.

***Keywords**: Ex-ante policy, Farmers' intention, Innovation, Smart farming, Technology adoption.*

1. Introduction

Since the beginning of human history, agriculture has been one of the oldest and most important occupations. Particularly for developing countries, the agricultural sector plays a pivotal role in driving economic growth (Byerlee *et al.*, 2009). However, there are several challenges facing the sector today, such as the abandonment of agricultural lands (Leal Filho *et al.*, 2017), the increasing demand for food (Elferink and Schierhorn, 2016), rising rural-to-urban migration (Goldsmith *et al.*, 2004), higher input costs (Mottaleb and Mohanty, 2015), and the harmful effects of chemical inputs on the environment (Wu, 2011), particularly in conventional farming.

In addressing the challenges confronting the agricultural sector, new technologies present themselves as promising alternative solutions. The widespread use of technology in agriculture has been found to result in higher productivity (Morantes *et al.*, 2022), lower costs (Bongiovanni and Lowenberg-DeBoer, 2000; Özgüven and Türker, 2010), water-saving (Belaidi *et al.*, 2022), and reduced chemical inputs (Ehlert *et al.*, 2004; Karimzadeh *et al.*, 2011).

In recent years, Agriculture 4.0, also known as Smart Farming or Digital Farming, has started integrating digital transformation with

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Industry 4.0, combining information technologies with industrial activities. The objective of smart farming is to implement a production model that is more efficient, with reduced input usage, lower cost, and environmentally friendly. While Precision Agriculture (PA) only takes in-field variability into account, Smart Farming (SF) goes beyond that by basing management tasks on location, data, and context situation awareness triggered by real-time events (Wolfert *et al.*, 2014). SF allows a large volume of data and information to be generated by incorporating information and communication technologies into machinery, equipment, and sensors in agricultural production systems, progressively automating the process (Pivoto *et al.*, 2017).

In Mediterranean countries where water scarcity (Iglesias *et al.*, 2007) and arid climate (Tramblay *et al.*, 2020) are prevalent, integrating technology into agriculture is crucial. However, in countries like Türkiye, where conventional farming is widespread, there is ongoing debate regarding the adoption of technology in agriculture, and its utilization remains limited. While agricultural technologies are widely used in some countries (Erickson and Widmar, 2015; Griffin *et al.*, 2017), there are still farmers who are hesitant to adopt the technology (Daberkow and McBride, 2003; Fountas *et al.*, 2005; Reichardt and Jürgens, 2009). At this point, agricultural supports are crucial for the adoption and advancement of technology in agriculture.

Agricultural support impacts farmers in many aspects, such as land use (Demirdöğen *et al.*, 2016) and farm income (Hennessy, 1998). Moreover, the quality and effectiveness of support initiatives significantly influence farmers' adoption of technology (Aubert *et al.*, 2012). In this study, we present support scenarios to the farmers to answer questions such as "Which policies can encourage farmers to use technology?" and "Which factors affect farmers' intentions?". Ex-ante support scenarios are designed because there is currently no policy supporting farmers' widespread use of technology in Türkiye.

The contribution of this article to the literature is the evaluation of policies that can be applied in the transition from conventional to smart agriculture. Our study presents ex-ante support scenarios and aims to provide suggestions to policymakers for encouraging farmers to use technology and contribute to developing countries' policies. Understanding how farmers respond to new technologies and supports that have not been previously utilized is crucial for developing countries to bridge the technological gap with advanced nations in agriculture.

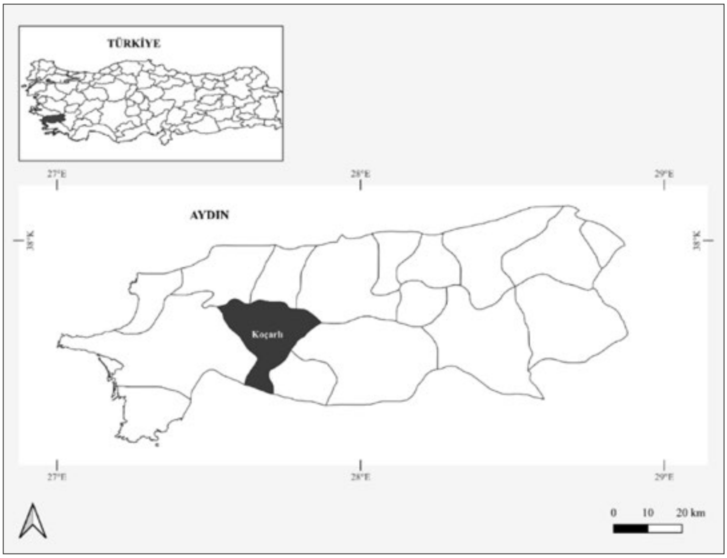


Figure 1 - Map of research area.

2. Research area and dataset

This study focuses on the Koçarlı district in Aydın province, with specific emphasis on Kasaplar village, renowned for its noteworthy smart farming enterprise. To ensure a comprehensive perspective, nine other villages were thoughtfully selected within the research area, considering their production patterns and geographical positions. By limiting the study area to Kasaplar village and its neighboring villages, we also acknowledge the potential awareness among farmers about the nearby enterprise and the benefits it provides (Figure 1).

The chosen smart farm in Kasaplar has been successfully operational since 2014, encompassing a vast land area of 29.8 hectares dedicated to both crop and animal production. This technologically advanced farm is equipped with various smart applications, including a sophisticated smart irrigation system, a comprehensive meteorology station, innovative smart pasture and fruit tools, advanced pest detection mechanisms, an agricultural monitoring center, and automated water tank systems. Notably, the farm has established valuable partnerships with industry leaders such as Vodafone and Tabit, which further contribute to its success.

Informations about the farmers collected through a survey in the 2017-2018 production period. In this period, the smart farm's five products with the largest production area were tomato, pepper, watermelon, melon, and eggplant. Therefore, the selection of conventional farmers that grow these products was considered. A total of 117 farmers in ten villages grow these products. We conducted a field survey with all these farmers.

3. Modeling farmers' responses

This study collects information on changes in farmers' intentions to use smart farming (SF) by directly asking them about various scenarios. The literature presents multiple pros and cons of stated intentions, which offer practical and guiding information, especially for the short term (Gorton *et al.*, 2008). Despite criticisms about the accuracy of stated intentions in revealing actual behavior, this method is widely documented in the literature. For instance, Lefebvre *et al.* (2014) analyzed the stated intentions about investments in land on the part of 171 farmers in 6 EU case study areas and their realized investments between 2006 and 2009. Barnes *et al.* (2016) examined the effect of past reforms on influencing farmers' intentions toward the most recent reform of the EU Common Agricultural Policy (CAP). Additionally, various studies claim that stated intention is not as problematic as previously mentioned and that farmers often behave as stated (Thomson and Tansey, 1982).

We prepare three scenarios to determine farmers' intentions toward SF:

Scenario 1 (S_1) (reference scenario): In case of the same market conditions (input and product price etc.) and probability of being affected by pests in the next five years.

Scenario 2 (S_2): In case of the same market conditions (input and product price etc.) and probability of being affected by pests in the next five years but 50,000 Turkish Lira/ha support to smart farming.

Scenario 3 (S_3): In case of the same market conditions (input and product price etc.) and probability of being affected by pests in the next five years but 0% interest rate agricultural loans given to smart farming by cooperatives or banks.

The minimal use of SF in Turkish agriculture and the absence of existing policies led the study to implement ex-ante scenarios. Ex-ante impact assessment is frequently used in the agricultural literature (Helming *et al.*, 2011; Lopez-Ridaura *et al.*, 2018; Paul *et al.*, 2018; Andrade *et al.*, 2019).

S_1 refers to the reference scenario where farmers are asked if they would prefer to use smart farming practices without any support. These responses to this scenario compare with S_2 and S_3.

In S_2, land-based payments are given to farmers. Agriculture is one of the economic sectors where support is most widespread (Vozarova and Kotulic, 2016). Researchers and policymakers have been interested in the effect of government payments to farms (Huffman and Evenson, 2001; Key and Roberts, 2006).

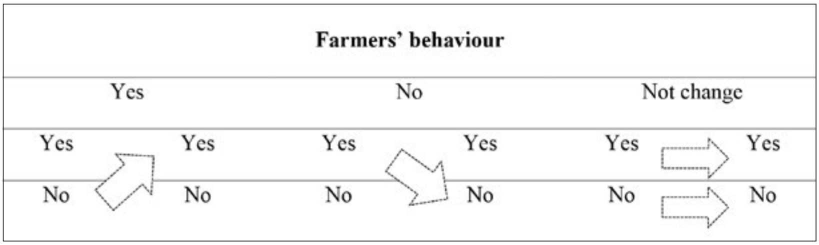


Figure 2 - Framework analysis applied.

Land-based payments are priority support in Turkish agriculture under different subheadings.[1] However, due to the cost of technological investments (Moss and Schmitz, 1999) and criticism of land-based payments (Uslu and Apaydın, 2021), we design the scenario to support farmers at 50,000 Turkish Lira per hectare. This amount is approximately ten times the average amount of support that Turkish farmers received in 2019, which was 5,000 TL per hectare. This scenario aims to provide support that will attract the attention of conventional farmers.

In S_3, a 0% interest rate is offered on agricultural loans to farmers. According to Ellis (1996), agricultural financing policies aim to provide the investment and input supply required for agricultural production, short-term cash needs, and access to new technology. Studies have shown that agricultural loans increase investment (De Rosari *et al.*, 2014). However, not all farmers have access to credit due to high-interest rates, especially small-scale farmers who cannot afford to purchase inputs or other technology (Olagunju, 2007). Similar to S_2, a new financing source is considered in S_3 to attract farmers' attention while they think about their new investment plans.

The model used in this study was inspired by Giannoccaro and Berbel (2013)[2] approach to determining farmers' intentions. We adapt their model to align with the aim of our study, which is to predict whether farmers would adopt smart farming applications based on different scenarios.

The smart farming applications discuss in the scenarios are "Thermo-hygrograph, Smart Irrigation, Yield Mapping, Terrain Monitoring with Drone and Early Warning Systems". These applications are used in the smart farm in this region, so we incorporate them into our scenarios.

The Thermo-hygrograph app measures moisture, temperature, soil moisture, and soil temperature continuously in the field using Internet of Things (IoT) sensors. The Smart Irrigation system records irrigation and fertilization information based on the plant's growth stages, which can be controlled from a computer, mobile, or panels. With the yield mapping system, it is possible to determine the changes in the productivity monitored in the field and thus determine the amount of agricultural input to be used. The drone creates visuals about the land, soil, and product. In addition, pesticides and chemical fertilizers are applied. Finally, the early warning system warns farmers about potential diseases or pests that meteorological conditions may cause on the farm.

To determine the "stated intention" variable, we first present the S_1 (reference scenario) to conventional farmers. Changes in farmer intentions are determined in S_2 and S_3 according to the reference scenario. For example, if the farmer's behavior is "No" in S_1 but "Yes" in S_2, it indicates a change in the stated intention. Conversely, if the farmer's response is "No" in S_1

1 Land-based payments are provided under the subcategories of small farmer support for crop production, hazelnut land-based income, alternative product support, support for good farming practices, fuel oil and fertilizer support, soil analysis support, and organic farming support (TOB, 2022).

2 Giannoccaro and Berbel (2013) considered farmers' stated responses to different CAP scenarios, examined the extent to which these plans would be influenced by the abolition of the CAP starting from 2014, and analyzed the implications of such abolition in terms of likely changes, such as increases or decreases in the use of chemicals and water resources on the farm.

Table 1 - Descriptive statistics.

Variables	*Description*	*Mean*	*Std.dev*
Dependent Variable			
Stated Intention	=1 if the farmer's intention changes to yes, not change 0	0.61	0.49
Independent Variables			
Farm Income	1000 TL*	111.58	159.47
Age	1: 15 - 49 years 2: 50 - 64 years 3: ≥ 65 years	1.81	0.63
Education	1: Primary school 2: Primary + secondary 3: High school 4: University	2.11	1.01
Land	1: ≤ 2 ha 2: 2.1 - 5 ha 3: ≥ 5.1 ha	2.29	0.77
Inheritor	=1 if the farmer has someone who will continue their farming in the future, otherwise 0	0.38	0.49
Knowledge	=1 if the farmer knows about smart farming, otherwise 0	0.31	0.46
Livestock	=1 if the farmer engaged in livestock, otherwise 0	0.39	0.49

* *1 $ = 5.70 TL.*

and S_2, it assumes that the stated intention of the farmers is not changed (see Figure 2). We include the stated intention variable as a dependent variable in the econometric model and analyzed the factors affecting farmers' intentions using logistic regression.

The economic theory that underlies stated preferences assumes that the decision maker's highest utility (or profit) is achieved through the most preferred option (Giannoccaro and Berbel, 2013). Initially, we planned to use a multinomial logistic regression model with the dependent variable in the analysis labeled as "0: Not change, 1: Yes, and 2: No". However, since all farmers indicated "No" in response to whether they would use any smart farming applications according to S_1, a binary logistic regression analysis was performed. The dependent variable is labeled as "0: Not change and 1: Yes".

The independent variables in this study include farm income, the age of farmers, farmers' education level, land size, whether the farmer has relatives to continue farming, and the status of livestock (see Table 1).

Our logistic model is specified as below:

$$Prob(Y_i=1)=P_i=F(Z_i)=F(\alpha+\sum_i\beta_iX_i)=\frac{1}{1+e^{-z_i}} \quad (1)$$

where is P_i is the probability that a farmer who wants to use smart farming tools; X_i represents explanatory variables; and α and β are parameters to be estimated.

$$Prob(Y_i=0)=1- Prob(Y_i=1)=(1-P_i)=\frac{1}{1+e^{z_i}} \quad (2)$$

From Equations (1) and (2), we get,

$$\frac{Prob(Y_i=1)}{Prob(Y_i=0)}=\frac{P_i}{1-P_i}=e^{z_i} \quad (3)$$

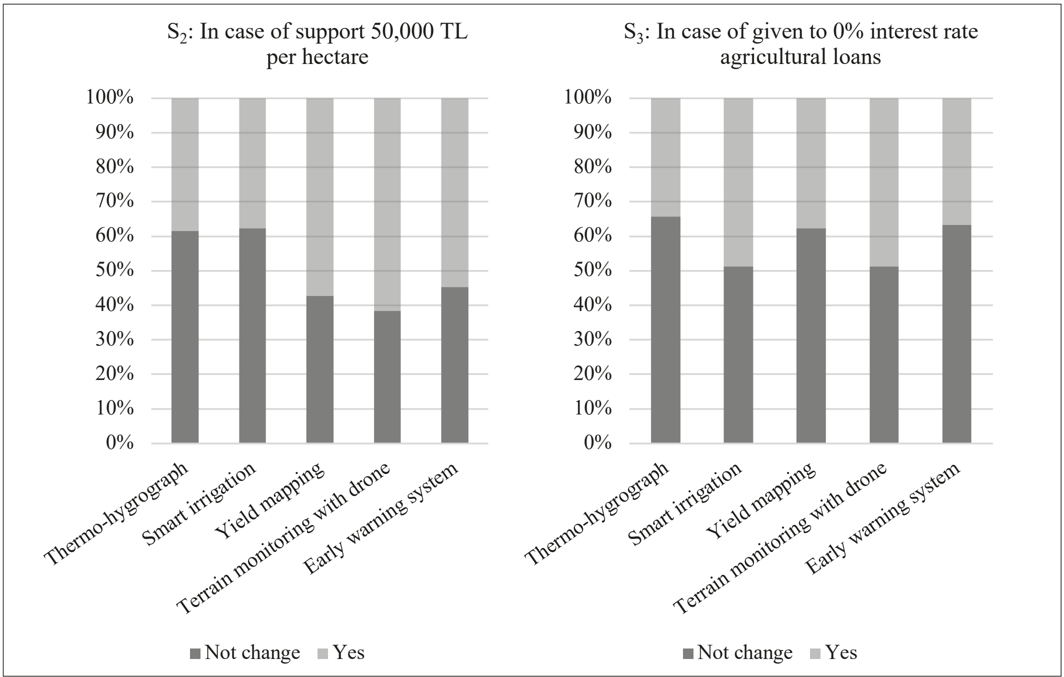
where P_i is the probability that Y_i takes the value 1 and then (1- P_i) is the probability that Y_i is 0, and e is the exponential constant.

Taking the natural log of both sides of Equation (3), we get,

$$Z_i= ln\left(\frac{P_i}{1-P_i}\right)=\beta_0+\beta_1X_{1i}+\beta_2X_{2i}+\ldots+\beta_kX_{ki}+u_i \quad (4)$$

A separate model was established for each smart farming application presented to the farmer in the scenarios.

Figure 3 - Farmers' intention to use SF regarding S_2 and S_3.



4. Results

To evaluate whether factors such as the age of the household head and education affect participation in extension programs and adoption of new farm technology, it is essential to consider farm household characteristics (Langyintuo and Mungoma, 2008). This study reveals that a significant portion of farmers in the research area, specifically the Koçarlı district of Aydın province and surrounding villages, fall within the age range of 50-64. Additionally, the level of education among farmers tends to be relatively low. A considerable proportion of farmers have completed primary school, while a smaller percentage have completed both primary and secondary education.

In terms of land ownership, a significant number of farmers own 5.1 hectares or more, with an average land size of 6.59 hectares. Moreover, a substantial portion of farmers lack a potential successor within their family who can continue farming after them. Furthermore, many farmers in the study area have limited or no knowledge about smart farming practices (see Table 1).

Figure 3 illustrates the change in farmers' intentions for smart farming between S_2 and S_3. In the reference scenario (S_1), none of the farmers change their intention. However, changes in farmers' intentions are observed in S_2 and S_3.

Decoupled supports can increase agricultural investments (Westcott and Young, 2004) and change and expand production (Goodwin and Mishra, 2005). In S_2, more than half of the farmers change their intentions to use decoupled supports, particularly in yield mapping, terrain monitoring with drones, and early warning system applications. Specifically, in S_2, 38.46% of the farmers change their intention to use thermo-hygrograph applications, 37.61% to use smart irrigation, 57.26% to use yield mapping, 61.54% to use terrain monitoring with drones, and 54.70% to use the early warning system (see Figure 3).

In S_3, the intention of farmers to use all smart applications, except for smart irrigation, is lower compared to S_2. According to the results, smart irrigation is the costliest smart investment equipment. In S_3, farmers are less likely to use thermo-hygrograph (34.19%), yield mapping (37.61%), terrain monitoring with a drone (48.72%), and early warning system (36.75%), compared to S_2.

Table 2 - Binary logistic regression on smart farming (S_2).

	Thermo-hygrograph			*Smart irrigation*			*Yield mapping*			*Terrain monitoring with a drone*			*Early warning system*		
	Coefficient	Std. Dev.	Odds Ratio	Coefficient	Std. Dev.	Odds Ratio	Coefficient	Std. Dev.	Odds Ratio	Coefficient	Std. Dev.	Odds Ratio	Coefficient	Std. Dev.	Odds Ratio
Farm income	0.02	0.001	1.002	**0.004****	0.002	1.004	0.002	0.002	1.002	0.002	0.002	1.002	0.001	0.001	1.001
Age															
15 - 49 ages (reference)															
50 - 64 ages	-1.001	0.685	0.368	**-2.123*****	0.802	0.120	**-2.192*****	0.751	0.112	**-2.743*****	0.823	0.064	**-1.955*****	0.726	0.142
≥ 65 ages	-0.778	0.914	0.460	**-3.795*****	1.131	0.022	**-3.093*****	1.008	0.045	**-4.048*****	1.116	0.017	**-3.280*****	1.008	0.038
Education															
Primary school (reference)															
Primary + secondary	0.304	0.698	1.355	-0.845	0.754	0.430	-0.569	0.702	0.566	-0.615	0.714	0.541	-0.708	0.702	0.493
High school	-0.509	0.633	0.601	-0.483	0.646	0.617	-0.808	0.612	0.446	**-1.417****	0.654	0.242	-0.995	0.619	0.370
University	-0.934	1.091	0.393	-1.516	1.248	0.220	**-2.177***	1.143	0.113	**-2.440***	1.255	0.087	-1.558	1.192	0.211
Land															
≤ 2 ha (reference)															
2.1 - 5 ha	0.030	0.627	1.030	-0.787	0.701	0.455	-0.600	0.657	0.549	-0.687	0.702	0.503	-0.475	0.654	0.622
≥ 5.1 ha	-0.402	0.647	0.669	-0.579	0.714	0.560	-0.313	0.662	0.731	-0.472	0.709	0.624	-0.357	0.665	0.700
Inheritor	0.610	0.476	1.840	**2.196*****	0.633	8.993	**1.441*****	0.514	4.224	**1.666*****	0.561	5.292	0.806	0.490	2.240
Knowledge	**1.233*****	0.469	3.431	0.739	0.552	2.095	**0.848***	0.513	2.335	**1.005***	0.544	2.732	**1.446*****	0.525	4.248
Livestock	0.070	0.444	1.072	-0.222	0.489	0.801	-0.385	0.457	0.680	-0.240	0.477	0.787	-0.162	0.453	0.850
Constant	-0.529	0.884	0.589	1.669	1.006	5.308	1.936	0.937	6.933	2.750	1.007	15.648	1.807	0.923	6.092
Level of significance:	$^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.10$														
-2 Log Likehood	135.521			112.888			128.565			118.388			130.769		
Nagelkerke R^2	0.217			0.411			0.314			0.373			0.306		
Percentage of correct predictions (%)	Overall = 73.5 Class "0" = 87.5 Class "1" = 51.1			Overall = 78.6 Class "0" = 70.5 Class "1" = 83.6			Overall = 70.1 Class "0" = 62.0 Class "1" = 76.1			Overall = 73.5 Class "0" = 57.8 Class "1" = 83.3			Overall = 66.7 Class "0" = 60.4 Class "1" = 71.9		

The factors that affect farmers' intentions in S_2 and S_3 are determined by binary logistic regression analysis. We use "Enter" method in the analysis and significance tests (Hosmer-Lemeshow and Omnibus) also perform, and the results show in Tables 2 and 3. The effects of these factors analysis separately for each smart app.

According to S_2, farm income, age, education, inheritor, and knowledge are statistically significant variables that affect farmers' intention to use smart apps. An increase in farm income has a positive effect (0.4% in a unit) on the intention to use the smart irrigation system ($p < 0.05$). However, there is an inverse

Table 3 - Binary logistic regression on smart farming (S_3).

	Thermo-hygrograph			*Smart irrigation*			*Yield mapping*			*Terrain monitoring with a drone*			*Early warning system*		
	Coefficient	Std. Dev.	Odds Ratio	Coefficient	Std. Dev.	Odds Ratio	Coefficient	Std. Dev.	Odds Ratio	Coefficient	Std. Dev.	Odds Ratio	Coefficient	Std. Dev.	Odds Ratio
Farm income	**0.004****	0.002	1.004	**0.005****	0.002	1.005	**0.004****	0.002	1.004	**0.003***	0.002	1.003	**0.004****	0.002	1.004
Age															
15 - 49 ages (reference)															
50 - 64 ages	-0.956	0.714	0.384	**-1.997*****	0.735	0.136	-0.935	0.707	0.393	**-2.269*****	0.746	0.103	**-1.262***	0.721	0.283
≥ 65 ages	**-2.241***	1.170	0.106	**-2.341****	1.002	0.096	-0.908	0.996	0.403	**-2.844*****	1.000	0.058	**-1.989***	1.096	0.137
Education															
Primary school (reference)															
Primary + secondary	**-1.652***	0.984	0.192	-0.982	0.786	0.375	**-1.903****	0.940	0.149	-0.385	0.728	0.680	-1.585	0.982	0.205
High school	-0.362	0.681	0.696	-1.009	0.660	0.365	-0.811	0.663	0.444	-0.816	0.644	0.442	-0.335	0.679	0.715
University	-0.464	1.172	0.629	-1.237	1.245	0.290	-0.677	1.137	0.508	**-1.931***	1.159	0.145	0.140	1.248	1.151
Land															
≤ 2 ha (reference)															
2.1 - 5 ha	0.732	0.687	2.080	-0.803	0.658	0.448	0.698	0.662	2.009	-0.712	0.650	0.491	0.571	0.692	1.769
≥ 5.1 ha	-0.842	0.742	0.431	**-1.321****	0.675	0.267	-0.326	0.687	0.721	-0.578	0.652	0.561	-0.572	0.734	0.564
Inheritor	0.774	0.534	2.169	0.514	0.498	1.672	0.784	0.503	2.191	**1.048****	0.493	2.851	0.849	0.535	2.338
Knowledge	**1.796*****	0.555	6.026	**1.259****	0.515	3.522	**1.613*****	0.520	5.020	**1.057****	0.499	2.877	**1.581*****	0.539	4.862
Livestock	0.336	0.505	1.400	**0.940****	0.480	2.560	0.085	0.473	1.088	0.414	0.457	1.512	0.720	0.502	2.055
Constant	-1.408	0.953	0.245	1.056	0.920	2.874	-1.007	0.925	0.365	1.233	0.910	3.431	-1.295	0.949	0.274
Level of significance:	***p<0.01, **p<0.05, * p<0.10														
-2 Log Likehood	109.647			122.896			121.125			128.966			110.787		
Nagelkerke R^2	0.406			0.380			0.342			0.329			0.421		
Percentage of correct predictions (%)	Overall = 76.9 Class "0" = 84.4 Class "1" = 62.5			Overall = 69.2 Class "0" = 71.7 Class "1" = 66.7			Overall = 73.5 Class "0" = 82.2 Class "1" = 59.1			Overall = 70.9 Class "0" = 73.3 Class "1" = 68.4			Overall = 78.6 Class "0" = 85.1 Class "1" = 67.4		

relationship between farmers' age and intention to use some technological applications. As farmers get older, their intention to use smart irrigation (8.33 times higher for the 50-64 age group and 45.45 times higher for those aged 65+ compared to the 15-49 age group), yield mapping (8.93 times higher for the 50-64 age group and 22.22 times higher for those aged 65+ compared to the 15-49 age group), terrain monitoring with a drone (15.62 times higher for the 50-64 age group and 58.82 times higher for those aged 65+ compared to the 15-49 age group), and early warning system (7.04 times higher for the 50-64 age group and 26.32 times higher for those aged 65+ compared to the 15-49 age group) do not change[3] ($p < 0.01$). Similarly, there is an inverse relationship between education and intention to use technological applications. The higher the education level, the lower the intention to use yield mapping and terrain monitoring with a drone ($p < 0.1$; $p < 0.05$). Those who have inheritors are more likely to use smart irrigation (8.99 times), yield mapping (4.22 times), and terrain monitoring with a drone (5.29 times) compared to those who do not ($p < 0.01$). Additionally, those who know about smart farming are more likely to use a thermo-hygrograph (3.43 times), terrain monitoring with a drone (2.73 times), and early warning system (4.25 times) compared to those who do not ($p < 0.01$; $p < 0.1$) (see Table 2).

According to S_3, there are several statistically significant variables that affect farmers' intention to use smart apps. These variables include farm income, age, education, land, inheritor, knowledge, and livestock. Increasing farm income has a positive impact on the intention to use thermo-hygrograph (0.4% in a unit), smart irrigation system (0.5% in a unit), yield mapping (0.4% in a unit), and terrain monitoring with a drone (0.3% in a unit) ($p < 0.1$; $p < 0.05$). Similarly to S_2, there is an inverse relationship between farmers' age and their intention to use technology. As farmers get older, their intention to use thermo-hygrograph (9.43 times higher for those aged 65+ compared to the 15-49 age group), smart irrigation (7.35 times higher for the 50-64 age group and 10.42 times higher for those aged 65+ compared to the 15-49 age group), terrain monitoring with a drone (9.71 times higher for the 50-64 age group and 17.24 times higher for those aged 65+ compared to the 15-49 age group), and early warning system (3.53 times higher for the 50-64 age group and 7.30 times higher for those aged 65+ compared to the 15-49 age group) do not change ($p < 0.1$; $p < 0.05$; $p < 0.01$). Education similarly affects farmers' intention to use technology in both S_2 and S_3. As the level of education increases, the intention to use thermo-hygrograph, yield mapping, and terrain monitoring with a drone decreases ($p < 0.1$; $p < 0.05$). Knowledge and inheritor variables are also significant in S_3. Farmers with knowledge about smart farming are more likely to use all smart apps ($p < 0.05$; $p < 0.01$). Furthermore, those who have inheritors are more likely to use terrain monitoring with a drone (2.85 times) than those who do not ($p < 0.05$) (see Table 3).

5. Discussion and conclusion

The results show that agricultural support is essential for farmers to consider adopting SF technologies. None of the farmers prefer SF technologies in the unsupported scenario (S_1), while in the supported scenarios (S_2 and S_3), farmers' intentions change significantly towards SF technologies. The cost of SF technologies remains a barrier to their widespread use, and credit and cash support can significantly influence investment preferences among farmers (De Rosari *et al.*, 2014). Especially in smart irrigation system[4], cash support covers only half of the cost, the application with the highest increase in intention to use is the smart irrigation system with credit support. Farmers are more likely to adopt these systems when provided with 0% interest rates and an attractive repayment schedule. It should be noted that the type of technology and its costs may significantly impact farmers' intentions to use SF technologies (Khatri-Chhetri *et al.*, 2017), particularly among those with low net returns (Suri, 2011), who tend to be more resistant to adoption.

Contrary to the expected positive relationship between education level and the adoption of innovations in agriculture (Aydoğan *et al.*, 2022), our study reveals an inverse association. This can be attributed to the high costs of advanced technology. The financial burden associated with implementing and maintaining innovative

[3] Farmers' unchanged intentions indicate their continued non-usage of smart apps, as highlighted in the "Modeling farmers' responses" section where all farmers responded "No" in S_1.

[4] The research also identified the investment costs associated with implementing a smart farm. The most expensive system was the smart irrigation system, with a cost of 102,040.80 TL per hectare.

agricultural practices and equipment appears to hinder adoption among individuals with higher educational attainment. The economic barriers posed by these costs outweigh the potential benefits of education in driving agricultural innovation adoption.

According to Higgins *et al.* (2017), rural sociologists and geographers have long argued that farmers' knowledge, along with the broader social and cultural relations in which such knowledge is embedded, is crucial to understanding farmer engagement with and adoption of new programs, techniques, and technologies (e.g., Oliver *et al.*, 2012; Warren *et al.*, 2016). To increase farmers' knowledge and awareness of SF applications, educational and outreach programs can be developed, which could involve working with agricultural extension services (Hussain *et al.*, 1994; Oyinbo *et al.*, 2019) and other organizations.

According to studies such as Akudugu *et al.* (2012) and Phi *et al.* (2021) that examine farmers' adoption of precision agriculture, younger farmers are more willing to adopt PA than older farmers. In our study, younger farmers are more willing to adopt SF than older farmers, and farmers with inheritors have higher intentions to use smart agriculture than those without. As May *et al.* (2019) suggested, tailored support programs and incentives can be developed to encourage younger farmers to adopt these technologies and promote SF's potential benefits to the next generation of farmers and landowners. This study can aid in designing policies that encourage the adoption of SF while considering farmer conditions in different regions and markets. However, one of the limitations of this study is the lack of support for policies, particularly cash and credit, prior to their implementation. In addition to these policies, training and technical support policies can be created to ensure the proper use of technology.

Currently, the bulk of technological innovation in the Mediterranean region is being developed and deployed by for-profit entities, including private-sector companies (Bedeau *et al.*, 2021). So, exploring additional ways to make smart systems more accessible and affordable to farmers could involve collaborating with technology providers to offer more competitive pricing or exploring alternative financing models, such as leasing or rental arrangements. Public-private partnerships can be formed to support the adoption of sustainable farming practices while considering farmer conditions in different regions and markets.

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