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The path to smart farming: Profiling farmers' adoption of technologies in Türkiye

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Abstract: This study investigates the characteristics associated with the adoption of smart farming technologies in Turkish agriculture. By surveying 325 farmers across six regions in Türkiye, the research identifies key attributes influencing adoption patterns. Four distinct profiles emerge: technology users, non-users, young educated female farmers, and traditionalists. Exploratory findings from Multiple Correspondence Analysis (MCA) indicate that attributes such as agricultural insurance, credit utilisation, knowledge of smart farming systems, and tractor ownership are commonly observed among technology users. Ordinal logistic regression further quantifies these associations, highlighting the significant role of financial accessibility and knowledge dissemination in shaping adoption likelihoods. Non-users, on the other hand, are characterised by smaller landholdings, lack of credit use, limited awareness, and absence of tractor ownership, reflecting structural barriers to adoption. Tailored financial solutions and shared machinery parks could help address these challenges. Empowering young, educated women farmers, identified as a key demographic for innovation, offers an opportunity to catalyse broader technology adoption. By addressing knowledge gaps and fostering inclusive policies, this study provides actionable insights to accelerate the technological transformation and sustainability of Türkiye's agricultural sector.

Keywords: agriculture 4.0; sustainability; innovation; technology adoption

The agricultural sector perpetually transforms, driven by the escalating demand for food, evolving climatic conditions, and mounting environmental concerns. In the midst of these transformative influences, technology has arisen as a central catalyst. Among global sectors, agriculture emerges as one of the most profoundly impacted by technological advancements. This transformative journey was inaugurated in the 1990s with the introduction of GPS systems to agriculture, marking the inception of precision agriculture (PA). During this epoch, characterised by data-driven spatial analyses, the primary imperatives were the augmentation of profitability, optimisation of crop yield and quality, concomitant with the reduction of costs and environmental footprints (Ehlert et al. 2004; Karimzadeh et al. 2011; Eory and Moran 2012; Balafoutis et al. 2017). Smart farming (SF), also denoted as Agriculture 4.0, has materialised through the amalgamation of industrial sector transformations with the principles of Industry 4.0 within agriculture. SF encompasses pioneering technologies, including the Internet of Things, cloud systems, robotics, artificial intelligence, and big data.

As Agriculture 3.0 and, subsequently, Agriculture 4.0 continue to proliferate in the global agricultural landscape, the discourse on the adoption of these technologies has become a recurring theme in the literature

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(Doss 2006; Chavas and Nauges 2020; Ofori et al. 2020; Yoon et al. 2020). Technology adoption constitutes a multifaceted process elucidating how individuals or organisations integrate novel technologies into their operations. Consequently, numerous actors exert influence upon this process, including both public and private sectors, as well as farmers.

Technology adoption is particularly associated with the availability of financial resources (e.g. credit and investment capital), farmers' socio-demographic characteristics (e.g. education and age), and competitive and contextual characteristics (e.g. farm size, soil and landscape characteristics, geographical location) (Reichardt and Jürgens 2009; Cavallo et al. 2014; Higgins et al. 2017; Suvedi et al. 2017; Kernecker et al. 2020). Nevertheless, it is worth noting that gender disparities and economic returns also wield significant influence over the adoption of agricultural technologies (Michler et al. 2019; Tufa et al. 2022).

Adoption rates of agricultural technologies exhibit notable disparities, with higher rates observed in countries where technological integration into agriculture is prevalent. In contrast, adoption levels tend to be significantly lower in developing countries characterised by the prevalence of small family farms (Mwangi and Kariuki 2015; Takahashi et al. 2020; Curry et al. 2021). For instance, Nonvide (2021) highlighted the low rates of technology adoption in developing countries, underlining the significance of education and extension services as key factors influencing farmers' adoption in Benin. Lowenberg-DeBoer and Erickson (2019) contend that medium- and small-scale farms in the developing world are being marginalised due to limited access to agricultural mechanisation.

In Türkiye, a developing country, the pace of technological transformation has been relatively slow compared to other nations, and it is still ongoing. With an average land size of around 6 ha and prevalent traditional farming practices, Türkiye began its transition to Agriculture 3.0 in the 1990s, coinciding with the public accessibility of GPS signals. A significant milestone was reached in 1999 when precision equipment was first integrated into a combine harvester (Türker et al. 2015). Despite the growing support from the private sector, particularly with the advent of Agriculture 4.0, the widespread adoption of these technologies has remained limited. This constraint can be attributed to various challenges that persist within Turkish agriculture, including entrenched conventional production methods, infrastructural deficiencies, small landholdings, the predominance of family farming, limited access to capital, inadequate information dissemination, and a limited farm-level data (Guldal and Ozcelik 2022). Limited farm-level data on technology adoption and utilisation is one of the reasons for the relatively underdeveloped literature in this area.

Adopting diverse technologies within agricultural enterprises plays a pivotal role in farmers' decision-making processes. Furthermore, it can result in a substantial reduction in production costs, primarily through these enterprises' efficient utilisation of production resources. Notably, one significant avenue through which technology can affect production costs is the potential reduction in labour expenses. The optimisation of labour costs within the overall operating expenses can exert a profound influence on profitability, particularly when gross income from agricultural products remains stable.

In this regard, the inclination of agricultural enterprises towards technological innovations is expected to yield positive outcomes. Such technological adoption can potentially elevate labour productivity within these enterprises, thereby contributing significantly to enhanced enterprises profitability and more informed decision-making processes.

In this study, our primary objective is to gain insights into the characteristics associated with the adoption of smart farming technologies within the Turkish agricultural sector. To achieve this, we conducted interviews with farmers across six of the seven geographical regions in Türkiye, including both users and non-users of smart farming systems. Our approach integrates exploratory and inferential analyses: Multiple Correspondence Analysis (MCA) to uncover patterns and associations among variables, and ordinal logistic regression to examine the relationships between these characteristics and technology adoption. By understanding these associated characteristics, we aim to contribute to the development of strategies that may accelerate the technological transformation process, ultimately supporting greater competitiveness, sustainability, and productivity in Turkish agriculture.

Comprehending the intricacies of the technology adoption process holds paramount importance in advancing the adoption of novel technologies, including smart farming practices. In light of the ongoing technological evolution within Turkish agriculture, which has yet to reach its full potential, this study expects to make a significant contribution towards resolving the challenges inherent in the transformation process.

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MATERIAL AND METHODS

Study area and data collection

We concentrated our research efforts on six out of the seven regions in Türkiye, specifically Central Anatolia, Aegean, Eastern Anatolia, Southeastern Anatolia, Black Sea, and Mediterranean regions. In the initial phase, our selection criteria for provinces within each region revolved around the machinery and equipment support allocated by the Ministry of Agriculture and Forestry (MoAF) in 2022. Within each region, we chose one province with the highest number of grants as a representative sample. Across Türkiye as a whole, all 81 provinces received grants, with the six provinces selected for our sample collectively representing 17.91% of the total grant amount disbursed (Figure 1) (MoAF 2022).

Furthermore, it's noteworthy that the selected provinces collectively encompass approximately 4.6 million ha of agricultural land, excluding meadows and pasture areas. These provinces represent a significant 19.40% share of Türkiye's total agricultural land distribution. (TurkStat 2022).

A total of 325 farmers participated in the survey, with varying numbers from different regions: 88 from Manisa in the Aegean region, 54 from Samsun in the Black Sea region, 31 from Konya in the Central Anatolia region, 71 from Erzurum in the Eastern Anatolia region, 46 from Antalya in the Mediterranean region, and 35 from Şanlıurfa, also in the Eastern Anatolia region (see Table 1). It's important to note that the MoAF organises agricultural training sessions in these provinces. The survey was conducted voluntarily among farmers attending these training sessions on the date specified. It's important to highlight that voluntary participation in survey data collection, as emphasised by Spruce and Bol (2015), is vital for ensuring the success and accuracy of research efforts.

The questionnaires, created using web-based survey software (google.docs.com), were administered to farmers attending the training sessions. This innovative method is deemed suitable given the emphasis on technological innovations. Surveys conducted in a web-based environment provide easy access to difficult-to-reach samples and special groups (Baltar and Brunet 2012). Additionally, Heiervang and Goodman (2011) emphasised the advantages of online survey techniques, noting their ability to efficiently and cost-effectively gather data.

Statistical analysis

The central question that this study endeavours to address is: 'Which characteristics are associated with the adoption of SF technologies among farmers in Türkiye?' By examining these characteristics, we aim to identify which farmer attributes are linked to the adoption of SF practices and which ones may hinder their broader im-

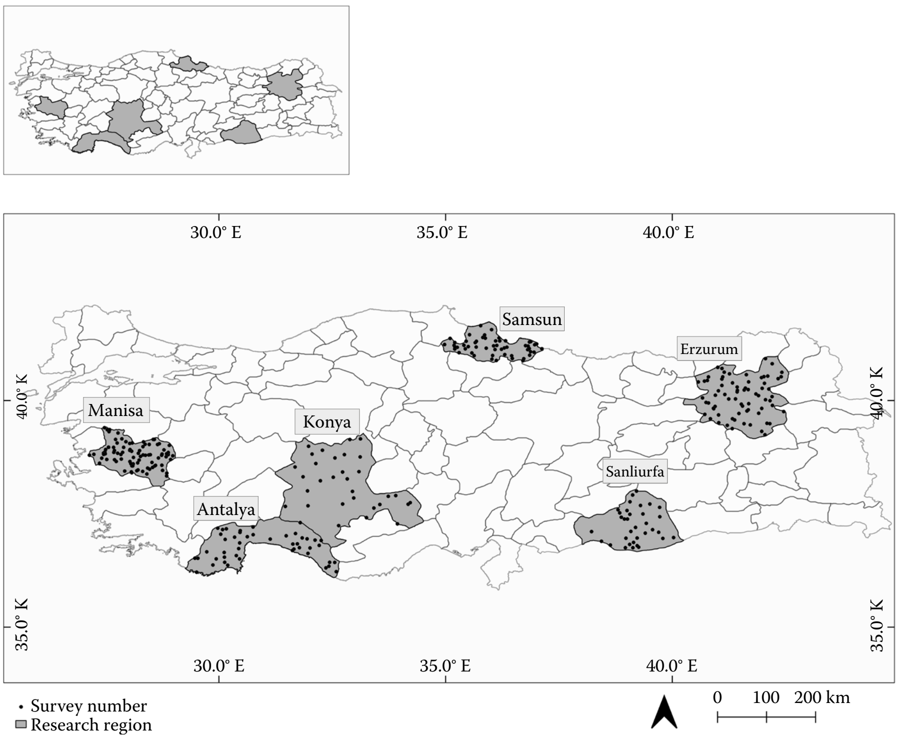

Figure 1. Maps of a research area

Source: Authors own elaboration

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Table 1. Number of surveys by region

Provinces	User		Non-user		Eager		Total	
	n	%	*n*	%	*n*	%	*n*	%
Manisa (Aegean)	21	23.9	19	21.6	48	54.5	88	100
Samsun (Black Sea)	7	13.0	28	51.8	19	35.2	54	100
Konya (Central Anatolia)	8	25.8	7	22.6	16	51.6	31	100
Erzurum (East Anatolia)	13	18.4	17	23.9	41	57.7	71	100
Antalya (Mediterranean)	8	17.4	14	30.4	24	52.2	46	100
Şanlıurfa (Southeast Anatolia)	9	25.7	4	11.4	22	62.9	35	100
Total	66	20.3	89	27.4	170	52.3	325	100

Source: Own calculations

plementation. Through this analysis, we seek to provide practical recommendations that could encourage a wider uptake of SF technologies within Turkish agriculture.

MCA is an extension of simple correspondence analysis used to summarise and visualise data tables containing multiple categorical variables. It functions as a generalisation of principal component analysis for categorical data (Husson et al. 2016). In this study, MCA was conducted using R software via the FactoMineR package to identify and visualise patterns in the data set (Murtagh 2007). MCA is an unsupervised learning method that reveals relationships among categorical variables and visualises the data structure in a reduced dimensional space. It generates graphs highlighting similarities or differences in profiles, with closely positioned features indicating statistically significant relationships.

However, MCA has certain limitations. Specifically, it does not establish causal relationships or support inferential analysis, as it focuses on pattern recognition and data visualisation (Myšiak 2006; Costa et al. 2013; Greenland 2021). To address these limitations and align with the structure of our data, we employed ordinal logistic regression analysis. This approach is suitable for our ordered categorical dependent variables, enabling us to assess how independent variables relate to different levels of technology adoption. The ordinal logistic regression model complements the exploratory findings from MCA by providing a more robust, inferential framework that quantifies these relationships.

Choice of variables

In our study, we examine the various characteristics associated with the adoption of smart farming technologies among Turkish farmers. The active variables span a wide range of dimensions crucial for understanding adoption behaviour within the agricultural landscape. Region is a key factor, as geographical differences may impact access to resources and exposure to technological innovations (Barnes et al. 2019). Gender and education levels are also important, as they are often linked to awareness, knowledge, and attitudes toward technology adoption (Reichardt and Jürgens 2009; Tufa et al. 2022). Farming type delineates different production systems, each presenting unique challenges and opportunities for technology integration. Land size and ownership status are indicators of farm scale and resources, which may influence the feasibility and extent of technology adoption (Hanson et al. 2022).

Non-agricultural income can relate to investment capacity, while farming experience and insurance coverage reflect risk perceptions and management strategies. Information access and spread channels shape farmers' exposure to new technologies, and tractor ownership serves as a proxy for mechanisation levels. The primary purpose of production provides insight into farmers' objectives and priorities, which can be associated with their openness to adopting technological solutions. Finally, credit availability is an important factor in enabling investments in modern farming practices (Guldal and Ozcelik 2024).

For the MCA, we categorised variables into active and supplementary groups. Active variables included *region*, *gender*, *age*, *education*, *farming type*, *land*, *landowner*, *non-agricultural income*, *experience*, *insurance*, *inheritor*, *info*, *tractor*, *purpose of production*, and *credit*. These active variables were used to identify patterns and relationships within the data. Supplementary variables user, eager, and non-user provided additional context but did not influence the construction of the MCA dimensions. The term 'user' refers to farmers employing various smart technologies, including smart irrigation, smart greenhouses, drones, herd manage-

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Table 2. Variables definition

Variables	Explanation	Frequency	Variables	Explanation	Frequency
Active variables					
Region			*Non-agricultural income*		
Manisa	Manisa	88	Non.agri. Income Y	having non-agricultural income	178
Samsun	Samsun	54	Non.agri. Income N	not having non-agricultural income	147
Konya	Konya	31	*Experience*		
Erzurum	Erzurum	71	< 10 years	less than 10 years	44
Antalya	Antalya	46	10–20 years	between 10 and 20 years	58
Şanlıurfa	Şanlıurfa	35	> 20 years	more than 20 years	223
Gender			*Insurance*		
M	male	308	Insurance Y	having agricultural insurance	138
F	female	17	Insurance N	not having agricultural insurance	187
Age			*Inheritor*		
18–25	between 18 and 25 years old	4	Inheritor Y	having heir	207
26–35	between 26 and 35 years old	43	Inheritor N	not having heir	118
36–45	between 36 and 45 years old	88	*Info*		
46–55	between 46 and 55 years old	97	Info Y	knowing agricultural technologies	177
> 55	more than 55 years old	93	Info N	not knowing agricultural technologies	148
Education			*Spread*		
Primary	primary school	105	Spread Y	supporting the spread of agricultural technologies	294
P+S	primary and secondary school	52	Spread N	not supporting the spread of agricultural technologies	31
HS	high school	88	*Tractor*		
University	university	80	0	not having tractor	69
Farming type			< 1 years	less than 1 year	35
Plant production	plant production	157	2–5 years	between 2 and 5 years	60
Livestock	livestock	15	6–10 years	between 6 and 10 years	66
Both of them	plant production + livestock	153	> 11 years	more than 11 years	95
Land			*Purpose of production*		
< 5 ha	less than 5 hectares	114	P	profit production	230
5–10 ha	between 5 and 10 hectares	71	E	environmental production	95
> 10 ha	more than 10 hectares	140	*Credit*		
Landowner			Credit Y	using agricultural credit	150
Landowner Y	who owns the land	291	Credit N	not using agricultural credit	175
Landowner N	landless	34			
Supplementary variables					
Desire					
User	using agricultural technologies	66			
Eager	not using agricultural technologies but want to use them	170			
Non-user	not using agricultural technologies	89			

(N = 325)
Source: Own calculations

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ment systems, sensor machines, and remote sensing applications (see Table 2).

In the ordinal logistic regression analysis, the supplementary variables identified through MCA were repurposed as the dependent variable categories, capturing the different levels of technology adoption: user, eager, and non-user. The active variables identified through MCA served as independent variables, allowing us to assess their associations with technology adoption levels.

To enhance the reliability and interpretability of the ordinal logistic regression model, certain adjustments were made to the dataset. Specifically, the 18–25 and 26–35 age groups were merged due to small sample sizes, mitigating potential issues of model overfitting and collinearity. Similarly, the farming type variable was excluded from the model for similar reasons, ensuring a more stable and robust analysis.

Additionally, only variables that showed significant associations in the MCA were included in the regression model. This selection process aimed to focus the analysis on the most relevant predictors of technology adoption, while excluding variables with limited explanatory power. These adjustments collectively strengthened the model, providing a clearer understanding of the factors associated with smart farming technology adoption.

The ordinal logistic regression model used in this study can be expressed as:

$$\text{Logit}\,[P\,(Y \le j)] = \alpha_j - \beta_1\,(\textit{Region}) - \beta_2\,(\textit{Gender}) - \beta_3\,(\textit{Age}) - \beta_4\,(\textit{Education}) - \beta_5\,(\textit{Land}) - \beta_6\,(\textit{Land-owner}) - \beta_7\,(\textit{Experience}) - \beta_8\,(\textit{Insurance}) - \beta_9\,(\textit{Info}) - \beta_{10}\,(\textit{Spread}) - \beta_{11}\,(\textit{Tractor}) - \beta_{12}\,(\textit{Credit})$$

where: $P\,(Y \le j)$ – cumulative probability of the dependent variable Y (technology adoption level: user, eager, non-user) being in category j or lower; α_j – threshold parameters separating the adoption levels; $\beta_1, \beta_2, \ldots, \beta_{12}$ – coefficients associated with each independent variable.

RESULTS AND DISCUSSION

Figure 2 illustrates the interrelationships among the variables, emphasising those with a high degree of association using ellipses. Notably, variables such as insurance, credit, farming type, and information appear distant and distinct from each other within the analysis. This distinction signifies a noteworthy separation among the subpopulations associated with these variables. In essence, it suggests that farmers who possess insurance and those who do not, individuals who utilise credit and those who do not, those with knowledge about agricultural technologies and those without, as well as those engaged in crop production and those focused on livestock, exhibit significant differences among their respective groups. These findings underscore the diversity and divergence of attitudes and practices within key aspects of the agricultural landscape, which are important considerations for understanding the characteristics associated with smart farming technology adoption.

Conversely, when analysing the 'region' variable, distinct groupings become apparent. Farmers in Antalya, Konya, Manisa, and Şanlıurfa often share similar characteristics. In contrast, farmers in Samsun and Erzurum differ significantly from this group and from each other, highlighting regional variations (Figure 2A). Additionally, we uncover noteworthy trends when we scrutinise the 'land' variable. Farmers on 5 ha or more land exhibit shared characteristics, reflecting similar adoption patterns (Figure 2B).

Finally, when the desire variable is analysed, although the three subgroups show different characteristics from each other, the eager group is close to both other groups. In other words, there are issues that have similar characteristics to the two groups (Figure 2G).

As a result of the MCA analysis, we categorise farmers into four different groups (Figure 3). The first group consists of farmers who use agricultural technologies. In this group, farmers have land sizes of 10 ha and above. It is well-known that farmers with larger land have more resources and greater production capacity. Additionally, MCA results indicate that larger land sizes are often associated with farmers who adopt technology to increase productivity and optimise production (Paustian and Theuvsen 2017; Houeninvo et al. 2020; Kernecker et al. 2020; Kolady et al. 2021; Hanson et al. 2022). Farmers in this group also possess agricultural insurance. MCA results indicate that possessing agricultural insurance is a characteristic associated with higher adoption rates among the 'user' group. Similarly, logistic regression results suggest that farmers who have agricultural insurance have a higher likelihood of adopting technology or expressing eagerness toward adoption compared to those without insurance ($P < 0.1$) (Table 3). This consistency across analyses underscores the importance of risk management tools, such as agricultural insurance, in supporting technology adoption. The motivations for having agricultural insurance can be assessed as follows: the enhancement of enterprise well-being,

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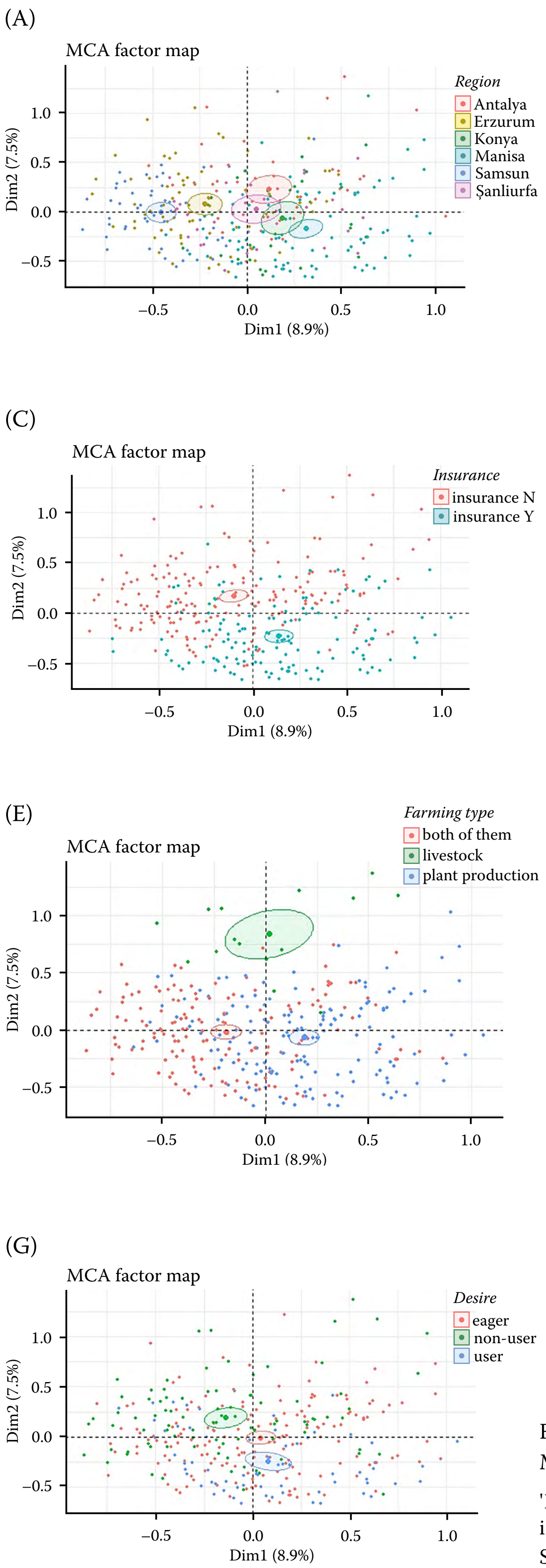

Figure 2. Distribution of significant variables Dim1 × Dim2 MCA factor map

'Dim1' and 'Dim2' – 'Dimensions', indicating the aspects in which the variables are described

Source: Own calculations

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Table 3. Logit model results

Variables	Coefficient	SE	Significance
Region			
Antalya	0.643	0.502	0.200
Erzurum	0.571	0.442	0.197
Konya	0.448	0.535	0.402
Manisa	0.955	0.443	0.031**
Samsun	1.700	0.487	0.000***
Şanlıurfa (reference)	–	–	–
Gender			
Male	–1.079	0.560	0.054*
Female (reference)	–	–	–
Age			
18–35 ages	0.101	0.442	0.819
36–45 ages	–0.491	0.343	0.153
46–55 ages	0.228	0.309	0.460
> 55 ages (reference)	–	–	–
Education			
Primary school	0.190	0.385	0.622
Primary + secondary	–0.262	0.410	0.523
High school	–0.126	0.360	0.726
University (reference)	–	–	–
Land			
< 5 ha	0.192	0.312	0.537
5–10 ha	0.423	0.311	0.174
> 10 ha (reference)	–	–	–
Landowner			
Landowner Y	–0.281	0.402	0.485
Landowner N (reference)	–	–	–
Experience			
< 10 years	0.020	0.448	0.965
10–20 years	0.108	0.367	0.768
> 20 years (reference)	–	–	–
Insurance			
Insurance Y	–0.551	0.284	0.052*
Insurance N (reference)	–	–	–
Info			
Info Y	–0.542	0.248	0.029**
Info N (reference)	–	–	–
Spread			
Spread Y	–1.442	0.440	0.001***
Spread N (reference)	–	–	–
Tractor			
0	0.833	0.356	0.019**
< 1 years	–0.150	0.441	0.116
2–5 years	–1.136	0.363	0.002***

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Table 3. To be continued

Variables	Coefficient	SE	Significance
6–10 years	0.312	0.339	0.358
> 11 years (reference)	–	–	–
Credit			
Credit Y	–0.674	0.275	0.014**
Credit N (reference)	–	–	–
Level of significance			
–2 Log likehood	531.828	–	–
Nagelkerke R^2	0.358	–	–

(*, **, ***P < 0.1; 0.05; 0.01); the detailed Wald statistics and confidence intervals for the logistic regression analysis can be found in Table S2 in Electronic Supplementary Materials (ESM)
Source: Own calculations

reduction in cultivation expenses, augmentation of income, the drive to secure income, and the mitigation of risks and uncertainties (Wu and Li 2023).

Another distinguishing characteristic within this group is the utilisation of agricultural credit. The cost associated with the use of technology in agriculture may present a barrier for farmers (Fountas et al. 2005; Guldal 2022; Toroiano et al. 2023). MCA results indicate that utilising agricultural credit is a characteristic associated with higher adoption rates among the 'user' group. Similarly, logistic regression results suggest that farmers who utilise credit have a higher likelihood of adopting technology or expressing eagerness toward adoption compared to those who do not use credit (P < 0.05) (Table 3). This highlights the potential role of accessible financial support in facilitating technology adoption. Financial support can improve farmers' access to technology, aligning with findings that suggest a positive relationship between credit availability and adoption rates (Abate et al. 2016; Nonvide 2021; Guldal and Ozcelik 2024). Additionally, farmers may prioritise the potential benefits of technology over the initial investment costs when making adoption decisions (Nguyen et al. 2023).

Knowledge is a crucial characteristic linked to technology adoption, particularly among the user group. MCA results indicate that having knowledge about agricultural technologies is a characteristic associated with higher adoption rates among technology users. Logistic regression results further support this observation, suggesting that farmers with knowledge about agricultural technologies are more likely to adopt technology or express eagerness toward adoption compared to those without such knowledge (P < 0.05) (Table 3). This consistency between the two analyses highlights the importance of knowledge in enhancing farmers' confidence in new agricultural technologies and fostering their openness to exploring and implementing innovative practices (Conteh 2023).

Furthermore, other attributes characterising farmers within the user group include their geographical location in Manisa and Konya provinces. MCA results highlight that tractor ownership is an associated characteristic within the user group. Logistic regression results further support this finding by showing that farmers owning tractors aged between two and five years have a higher likelihood of adopting technology compared to those without tractors (P < 0.01) (Table 3).

The other significant group is the non-user. Farmers in this category generally do not utilise agricultural credit, lack information about new agricultural technologies, do not have agricultural insurance, and do not own tractors. Additionally, they often operate on land smaller than 5 ha (Figure 3). In contrast to the user group, the non-user group displays characteristics associated with limited resources and smaller-scale farming, reflecting differences in access and capacity within the agricultural landscape of Türkiye.

Furthermore, farmers lacking knowledge about new technologies may face challenges in understanding how to utilise and benefit from them effectively. For agricultural enterprises, operating at a scale smaller than an economically viable size is often associated with difficulties in decision-making and adopting innovations with an entrepreneurial mindset. This association may also shape their perceptions, making technological innovations appear riskier compared to traditional practices (Feder et al. 1985; Daberkow and McBride 2003). For many family farms, highlighting the potential benefits of technology to increase farm income remains crucial (Wu 2022).

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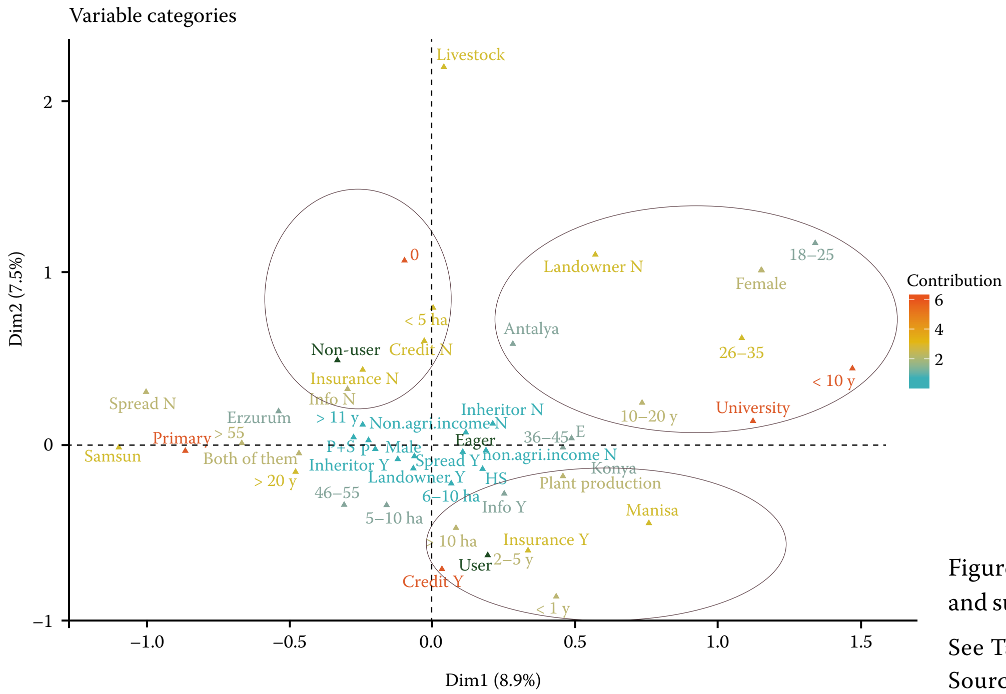

Figure 3. Projection of active and supplementary variables

See Table 1 for abbreviations

Source: Own calculations

Nonetheless, the reliance on their own resources to meet financing needs, along with limited access to or the inability to utilise external financing, is often associated with challenges in making decisions about new investments. Additionally, the high cost of modern technologies can strain farm capital budgets, presenting difficulties for farmers considering the adoption of such technologies (Guldal and Ozcelik 2022; Puppala et al. 2023).

'Dim1' and 'Dim2' represent dimensions, indicating the aspects in which the variables are described. The variable contributions are encapsulated in 'contrib,' detailing their role in defining these dimensions. Contribution levels range from 0 to infinity. Specifics on the degree of variable contribution can be found in Table S1 in the ESM.

The third group consists of university graduates and female farmers under the age of 35. These farmers, with up to 20 years of experience in the agricultural sector and typically without land ownership, are predominantly located in the Antalya province. Young women farmers, who generally have higher education levels than their counterparts in the farming population, display characteristics associated with a greater openness to new agricultural technologies. Recognising that young and educated farmers are more inclined toward technology adoption (Lencsés et al. 2014), harnessing this potential can be viewed as a valuable opportunity.

The fourth group consists of more traditionalist farmers, a common archetype in Turkish agriculture. These farmers are generally characterised by lower education levels, an age of 55 years or older, and more than two decades of agricultural experience. Older farmers often display a preference for established methods, adhering to the belief that practices they have relied on over the years are sufficient (Aubert et al. 2012). The inherent uncertainty and learning curve associated with new practices are factors that may contribute to their reluctance to adopt technology.

Furthermore, individuals with limited educational backgrounds may encounter difficulties comprehending and effectively utilising novel agricultural technologies. To surmount this challenge and motivate farmers to engage with technology, it becomes imperative to ensure access to effective extension services (Akudugu et al. 2012; Suvedi et al. 2017).

Limitations

In this study, as detailed in the statistical analysis section, farmers who employed any of the identified technological applications were categorised as 'Users.' These applications encompass a wide array of diverse technologies, making it impractical to analyse farmers utilising similar applications together. This limitation arose from the absence of a comprehensive database on this subject, which precluded a more nuanced examination of specific technology categories.

Furthermore, farmers involved in both livestock and crop production were collectively examined in this study.

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Future research endeavours are anticipated to delve into more micro-level investigations, allowing for a more granular examination of specific agricultural subsectors.

Additionally, the farmers surveyed in this study were voluntary participants in training sessions organised by the MoAF. While this approach facilitated access to a diverse group of respondents, it may have introduced a degree of selection bias. Farmers attending such sessions are likely more open to acquiring information or engaging with extension programs compared to the broader farming population. Despite this, the significant heterogeneity observed within the sample provides valuable insights into varying adoption behaviours, underscoring the robustness of the findings.

CONCLUSION

This study reveals that larger land sizes are often associated with technology adoption, suggesting promising prospects for agricultural modernisation. Farmers with more extensive land holdings commonly exhibit characteristics linked to a greater openness to new technologies, presenting an opportunity for targeted investment in this area. Providing favourable agricultural credit options to these farmers may support increased technology use and contribute to sectoral development.

On the other hand, the non-user group tends to be risk-averse and generally avoids agricultural credit, which may be associated with their smaller land holdings. Tailored financing options designed for this group could provide support for technology uptake. Additionally, establishing shared machinery parks could help reduce investment costs and make technology more accessible to these farmers.

The lack of awareness and knowledge among non-users and traditionalist farmers poses a significant challenge for the agricultural sector's future. Addressing this challenge may require tailored training programs and expanded extension initiatives to emphasise the benefits of new agricultural technologies. Additionally, young, university-educated women farmers bring valuable new perspectives and could benefit from strong support. Empowering this demographic has the potential to encourage the return of young individuals to rural areas and enhance women's employment opportunities, contributing to positive changes in the agricultural sector.

Finally, addressing the conservative mindset of traditionalist farmers may benefit from targeted educational efforts and persuasive campaigns. Introducing incentives like rewards and cash subsidies can motivate these groups to be more receptive to new technologies. By combining tailored education with tangible benefits, a more favourable attitude toward modern agricultural innovations may be fostered, supporting their gradual transition.

This study is expected to provide valuable insights forshaping policies aimed at accelerating the technological transformation of Turkish agriculture. It is envisioned to serve as a vital roadmap for promoting technology adoption within the sector, thereby improving its sustainability. These findings are anticipated to mobilise policymakers and agricultural experts, prompting them to effectively address farmers' needs and untapped potential. Aligning policy initiatives with these insights could help guide Turkish agriculture towards a more prosperous and sustainable future.

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