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Examining the Adoption of Drones and Categorisation of Precision Elements among Hungarian Precision Farmers Using a Trans-Theoretical Model

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Abstract: This article discusses the use of drones in Hungary and considers their future penetration, based on the responses to a nationally representative 2021 questionnaire among 200 large-scale farmers engaged in precision farming and in crop production. Both the applied trans-theoretical model (with ordinal logit regression model) and the questionnaire design are suitable for comparison with the results of a similar survey in Germany. In this study, similar results were found for farm size, age, main job and education, but the evidence that higher education in agriculture has the largest positive effect on the use of drones is a novelty. The frequency values obtained for adopting precision technology elements are not fully suitable for classification due to interpretational shortcomings. The use of drones within precision technologies is no longer negligible (17%), but is nevertheless expected to grow significantly due to continuous innovation and the selective application of inputs. The state could play a major role in future uptake, particularly in the areas of training and harmonisation of legislation.

Keywords: precision technology; ordinal logistics regression; level of precision farming; Gartner hype cycle

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1. Introduction

Although agriculture represents only 6.4% of global GDP in Hungary, it is a strategic sector whose efficiency cannot be easily increased by conventional methods [1]. Any crop production operation (from sowing to harvesting) is highly suitable for the adaptation of precision farming (PF) technologies and associated AI [2], and PF can therefore be considered an essential element of agricultural innovation. PF can be understood as an agricultural revolution, positioned by its three basic elements to enhance economic outcomes in an environmentally friendly way for societal benefits [3].

According to the researchers of the Fourth Industrial Revolution (4IR), technological development and the implementation of farm management with scientific strategies may be of particular importance in agriculture due to the magnitude of difference between food production and demand [4]. Information technology has a decisive share in the 4IR [5], the prevalence of which is illustrated by the fact that 100 billion internet-connected devices were expected by 2020 [6,7]. Agriculture is predicted to be the second largest sector of drone use [4], leading to profound transformations in the production, consumption and distribution of food, the rural environment, rural life and lifestyle. The agricultural robotic market was expected to grow twentyfold between 2013 and 2020 [8].

The global market for drones is forecast to grow from 14.1 billion USD in 2019 to 43.1 billion USD in 2024, an annual growth rate of 20.4%, according to Droneii's 2019 data [9]. The actual figure for 2021 was 26.3 billion USD, but the current crisis has made the forecasts more cautious (9.4% p.a. to 2026). Of this, hardware devices account for only 16%, with services dominating, due in part to the significant investment costs (a fully equipped agricultural drone costs around 25,000 USD, [10]) and the expertise required for operation. At the same time, Wackwitz et al. (2021) [11] found that only 3% of drones on the market are specifically for agricultural purposes, with user expectations generally linked to quality improvement and time savings. The impact of the coronavirus on this industry has been positive, with the most significant growth expected in Asia and Oceania. Europe is currently made up of very different markets in each country, due to the very different national regulations and licensing of drone use.

The adoption of precision technologies in Hungary is increasing year by year. In 2019, 23% of crop farms reported using the technology, which is a threefold increase compared to 2016. This is only a minimal difference from the EU average (25%) [12], but is significantly lower than the US (67% in 2016 [13]).

A survey pointed out that two-thirds of Hungarian farmers indicated that they use at least one of the 10 listed precision technologies, which shows the high level of uncertainty that is inherent in the interpretation of PF. Balogh et al. (2021) [14] examined Hungarian farmers' very differential interpretations of PF.

According to [15], 79% of Hungarian farmers are satisfied with using PF (Of the various precision technologies, the use of GPS (58%), row guides (47%) and automatic steering (24%) are the most widespread, while the use of drones and robots were still negligible in 2019. Regarding different technological elements, farmers typically used their own machines, with the exception of drones, where the use of contracting services exceeded 50% [15]). Among the factors influencing future uptake, the use of digital devices has grown dynamically, with the vast majority of households reporting usage (93%) [16].

In addition to the digital background, the future uptake of PF is also strongly influenced by farm size, as the farmers' use of their own precision equipment and the deployment of those systems entail significant investment, and consequently, high fixed costs (depreciation, consultancy) during operation, where economies of scale are significant. In Hungary, 41% of the agricultural area is cultivated by farms larger than 300 ha, with only 4.7% being vineyards and 8% being orchards [15], and the concentration of holdings is still continuing. This provides much more favourable conditions for future expansion compared to the EU average, where 86% of farms have less than 20 ha [12].

Future prospects are also strongly related to education and age, with the younger, more educated, more computer literate segment of entrepreneurs typically being more open to PF. They also tend to obtain information from more reliable sources. Older farmers are slower to change their sets of values and slower to respond to changes, which may be a significant barrier to future uptake of precision technologies [17].

The digital infrastructure and plant size are not major limitations for the uptake of PF, including drones, but are limited by personnel and compatibility factors [3]. The income-generating capacity and demographic/skill trends are of the greatest relevance when examining the adoption of use and further uptake of drones. Our study aims to show the components for the spread of drone use in Hungary through a comparative analysis with the results of a German study.

1.1. Literature Review on Determinants of Drone Use

1.1.1. Farm Size

As explained by Pivoto et al. (2019) [18], in agriculture, farm size, and hence access to resources, the costs of technology adoption, and knowledge about the use of computers and new software have a significant impact on technology adoption decisions. Based on an examination of economies of scale, Pierpaoli et al. (2013) [19] found a positive relationship between farm size and PF adoption. The larger a farmer's land area, the higher their likelihood of adopting PF [20,21]. This is also true for the size of owned and leased land. However, it has also been shown that owning more land also leads to greater openness among farmers to adopt PF [22]. Michels et al. (2020) [23] also hypothesised that farm size is an important factor in the context of drone adoption, mainly due to economies of scale. The European Commission (2018) [24] expressed it in a similar way, i.e., larger farms are more likely to adopt drones. Zhang et al. (2019) [25], on the other hand, found no correlation between farm size and the willingness to adopt drones.

The effects of demographic variables and economic characteristics were examined by Ruzzante et al. (2021) [26] in a meta-analysis comparing the results of 204 studies. The results show that farm size is the most frequently examined effect factor. They concluded that if the adoption of a technology was not a significant factor in terms of economies of scale, then farm size was not an essential factor. Still, if economies of scale in technology adoption mattered, then farm size mattered.

In an analysis of the relationship between farm size and drone adoption, Zou et al. (2021) [27] found the important result that the probability of drone adoption in the Australian irrigation system increases with increasing farm size over the years, up to 11,022 ha, but may decrease with further increases in farm size.

1.1.2. Age

Age is usually a determinant of the farming experience for the people involved. Younger farmers with less experience in crop production have a longer planning horizon, as found by Aubert et al. (2012) [28], and this, combined with higher education, develops the openness and skills needed to adopt PF. Paustian and Theuvsen's (2016) [29] research demonstrated that the likelihood of adopting PF increases among crop farms where the farmer's experience in crop production is greater than 16 years or less than 5 years. This indicates both well-educated, experienced farmers and the young, IT-savvy offspring of farmers. There are clear economic benefits for these two groups of German farmers that may outweigh the costs of adopting PF.

According to research by Zou et al. (2021) [27], age or marriage was not statistically significantly associated with the choice to use drones. The average age of farmers intending to use drones in the future was 56 years, suggesting that age is likely to be a significant factor in the adoption of drones on irrigated farms.

1.1.3. Education

The diffusion of innovative technologies is an area where the distribution of knowledge is particularly unequal, leading to power imbalances [30], which is why we see it as particularly important to analyse the issue of education when considering the factors influencing drone use.

Higher levels of education have a positive effect on PF adoption [20,31]. High levels of education provide the skills and knowledge needed to understand PF technology, increase farmers' willingness to experiment with different PF technologies and contribute to increasing PF adoption among farmers.

Education has a linear relationship with the adoption of precision solutions. As education increases, the likelihood of using PF technology increases, as shown by Ruzzante et al. (2021) [26] in their analysis of several studies. However, Caffaro et al. (2020) [32] specifically emphasise the importance of extracurricular training in the adoption of precision techniques.

Barnes et al. (2019) [33], in a study comparing the use of PF technologies in five countries, found that the influence of socio-demographic factors is not negligible. Education is of paramount importance, however, attitude towards technologies, household income, the nature of the farm and the information sources available also significantly influence the ways in which producers engage with PF.

Vecchio et al. (2020) [34] argue, using the theory of diffusion of innovations, that the laggards, the group of non-innovators, are more likely to avoid encountering the innovation, in this case, the use of drones. The final conclusion is that, with education, the likelihood of encountering new technologies, and hence that of adopting innovation, increases.

1.1.4. Gender

Gender characteristics in the use of PF show that the predominance of men among farmers [29,35] does not make gender differences easy to examine. However, a German study on IT technologies in Germany showed that women over 60 are more reluctant to use IT technologies than men over 60 [36]. However, research by Zhang et al. (2019) [25] demonstrated that male farmers show a higher propensity to adopt drones. Consequently, Michels et al. (2020) [23] hypothesised that male farmers have a positive effect on the process of adopting drones.

According to Zou et al. (2021) [27], men were previously more likely to have used drones than women (6% of men working on irrigated farms used drones compared to only 1.5% of women farmers). Still, when analysing drone adoption, there was no statistically significant association between drone use and gender (30% of men planned to use drones compared to 23% of women).

1.1.5. Importance of Full/Part-Time Employment

Farmers who focus solely on their agricultural activities are more interested in adopting new technologies than those who are not involved in farming full-time, but only part-time [31]. Michels et al. (2020) [23] found that this may also be true in the context of drone use. Farmers working full-time in agricultural jobs are more likely to introduce drone use on their farms than those working part-time.

In the context of precision technologies, several studies have examined the role of economic profitability in the data production process. D'Antoni et al. (2012) [37] found that farmers typically have difficulty in assessing the economic benefits of a technology in advance. This is an important issue because the results of Zhang et al. (2019) [25] regarding the adoption of drones demonstrated that an increase in the level of perceived usefulness in the farming community increases the willingness to adopt drones. Since drones do not provide immediate economic benefits, rather the information they provide can be used in several areas of farm business decision-making, they are still ultimately useful through the information they provide. Related to this finding, Michels et al. (2020) [23] suggested that the extent to which farmers perceive the suitability and usefulness of drones in agricultural operations plays a vital role in the drone adoption process.

1.1.6. Agricultural Higher Education

The spread of information and new technologies related to precision technologies, including drones, has accelerated very rapidly, i.e., it is particularly important to analyse the issue of professional qualifications in addition to the previous factors when examining the factors influencing drone use. Paustian and Theuvsen (2016) [29] note that drone use can also be significantly positively influenced by agricultural vocational education.

Most studies support the assertion that younger age, higher education and income, larger farm size, male farmers, full-time employment and positive attitude positively affect the adoption of precision techniques. However, contrary research has also been published. Aubert et al. (2012) [28] found that farmers' age and farm size do not affect the adoption of precision techniques. The only control variable was the educational level of respondents, which had a significant positive effect on the adoption of precision tools (Table 1).

Table 1. The influencing factors and their effects on the adoption of precision farming or using drones.

Influencing Factor	Direction of Effect *	References
farm size	+	[18–21,23,24]
	0	[25–28]
land use	+	[22]
	0	[19]

Table 1. *Cont.*

Influencing Factor	Direction of Effect *	References
Age	–	[27,28]
	0	[27]
nature of the farm	0	[33]
computer knowledge	+	[18,23,28]
new software	+	[18,23,28]
agricultural experience	+	[29]
education (generally)	+	[24,26,30–33]
agricultural higher education	+	[29]
Marriage	0	[27]
attitude, household income	+	[33]
gender (male)	+	[23,25,27,36]
full-time employment	+	[23,31]
assessing of economic benefits	+	[23,25,37]

Note: * between the given factor and PF/drones adoption: "+" congruent, "−" opposite, "0" no connection, or uncertain.

1.2. Examining the Level of PF

The Gartner Hype-Cycle is often used to predict the future uptake of innovative technologies, with Blackmore [38,39] placing the elements of precision farming in 2016 as follows (Figure 1).

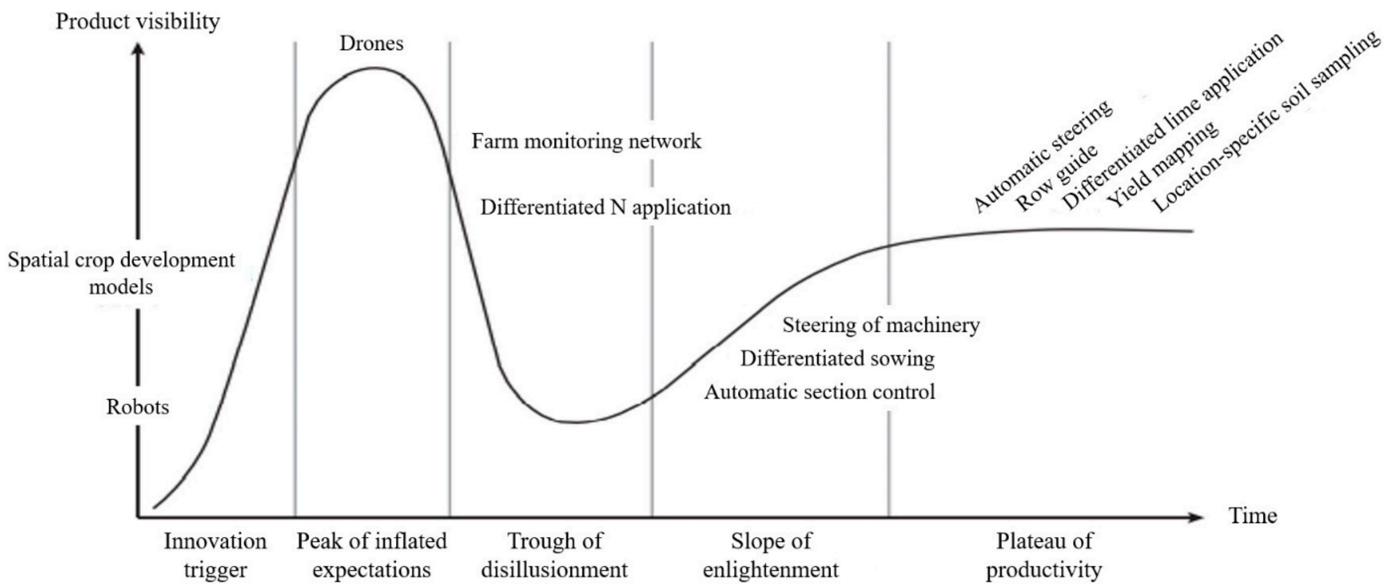

Figure 1. The place of precision technologies in the Gartner Hype Cycle. Source: [38,39].

1. Automated steering, GPS and row guide are the most commonly used elements—the basic elements of precision technology—not only in Hungary but worldwide. Their production and usability are well established, and new entrants are typically the first to buy them.
2. In the case of machinery steering, automatic section control and differential sowing, experience shows that their use is becoming more effective, although their customers are still only among those farmers who have been using PF for a longer period and are thinking of further developing it.
3. In the case of farm monitoring and differentiated fertiliser application, the lack of the technology's maturity has meant that it has not been able to meet the heightened expectations, leading to a periodic decline in demand (and capital invested) until the technologies are further developed.

4. Drones were at the peak of interest, the media were increasingly covering their potential, and potential problems had not yet emerged due to a lack of reliable, long-term practical experience.
5. Research has focused on developing spatial plant development models and robotics. Interest is growing thanks to early results and success stories.

According to research published in the US in 2020 [40], the following levels of precision technology can be distinguished:

6. Basic technologies are used (auto-steering system, section control). Data collection is not available or, if it is, it is not integrated into production plans.
7. For at least one technological element (typically nutrient management systems), (mostly aggregated) GPS data are already collected and can be used as a basis for medium-term plans. However, these data are not suitable for integrated decision-making.
8. Collecting high accuracy GPS data via multiple technological processes, yield mapping and weather data evaluation. These data are already suitable for integrated assessment, sometimes carried out by an external consultant.
9. Data are collected for all field operations, allowing immediate in-season decision-making and correction. The evaluation is carried out by a specialised (in-house or external) expert.
10. A complete data set of at least three years will ensure that an optimal decision is made during the growing season, considering annual and seasonal variations.
11. The highest level is suitable for system-level optimal decision making and forecasting, and for further development of the optimising production models used in the previous levels.

Since 2016, there has been significant progress, and the categories on the Gartner cycle in Figure 1, which represents the situation in Europe in 2016, have shifted to the right. The exception to this is the use of drones, which in our view, could be classified as both category 2 and 4, as there are still significant innovations emerging (peak of interest). Still, the scale of use is now above the experimental level. In Hungary, the spread of the network of expert advisors has also played a major role in accelerating innovation development. The history and prevalence of PF use in Hungary are significantly lower than in the US. For this reason, a tiered approach was developed that takes into account the principles of the above sources and international trends since then, but also Hungarian specificities.

The use of drones can be considered technically mature in Hungary, but mass application is still anticipated mainly due to the lack of legislation, investment, knowledge and practical experience. At the same time, the high contracting rate could help make it worthwhile to purchase drones in Hungary, even for service-providing purposes, or to use them only in certain sectors or for work processes. Michels et al. (2020) [21] identified that the farmers' age, precision agriculture technology literacy and farm size affect farmers' drone adoption processes. The authors have also formulated the main areas of drone application and the reasons that German farmers oppose the usage of drones.

2. Hypothesis, Materials and Methods

2.1. Hypothesis and Structure

Due to historical and economic factors, the intention of German farmers to use drones is expected to be very similar to the behaviour of Hungarian crop farmers. For this reason, we chose the articles by Pierpaoli et al. (2013) [19] and Michels et al. (2020) [23] as samples for the design of our questionnaire. We thought that the expected results could provide a good basis to understand the drone use intention of Hungarian farmers in addition to the behaviour of German farmers.

Following the structure of Michels et al. (2020) [23], this paper presents the most important factors influencing the use of drones, and—in the same structure—the experiences of our Hungarian survey, which can be considered representative at the national level.

Michels et al. (2020) [21] hypothesis:

- Cultivated land size has a positive effect on the adoption process.
- Age has a negative effect on the drone adoption process.
- Higher education has a positive impact on the process of the adoption of drones.
- Being a male farmer has a positive impact on the adoption process.
- Being a full-time farmer has a positive effect on the adoption process.
- Drone technology literacy has a positive impact on the adoption process.
- Increasing the perceived job relevance of drones for operational procedures positively affects the adoption process.
- Increased confidence in the process of working with drones has a positive effect on the process of acceptance.

Since one of the methodological goals of our research is the comparison with the research results of Michels et al. (2020) [21], we followed and tested the hypotheses of that work on the Hungarian data.

In addition to the hypothesis put forward by Michels et al. (2020), we extended our research to additional determinants of the spread of drone use defined in the literature.

The extended new hypothesis:

- Higher education in agriculture has a positive effect on the adoption process.

2.2. Survey and Sample Description

The data sources for our analysis were semi-structured questionnaires completed face-to-face with 200 precision farmers (the sample was targeted at arable crop farmers and farm managers). As there are no official data and no list of the exact number of precision farms in Hungary, a public opinion research company (Kynetec, who is a global leader in market research for animal health and agriculture) was commissioned to fill in the questionnaires personally. They had their own database of farmers who, as precision farmers, could be included in the group of farmers we wanted to study. The distribution of the frequency of precision farms surveyed by the company by region (the four regions cover the whole country) and by area cultivated is shown in Table 2. Categories below and above 300 ha were developed in order to be able to interview farmers with smaller and larger areas in all four regions. A trained team administered the questionnaire in January 2022. Participating farmers had to answer all questions. The questionnaire was designed to collect data from farmers on various topics, including farming practices, farm profiles, precision agriculture techniques, intention to use drones and socio-demographics.

Table 2. Distribution of precision farmers who completed the questionnaire for Hungary (n = 200).

Name of the Regional Unit	≤300 ha	>300 ha	Total
North-West (Fejér, Komárom, Veszprém, Győr, Vas counties)	16	15	31
South-West (Zala, Somogy, Tolna, Baranya counties)	19	20	39
South-East (Pest, Bács, Csongrád, Békés counties)	26	27	53
North-East (Jász, Hajdú, Szabolcs, Borsod, Heves, Nógrád counties)	34	43	77
Total	95	105	200

Source: Database of the Kynetec survey (2021).

2.3. The Transtheoretical Model of Adoption

We propose the trans-theoretical model of behavioural change (TTMC), which can account for gradual adoption tendencies. TTMC is designed to analyse the progress of an individual in changing a specific behaviour [41]. In order to study the process of adoption, we used the modified method by Michels et al. (2020) [23] of TTMC called the trans-theoretical model of adoption (TTMA) for drones in agriculture. This model form accounts for more than two stages in the adoption process. A binary classification of the adoption decision was applied in previous literature regarding the adoption of precision agriculture techniques [19]. For this model type, a lot of information is left unmonitored during the adoption process. At present, the use of TTMC in agricultural studies is not well developed or widely used. Lemken et al. (2017) [42] applied the TTMC using an ordinal logit regression to adopt mixed cropping practices. Michels et al.'s (2020) [23] paper presented a novel modification of the TTMC to gain deeper insights into farmers' technology adoption processes. In this study, the 4 stages of the intention to use drones: precontemplation, contemplation, preparation and action, impose an ordinal variable structure (Table 3).

Table 3. The percentage of drone use intention in the trans-theoretical model of adoption (TTMA).

Categories *	*n*	Percentage
I will not use drones on my farm (TTMA = 1; precontemplation)	47	23.5
I am principally willing to try out the application of drones on my farm (TTMA = 2; contemplation)	85	42.5
I have concrete plans to use drones on my farm (TTMA = 3 preparation)	35	17.5
I already use drones on my farm (own or as a service; action) (TTMA = 4)	33	16.5

* Sources: Based on [41] and adapted by [42,43] IN: Michels et al. (2020) [23].

2.4. Descriptive Statistics and Econometric Model

The descriptive statistical results for the variables that were analysed in the hypothesis test and the predictors of the hypothesis are shown in Table 4.

Table 4. Descriptive statistics and the expected effects of the variables (n = 200).

	Hypothesis	Expected Sign	Mean	Std. Deviation	Minimum	Maximum
TTMA [a]			2.27	1.00	1	4
Drone [b]			0.16	-	0	1
LandSize (Farm size in hectares of arable land)	H1	+	672.63	791.75	3	4000
Age (Farmer's age in years)	H2	−	53.19	12.33	26	91
Education [c]	H3	+	0.49	-	0	1
Gender [d]	H4	+	0.94	-	0	1
FullTime [e]	H5	+	0.55	-	0	1
DroneTechLit [f]	H6	+	3.58	1.02	1	5
PjobRel [g]	H7	+	2.71	1.17	1	5
AttConf [h]	H8	+	4.03	1.05	1	5
AgrHighEdu [i]	H9	+	0.45	-	0	1

[a] Transtheoretical Model of Adoption: the four categories in Table 3 (coded 1–4), [b] 1, if the farmer uses a drone on his/her farm; 0 otherwise, [c] 1, if the farmer holds a university degree; 0 otherwise, [d] 1, if the farmer is male; 0 otherwise, [e] 1, if the farmer is a full-time farmer; 0 otherwise, [f] the farmer has Drone Technology Literacy (5-point Likert scale (1 = strongly disagrees; 5 = strongly agrees)), [g] Usage of drones is of high relevance for several operational procedures on my farm" (5-point Likert scale (1 = strongly disagrees; 5 = strongly agrees), [h] I think I am not the type of farmer who is good at working with drones and other digital instruments" Reversed question (5-point Likert scale (1 = strongly disagrees; 5 = strongly agrees) Reversed question will be used in the econometric analysis, [i] 1, if the farmer holds an agricultural university degree; 0 otherwise.

Four categories of responses to the TTMA question were used as dependent variables in the econometric modelling. The process of gradual adoption can be characterised as

$$y' = X\beta + \varepsilon$$

where y' is the unobserved dependent variable and X is the vector of independent variables. The vector includes the regression coefficients to be estimated. The parameter ε is the error term. An ordinal logistic regression model was used to test whether the different independent variables had a significant effect on the different levels of drone use:

$$\begin{aligned} \text{TTMAi} = \beta0 + \beta1\ \text{LandSize} + \beta2\ \text{Age} + \beta3\ \text{Education} + \beta4\ \text{Gender} + \beta5\ \text{FullTime} + \beta6\ \text{DroneTechLit} + \\ \beta7\ \text{PJobRel} + \beta8\ \text{AttConf} + \beta9\ \text{AgrHighEdu} + \text{ei} \end{aligned} \tag{1}$$

where i represents the individual respondent and ei is assumed to be an error term with a logistic distribution. The Trans-theoretical Model provides a gradual measure of farmers' decision-making with respect to the adoption of drones, which gives more detailed insight into farmers' adoption processes than the more common approach of applied binary classifications.

Data cleaning and other calculations were executed by the STATA software version 16. The β coefficients represent the odd ratios (OR) in this model. The model was estimated using the maximum likelihood approach. The parallel regression assumption, the null hypothesis, which stated that the location parameters (slope coefficients) were the same across response categories, was tested using the Brant test [44]. A non-statistically significant Brant test (χ^2 = 15.06; p = 0.66) implied that the assumption was not violated and the model results shown in Tables 5 and 6 are valid. To ensure the absence of multicollinearity, the VIF test statistics were calculated (mean VIF = 1.42, max VIF = 1.96). After checking for multicollinearity, results for the parallel regression assumptions were obtained.

Table 5. Results of the ordinal logistic regression for the TTMA (n = 200).

Hypothesis	Variable [a]	Odds Ratio	Std. Error	p-Value	95% Confidence Interval	
					Lower Bound	Upper Bound
H1	LandSize	1.00009	0	0.64	1.00	1.00
H2	Age	0.97 **	0.014	0.03	0.94	1.00
H3	Education	0.45	0.802	0.33	0.09	2.19
H4	Gender	0.52	0.614	0.28	0.16	1.72
H5	FullTime	3.34 ***	0.321	<0.01	1.78	6.26
H6	DroneTechLit [b]	1.54 **	0.207	0.04	1.03	2.31
H7	PjobbRel [b]	3.67 ***	0.173	<0.01	2.62	5.16
H8	AttConf [bc]	1.47 *	0.204	0.06	0.99	2.19
H9	AgrHighEdu	6.33 **	0.817	0.02	1.28	31.37

Single, double, and triple asterisk (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level. [a] Dependent variable TTMA with four categories. [b] 5-point Likert scale (1 = high disagreement; 5 = high agreement). [c] Reverse scale was used.

Table 6. Marginal effects and predicted probabilities (n = 200).

	TTMA Categories [a]	1	2	3	4
	Predicted Probability	**0.24**	**0.43**	**0.17**	**0.16**
		Marginal Effects			
H1	LandSize	-8.2×10^{-6}	-7.2×10^{-6}	0.00001	3.9×10^{-6}
H2	Age	0.003 **	0.002 *	−0.004 **	−0.001 **
H3	Education	0.07	0.06	−0.10	−0.03
H4	Gender	0.05	0.08	−0.09	−0.04
H5	FullTime	−0.12 ***	−0.08 **	0.14 ***	0.05 ***
H6	DroneTechLit [b]	−0.04 *	−0.03 *	0.05 *	0.02 *
H7	PjobbRel [b]	−0.12 ***	−0.10 ***	0.16 ***	0.06 ***
H8	AttConf [bc]	−0.03 *	−0.03	0.05 *	0.02 *
H9	AgrHighEdu	−0.16 **	−0.16 *	0.23 **	0.09 *

Single, double, and triple asterisk (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level. [a] Dependent variable TTMA with four categories. [b] 5-point Likert scale (1 = high disagreement; 5 = high agreement). [c] Reverse scale was used.

3. Results and Discussion

3.1. Descriptive Statistics Results

The descriptive results are given in Table 3.

The mean value for the TTMA question is 2.27, indicating that the average farmer in our sample belongs in the contemplation stage (TTMA = 2). In our sample of 200 farmers, 16% currently use a drone on their farm (Drone; TTMA = 4).

On average, farmers in our sample cultivated 672 ha of arable land, which is far above the Hungarian average of 20 ha [45] of arable land (Table 4). The average farmer in our sample is 53 years old, similar to the Hungarian average of 58 years [45]. Concerning education, 49% of the farmers in our sample hold a university degree, which lies above the Hungarian average in agriculture of 3.4% [46]. 6% of the participating farmers are female (Gender), which is significantly lower than the Hungarian average of 29% [47]. The share of full-time farmers (55%) is slightly lower than the Hungarian average of 63% [46]. Drone technology literacy reached 3.58 points on the 5-point Likert scale. Job relevance of drones for farm operations reached 2.71 points on the 5-point Likert scale. The attitude of confidence reached 4.03 points on the 5-point Likert scale. Since this scale is tautologically negatively generated, a decreasing value implies a higher measure of confidence. With respect to agricultural higher education, 45% of the farmers in our sample hold an agricultural university degree, which is higher than the Hungarian average of 9% [47]. The reason for these differences lie in the fact that precision technology (especially drones) is typically used in large scale farms run by those with a higher education degree in agriculture.

Taking into account the data in Figure 2, as well as expert opinions, we argue that the following levels adequately characterise the levels of application of precision technology elements in Hungary:

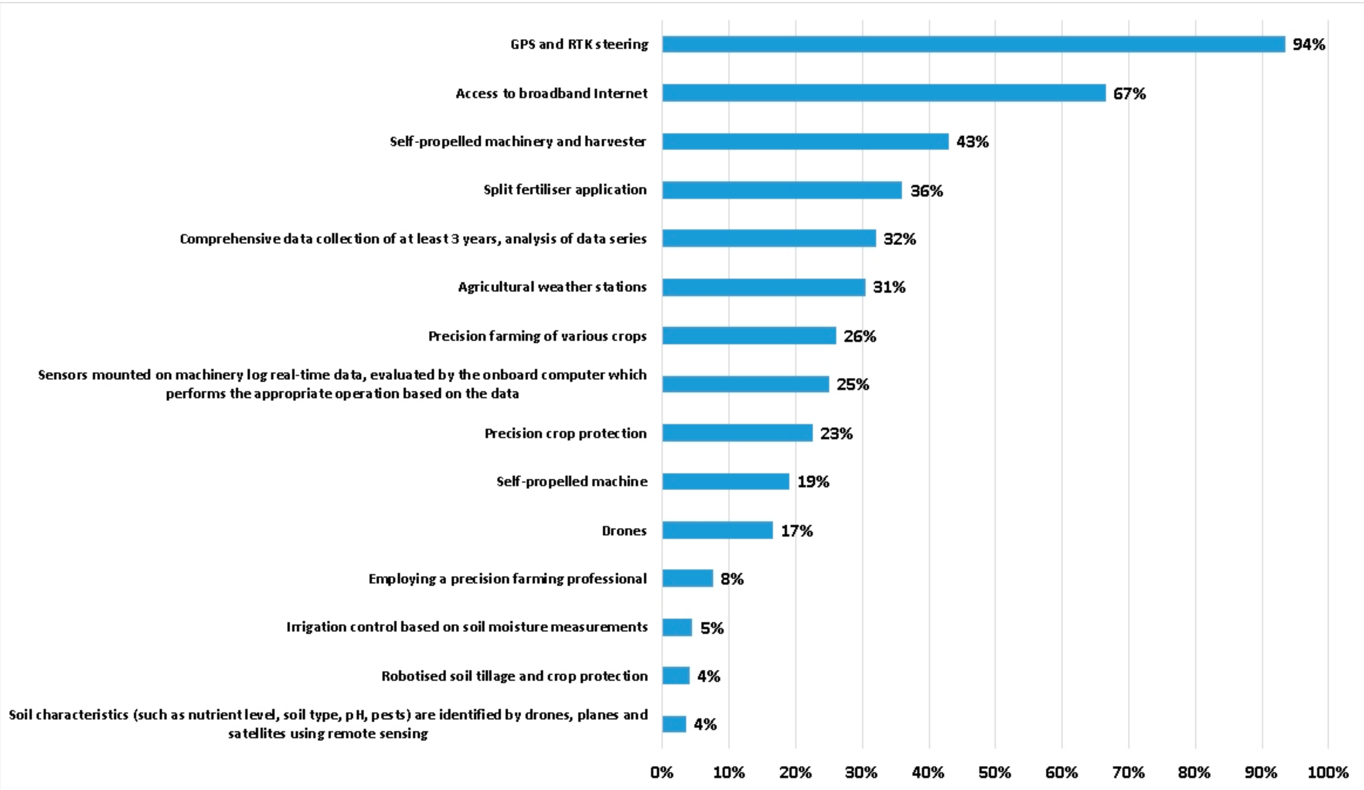

Figure 2. Applied precision agriculture technologies (n = 200). Multiple answers were possible.

Basics of PF (43–94%)

At this level, we have taken into account the elements without which the application of PT (precision technology) is unthinkable. In addition to the availability of GPS, RTK and broadband internet, automatic steering machines have been included here because this is what justifies the purchase of RTK.

Data collection phase (external or internal sources, 25–32%)

Time series of at least three years for several crops and up-to-date information on remote sensing are essential for a reliable basis for decisions. Survey responses are unlikely to include precision tillage, which precedes the actual cultivation of the crop. The network of agricultural weather stations covers the whole country and provides farmers with real-time data, but they tend to use only the data that are most relevant to them. To optimise machine operation, data packages have been developed to facilitate this, which could play a vital role in disseminating relevant Green Deal standards (pesticides, fuel saving). Another limitation of the application is the availability of appropriate technology for measuring yields of only the most important arable crops.

Use of database to extract information (5–23%)

Smart data generation and its professional use is the next level of technology and a value creator. Precision crop protection is also increasingly linked to other technological elements (e.g., coupled nutrient supply). Although split fertilisation is widely used in conventional technologies (e.g., spots where the machines turn, no sowing on ditch banks—we believe this explains a large proportion of the positive responses), it is significantly different from differential nutrient application in precision technology (e.g., differential fertilisation of saline soil patches), which is a significantly higher and less frequently used technological element. The measurement of soil moisture is important information available in the database of all soil weather stations. Still, practical experience shows that only a minority of farmers use that information, which also requires the use of specialised experts for its development.

The future (4–17%)

This category includes only drones, apart from robotics. The use of drones is already of considerable importance (17% of the data received for this use) in the field (especially in the differentiated treatment of soil and plant patches with different conditions and infestations). However, their use in imaging is still negligible. Drone technology capable of performing both functions has already emerged at the experimental level, so we consider the inclusion of drones in this category to be justified. In Hungary, aerial crop protection, for which drones can play an vital role, is experiencing a revival, since, in addition to the precision treatment of infested patches, they are also able to work at night, when wind conditions are more favourable than during the day.

The responses of Hungarian farmers using precision technology provide a good basis for categorising precision technology elements. Still, due to gaps in interpretation, the results obtained are over-represented for drones and split fertilization, and under-represented for remote sensing systems.

3.2. Results of the Ordinal Logistic Regression

The ordinal logit model helps explain the relationship between the outlined perceptions regarding the technical barriers to drone adoption and the attitudes towards the use of drones. The model also draws attention to on-farm characteristics that authenticate potential early adopters. The ordinal dependent variable reflects the adoption stages regarding the intention to use drones, namely precontemplation, contemplation, preparation and action. The results of the ordinal logistic regression are provided in Table 5. This table contains the OR, the standard errors, the significance levels and the 95% confidence intervals. A likelihood ratio test was significant (LR χ^2 (9) = 175.93; $p < 0.001$), indicating that one or more coefficients significantly differ from zero. The log-likelihood value is -346.59. Other model fit criteria imply quite an acceptable model fit with McFadden Pseudo-R^2 and Nagelkerke Pseudo-R^2 (0.34–0.63) and a significant chi-squared value ($p < 0.001$).

Predicted probabilities and marginal effects for each category of the TTMA variable are given in Table 6. Predicted probabilities show that half of the farmers of the sample belong with 43% probability in the contemplation stage (TTMA = 2). There is a change in the sign for all variables between the contemplation stage (TTMA = 2) and the preparation stage (TTMA = 3) of the model. These results are similar to Michels et al. (2020) [23]. This indicates that variables with a statistically significant effect make a difference between farmers with no or only overall interest in drones and farmers with concrete plans to use or who already use a drone. The result is a unique Hungarian case study on TTMA, which can be complemented by research in several technological, socio-economic and other country-specific contexts.

Table 5 shows that the highest exponential beta (Odds Ratio) was observed for the variable of higher agricultural education. It can be concluded that someone with higher education in agriculture is 6.33 times more likely to (intend to) use a drone than someone without such education. In second place was the question "the use of drones is important for my job" (OR: 3.67). In this case, the exponential beta means that if someone rated their answer to this question one category higher (agreed more with the question), they were 3.67 times more likely to have an intention to use drones. Among German farmers, Paustian–Theuvsen (2016) [29] could not detect a significant effect of higher education (OR = 1.28, $p = 0.46$). When we interpreted education uniformly as higher education, similar to the German method, we obtained the same result (OR = 6.33, $p = 0.024$) as Michels et al. (2020) [23] (OR = 0.45, $p = 0.326$). However, when we separately examined the effect of higher education in agriculture on openness to drone use, we found the positive effect reported earlier. According to our results, those with tertiary education in agriculture were 6.33 times more likely to decide to use a drone than those without such education. According to Paustian–Theuvsen (2016) [29], the explanation for this finding could be that agricultural education has an impact on openness to precision farming, and we were able to demonstrate this in the case of Hungarian farmers.

The same was observed (but to a lesser extent) for full-time farmers, as the exponential beta (Odds Ratio) was 3.34. This implied that farmers who produce full-time were much more likely to use a drone on their farm than those who only produce part-time, i.e., the odds of using a drone increased by a factor of 3.34 for full-time farmers. For Hungarian farmers, we find similar correlations to those formulated for German farmers by Michels et al. (2020) [23].

Significant differences were also found for the question "learning to use drones is not a problem for me", where the exponential beta (Odds ratio) was 1.54, and for the question "I don't think I would use drones because using them seems too complicated for me". For the latter, the exponential beta (Odds Ratio) was 1.47. In these cases, the exponential betas mean that if someone rated their answers to the questions one category higher (agreed more with the questions), those farmers were 1.54 and 1.47 times more likely to want to use drones.

This area of study is crucial because, as an Australian study (Higgins et al., 2017.) [48] pointed out, even though farmers adopt technology learned through their partners, this technology adoption is often accompanied by negative emotions. Also, the presence or absence of advisors may be a factor affecting diffusion [33].

The effect of age was the opposite of the variables presented so far, as the exponential beta was less than 1 (Odds Ratio: 0.97), meaning that an increase in age decreases the probability of using a drone. Our results (OR = 0.97, $p = 0.029$) are similar to those of large-scale farmers in Germany (OR = 0.97, $p = 0.06$ in Michels et al., 2020 [23]), showing that openness to adopting new technologies, in this case drones, decreases with age. This result is in line with findings in the international literature on the adoption of innovative technologies [19,37]), which may be due to the fact that older farmers may have less experience with digital technologies (smartphone, computer), a shorter time horizon available to them, and a tendency to stick to habits [20], as well as a greater reliance on their practical experience with new technologies [29].

Among German farmers, Michels et al., 2020 [23] were able to show a clear relationship based on gender (OR = 4.18, $p < 0.01$) for openness to drone use, i.e., male farmers are 4.18 times more likely to accept the use of drones than female farmers. Due to the low number of respondents in the sample, we were not able to detect any association with women among Hungarian farmers. The German results are also in line with those of Zhang et al. (2019) [25]. In the context of German farmers, the authors note that their results are also noteworthy because the European Commission (2017) data show a steady increase in the proportion of farms headed by female farmers [23]. We could not show any relevant gender differences among the Hungarian farmers, because the proportion of women among the precision farmers was very low.

4. Conclusions

The share of Hungarian farmers using precision farming technologies (23%) is almost the same as the EU-28 average (25%). Still, the larger farm sizes, the concentration of farms and the available digital infrastructure provide a good basis for further expansion, provided that the human resources are available. The use of drones within precision technology is 17% based on our questionnaire surveys, but the constantly emerging technological innovations and new application opportunities predict a large increase. Due to the latter, drones also appear in two phases of the Gartner hype cycle (peak interest, preference for benefits).

Larger farm size, younger age, full-time employment and higher education, as well as openness to training and employment, also improve the chances of drone adoption in Hungary, a finding that is similar to previous international results.

Our survey of precision farmers has explicitly shown that a degree in agriculture has a positive impact on adoption and willingness to adopt drones.

Although the small number of data did not allow for a statistically reliable conclusion, international data underlines the need to take the gender of farmers into account in the future of drone advisory services in order to ensure equal opportunities for the adoption of drones, regardless of gender. This will also be an important factor among Hungarian farmers.

The government sector can play a significant role in the expansion of drones, especially in the swift and professional development of specific legislation on the use of drones, and in the modernisation and expansion of university education and training in agriculture and engineering. Economic considerations, especially future trends in the price change of drones, as well as the price change of saved inputs and of surplus output due to the technology, also have a significant impact on the uptake of drones. The latter are mainly market-driven, but the investment cost of drones can also be influenced by public instruments (e.g., target subsidies).

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