From Perception to Practice: Drone Technology in Romanian Agriculture

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ABSTRACT
The paper focuses on the adoption of drone technology in Romanian agriculture, examining the perceptions and challenges faced by local farmers. A survey was conducted to gather data from Romanian farmers, highlighting their awareness, attitudes, and usage of drones. Five key hypotheses were proposed: age, education, land size, legislative concerns, and challenges in drone adoption. Findings suggest that legislative barriers are the most significant issue, while other challenges include high costs and limited technical support. The study reveals that younger and more educated farmers are more likely to adopt drones, with larger farms showing a higher adoption rate. Despite these challenges, many farmers report satisfaction with drone technology, using it primarily for tasks such as precision spraying and mapping. The study concludes that drones hold significant potential for improving efficiency and sustainability in Romanian agriculture, but legislative reforms are essential for broader adoption. The paper offers a foundational perspective for further research on drone usage in this sector.

KEYWORDS: *drone technology, legislative barriers, precision agriculture, Romanian agriculture*

JEL CLASSIFICATION: *Q10, Q16, Q12.*

1. INTRODUCTION

In this paper, we are going to present the current situation of unmanned aerial vehicles (UAV), also known as drones in the Romanian agriculture, investigating how do Romanian farmers perceive and adopt drone technology for agricultural purposes, respectively what are the main challenges of drone adoption in Romania for agriculturists. Based on growing evidence from recent studies, the use of drones to address various challenges in agriculture is becoming increasingly widespread among farmers globally.

Drones are being adopted for their ability to enhance precision agriculture, improve efficiency in monitoring crop health, and reduce resource wastage through targeted interventions, as noted in multiple sources on drone technology in agriculture. For instance, precision agriculture practices, supported by drones, enable better crop management and real-time data collection, resulting in cost and time savings, as well as environmental benefits. To the best of our knowledge, no existing studies have explored either Romanian farmers' perceptions of drone technology or the current state of unmanned aerial vehicles in Romanian agriculture. Therefore, we have deemed this a relevant topic for our paper.
As the existing Romanian literature about the local impact of agricultural drones is scarce and the available statistical data presenting either the situation of UAVs in the country's

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agriculture or the existing farms in detail is even more sparse, I also had to collect the data from farmers, using online surveys, asking them to express their opinion about drones and their experience (if any).

During the design of research methodology, we considered the existing literature, analysing how others handled different stages of such a research, starting from the survey design, to data collection and processing. Relevant observations and information from existing literature will be presented in following section, while the applied methodology, hypotheses, and limitations of my thesis will be presented in section 3. Section 4 discusses the implementation of the previously described methodology, and it will also present the results of our research in detail.

2. LITERATURE REVIEW

2.1 Precision agriculture

Agriculture has consistently held a pivotal role in Romania's economy (Albu et al., 2018). According to data from the Romanian National Institute of Statistics, agriculture, forestry, and fishing contributed 18.16% to Romania's GDP in 1995. However, over the past two to three decades, this sector's contribution has steadily declined, reaching only 3.94% of the current GDP (Institutul Național de Statistică, 2023), as illustrated in Figure 1. This trend underscores a significant decrease in the relative performance of these sectors. Despite accounting for only 4% of GDP, agriculture and its associated industries still employed roughly a third of Romania's workforce as of 2019, demonstrating a clear imbalance between the sector's contribution to employment and its economic output (Fertu et al., 2019).

Figure 1. Contribution of Agriculture, Silviculture, and Fishing to Romania's GPD
Source: National Institute of Statistics (INSS, 2023)

As Bai et al. (2022) note, agriculture is becoming increasingly competitive, with farmers facing not only local but also European and global competition. Consequently, economies of scale have become crucial. To remain competitive, farmers must enhance efficiency, and as Pathan et al. (2020) emphasise, traditional agricultural methods alone offer limited scope for improvement. In this context, precision agriculture emerges as a transformative solution, offering a modern management approach that enhances decision-making through precise data collected from various sources, such as the Internet of Things (IoT), robotics, artificial intelligence (AI), and unmanned aerial vehicles (UAVs) (Candiago et al., 2015).

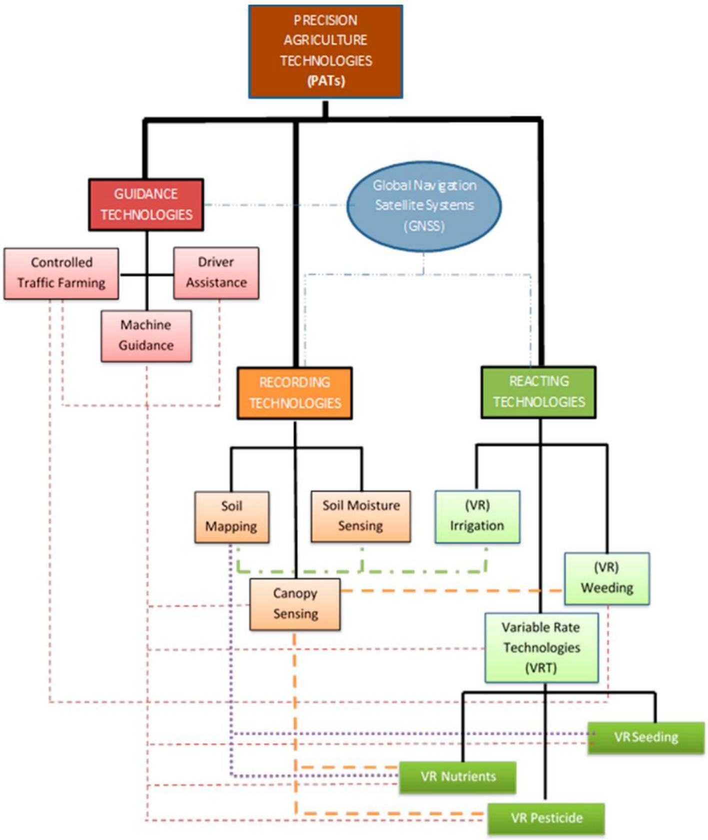

Figure 2. Technologies and application areas related to Precision Agriculture
Source: Balafoutis et al. (2017)

Through precision agriculture, farmers can continuously monitor crop conditions and respond effectively to potential threats. Advancement in information technology, communication protocols, and data processing has ushered in a new era of sustainable agricultural productivity (Aubert et al., 2012). As Balafoutis et al. (2017) have categorised, precision agriculture technologies primarily focus on guidance, recording, and reacting, relying on mapping or navigation systems like Global Navigation Satellite Systems (GNSS) or Global Positioning Systems (GPS). Figure 2 presents an overview of these technologies and their applications, with UAVs offering solutions for real-time crop monitoring across large-scale farms.

2.2 Unmanned aerial vehicles

As Urbahs and Jonaite (2013) noted, UAVs were initially designed for military purposes, but soon gained popularity among civilian users. Hayat et al. (2016) highlight that drones cover large areas with high mobility, offer relatively low maintenance costs, and are user-friendly.
From a technological perspective, the literature identifies several types of UAVs, including fixed-wing, rotary-wing, blimp, flapping-wing, and parafoil-wing UAVs (Tsouros et al., 2019). Among these, two types are widely used in agriculture, as shown in Figure 3:

- Rotary-wing UAVs: These include helicopters and multi-rotor UAVs, with the latter (tricopters, quadcopters, etc.) being the most commonly employed in agriculture (Tsouros et al., 2019). Figure 3a illustrates these UAVs.

- Fixed-wing UAVs: These resemble airplanes and are controlled remotely. Tsouros' meta-study reveals that 22% of reviewed studies used fixed-wing UAVs, valued for their aerodynamic efficiency and potential for solar power, although their high-speed flight limits data collection (Tsouros et al., 2019). Figure 3b illustrates this type.

Almalki et al. (2021) suggest that agriculture may become one of the most significant civilian applications of UAVs, as farmers increasingly adopt drone-based solutions. Researchers agree that UAVs are integral to precision agriculture, with their adoption following similar patterns to other modern agricultural technologies (Bai et al., 2022; Barnes et al., 2019).

Radoglou-Grammatikis et al. (2020) identify two key UAV applications in precision agriculture: data collection and spraying tasks. Data collection includes monitoring crop health, detecting diseases, assessing soil conditions, and estimating yields. Spraying tasks involve precision fertilisation and efficient water management, crucial in light of climate change. Drones can create irrigation maps and detect soil variability, enhancing water usage efficiency (Zuo et al., 2021).

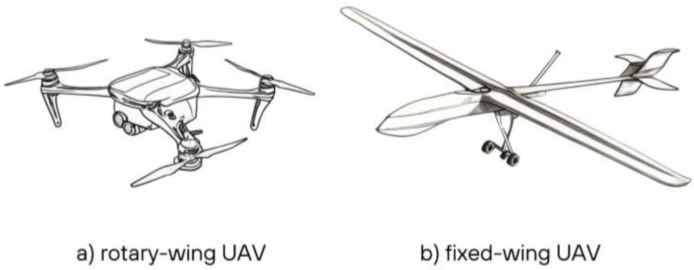

Figure 3. a) rotary-wing and b) fixed-wing UAVs

Source: Generated images using AI image generator tool. Prompts: "representation of a rotary-wind UAV in a sketch" respectively "representation of a fixed-wing UAV in a sketch" using the minimalist style (Canva, 2024)

2.3 Farmer perceptions and adoption of UAVs

Since the emergence of precision agriculture and, later, UAV-based solutions for agricultural challenges, numerous studies have explored farmers' perceptions of these technologies, analysing the factors influencing their adoption. In this chapter, we summarise key studies focusing on the determinants of drone adoption. Pivoto et al. (2019) argued that farm size, farmers' resources, education, and age significantly impact decisions to adopt new technologies.

This is corroborated by Ruzzante et al. (2021), who emphasised the role of farm size in decision-making, especially when economies of scale are considered. Education is another critical factor, as demonstrated by Daberkow and McBride's (2003) study on U.S. farmers, which found a positive correlation between higher education levels and the adoption of new technologies. Vecchio et al. (2020), in a study on Italian farmers, used the diffusion theory to show that education increases exposure to new technologies, thus enhancing the likelihood of adoption. Furthermore, Aubert et al. (2012) noted that age plays an important role, with younger farmers being more inclined to adopt new solutions due to their long-term planning horizons.

Barnes et al. (2019) extended the discussion by identifying additional socioeconomic factors affecting European farmers' adoption of precision agriculture technologies, such as income, information sources, and gender. Zuo et al. (2021) suggested that other demographic and behavioural factors also influence adoption. Wheeler et al. (2017) introduced the concept of "soft" and "hard" technology adoption, with hard adoptions involving infrastructure investments, and soft adoptions relating to skills, management, and knowledge—typically more difficult and time-consuming to acquire.

Drone adoption shares many similarities with other precision agriculture technologies (Barnes et al., 2019), but as drone research is still relatively new, there are some contradictions. Skevas and Kalaitzandonakes (2020) found that economic expectations and profitability were the main drivers for Missouri farmers investing in drone technology, while environmental benefits, age, and openness to cooperation also played a role. Michels et al. (2020) found that farm size was a key factor in German farmers' adoption of drones, as larger farms could better exploit economies of scale - a conclusion also reached by Bai et al. (2022) in Hungary.

However, Zhang et al. (2019) found no correlation between farm size and drone adoption in China. Zuo et al. (2021), in their study of Australian farms, found an inverted U-shaped relationship between farm size and drone adoption for irrigation management: adoption probability increased with farm size up to a point, then declined. This pattern is not directly comparable to Europe, where farms rarely exceed 11,000 hectares, a common size in Australia.

Wachenheim et al. (2021) concluded that higher income and satisfaction with traditional methods reduced the likelihood of Chinese farmers adopting UAVs. Michels et al. (2020) identified cost, mistrust of UAV data, and legal issues as the main barriers to adoption in Germany. In contrast, Bai et al. (2022) found high satisfaction among Hungarian farmers, with factors such as farm size, age, education, and openness correlating positively with drone adoption.

3. METHODOLODOLOGICAL APPROACH

3.1 Methodology

For our research, we used a quantitative methodology, conducting a survey among a sample of Romanian farmers to examine their perceptions of drone technology and their adoption behaviours.

Data Collection. Although previous studies have also relied on surveys, there are significant differences in data acquisition methods, specific goals, and data processing due to the general lack of data on drone adoption (Bai et al., 2022; Michels et al., 2020; Skevas & Kalaitzandonakes, 2020; Wachenheim et al., 2021; Zuo et al., 2021). For instance, Skevas and Kalaitzandonakes (2020) mailed surveys to 3,000 Missouri farmers owning more than 100 acres, receiving 946 responses.

Similarly, Wachenheim et al. (2021) distributed 1,300 surveys to Chinese farmers in Jilin Province, achieving a 65.7% response rate across farms of various sizes. Zuo et al. (2021) used telephone interviews, reaching 1,000 farmers with 991 responses, while Michels et al. (2020) and Bai et al. (2022) conducted online and in-person surveys in Germany and Hungary, respectively.

Given the lack of data from Romanian statistical institutes and other limitations, such as resource constraints and limited access to professional forums, we opted for an online survey, distributed via personal networks and social media groups. This method led to some limitations, discussed in the limitations section. The data was collected primarily in May and early June 2024. We personally reached out to 83 individuals and shared the survey in 26 agriculture-related Facebook groups, most of which communicated in Romanian, with two smaller Hungarian-speaking groups. These groups range from large public forums to smaller, regionally focused communities.

Ultimately, we collected 61 responses. Most of the responses were gathered by directly contacting potential participants identified as drone users or farmers working on larger plots of land. The regional distribution of the responses, illustrated in Figure 4, shows that while answers were obtained from various parts of Romania, Harghita County contributed the most responses due to pre-existing personal connections.

Survey Structure

The survey consisted of three major sections:

1. General Information: Age, education, and place of residence.
2. Farming Experience: Land size, agricultural activities, and general knowledge about drones.
3. Drone Perception and Experience:

a. If respondents had drone experience, they were asked about their motivations, participation in professional training, usage frequency, satisfaction levels, and challenges faced.
b. If they had no experience, they were asked why they had not adopted drones, how likely they were to do so in the future, and what resources they used to learn about agricultural innovations. The questions also focused on perceived costs, efficiency, legislation, and technical support.

The survey was available in both Romanian and Hungarian, with responses mapped to English during data processing. The survey was simplified, so that an average responder could answer it in 6-8 minutes. To the best of our knowledge, no prior research has been conducted on this topic in Romania, so we based our hypotheses on existing studies from other European countries.

Hypotheses

Following the models of Michels et al. (2020) and Bai et al. (2022), who examined drone adoption among German and Hungarian farmers, we formulated the following hypotheses:

- Hypothesis 1: Younger Romanian farmers are more likely to adopt drone technology than older farmers.
- Hypothesis 2: There is a positive correlation between the education level of Romanian farmers and their adoption of drone technology.
- Hypothesis 3: Larger farm sizes are positively correlated with drone adoption. Additionally, we proposed two hypotheses specific to the Romanian context, particularly related to bureaucracy and legislative challenges, which may affect both adoption decisions and current users:
- Hypothesis 4: Concerns about regulatory issues and legislative hurdles significantly influence drone adoption among Romanian farmers.
- Hypothesis 5: Legislative deficiencies are the greatest challenge Romanian farmers face in using drones.

To evaluate these hypotheses, we primarily used Chi-Square Tests. A detailed explanation of the methodology for each hypothesis is provided in the following chapter.

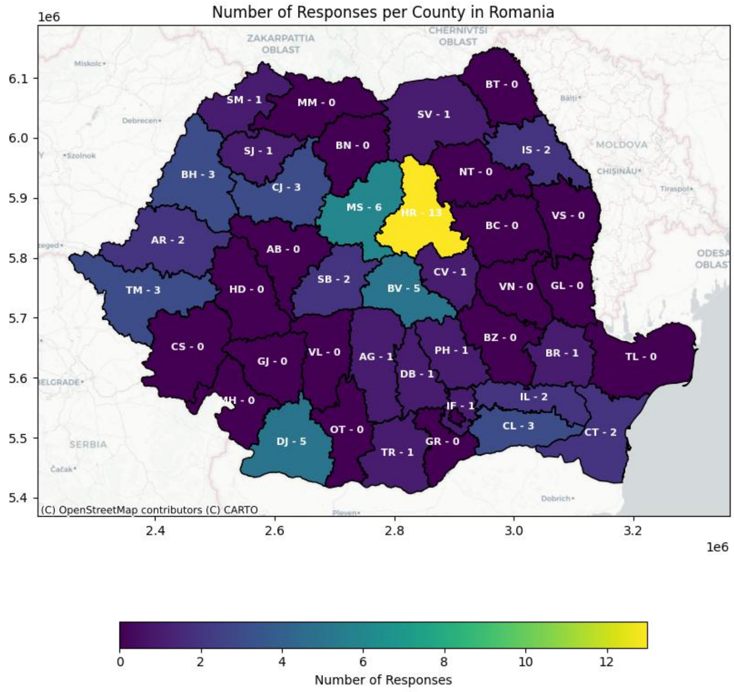

Figure 4. Survey response distribution per County in Romania
Source: GeoJSON: Geo-Spatial (geo-spatial.org, 2021)

Data Processing
Data processing and visualisation were conducted using Python, employing open-source libraries such as pandas, SciPy, and re for data handling, and GeoPandas, Matplotlib, Contextily, and Seaborn for visual representation. This approach allowed us to organise and analyse the survey data efficiently, ensuring that the findings are robust and reliable.

3.2 Limitations

The chosen methodology for our research presents several limitations. The primary limitation lies in data collection, as the number of respondents is low and the sample is not sufficiently representative, primarily due to resource constraints. Farmers are generally less accessible online, making it necessary for future research to invest more resources in data collection. Additionally, since the survey was shared online in public groups and completed anonymously in many cases, the data cannot be fully validated.

However, given the lack of previous studies on this topic in Romanian agriculture and the relatively simple relationships investigated between dependent and independent variables, we believe the results offer valuable insights and provide a strong foundation for future research.

Another limitation is the lack of comprehensive statistical data. Government institutions do not collect detailed information about farmers, their adoption of innovative technologies, or the specifics of their agricultural practices. In contrast, countries like Hungary conduct regular agricultural censuses, offering valuable data on farmers' needs and behaviours, including their use of precision agriculture (Hungarian Central Statistical Office, 2023).

This type of data is essential for both researchers and policymakers. Additionally, during data collection, we identified two other issues. Many farmers who use drones do not own them, but hire service providers. Furthermore, allowing respondents to select multiple agricultural activities created noise in the data, complicating the analysis of correlations. Future surveys should address these issues to enhance data accuracy.

4. RESULTS AND DISCUSSION

As previously indicated, a total of 61 respondents completed the survey. In the first section, participants were asked to specify their age groups. Figure 5 illustrates the age distribution, with the majority of respondents falling between 36-45 years old. A relatively high number of respondents were also from the 18-25 and 26-35 age groups, compared to older age groups. This may be due to the online nature of the survey, which likely made it more accessible to younger generations. As noted in the Limitations section, the sample is not representative, although some older farmers participated.

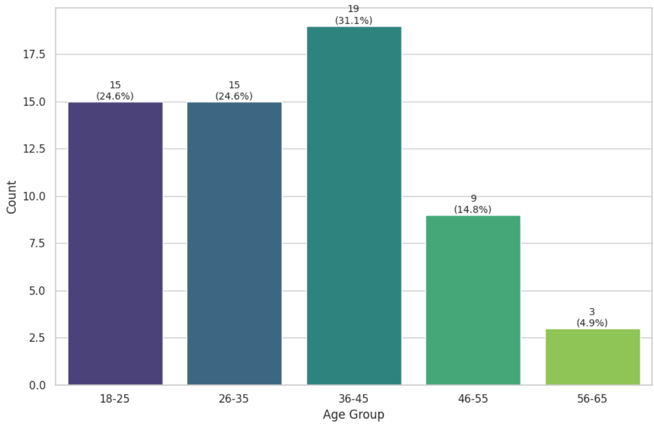

Figure 5. Age distribution of the responders
Source: Authors' own elaboration

The highest level of education reported is similarly unrepresentative. While there is no recent census data on Romanian farmers' educational backgrounds, it is unlikely that most have bachelor's or master's degrees. However, in our sample, 44.3% of respondents had completed university, and 62.3% had some level of academic education. This result likely stems from targeting farmers who shared information about agricultural drones on social media, as well as those within our personal networks.
Most respondents (40%) were involved in cereal crop production, with many also engaged in vegetable, fruit, and oilseed cultivation, while 11.7% worked in non-farming roles, such as drone service providers. Among the respondents, 47.5% had used UAVs, although this figure likely overrepresents the broader population due to the targeted sampling.

Another important aspect to overview the responders' background is their experience in agriculture. There have been 4 potential selections provided in the survey, based on the previously reviewed surveys presented in the Theoretical Background chapters, namely:

- Less than 5 years;
- Between 5-10 years;
- Between 11-20 years;
- More than 20 years;

A part of the responders (21.3%) told that they have less than 5 years of experience, the largest group was the farmers with an experience between 5-10 years (36.1%) while 27.9% of the responders have more than 11 years of experience but less than 20. 14.8% of the farmers responded that they have more than 20 years of experience.

To verify hypothesis 1, which posits that younger Romanian farmers are more likely to adopt drone technology compared to older farmers, we employed the Chi-Square Test. This test allows us to measure the correlation between two categorical variables and their associated frequencies. Initially, we examined whether a correlation exists between the observed age groups and the farmers' usage of drones.

For data preparation, we utilised the crosstab function from the pandas library to create a contingency table for the two categories. The results of this table, visualised in Figure 6, show that only 20% (3 individuals) of the youngest age group had used drones, while in the 26-35 age group, 60% of respondents had already adopted the technology. Notably, 73.7% of respondents in the 36-45 age group reported having used drones. In contrast, only 22.2% (2 individuals) in the 46-55 age group had done so, and just one person in the 56-65 age group had used drones, although given the small sample size (3 individuals), 33.3% appears significant.

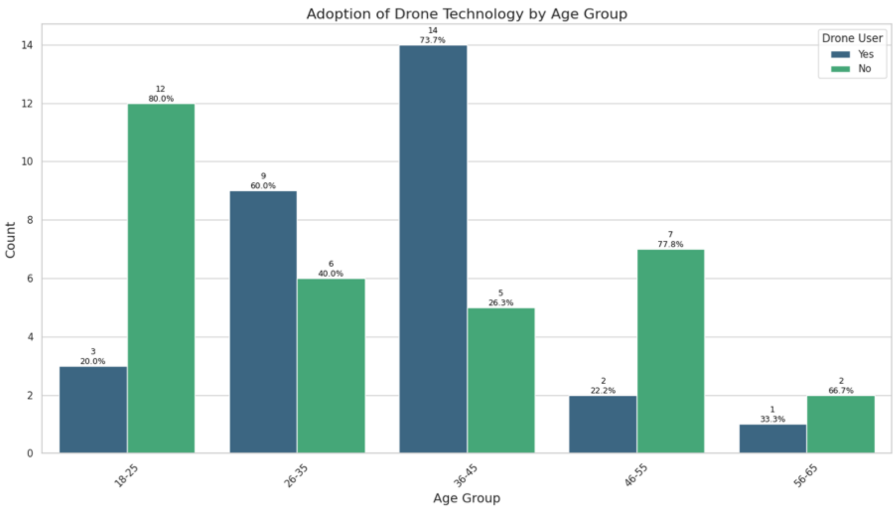

Figure 6. Adoption of drone technology by Age Group

Source: Authors' own elaboration

To perform the Chi-Square Test, we applied the chi-contingency method from Python's scipy library. The resulting Chi-Square value was 13.258, which indicates a significant deviation between the observed and expected frequencies, suggesting a potential correlation between the tested variables. The p-value was 0.01007, and at a significance level of 0.05, this result indicates an association between age groups and drone usage, allowing us to reject the null hypothesis and conclude that there is a positive relationship between certain age groups and drone adoption.

However, we find a paradoxical outcome: the youngest age group exhibits the largest deviation, effectively supporting the null hypothesis. Upon excluding this group, the Chi-Square statistic decreased to 7.3161, and the p-value increased to 0.0624, weakening the evidence for correlation. Additionally, we illustrated in Figure 7.a the relationship between age and farming experience, which revealed that most younger farmers have less than 5 years of experience.

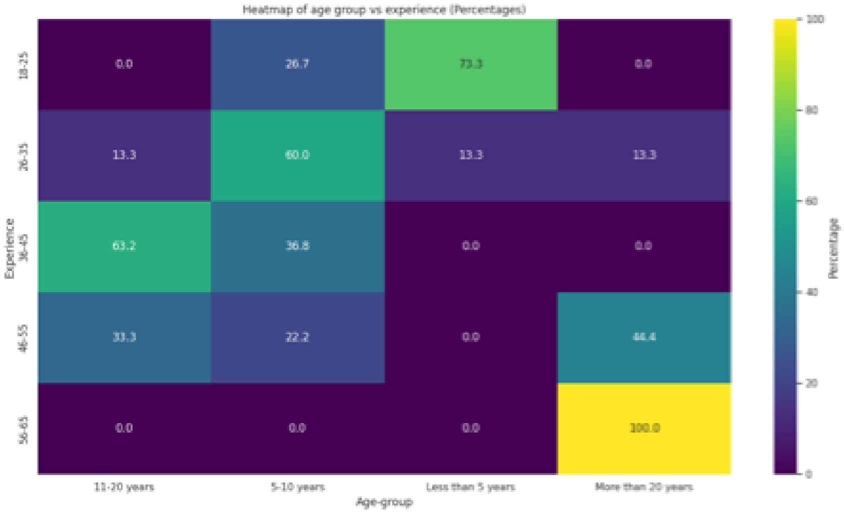

Figure 7. a. Relationship between age groups and experience in percentages, illustrated on a heatmap.
Source: Authors' own elaboration

We can reverse this analysis to explore how experience correlates with different age groups. This approach highlights an intriguing pattern, as shown in Figure 7.b. From the results of the first Chi-Square Test, we observe that in the 26-35 and 36-45 age groups, the majority of respondents use drones, and most have between 5-20 years of experience. Conversely, respondents with less than 5 years or more than 20 years of experience have generally not used drones.

Based on this, we further examined the relationship between drone adoption and experience using the same Chi-Square Test methodology. The resulting Chi-Square statistic is 12.0137, indicating a significant deviation between the observed and expected groups, suggesting a potential correlation. The p-value of 0.00733 provides strong evidence of a correlation between experience and drone usage at both the 0.05 and 0.01 significance levels.

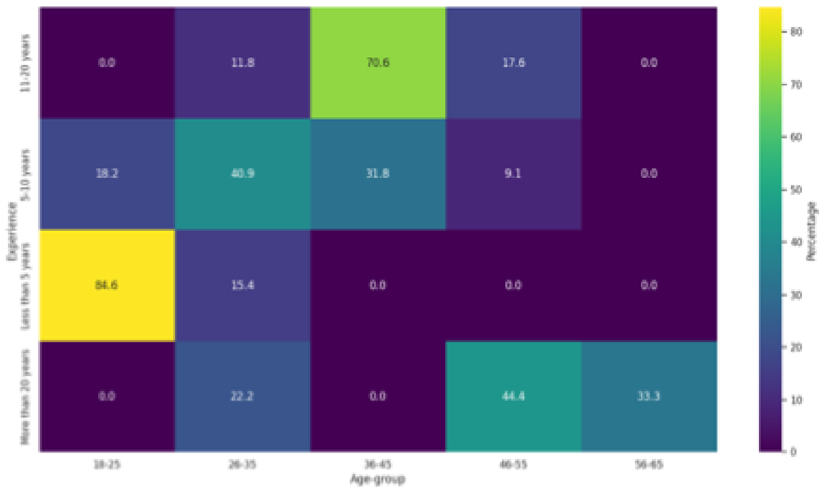

Figure 7. b. Relationship between experience and age-groups in percentages.
Source: Authors' own elaboration

Figure 8 illustrates how reported experience correlates with drone adoption, showing a significant relationship between different experience levels and drone usage, especially in the 11-20 years experience group, though the 5-10 years group presents an exception.

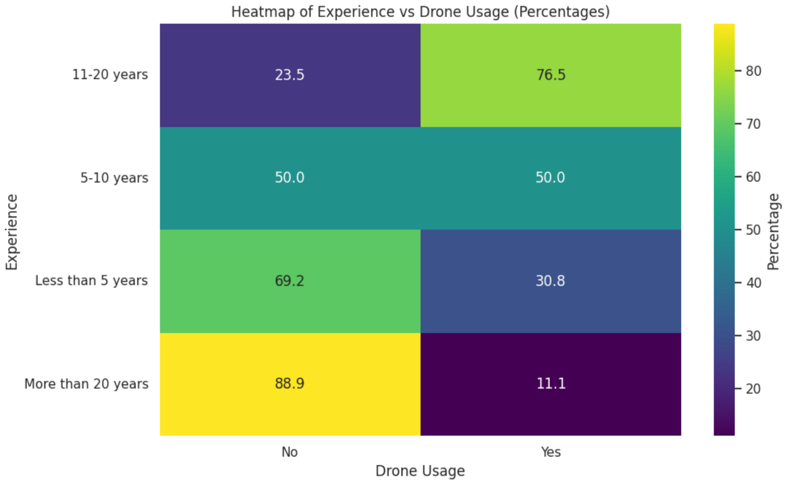

Figure 8. Association between experience and drone usage
Source: Authors' own elaboration

Table 1 summarises the results of all three Chi-Square Tests. Based on these findings, we conclude that while there is an association between age groups and drone adoption, the relationship between experience and drone usage is even stronger.

However, Hypothesis 1 is largely disproven, likely due to the limitations of the data. If more data were collected, excluding the 18-25 age group, Hypothesis 1 could potentially be supported. The findings may be reformulated as follows:

- There is a positive relationship between different age groups and drone adoption.
- There is a positive correlation between farmers' experience and their likelihood of adopting drones.

Table 1. Chi-Square Test results for Hypothesis 1.

Chi-Square Test	*Chi-Square Statistic*	*p-value*	*Sign*
AG and DA	13.2587	0.01007	+
YF and DA	7.3161	0.06247	/
E and DA	12.0137	0.00733	+

Source: Authors' own elaboration

Explanation: AG = age group, DA = drone adoption, YF = younger farmers, E = experience

In the second hypothesis, we seek to identify a correlation between the level of education and the adoption of drone technology. To test this, we applied the same algorithm and methodology, creating a contingency table between the two categorical variables.

As shown in Figure 9, most of the respondents with a high school or technical school education do not use drones, while most of those with a Bachelor's or Doctorate degree have adopted drone technology. Respondents with a Master's degree are evenly split. We then applied the Chi-Square Test to determine if an association exists. As indicated in Table 2, the chi-square statistic is 6.895, with a p-value of 0.141, exceeding the 0.05 threshold, which leads us to conclude that there is no significant correlation between education level and drone adoption.

Table 2. Chi-Square Test results for Hypothesis 2.

Chi-Square Test	*Chi-Square Statistic*	*p-value*	*Sign*
AG and DA	6.89506	0.14153	/

Source: Authors' own elaboration

Explanation: EL = educational level, DA = drone adoption

Although this hypothesis has been supported in previous studies (Aubert et al., 2012; Bai et al., 2022), we attribute our result to limitations in data collection methodology. Expanding the sample size may yield significant results.

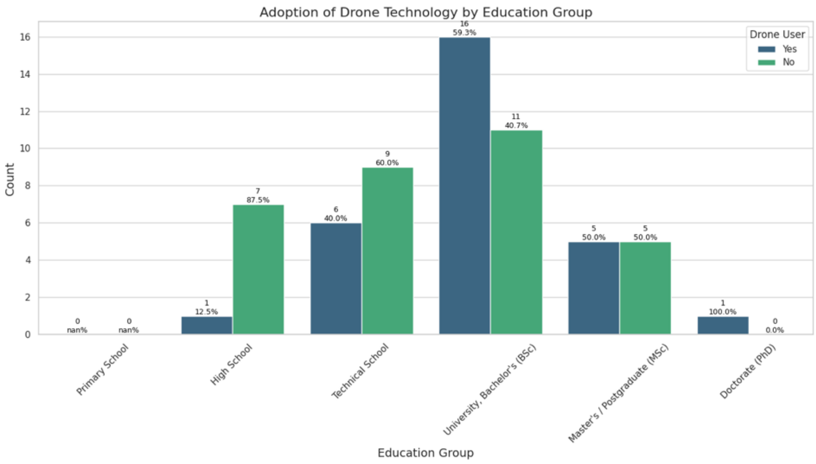

Figure 9. Association between Adoption of Drone Technology and Education Groups
Source: Authors' own elaboration

In the third hypothesis, we examine the correlation between the size of a farmer's operational territory and their adoption of drone technology. As with the previous hypotheses, we first constructed a contingency table, with the results displayed in Figure 10.

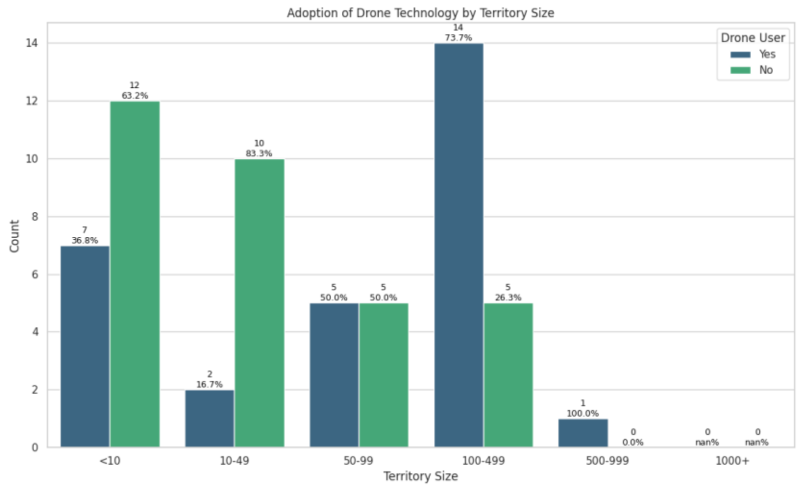

Figure 10. Association between Adoption of Drone Technology and Education Groups
Source: Authors' own elaboration

The data suggest that the majority of farmers operating on land smaller than 50 hectares do not use drones. A notable exception is that 36.8% of these farmers do use drones, which can be attributed to a limitation of this study: some respondents who use drones daily are not necessarily applying them on their own land but are offering drone-related services, such as spraying or mapping, to other landowners. For farmers working on land between 50-99 hectares, 50% have adopted drones, while 73.7% of those managing more than 100 hectares use them. Out of 20 respondents working on land larger than 100 hectares, only 5 indicated they do not use drones.

As shown in Table 3, the Chi-Square Test results demonstrate a positive correlation between larger land sizes and drone adoption, with a chi-square statistic of 11.7932 and a p-value of 0.01895, indicating a strong association between these variables.

Table 3. Chi-Square Test results for Hypothesis 3.

Chi-Square Test	***Chi-Square Statistic***	***p-value***	***Sign***
LS and DA	11.2587	0.01007	+

Source: Authors' own elaboration

Explanation: LS = educational level, DA = drone adoption

In developing the survey, we sought to understand both the perspective of farmers who have adopted drones and those who have not. In the fourth hypothesis, we focus on non-users, investigating whether concerns about regulatory and legislative hurdles significantly influence drone adoption. The next finding is that, of the 61 respondents, 52.5% (32 individuals) had not used drones before, citing high initial costs, lack of perceived advantages, and information deficits as primary reasons. Only 8 respondents (25%) mentioned legal barriers as a reason.

Respondents were also asked to rate on a 1-5 scale the likelihood of adopting drones in the future. Most chose a neutral value of 3, reflecting uncertainty. In addition, participants rated four factors—costs, legislative problems, technical support, and efficiency—on a 1-5 scale based on their influence on drone adoption (Figure 11). Legislation was ranked lower than costs, efficiency, and technical support, with only 50% choosing the highest value, compared to 62.5% for the other factors.

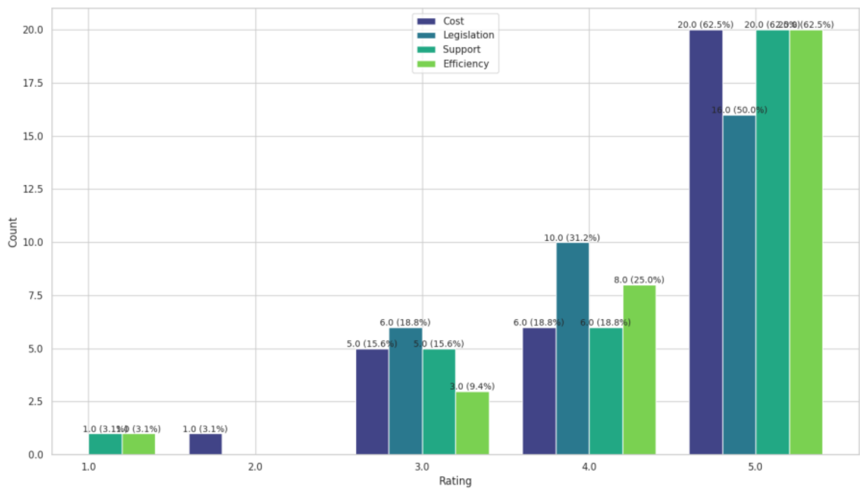

Figure 11. Comparison of the importance of different aspects when opting for drone adoption in the responders' view who did not use UAVs for agriculture before.

Source: Authors' own elaboration

Although the fourth hypothesis explores the relationship between drone adoption and legal concerns, our analysis suggests no significant correlation between legal barriers and drone usage. However, there may be an association between those who reject drones entirely and those who adopt them (Table 4).

Table 4. Chi-Square Tests to verify relationships between reasons of not adopting drones and probability of future usage.

Reason	*Chi2*	*p-value*	*Sign*
High initial costs.	1.68	0.794	/
Unsure about effectiveness	3.28	0.511	/
Not seeing advantage	10.16	0.0378	-
Lack of training	7.62	0.1066	/
Legal barriers	6.60	0.1066	/

Source: Authors' own elaboration

In the fifth hypothesis, we aimed to identify if legislative deficiencies are the greatest challenge faced by Romanian farmers. To explore this, we surveyed farmers who have already used drones, asking them to report their main challenges. As shown in Figure 12, the majority of respondents indicated that legislation and regulation are key challenges, with nearly all (27 out of 29) including legislative issues in their responses. Additional challenges, such as weather, initial costs, profitability, and technical support, were also noted.

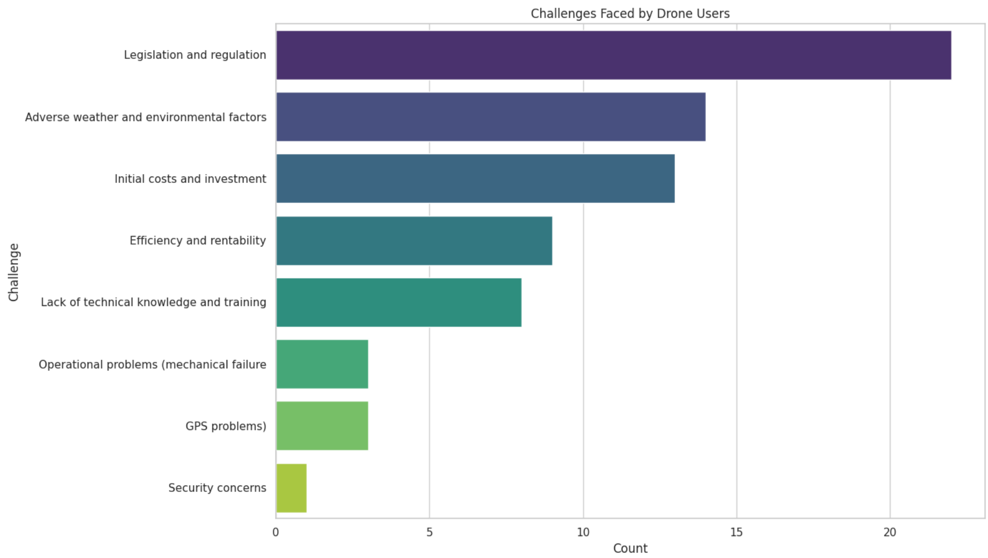

Figure 12. Challenges faced by Romanian farmers using UAVs
Source: Authors' own elaboration

Additionally, we asked respondents to rate the extent to which regulatory issues influence their use of UAVs on a scale of 1-5. More than 41% selected the maximum value and a total of 79.3% chose high or extremely high values, indicating a significant impact of legislative barriers on daily operations.

Additionally, in an open-ended question, 11 respondents offered suggestions for improving UAV usage, with all emphasising the need for legislative improvements. Other suggestions included standardising spraying systems and introducing national training programmes.

Common responses included:

- Approval of UAV products (as many are not yet approved in Romania, causing delays)
- Legislative improvement

Thus, based on the collected data, we conclude that legislative and regulatory issues are indeed the greatest challenge faced by Romanian farmers, supporting the hypothesis.

Other Results. One of our key objectives in designing the survey was to gain a better understanding of Romanian farmers' perceptions of drones, as previous research on this topic appeared limited. Although the responses were not collected from a representative sample, we believe that the findings can provide a valuable foundation for future research. The majority of farmers are highly satisfied with their drones, with 75.9% rating their satisfaction as a 5, and an additional 17.2% reporting that they are somewhat satisfied. Despite the administrative challenges, those who use drones view them as valuable tools.

We also explored the reasons that positively influenced farmers' decisions to adopt drones. We conclude that increasing efficiency, an interest in innovation, and cost reduction were the dominant factors. Interestingly, environmental protection was not a primary motivator, unlike findings from other studies (Michels et al., 2020; Skevas & Kalaitzandonakes, 2020). However, accurate data collection emerged as a significant reason.

Additionally, we asked farmers about the frequency of drone usage in their operations. While one-third reported using drones daily, the remaining two-thirds indicated either monthly or seasonal use. This suggests that many farmers may rely on contracted services rather than owning their own drones.

To further understand drone applications in Romanian agriculture, we analysed the main areas of use. Precision spraying, soil and land mapping, and health monitoring have emerged as key applications. The relationship between these activities and drone usage was further explored through a heatmap, revealing that cereal crops, oilseeds, and vegetable cultivation are the dominant sectors where drones are applied. Lastly, we find that most farmers rate their knowledge of drone technology in agriculture as fairly good, offering a solid foundation for future research on this topic.

5. CONCLUSIONS

In this paper, we have summarised relevant literature and methodologies applied in other countries. Based on this foundation, we designed a survey to gather insights on Romanian farmers' attitudes towards drone technologies. Additionally, we formulated five hypotheses grounded in theoretical frameworks and personal experience. The first hypothesis was not validated, despite identifying correlations between age groups, experience, and drone usage.

However, the hypothesis itself did not hold. We have explored potential reasons and provided suggestions for further research, noting interesting patterns. Similarly, the second hypothesis was not validated due to data collection limitations, though promising trends were observed.
The third hypothesis was validated, confirming a positive correlation between larger land size and drone adoption. The fourth hypothesis was rejected, though it revealed other notable patterns. The final hypothesis was validated, highlighting that the primary challenge for Romanian farmers using drones lies in regulatory issues, with legislation lagging behind technological advancements.

In addition to hypothesis validation, we collected valuable data on farmers' general perceptions and knowledge of drone technology, identifying key activity areas and challenges. Despite limitations, as outlined in the Limitations subchapter, this is, to our knowledge, the first study investigating farmers' perceptions and drone adoption in Romania. We believe that it will serve as a useful starting point for future research. For future research, we have outlined several suggestions, particularly regarding data collection and survey design challenges. In conclusion, this research topic holds significant potential, and future studies could deepen our understanding of UAV adoption in Romanian agriculture.

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