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Prioritizing Critical Factors for Agricultural Spraying Drones Adoption: A Multi-Criteria Decision-Making Approach in Adana

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ABSTRACT

The adoption of Unmanned Aerial Vehicles (UAVs) for agricultural spraying offers significant advantages in efficiency, precision, and sustainability. However, various factors influence their widespread adoption of this technology. This study aims to identify and prioritize the critical factors influencing the adoption of agricultural spraying UAVs in Adana using the Analytic Hierarchy Process (AHP), a robust Multi-Criteria Decision-Making (MCDM) technique.

The research draws on data collected through detailed surveys with farmers in Adana, capturing their perceptions and challenges regarding UAV adoption. The findings reveal that social factors, including lack of awareness, perceived ease of use, and perceived usefulness, are the most critical factors affecting adoption, followed by operational factors such as labor scarcity and lack of technical assistance. Economic barriers and farm-related characteristics, though significant, rank lower in priority. Among the sub-factors, "lack of awareness" and "labor scarcity" emerge as the most influential. The findings emphasize the need for targeted interventions, including awareness campaigns, hands-on training, and enhanced technical infrastructure, to address these factors.

Tarımsal İlaçlama İnsansız Hava Araçlarının Benimsenmesi İçin Kritik Faktörlerin Sıralanması: Adana'da Çok Kriterli Karar Verme Yaklaşımı

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ÖZ

Tarımsal ilaçlama için İnsansız Hava Araçlarının (İHA) benimsenmesi verimlilik, hassasiyet ve sürdürülebilirlik açısından önemli avantajlar sunmaktadır. Ancak, çeşitli faktörler bu teknolojinin yaygın olarak benimsenmesini etkilemektedir. Bu çalışma, sağlam bir Çok Kriterli Karar Verme (ÇKKV) tekniği olan Analitik Hiyerarşi Süreci'ni (AHP) kullanarak Adana'da tarımsal ilaçlama İHA'larının benimsenmesini etkileyen kritik faktörleri belirlemeyi ve sıralamayı amaçlamaktadır.

Araştırma, Adana'daki çiftçilerle yapılan detaylı anketler yoluyla toplanan verilere dayanmakta ve çiftçilerin İHA'ların benimsenmesine ilişkin algılarını ve karşılaştıkları zorlukları ortaya koymaktadır. Bulgular, farkındalık eksikliği, algılanan kullanım kolaylığı ve algılanan yararlılık gibi sosyal faktörlerin benimsenmeyi etkileyen en kritik faktörler olduğunu, bunları işgücü kıtlığı ve teknik yardım eksikliği gibi operasyonel faktörlerin izlediğini ortaya koymaktadır. Ekonomik engeller ve çiftlikle ilgili özellikler önemli olmakla birlikte öncelik sıralamasında daha alt sıralarda yer almaktadır. Alt faktörler arasında "farkındalık eksikliği" ve "işgücü kıtlığı" en etkili faktörler olarak ortaya çıkmaktadır. Bulgular, bu faktörleri ele almak için farkındalık kampanyaları, uygulamalı eğitim ve gelişmiş teknik altyapı dahil olmak üzere hedefe yönelik müdahalelere duyulan ihtiyacı vurgulamaktadır.

1. INTRODUCTION

Increasing agricultural productivity is crucial to meet the expected rise in food demand. Reports published by the United Nations indicate that the world population will reach approximately 8.5 billion in 2030, and 9.7 billion in 2050. Overall food demand is expected to increase by between 59% and 98% by 2050 [1].

Many studies emphasize the crucial role of modern production technologies in boosting food productivity, highlighting their essential contribution to meeting the growing demand for food. Using improved technology in food production, starting from agricultural lands is getting more and more important. Because reaching a higher production rate, using the same size of land, is only possible by integrating the technology into this sector.

However, the integration of new technologies across the globe typically doesn't happen instantly. For technologies to enhance productivity, they must be embraced and utilized by employees within organizations [2]. The same holds true for the adoption of new technologies in agriculture. The impact of innovations on productivity growth depends on how much farmers accept and start using available innovations, as well as how quickly they do so [3]. Adoption of improved agricultural technologies has also been correlated with augmented incomes and a decline in rural poverty among farming communities, alongside improvements in nutritional standards, decreased prices of staple foods, and increased employment opportunities [4]. In this context, analyzing the barriers to the adoption of modern agricultural technologies and identifying the factors that affect farmers' attitudes toward adoption is crucial [5].

Starting from a more general view, the perception of technology by users was studied more extensively, and two main factors were defined as "usefulness" and "ease of use" [6]. And more specifically for agriculture, some studies analyzed the specific factors that are being a hinder for adoption of new agricultural technologies [7]. It is important to recognize that technology adoption is a complex and multifaceted process, influenced by a wide range of factors [8]. These factors can include the farmers' individual characteristics, such as age, education level, and farming experience, as well as their perception of technology, the availability of resources, access to information and training, economic considerations, and social factors such as peer influence and community support.

The literature presents a variety of Multi-Criteria Decision-Making (MCDM) methodologies for analyzing barriers or influencing factors for new technology adoption in farming. These include Interpretive Structural Modeling (ISM), Decision-Making Trial and Evaluation Laboratory (DEMATEL), Analytic Network Process (ANP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), and the Analytic Hierarchy Process (AHP) [9]. In agricultural studies, the literature predominantly focuses on identifying and addressing obstacles to the implementation of sustainable and organic farming methods. A literature review presented by C.R. Foguesatto et al. [10] lists most of the articles focusing on the factors influencing sustainable agriculture practices. Table 1 has identified the most relevant studies on these topics.

Table 1. List of relevant articles

Article Title and Year	Goal	MCDM Method	Ref.
Agriculture for sustainable development: A SWOT-AHP assessment of Ghana’s planting for food and jobs initiative (2021)	To evaluate the strengths, weaknesses, opportunities, and threats for the implementation of the PFJ (Planting for Food and Jobs) program based on sustainable agriculture.	AHP	[11]
Assessing the important factors of sustainable agriculture development: Analytic Hierarchy Process study in the northern region of Vietnam (2021)	To assess key sustainable agriculture factors	AHP	[12]
How to Identify Barriers to the Adoption of Sustainable Agriculture? A Study Based on a Multi-Criteria Model (2022)	To propose a multi-criteria model, to identify the main barriers that impede the adoption of sustainable agriculture	Fuzzy DEMATEL	[13]

Table 1. Continued

Analyzing and Prioritizing the Barriers and Solutions of Sustainable Agriculture for Promoting Sustainable Development Goals in China (2023)	To analyze the challenges and opportunities facing sustainable agriculture in China’s economy	AHP and SAW	[14]
Barriers to the adoption of new technologies in rural areas: The case of unmanned aerial vehicles for precision agriculture in India (2023)	To identify and evaluate the barriers to adopting UAVs by farmers for agricultural operations in India.	Fuzzy Delphi and Fuzzy AHP	[15]
Analysis of barriers to organic farming adoption in developing countries: a grey-DEMATEL and ISM approach (2024)	To assess the organic farming adoption barriers faced by Indian farmers using a systematic method of multi-criteria decision making (MCDM).	Grey-DEMATEL and ISM	[9]

In this paper, we examine the critical factors influencing the adoption of spraying UAVs, within the context of the Adana region. Spraying UAVs represent a cutting-edge innovation in agriculture, offering significant advancements in crop spraying and weed management [16]. It offers several significant advantages in modern agricultural practices, particularly in terms of efficiency, precision, and sustainability. UAVs enable precise application of pesticides and fertilizers, reducing the overall usage of chemicals and minimizing environmental impact. According to Chen et al. (2022), these systems have the potential to reduce chemical usage by up to 45% compared to conventional spraying methods [17]. Modern spraying drones can cover areas of up to 10 hectares per hour, with tank capacities ranging from 10 to 20 liters. Equipped with variable-flow nozzles, these drones deliver highly precise applications, with rates as low as 1 mL/m^2. Additionally, automatic flow control systems, along with speed and altitude sensors, help maintain consistent application rates, even in varying flight conditions [18].

Adana was selected as the focus of this study due to its pivotal role in Turkish agriculture, supported by its fertile plains and favorable climate. The region accounts for 50% of Turkey’s corn and soybean production, as well as 34% of its peanuts and 29% of its oranges [19]. The adoption of advanced technologies, such as agricultural UAVs, is essential to further enhance these yields and ensure sustainable agricultural practices. The findings of this study aim to provide policymakers and agricultural stakeholders with valuable insights to develop targeted strategies and interventions, facilitating the adoption of UAV technology in the region.

2. MATERIAL AND METHOD

This study investigates the key factors influencing the adoption of agricultural unmanned aerial vehicles (UAVs) among farmers in the Adana region. To systematically and comprehensively analyze these factors, Analytic Hierarchy Process (AHP) were employed. The primary aim of the research is to identify and prioritize the economic, social, technical, and environmental barriers that shape the adoption process of UAV technology.

Data collection involved administering surveys to farmers operating in the agricultural sector of Adana. These surveys captured quantitative and qualitative data regarding farmers' perceptions and challenges associated with UAV usage. The collected data were used to get comparison matrix and analyzed using Analytic Hierarchy Process (AHP). AHP enable the integration of both subjective judgments and objective data to determine the relative importance of the influencing factors.

This section provides a detailed description of the data sources, survey design, and analytical procedures utilized in the study.

2.1. Material

The adoption of innovative technologies in agriculture, such as spraying UAVs, is influenced by a variety of factors that require systematic investigation. Understanding these factors is essential for developing strategies to facilitate the integration of UAV technology into agricultural practices. To this end, the material foundation of this study is based on a comprehensive approach that combines literature insights with targeted field data to ensure the relevance and applicability of the identified factors.

Initially, an extensive literature review was conducted to identify the factors affecting the adoption of new technologies. A thorough examination of numerous articles was undertaken to identify the most relevant factors. After identifying most of the factors cited in the literature, it was observed that certain factors were highly similar, while others conveyed the same meaning through different terminology. Also, these articles focus on all types of UAVs, including surveillance UAVs, field mapping UAVs, and multispectral camera UAVs for field analysis, beyond the scope of this study, which specifically considers spraying UAVs. Therefore, certain categories that are deemed irrelevant to spraying UAVs have been excluded from the list; for example, privacy concerns were not considered highly relevant for spraying UAVs and were thus omitted from the list of factors in our study.

As a result, below is the list of selected 4 main factors and related 19 sub-factors chosen for this study (Table 2).

Table 2. Factors and sub-factors Influencing the adoption of spraying UAVs

Main Factor	Sub-Factor	Description	Reference
Economic Barriers (E)	High maintenance cost (E1)	The high expenses required for the regular maintenance and repair of agricultural technologies or equipment.	[15]
	Cost of components (E2)	The expensive parts or components of the equipment or technologies being used.	[15], [20]
	Cost of skilled labor (E3)	The high wages needed to hire trained and skilled personnel.	[15], [20]
	High investment cost (E4)	The large initial expenditure required to purchase or install new technologies or equipment.	[15], [20], [21], [22], [23]
	Limited access to credit (E5)	The difficulties farmers face in obtaining financial support or loans.	[21]
Farmers and Farm Characteristics (F)	Gender (F1)	The gender of the farmer and how it affects their access to or use of agricultural technologies.	[21]
	(Household) income (F2)	The total income level of the farmer's household and its impact on their ability to invest in technology.	[21]
	Share of agricultural income (F3)	The percentage of the farmer's total income derived from agricultural activities.	[21]
	(Agricultural/technical) education (F4)	The level of agricultural or technical education attained by the farmer, influencing their ability to adopt innovations.	[15], [21]
	Full-time farming (F5)	Whether the farmer engages in farming as their primary occupation.	[21], [22]
	Land ownership (F6)	Whether the farmer owns the land they cultivate, which can influence their willingness to invest in long-term improvements.	[21]
	Land size (F7)	The size of the land being cultivated, affecting the scale of investments and technology adoption..	[21], [22]
Social (S)	Lack of Awareness (S1)	Farmers not being aware of the existence, benefits, or functionalities of certain technologies.	[15], [21], [23]
	Perceived ease of use (S2)	How easy or difficult farmers believe it is to use a particular technology.	[15], [21], [22], [23]
	Perceived usefulness (S3)	Farmers’ belief in how much a technology can improve their productivity or efficiency.	[21], [22], [23]

Table 2. Continued

Operational (O)	Policy and regulations (O1)	The impact of government policies and regulatory frameworks on technology adoption in agriculture..	[15], [20], [21]
	Lack of service centers (O2)	The unavailability of nearby service centers for maintenance, repair, or technical support..	[15]
	Lack of technical assistance (O3)	Insufficient support or guidance provided to farmers for understanding or implementing technologies.	[21], [23]
	Labor scarcity (O4)	A shortage of available labor to operate and manage advanced technologies or farming operations.	[15], [22], [23]

To facilitate pairwise comparisons of all identified factors, additional demographic and contextual information was collected from the participants. This included data on their age, farming experience, and the characteristics of their farmland. These variables were assessed to evaluate the representativeness of the selected participants in relation to the broader population of farmers in Adana. The attendees represented different age groups, and landholding sizes, supporting the conclusion that the sample is representative of the regional farming community.

Data collection was conducted through one-on-one interviews with seven farmers. During these interactions, participants were provided with detailed explanations about the research objectives and the content of the factors included in the questionnaire. This step was crucial, as the factors, when presented solely by their titles, might not have been readily comprehensible to all participants. To enhance the consistency of responses, participants were encouraged to ask questions and seek clarification, ensuring a deeper understanding of each factor. This interactive approach reduced the risk of superficial or inconsistent responses, fostering a more reliable dataset.

2.1. Method

This study employs the Analytic Hierarchy Process (AHP) to determine the relative importance of barriers to the adoption of spraying UAVs in agriculture. Developed by Thomas Saaty in 1980, AHP is a widely recognized method in Multi-Criteria Decision Making (MCDM) due to its straightforward computations and effectiveness in addressing complex decision scenarios [24]. It effectively integrates both qualitative and quantitative factors into a structured decision framework [25]. AHP's versatility and robustness have led to its extensive application across diverse fields. For example, Kalan [26] employed AHP to identify optimal station locations along the Mersin–Gaziantep high-speed train line, highlighting its utility in transportation planning. In the energy sector, Güner et al. [27] integrated AHP with GIS to select suitable sites for solar power plants in Mersin, considering environmental, economic, and topographic factors. In the manufacturing domain, Özmen and Antmen [28] combined AHP with TOPSIS to evaluate passenger seat models for a new bus design. Similarly, Işık [29] used AHP in conjunction with ELECTRE to prioritize safety hazards in soil microbiology laboratories. These diverse applications underscore AHP's methodological flexibility, consistency in priority setting, and continued relevance across domains such as engineering, environmental planning, industrial product development, and occupational safety.

The AHP methodology can be summarized in the following steps:

Step 1: Identifying the criteria and sub-criteria.

Step 2: Formation of a pair-wise comparison matrix of the decision-problem using Saaty's 1–9-point scale and normalization of the pairwise comparison matrix. Saaty's 1–9 points scale was given in Table 3.

Table 3. Scale of the ratios for importance valuation

Intensity of Importance	Definition	Explanation
1	Equal importance	Two barriers are equally important
3	Somewhat more important	Barrier is slightly more important over the other
5	Much more important	Barrier is strongly more important over the other
7	Very much more important	Barrier is very strongly more important over the other
9	Absolutely more important	Barrier is definitely more important over the other
2, 4, 6, 8	Intermediate values	When compromise is needed in between

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} = \begin{bmatrix} w_1/w_1 & w_1/w_2 & \cdots & w_1/w_n \\ w_2/w_1 & w_2/w_2 & \cdots & w_2/w_n \\ \vdots & \vdots & \ddots & \vdots \\ w_n/w_1 & w_n/w_2 & \cdots & w_n/w_n \end{bmatrix} \tag{1}$$

$$a_{ij} = 1, where\ i = j, since\ \ w_i/w_i = 1 \tag{2}$$

and

$$a_{ji} = 1/a_{ij} \tag{3}$$

$$A = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ {}^{1}/_{a_{12}} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ {}^{1}/_{a_{1n}} & {}^{1}/_{a_{2n}} & \cdots & 1 \end{bmatrix} \tag{4}$$

If all attributes are considered as benefit criteria formula to be used is given as below:

$$n_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{5}$$

Resulting matrix is as follows:

$$\begin{pmatrix} 1 & n_{12} & \cdots & n_{1n} \\ n_{21} & 1 & \cdots & n_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ n_{n1} & n_{n2} & \cdots & 1 \end{pmatrix} \tag{6}$$

Step 3. Computation of relative importance weights:

$$w_i = \frac{\sum_{j=1}^{n} n_{ij}}{n} \tag{7}$$

Step 4. Evaluation of the consistency ratio:

The consistency ratio (CR) is calculated to ensure the consistency of pair wise comparisons.

The equation of *C.I.* is a follows:

$$C.I. = (\lambda_{max} - k)/(k - 1) \tag{8}$$

where, λ_{max} is the largest eigenvalue, and k represents the number of attributes.

The mathematical expression for the CR is given as:

$$C.R. = \frac{C.I.}{R.I.} \tag{9}$$

The value of the random consistency index (R.I) depends upon value of (n) given in Table 4.

Table 4. The *R.I.* values for different matrix sizes

Number of elements	3	4	5	6	7	8	9	10	11	12	13
R.I.	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49	1.51	1.54	1.56

The value of C.R should be less than 0.10 to have better level of consistency.

3. RESULTS AND DISCUSSION

In this study, the case of Adana has been taken to determine the factors and sub-factors that impede the adoption of agricultural spraying drones by farmers. Potential factors that influence the adoption of agricultural spraying UAVs were identified through a review of the literature. Then, the questionnaire, detailed in Appendix I, was developed and administered through one-on-one interviews with seven farmers. During these sessions, participants were thoroughly briefed on the research objectives and the factors listed in the questionnaire to ensure clarity and comprehension. To enhance response consistency, participants were encouraged to ask questions and seek clarification. This interactive approach minimized the risk of superficial or inconsistent answers, resulting in a more reliable dataset. Then, pairwise comparison matrices for main factors and sub-factors were subsequently constructed using the collected data.

Firstly, the weights of the main factors were determined through pairwise comparisons. Table 5 presents the results of these comparisons along with the corresponding weights calculated using the Analytic Hierarchy Process (AHP).

Table 5. Pairwise comparison matrix and weights of the main factors

Main Factor	E	F	S	O	Weight	Rank
E	1	0.750	0.447	0.404	0.143	4
F	1.334	1	0.624	0.645	0.202	3
S	2.237	1.601	1	1.214	0.340	1
O	2.474	1.551	0.824	1	0.315	2
Consistency ratio: 0.00341						

The results indicate that social (S) factors hold the highest significance with a weight of 0.340. These are followed by operational (O) factors, which have a weight of 0.315, and factors related to farmers and farm characteristics (F), with a weight of 0.202. Economic (E) factors, with a weight of 0.143, were found to be the least significant.

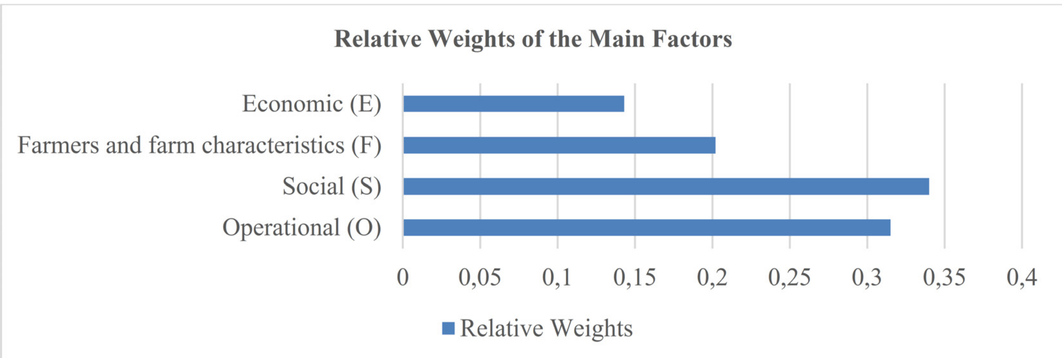

Figure 1. Relative weights of the main factors

It can also be observed from the Figure 1 that difference between the operational (O) and social (S) is not highly significant, compared to the other main factors.

Additionally, the AHP technique was employed to determine the weights of the sub-factors associated with the use of spraying UAVs. Tables 6, 7, 8, and 9 present the pairwise comparisons of the sub-factors within each main barrier category, along with their respective AHP weights.

Table 6. Pairwise comparison matrix of social sub-factors

Social sub-factors	S1	S2	S3	Weight	Rank
S1	1	1.211	1.305	0.385	1
S2	0.826	1	1.170	0.327	2
S3	0.767	0.855	1	0.287	3
Consistency ratio: 0.00065					

According to Table 6, "lack of awareness" (S1) emerged as the most significant sub-barrier within the category of social factors, with a weight of 0.385. This was followed by "perceived ease of use" (S2), which had a weight of 0.327, and "perceived usefulness," with a weight of 0.287.

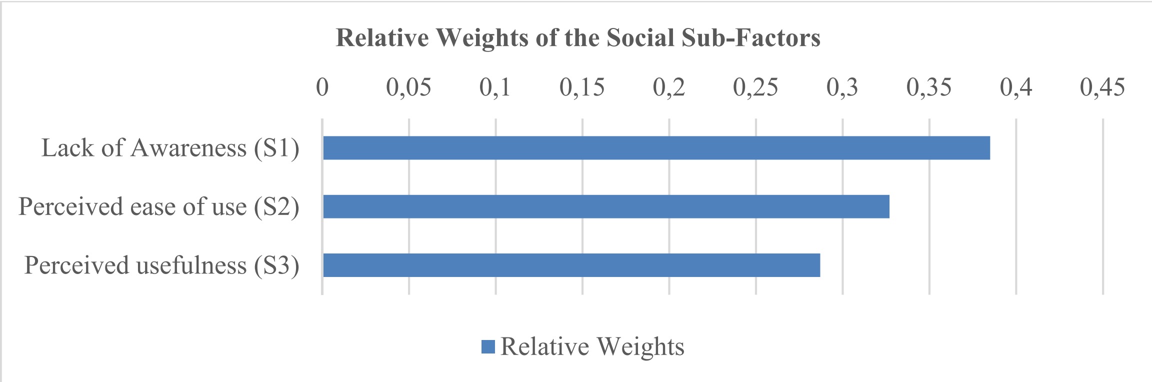

Figure 2. Relative weights of the social sub-factors

Graphical representation of the Table 6 is given on Figure 2, which shows the relative differences of the weights as not much significant from each other. However, it is obvious that lack of awareness (S1) is the key barrier among them.

Social factors, which were identified as the most significant main category, underline the importance of raising awareness and providing targeted education to stakeholders about the benefits and feasibility of UAV-based spraying.

The lack of awareness (S1), as the most impactful sub-barrier, underscores the need for targeted education and outreach programs to inform stakeholders about the benefits and applications of UAV-based spraying technologies. Perceived ease of use (S2) suggests that improving user-friendly designs and offering hands-on training can significantly enhance adoption rates. Finally, addressing perceived usefulness (S3) through demonstrations and sharing success stories can further build trust and confidence in these technologies, encouraging wider adoption among farmers and stakeholders.

Table 7. Pairwise comparison of operational sub-factors

Operational sub-factors	O1	O2	O3	O4	Weights	Ranks
O1	1	1.000	0.593	0.520	0.180	4
O2	1.000	1	1.000	0.557	0.206	3
O3	1.685	1.000	1	0.545	0.236	2
O4	1.923	1.795	1.835	1	0.378	1
Consistency ratio: 0.01172						

The results of the pairwise comparisons among the operational sub-factors (Table 7) indicate that "labor scarcity" (O4) was the most significant with a weight of 0.378. This was followed by "lack of technical assistance" (O3), which had a weight of 0.236, and "lack of service centers" (O2), with a weight of 0.206. "Policy and regulation" (O1) was identified as the least significant sub-factor, with a weight of 0.180.

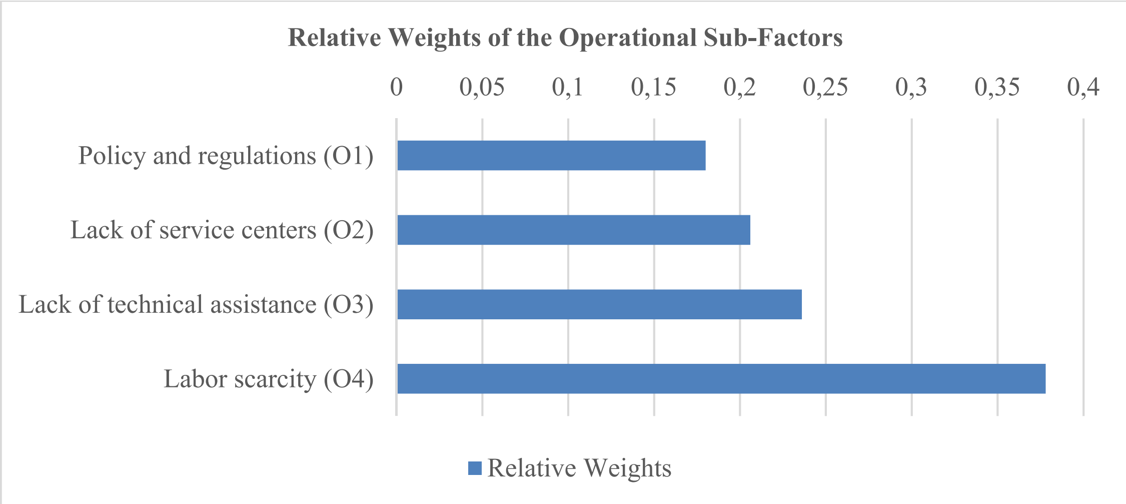

Figure 3. Relative weights of the operational sub-factors

Graphical representation (Figure 3) also shows the superiority of the labor scarcity (O4) barrier, leaving the other barriers much behind. The findings highlight that labor scarcity (O4), as the most significant operational sub-factor, underscores the critical challenge posed by workforce shortages in adopting new agricultural technologies, such as UAV-based spraying. The lack of technical assistance (O3) points to insufficient knowledge and support for effectively utilizing these technologies, underscoring the importance of targeted training programs and robust support networks. The lack of service centers (O2) reflects infrastructural limitations that hinder access to maintenance and repair services, indicating a need for increased investment in such facilities. Although policy and regulation (O1) were the least significant sub-barrier, the absence of enabling policies could still act as a barrier to widespread adoption. Overall, addressing labor scarcity and improving technical and infrastructural support should be prioritized to enhance the adoption of innovative agricultural practices.

Table 8. Pairwise comparison matrix and weights of the economic sub-factors.

Economic sub-factors	E1	E2	E3	E4	E5	Weight	Rank
E1	1	0.815	0.944	0.390	1.000	0.149	4
E2	1.228	1	0.472	0.447	1.405	0.155	3
E3	1.060	2.119	1	0.696	1.534	0.226	2
E4	2.567	2.237	1.436	1	2.225	0.333	1
E5	1.000	0.712	0.652	0.449	1	0.137	5
Consistency ratio: 0.01731							

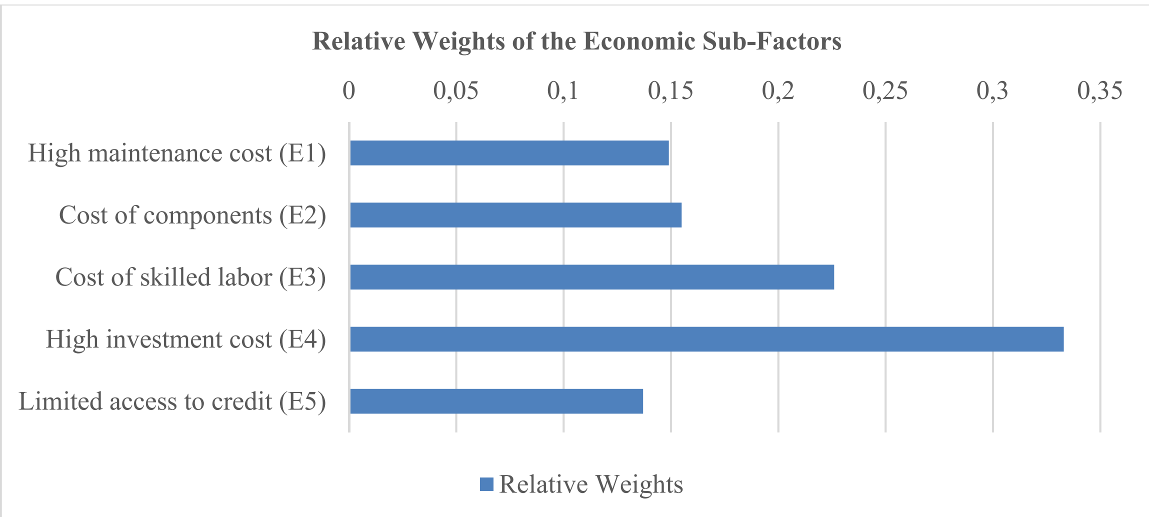

Figure 4. Relative weights of the economic sub-factors

Table 8 presents the pairwise comparison matrix and calculated weights for the economic sub-factors. The sub-barrier investment cost (E4) with a weight of 0.333 was identified as the most significant economic sub-factor, reflecting its strong influence compared to other sub-factors. It is followed by cost of skilled labor (E3) with a weight of 0.226, which holds the second rank, suggesting moderate importance in this category. Cost of components (E2) with a weight of 0.155 and high maintenance cost (E1) with a weight of 0.149 were found to have similar, but relatively lower significance. Lastly, limited access to credit (E5), with the lowest weight of 0.137, ranked as the least impactful economic sub-factor. Considering the graphical representation (Figure 4), highest weighted barrier of high investment cost (E4) is very dominant.

Table 9. Pairwise comparison matrix of farmers and farm characteristics sub-barriers

Farm char. sub-factors	F1	F2	F3	F4	F5	F6	F7	Weight	Rank
F1	1	0.349	0.385	0.231	0.431	0.465	0.293	0.054	7
F2	2.869	1	0.590	0.514	1.112	1.150	0.611	0.127	5
F3	2.599	1.694	1	0.621	0.691	1.065	0.566	0.135	4
F4	4.336	1.944	1.610	1	1.320	1.435	0.672	0.198	2
F5	2.318	0.899	1.448	0.757	1	1.505	0.807	0.154	3
F6	2.153	0.869	0.939	0.697	0.664	1	0.679	0.121	6
F7	3.413	1.637	1.768	1.489	1.240	1.472	1	0.211	1
Consistency ratio: 0.01411									

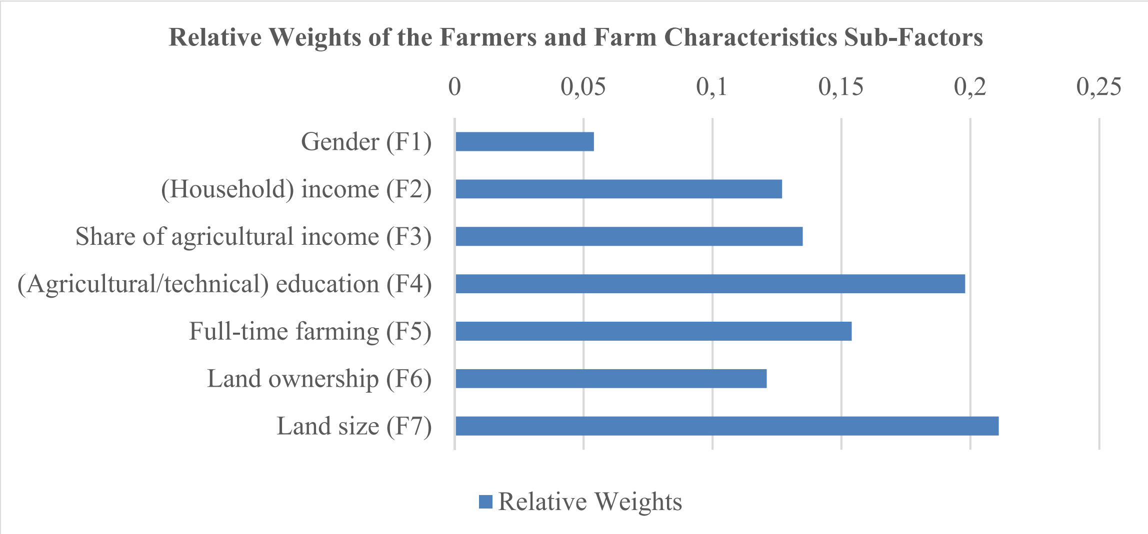

Figure 5. Relative weights of the farmers and farm characteristics sub-factors

The analysis of farmer-related sub-factors (Table 9) reveals that land size (F7), with the highest weight of 0.211, is the most significant factor influencing the adoption of UAV technology in agriculture. This result is expected given the inherent economic dynamics of agricultural technology adoption. Larger farms can benefit from economies of scale, making the high initial investment and operational costs of UAVs more manageable. In contrast, smaller farms often struggle with limited financial resources, which can hinder their ability to adopt such technologies. Agricultural/technical education (F4), which had a weight of 0.198 ranked second, indicating the crucial role that education plays in the adoption of UAV technology. Considering the graphic on Figure 5, the difference between F7 and F4 is not very significant, which leads to considering the importance of agricultural/technical education. These two barriers were followed by Full-time farming (F5) with a weight of 0.154, Share of agricultural income (F3) with the weight of 0.135, household income (F2) with the weight of 0.127, Land ownership (F6) with the weight of 0.12. Finally, gender (F1), with the lowest weight of 0.054 was identified as the least significant sub-barrier indicating a relatively minor role in this context.

Table 10. Results of overall sub-barriers via AHP

Main factor	Relative weight	Relative rank	Sub-barrier	Relative weight	Relative rank	Global weight	Global rank
E	0.143	4	**E1**	0.149	4	0.021	17
			E2	0.155	3	0.022	16
			E3	0.226	2	0.032	11
			E4	0.333	1	0.048	8
			E5	0.137	5	0.020	18
F	0.202	3	**F1**	0.054	7	0.011	19
			F2	0.127	5	0.026	14
			F3	0.135	4	0.027	13
			F4	0.198	2	0.040	10
			F5	0.154	3	0.031	12
			F6	0.121	6	0.024	15
			F7	0.211	1	0.043	9
S	0.340	1	**S1**	0.385	1	0.131	1
			S2	0.327	2	0.111	3
			S3	0.287	3	0.098	4
O	0.315	2	**O1**	0.180	4	0.057	7
			O2	0.206	3	0.065	6
			O3	0.236	2	0.074	5
			O4	0.378	1	0.119	2

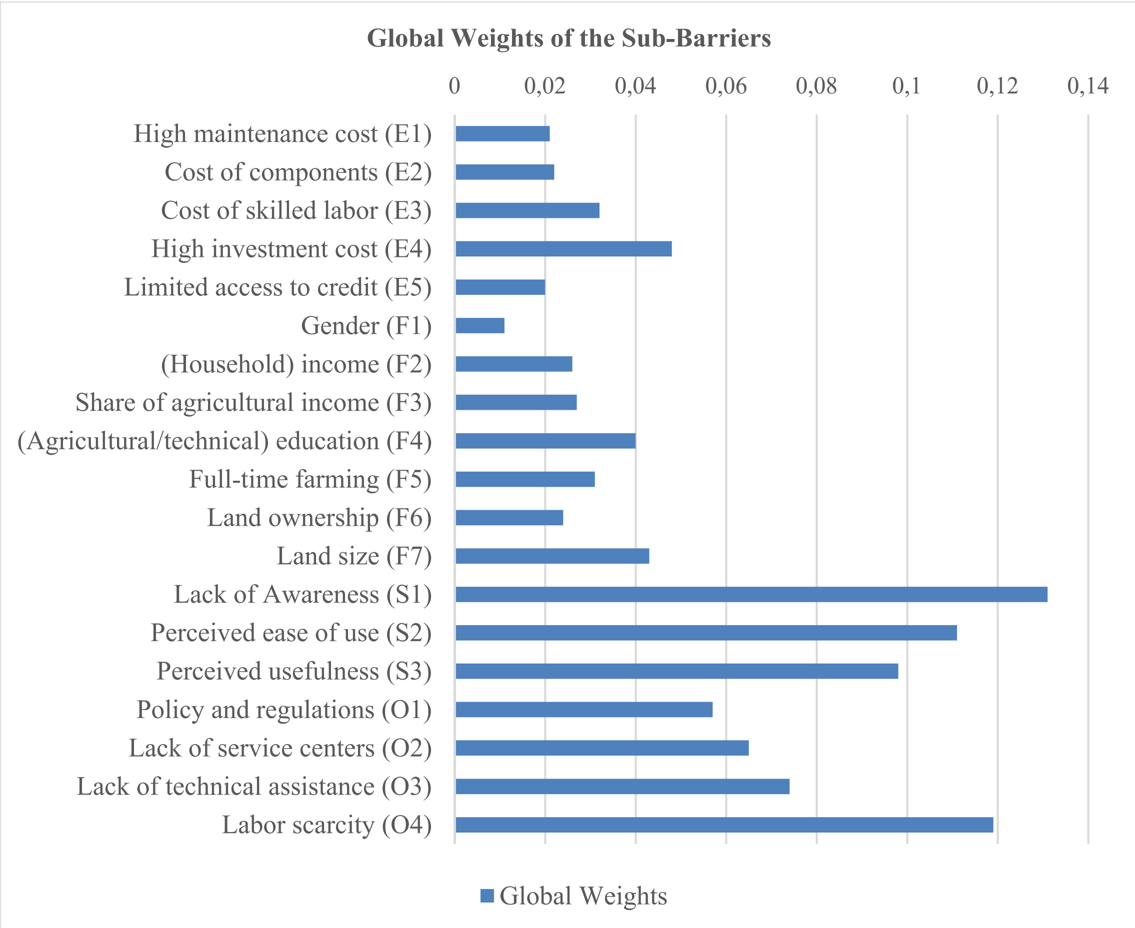

Figure 6. Global weight results of overall sub-barriers via AHP

Based on the AHP analysis, the overall sub-factors influencing the use of spraying UAVs have been ranked. Table 10 presents the overall sub-factor ranking, and Figure 6 shows the weights in graphics for easier assessment. The results show that the lack of awareness (S1) is the most significant sub-factor, followed by perceived ease of use (S2) and perceived usefulness (S3). These findings suggest that social factors play a critical role in the adoption of spraying UAVs, particularly in the context of Adana. Following the social sub-factors, the ranking continues with operational sub-factors. The labor scarcity (O4) ranks fourth, followed by lack of technical assistance (O3), lack of service centers (O2), and finally, policy and regulations (O1).

These findings clearly indicate that in order to enhance the adoption of UAVs, it is essential to raise social awareness, provide user-friendly training programs, and strengthen operational infrastructure. Specifically, addressing the knowledge gaps among farmers regarding UAV technologies will help build their confidence and facilitate adoption. Additionally, improving the perception of ease of use can be achieved through practical training and support services, which will play a significant role in increasing the widespread use of UAVs. Strengthening the operational infrastructure can help address challenges such as labor scarcity and lack of technical assistance. Expanding service centers and support networks will further enhance the accessibility and effective utilization of UAVs for farmers, ultimately contributing to greater adoption.

4. CONCLUSION

This study identifies and prioritizes the factors influencing the adoption of agricultural spraying UAVs in Adana, Turkey, using the Analytic Hierarchy Process (AHP). The findings indicate that social factors hold the highest significance, with a weight of 0.340, emphasizing the critical role of aspects such as lack of awareness (0.385), perceived ease of use (0.327), and perceived usefulness (0.287). Operational factors, with a weight of 0.315, rank second, driven by challenges like labor scarcity (0.378) and lack of technical assistance (0.236). Economic factors and farm-related characteristics, although relevant, carry comparatively lower weights of 0.143 and 0.202, respectively. Among all sub-factors, lack of awareness and labor scarcity emerge as the most influential, with global weights of 0.131 and 0.119.

These results highlight the importance of addressing the multifaceted factors influencing UAV adoption. Raising social awareness through targeted education campaigns, conducting hands-on training programs to improve ease of use, and sharing success stories are essential to mitigate social barriers. Simultaneously, operational challenges can be addressed by expanding technical support networks, investing in automation to offset labor shortages, and improving access to maintenance and service centers.

The importance of this study lies in its ability to provide a structured framework for identifying and prioritizing the key factors affecting UAV adoption. Given Adana’s pivotal role in Turkey’s agricultural sector—producing 50% of the country’s corn and soybeans, 34% of its peanuts, and 29% of its oranges—enhancing UAV adoption could significantly improve productivity, efficiency, and sustainability. By reducing chemical use by up to 45% and enabling the efficient coverage of 10 hectares per hour, UAVs offer transformative potential for modern agriculture.

These findings offer actionable insights for policymakers, agricultural stakeholders, and technology developers, both in Adana and similar agricultural regions. Future research should explore the long-term economic and environmental impacts of UAV adoption and investigate how these findings can be adapted to other regions with varying agricultural practices and needs.

By addressing the factors outlined in this study, agricultural UAV technology can be more effectively integrated into farming practices, leading to a more sustainable, precise, and efficient agricultural sector. However, since this study was limited to a single location and focused on the factors influencing the adoption of agricultural spraying UAVs in Adana, its findings may not be fully generalizable to other regions in Türkiye. To develop region-specific policies and strategies, future research should explore key adoption factors across different geographical contexts. Additionally, while this study utilized the AHP method to evaluate these factors, alternative methodologies such as VIKOR, TOPSIS, DEMATEL, and fuzzy MCDM approaches may provide different perspectives on their prioritization. To enhance the robustness and validity of the findings, future studies should incorporate multiple decision-making techniques for a more comprehensive comparative analysis.

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