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Determinants of the Use and Extent of Digital Agriculture Among Moroccan Farmers

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ABSTRACT

Digital agriculture, driven by advancements in financial engineering, holds significant potential to enhance productivity and sustainability in agricultural production. However, the adoption and extent of these technologies fundamentally depend on farmers' willingness to accept and use them. While recent studies have identified key factors influencing the adoption of digital agriculture, to the best of our knowledge, no academic study has specifically examined the determinants of both the use and the extent of adoption, particularly within the Moroccan context. This study investigates both the adoption and intensity of digital agriculture among a sample of 250 Moroccan farmers, utilizing a paper-based survey and two econometric approaches: a multinomial logit model and the Heckman model. The findings reveal that farmer age has a negative and significant impact on digital agriculture adoption. At the same time, crop type and risk aversion emerge as significant positive determinants of both the adoption and the extent of smart farming use. Specifically, technology adoption is mainly influenced by age, crop type, and risk aversion, whereas the extent of use is primarily driven by risk aversion and the type of crops cultivated. These results highlight the importance of implementing targeted policies and training programs to promote broader and more intensive use of digital agriculture technologies. Additionally, these findings open up avenues for further research aimed at better understanding the underlying factors that shape Moroccan farmers' behavior toward digital

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agriculture adoption.

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1. Introduction

In recent years, advancements in financial engineering have been revolutionizing various economic sectors, including financial technology (fintech), insurance technology (Insurtech), and digital agriculture [1]. These agricultural innovations have not only transformed financial markets for both individuals and professionals through mechanisms such as precision farming solutions, climate-smart agriculture, and drone technologies, but have also aimed to overcome climate risk and reduce food insecurity [2–4].

Digital agriculture, also known as Digital Farming, Smart Farming, or Smart Agriculture, encompasses the use of technologies to collect, generate, transmit, store, and analyze data, to enhance decision-making across all stages of the agricultural value chain [5]. It is widely regarded as a tool for increasing transparency and reducing costs in the agricultural sector, thereby improving efficiency, sustainability, and flexibility [6, 7]. Moreover, the integration of these technologies has the potential to revolutionize agriculture by transforming the design, implementation, and monitoring of services such as irrigation, fertilization, and crop harvesting, enabling farmers to operate with greater flexibility [4].

In Morocco, the agricultural sector represents a cornerstone of the national economy, contributing approximately 12 to 17% of the country's GDP, with a significant portion of the population still relying on agriculture as a primary source of income [8]. However, it faces persistent challenges, primarily stemming from climate change and water scarcity. Despite government initiatives aimed at accelerating the digital transformation of agriculture—such as the Generation Green strategy, which targets 2 million farmers and users of agricultural e-services by 2030—the adoption of new agricultural technologies remains uneven, particularly in rural areas and among smallholders [9].

Considerable attention has been given in the empirical literature to identifying the factors influencing the adoption of digital agriculture [8–12]. However, to the best of our knowledge, no academic studies have specifically examined digital agriculture adoption by considering both the decision to use and the extent of use as key variables. This paper aims to address this gap by providing relevant insights into the main determinants that shape farmers' adoption and intensity of use of smart farming solutions. To achieve this objective, the first section presents a brief review of the relevant literature. Section 2 outlines the methodological approach adopted to answer the research questions. The results, discussion, and concluding remarks are presented in the following sections.

2. Literature Review

The identification of the determinants of technology adoption has been widely studied, with existing research generally categorized into four clusters: (1) Technology Acceptance Model (TAM)-related determinants, (2) Unified Theory of Acceptance and Use of Technology (UTAUT)-related determinants, (3) determinants based on the Theory of Perceived Risk and the Theory of Planned Behavior, and (4) findings from other empirical studies and self-developed constructs.

The TAM, introduced by Davis [13], explains how individuals adopt and utilize new technologies, offering theoretical insights into the practical design and implementation of information systems. The model identifies factors such as consumers' attitudes, perceived usefulness, mass media influence, and subjective interpersonal norms as having a positive impact on technology acceptance [14]. However, these findings are not supported by Ngo and Nguyen [15], who found that TAM-related factors do not significantly influence fintech adoption in Vietnam's bank-based financial system. Instead, they highlight that consumers' latent needs play a more critical role in motivating the use of fintech services.

The second theory, known as the Unified Theory of Acceptance and Use of Technology (UTAUT), suggests that four key factors—performance expectancy, effort expectancy, facilitating conditions, and social influence—primarily drive technology adoption [16]. Based on an extended version of the UTAUT model, Schukat and Heise [17] conducted a Partial Least Squares (PLS) analysis to examine the determinants of smart farming solution adoption among 523 German farmers. Their findings revealed that hedonic motivation, social influence, and individual performance expectations significantly impact farmers' behavioral intentions to adopt smart agricultural technologies.

Turning to the Theory of Perceived Risk (TPR) and the Theory of Planned Behavior (TPB), both emphasize that trust plays a more critical role than other factors, particularly in contexts involving financial risk and uncertainty [18]. Sun et al. [19] applied the TPB using Structural Equation Modeling to examine the adoption intentions of 219 farmers toward a digital agricultural management system. Their findings revealed that availability bias and loss aversion significantly predicted the adoption of digital agriculture.

On the other hand, other empirical studies have investigated the key determinants of smart farming technology. Caffaro and Cavallo [20], using a mediation model with data from 310 Italian farmers, found that farm size had a positive direct effect on the adoption of smart farming technologies, while lower education levels and working alone on the farm were negatively associated with the adoption of these technologies. Michels et al. [21] demonstrated, using a bivariate probit model with data from 815 German farmers, that factors such as age, farm size and location, and familiarity with internet-related risks significantly influence the adoption of mobile internet in agriculture. Andati et al. [4] employed a multivariate probit regression model to investigate the factors influencing the adoption of Climate-Smart Agriculture (CSA) among 350 potato farmers in Kenya. Their findings highlighted the importance of fostering farmers' entrepreneurial orientation, innovativeness, and proactiveness in promoting CSA adoption. A similar model was applied by Musafiri et al. [22] to assess the determinants of CSA practices adoption. The study found that several factors significantly influenced adoption, including the household head's gender, education level, age, family size, access to weather information, size of arable land, livestock ownership, perception of climate change, soil infertility, and persistent soil erosion. Mashi et al. [23] evaluated the determinants influencing the level of awareness regarding CSA technologies among a sample of 491 Nigerian farmers. Their findings revealed that higher awareness was associated with farmers who were more educated, older, had larger family sizes, multiple income sources, and greater economic assets, as well as greater experience with climate change. Furthermore, gender equity was identified as a key determinant in the adoption of CSA practices as demonstrated by Agarwal et al. [24] using principal component analysis.

Continuing the list, Sood et al. [25] employed an algorithmic approach to identify key determinants influencing the adoption of Artificial Intelligence in agriculture. These determinants were classified into five categories: individual characteristics, environmental factors, structural factors, technological factors, and demographic variables. Mi et al. [12] identified the determinants of smart farming technology adoption among 183 Japanese agricultural corporations using descriptive analysis and negative binomial modeling. Their results indicated that factors such as corporate structure, eligibility for farmland ownership, sales and profit targets, and the main product type significantly influence the adoption of smart farming technologies.

Giua et al. [26] applied Structural Equation Modeling (SEM) and a Zero-Inflated Poisson Regression to investigate the adoption of Smart Farming Technologies. They identified key determinants, including perceived improvements in productivity, cost efficiency, and sustainability, ease of use, social support, and farm size. Harisudin et al. [11] investigated the factors influencing Indonesian millennial farmers' adoption of the Internet of Things (IoT) and found that adoption decisions were primarily driven by perceived relative advantage and social influence. Lassoued et al. [27] explored the transformation of agriculture in the Canadian context, identifying key drivers of digital technology adoption, including economic benefits, market size, organizational strategic goals, the availability of skilled personnel, access to information about new products and technologies, and government financial support. In a recent study, Adimassu et al.[10] identified key determinants influencing farmers' satisfaction with site-specific fertilizer recommendations (SSFR) in Ethiopia, using Principal Component Analysis (PCA) and an Ordered Probit Model based on data from 202 households. The results highlighted education level, farm size, availability and affordability of SSFR, quality of information on planting time, and livestock size as the main determinants. Taner[6] emphasized that the successful implementation of technological advancements depends on overcoming several challenges, including implementation costs, lack of standardization and interoperability, privacy and security concerns, insufficient government support, and limited business opportunities.

3. Materials and Methods

This paper aims to analyze the determinants and extent of Smart Farming adoption among Moroccan farmers. The adopted methodology combines field surveys with econometric modeling. The first component gathers essential data on farmers' adoption of financial technology, while the second investigates the factors influencing their use of these technologies for business management. The variables of interest include the farmer's decision to adopt digital agriculture and, if applicable, the extent of use within the agribusiness.

3.1. Study Model

Various econometric models, such as Logit, Probit, and Tobit, have been widely used in the literature to study user behavior. In our case, the data are censored, as information on the extent of digital agriculture adoption is only observed for farmers who have already adopted smart farming technologies. In other words, analyzing the factors influencing the extent of adoption requires conditioning on the farmer's initial decision to adopt such technologies.

The model developed by Heckman[28] serves as the foundational theoretical framework for analyzing the factors influencing the adoption of smart farming innovations among Moroccan farmers. This model is particularly appropriate in this context, as it corrects for potential sample selection bias by accounting for the fact that usage-level data are only observed for individuals who have already opted to adopt digital agriculture solutions. The first step involves estimating a Probit model to examine how various explanatory variables influence the selection equation (i.e., the farmer's decision to adopt digital farming solutions). This step also produces the inverse Mills ratio λ_i, which is included as a regressor in the second stage to correct for selection bias, with appropriate adjustments to standard errors and corresponding t-values.

To address potential selection bias, the inverse Mills ratio λ_i is introduced to capture the influence of both observable and unobservable factors affecting a farmer's decision to adopt digital agriculture. It is expressed as the ratio of the standard normal density function, φ, to the cumulative distribution function, ϕ, as shown in Equation (1).

$$\lambda_i = {}^{\varphi(W_i\widehat{\alpha})}/_{\phi(W_i\widehat{\alpha})} \tag{1}$$

In the second stage, a linear regression is performed using only the subsample of farmers who use digital agriculture solutions. Therefore, the model consists of two components: a selection equation (associated with the first dependent variable) and an outcome equation (associated with the second dependent variable), specified as follows.

- First dependent variable: The use of digital agriculture solutions is observed only if farmers have adopted digital agriculture. This relationship is modeled in Equation (2).

$$z_i = \omega_i\gamma + \mu_i \tag{2}$$

- Second dependent variable: The usage level of digital agriculture solutions is observed only if $z_i > 0$. This relationship is modeled in Equation (3).

$$y_i = x_i\beta + \varepsilon_i \tag{3}$$

Where ω_i and x_i represent the observed explanatory variables, while μ_i and ε_i are normally distributed error terms.

3.2. Empirical Approach

The factors influencing the adoption of digital agriculture can be grouped into three categories. The first pertains to individual factors, which encompass farmer characteristics (age, education level, Farming experience) and environmental factors (Internet access, monitoring team, social influence). The second category stands for technology, risk aversion, and perception factors, such as TAM and UTAUT-related determinants (Farmer innovativeness, Risk aversion, Risk perception, Perceived usefulness, Perceived ease of use, Perceived benefit). Lastly, the third category focuses on macro-level factors, such as government regulation and market trends.

The econometric analysis was conducted in two stages. Stage 1 involves performing a univariate analysis using a simple Logit model to examine the relationship between the dependent variable and each explanatory variable. This stage is further supported by a multinomial logit model, which confirms the relationship between the use of smart farming solutions and the independent variables. In the second stage, only the selected explanatory variables that are strongly linked to the dependent variable are included, and they are then estimated using the Heckman model.

3.3. Research Data

The data for this study were collected through an original survey, with respondents recruited from attendees of the 16th International Agricultural Exhibition in Morocco. The survey included 250 farmers, comprising 189 individual farmers and 61 business farmers. The questionnaire was pre-tested with four farmers to identify and revise ambiguous or poorly worded items. Then, the responses were examined to assess the reliability and unidimensionality of the scale, allowing for the elimination of ambiguous or weakly correlated items.

The survey questions were divided into five categories: (1) basic information about farmers (such as age, city of residence, education,) and business nature (such as years of experience, surface area, number of plots, crop yield); (2) use of digital agriculture solutions (such as purpose, frequency, and number of platforms used); (3) corporate and environmental factors (such as internet access and monitoring team); (4) technology and risk perception factors; (5) Cost Security and Privacy Concerns; and (6) macro-level factors.

The selection of our variables was based on existing literature and a contextual analysis of the Moroccan agricultural sector. Four dependent variables are used to capture the usage of smart farming solutions: Ag_us (use of digital agriculture solutions), Ag_fr (frequency of use), Ag_pl (Number of platforms/applications used), and Ag_int (Interaction between frequency and number of platforms used). **Table 1** defines the 24 key variables used in this study.

It should be noted that farmers' risk aversion was determined by calculating the risk premium they would be willing to accept in order to avoid the risk of failure. To determine the risk premium for each farmer, we implement an adapted version of the urn games originally proposed by Luttmer and Samwick [29], and later applied by Jouamaa et al. [30], in our experimental design. Respondents were asked to choose between two options for using a "Precision Farming solution" at prices P_1 and P_2, with a fixed term ending in December 2025. We present a scenario involving a new irrigation system that could reduce water usage by half but requires a \$2,500 installation cost (P_2), with a free demo of a new farming app (P_1) with uncertain outcomes. If the respondent rejects P_2, we repeat the same question with a lower $P_{2(i)} < P_{2(i-1)}$, gradually reducing the difference between $P_{2(i)}$ and $P_{2(i-1)}$ until the subject accepts the new farming app at the guaranteed $P_{2(i)}$. The average price between $P_{2(i)}$, representing the price at which the respondent accepts the new farming system, and $P_{2(i-1)}$, corresponding to the price at which the respondent rejects the new solution, represents the certainty equivalent. The difference between the accepted price $P_{2(i)}$ and the price P_1, which reflects uncertainty, represents the risk premium, measuring how much the farmer is willing to pay to mitigate the risk of failure associated with adopting the new farming system.

Table 1. Description of variables used.

Variable	Description
Age	Farmer's age group. Takes the value 1 for individuals between 20 and 30 years old; 2 for those between 31 and 45 years old; 3 for those between 46 and 60 years old; and 4 for those over 61 years old.
Edu	Education level of the farmer. Takes the value 1 for primary education, 2 for secondary education, and 3 for higher education.
Exp	Years of agricultural experience. Takes the value 0 for less than 5 years, and 1 for 5 years or more.
Ar	Surface area in hectares. Takes the value 0 for less than 5 hectares, and 1 for 5 hectares or more.
Pl	Number of agricultural plots. Takes the value 0 for individuals with a single plot and 1 for those with more than 2 plots.
Yi	Crop yield. Takes the value 0 when yield is below the national average and 1 when it is above.
Cr	Main Product Category. This variable is coded as follows: 1 = cereals and legumes, 2 = vegetables, 3 = fruit, and 4 = livestock.
Ow	Proportion of the owned land currently cultivated. Takes the value 0 if the proportion is 0 (fully leased land), 1 if the proportion is less than 100%, and 2 if the proportion is 100% (fully owned land).
Tur	Farmer's turnover per hectare.
No	Number of computers/tablets in use.
In	Internet access. Takes the value 0 if there is no Internet access, and 1 when it is available.
Mt	Presence of a monitoring team. Takes the value 0 if the farmer does not have a monitoring team, and 1 if they do.
Si	Social influence. Takes the value 1 if other farmers can influence the farmer's decision to try a new technology, and 0 otherwise.
Ag_us	Indicates whether the respondent uses digital agriculture solutions. Takes the value 1 if the farmer reports using at least one form of digital technology in their agricultural practices, and 0 otherwise.
Ag_fr	Daily frequency of use of Digital agriculture Solutions.
Ag_pl	Number of platforms/app used.
Ag_Int	A composite variable reflecting the extent of digital agriculture use. It is constructed as the interaction between the number of different platforms or tools used and the daily frequency of use, providing a proxy for the intensity of digital adoption.
R_av	Farmer's risk aversion, calculated by measuring the risk premium.
R_pr	Risk perception. Measured by calculating a score for each farmer, reflecting their perception of risk.
P_eu	Perceived Ease of Use. Takes the value 1 if the user feels confident using digital agriculture services without needing assistance, and 0 otherwise.
P_us	Perceived Usefulness. Takes the value 1 if the digital agriculture solution helped the farmer manage project more effectively, and 0 otherwise.
P_bn	Perceived benefit. Takes the value 1 if the digital agriculture solution helped the farmer save money or reduce fees, and 0 otherwise.
Beh	Farmers' attitudes toward digital agriculture solutions. Takes the value 1 if the farmer intends to use the service more frequently, and 0 otherwise.
Inn	Farmer innovativeness. Takes the value 1 if the farmer is open to exploring new agricultural innovations, and 0 otherwise.

Our methodology for capturing the risk perception variable involves assessing individuals' perceived level of risk associated with the use of smart farming solutions, considering several sources of risk, namely, demonstrations and trials, subsidies and incentives, training and support, and community and peer influence. Participants were asked to express their risk attitude on a 5-point Likert scale, with response options ranging from 'Strongly Disagree' to 'Strongly Agree' with the following criteria:

1. Strongly Agree (5)
2. Agree (4)
3. Neutral (3)
4. Disagree (2)
5. Strongly Disagree (1)

We asked five questions to capture both the farmers' attitudes toward risk and their levels of digital agriculture adoption. The items primarily address risks related to decision-making, potential failure, peer influence, duration, and financial risk. These items were pretested with four farmers to identify any that were ambiguous or poorly formulated, allowing for necessary revisions to the initial version. Subsequently, the items were analyzed to assess the reliability and unidimensionality of the scale, and to remove items that were ambiguous or showed weak or no correlation with the overall construct. As a result of this step, the first of the five proposed items was eliminated. These items were selected based on the conclusions of Venkatesh et al.[31] and the specifics of the Moroccan agricultural context. Subsequently, a score is computed and standardized for each respondent to construct a composite risk perception variable, denoted as x', following the methodology of Lusk and Coble[32], as shown in Equation (4).

$$x' = \frac{(x - \mu)}{\sigma} \tag{4}$$

With x: Cumulative item score.
μ: Average value.
σ: Standard deviation.

To determine the "Perceived Ease of Use", Perceived Usefulness, Perceived Benefit, and Farmers' Attitude Variables, we have adopted the same approach to determine risk perception. The items tested and validated for each variable are shown in the appended questionnaire (**Appendix A**). The correction of non-response was carried out using various statistical adjustment techniques, including imputation by the mean and logistic modeling.

To ensure the reliability of the regression estimates, we also tested for multicollinearity among the independent variables using the Variance Inflation Factor (VIF). All VIF values were well below the commonly accepted threshold of 5, with the highest being 1.27, indicating no significant multicollinearity issues. Additionally, pairwise correlation coefficients were examined among the independent variables to detect potential multicollinearity. The results showed that all correlations were below 0.7, confirming the absence of strong correlations and supporting the robustness of the model estimations.

4. Results

4.1. Descriptive Analysis

The adoption of digital agriculture solutions remains low among Moroccan farmers, with only 57% utilizing them. Among individual farmers, 67% use these solutions to optimize fertilization and modulate irrigation systems, 19% to conduct home schedule inspection, and 14% to monitor plots and improve financial and technical decision-making. This indicates that most smart farming users are aware of the broader climatic challenges resulting from the drought and water shortages the country has faced over the past six years. Furthermore, as shown in **Table 2**, although 87% of respondents believe that existing digital farming solutions are effective and 93% are confident in their functions, a total of 107 non-users indicated that high costs (37%) and technological complexity (33%) are the main barriers to digital agriculture adoption.

The degree of risk aversion is determined using the certainty equivalent approach, which evaluates the risk premium farmers are prepared to incur in order to mitigate the risk of failure partially. On average, the certainty equivalent was 486.10 USD (SD = 238.91 USD), while the risk premium averaged 478.40 USD (SD = 295.84 USD), illustrating the amount farmers are willing to accept or pay to avoid uncertainty associated with adopting digital agriculture solutions. Specifically, 29% of farmers who do not use digital agriculture solutions are willing to pay a premium of less than $250 to mitigate failure risk, and 19% of the respondents indicate readiness to pay a premium of less than $500 (**Figure 1**). On the other hand, 31% of farmers who currently use these solutions are willing to forgo a risk premium of $750. In comparison, 21% of all respondents are willing to bear a risk premium exceeding $750 to adopt digital agriculture solutions and avoid potential failure. These findings confirm that the magnitude of the risk premium negatively affects the preference for digital agriculture adoption among both users and non-users, highlighting the pivotal role of farmers' risk preferences in determining their adoption behavior.

Table 2. Summary of digital agriculture adoption: usage, barriers, and effectiveness perceptions.

	Frequency (%)	Total Number of Farmers
A. Reasons for using digital agriculture	**57%**	**143**
• Monitoring plots	14%	20
• Optimizing fertilization • Modulating irrigation	67%	96
• Other reasons (Monitoring dry matter, Investigating from home…)	19%	27
B. Barriers to digital agriculture adoption	**43%**	**107**
• Technological complexity	33%	35
• Data security and privacy	9%	10
• Cost greater than benefits	37%	40
• Lack of information	9%	10
• Other factors (regulatory challenges, government policy…)	11%	12
C. Effectiveness of digital agriculture solutions	**100%**	**250**
• Effective	87%	217
• Ineffective	13%	33
D. Functions of digital agriculture solutions	**100%**	**250**
• Very confident	75%	187
• Moderately confident	18%	46
• Less confident	6%	14
• Unconfident	1%	3

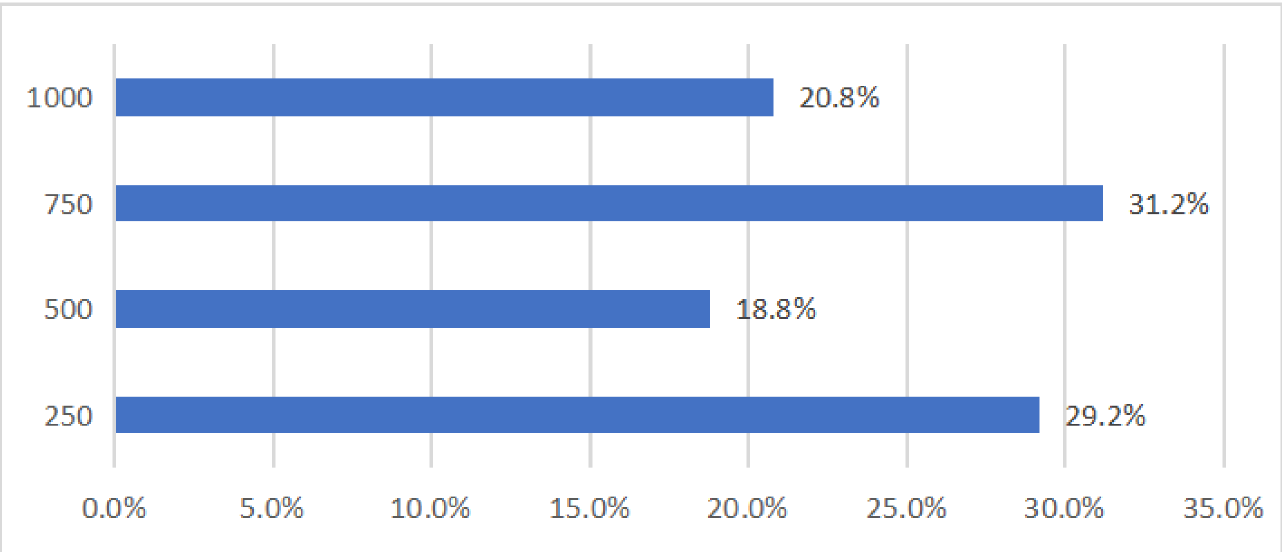

Figure 1. Distribution of the risk premium across respondents (%).

4.2. Econometric Analysis

To understand the main determinants of farmers' use of smart farming solutions and the importance of these solutions in their management processes, we carried out three types of analysis: univariate analysis, multivariate logit model, and the Heckman model. The univariate analysis and the multivariate logit model are suggested to confirm the factors influencing the adoption of digital agriculture solutions. This approach retains only those explanatory variables that exhibit a strong association with digital agriculture adoption, represented by the variable "Ag_us", in order to explain the key determinants of the intensity of adoption, captured by the variable "Ag_int". The results indicate that farmer age, landholding size, number of plots, crop yield level, product category, and ownership structure are key factors affecting digital agriculture adoption (**Table 3**). However, education level (Edu), turnover (Tur), internet access (In), the presence of a monitoring team (Mt), and social influence (Si) are not statistically significant variables in explaining the adoption of digital agriculture. Additionally, and unexpectedly, risk perception, perceived ease of use, perceived usefulness, perceived benefits, and attitudes toward smart farming solutions do not emerge as determining factors. In contrast, farmers' risk aversion and innovativeness are found to be highly significant determinants of adoption.

Table 3. Univariate analysis results for digital agriculture adoption.

Explanatory Variables	Coefficient	z-Statistic	p-Value
1. Age	−5.438	−5.240	0.000***
2. Edu	−0.017	−0.109	0.912
3. Exp	0.237	1.328	0.184
4. Ar	0.296	1.667	0.095*
5. Pl	0.074	1.977	0.048**
6. Yi	0.453	2.434	0.014**
7. Cr	0.147	3.264	0.001***
8. Ow	0.168	1.703	0.088*
9. Tur	0.206	1.413	0.157
10. No	0.084	1.931	0.053*
11. In	0.170	0.9673	0.333
12. Mt	0.261	1.481	0.138
13. Si	0.423	2.441	0.014
14. R_av	0.019	2.458	0.014**
15. R_pr	0.0003	1.401	0.161
16. P_eu	0.215	1.132	0.257
17. P_us	0.156	0.8384	0.401
18. P_bn	0.176	0.9826	0.325
19. Beh	0.214	1.082	0.27
20. Inn	0.380	2.155	0.031**

Notes: Statistical significance is denoted as follows: ***p < 0.01 ; **p < 0.05 ; *p < 0.10.

Following these results, we conducted a new verification and re-estimated the Multinomial Logit model by successively removing non-significant variables. The final model, selected based on the Schwarz Information Criterion (SIC) and the Akaike Information Criterion (AIC), confirms that risk perception, perceived ease of use, perceived usefulness, and perceived benefits are not statistically significant determinants of digital agriculture adoption (**Table 4**). In addition, no significant relationship was found between farmers' experience, surface area, and ownership structure, on the one hand, and the use of smart agriculture, on the other hand. Moreover, the number of plots, crop yield level, and the nature of agricultural products have a positive and significant influence on farmers' decisions regarding technology adoption. However, the results indicate that the age of farmers is negatively and highly significantly associated with digital agriculture adoption, suggesting that younger farmers tend to exhibit a higher propensity for adopting digital agriculture. The findings also indicate that farmers' risk aversion has a strong and positive influence on the adoption of digital agricultural technologies.

In the next step, the Heckman model was employed to identify the factors influencing the level of smart agriculture adoption, measured by the interaction between the number of platforms used and the daily frequency of use. The results obtained from the model are reported in **Table 5**.

The estimated Heckman model was found to be statistically significant at the 5% level, indicating that it reliably explains the observed variation in the data.

Table 4. Multinomial logit model results.

Multinomial Logit, using observations 1–250
Dependent variable: Ag_us
Standard errors based on Hessian

Variables	Coefficient	Std Error	z-Statistic	Probability
Exp	0.090	0.610	0.147	0.882
Age	−4.351	0.685	−6.349	0.000***
Ar	−0.232	0.621	−0.373	0.708
Pl	0.810	0.227	3.568	0.000***
Yi	1.656	0.706	2.343	0.019**
Cr	1.888	0.397	4.755	0.000***
Ow	0.497	0.379	1.312	0.189
R_av	0.242	0.055	4.368	0.000***
Inn	0.927	0.629	1.473	0.140
Mean dependent var	0.572000		S.D. dependent var	0.495781
Log-likelihood	−38.00080		Akaike criterion	94.00159
Schwarz criterion	125.6947		Hannan-Quinn	106.7572

Number of cases 'correctly predicted' = 237 (94.8%)
Likelihood ratio test: Chi-square (9) = 270.572 [0.0000]

Notes: ***p < 0.01 ; **p < 0.05 ; *p < 0.10.

Table 5. Estimation results of the Heckman Selection Model.

Heck_MLM: ML Heckit, using observations 1-250
Dependent variable: Ag_int
Selection variable: Ag_us

Variables	Coefficient	Std Error	z-Statistic	Probability
Cr	0.825	0.214	3.852	0.000***
R_av	0.095	0.038	2.469	0.013**
lambda	3.934	0.232	16.95	0.000***
Selection equation				
const	8.224	2.228	3.691	0.000***
Cr	0.667	0.403	1.653	0.098*
Age	−3.293	0.883	−3.726	0.000***
Inn	0.442	0.419	1.054	0.291
R_av	0.054	0.028	1.938	0.052**

Mean dependent variable 4.188
S.D. dependent variable 3.978
Sigma 3.941
Rho 0.998
Likelihood log −411.747
Schwarz criterion 838.383
Akaike criterion 829.495
Total observations: 250
Censored observations: 107 (42.8%)

Notes: ***p < 0.01 ; **p < 0.05 ; *p < 0.10.

The estimated Lambda, corresponding to the Inverse Mills Ratio, is positive and highly statistically significant, indicating the presence of selection bias in the farmer sample and thereby justifying the use of the Heckman correction model as an appropriate method to analyze both the likelihood and extent of digital agriculture adoption among Moroccan farmers.

Moreover, the estimated coefficient signs confirm to theoretical expectations across all variables. Risk aversion is found to be highly significant at the 5% level and exhibits a positive effect in both the selection and outcome equations. This suggests that an increase in farmers' risk aversion is associated with a higher likelihood of adopting smart farming solutions, as well as with greater intensity of use. This result may be attributed to the fact that certain smart farming tools, such as precision farming technologies, are particularly attractive to risk-averse farmers seeking to mitigate potential losses. As an illustration, 67% of users report adopting these tools to optimize fertilization and modulate irrigation systems. Moreover, the extent of use appears more closely linked to farmers who perceive the benefits of digital agricultural technologies as outweighing their associated risks.

In addition, the category of agricultural products cultivated by farmers emerges as a key determinant of both the adoption and intensity of digital agriculture use. Farmers engaged in high-value-added production, such as fruit, berries, and livestock, are more likely to adopt precision farming technologies compared to those focused on lower-value-added crops. Conversely, small-scale farmers producing cereals and legumes are less likely to adopt digital agricultural solutions to monitor and manage their plots, potentially due to lower perceived returns on such investments.

On the other hand, the variable "Age" exhibits a negative and statistically significant effect, indicating that it is a key factor influencing the adoption of smart farming solutions. This result aligns with expectations, as younger farmers tend to be more open to experimenting with new technologies. In contrast, older farmers are generally more resistant to change and tend to maintain traditional practices. However, once the adoption decision is made, age does not appear to significantly influence the extent to which the technology is used. This implies that other factors—such as the type of crops cultivated and risk aversion—may be more critical in shaping the extent of use. In other words, while younger farmers are more likely to adopt digital solutions, the degree to which they integrate them into their operations is influenced by other determinants.

Regarding the non-significant variables, our findings indicate that innovativeness, risk perception, perceived ease of use, perceived usefulness, and perceived benefits do not exhibit statistically significant effects, contrary to the results reported in some previous studies [23–25]. Furthermore, no significant relationship was found between farmers' experience, education level, surface area, or ownership structure and the adoption of digital agriculture solutions. These findings can be attributed to several contextual factors. First, Moroccan agriculture is highly dependent on water availability and rainfall, making climate variability a more pressing concern for farmers than alignment with global innovation trends, particularly in light of consecutive years of drought [30, 31]. Second, the predominance of traditional farming practices, low level of technological literacy, and a general reluctance to share personal and professional information may limit farmers' openness to adopting digital tools [32–36]. Third, variables such as perceived ease of use, usefulness, and benefits may play a more central role in the adoption of other digital technologies, such as financial technology, than in agricultural contexts, where adoption decisions are more closely tied to environmental constraints and operational practicality.

5. Discussion

This study offers valuable insights into the factors influencing farmers' adoption and the intensity of use of smart farming technologies in Morocco, utilizing a Multinomial Logit Model and the Heckman model. The majority of explanatory variables validated in the Multivariate analysis significantly influence the dependent variables. Consistent estimators based on quasi-likelihood methods were obtained, aligning with economic intuition. The estimated Heckman model proved statistically adequate and significant at the 5% level, confirming its robustness in explaining the observed variation. Additionally, the model effectively addresses over-dispersion issues often encountered in binary and ordered probit models, making it particularly well-suited for the current analysis.

The methodology employed in the current study uses the Heckman model as a robust econometric approach to analyze both the adoption and extent of digital agriculture, based on data from 250 Moroccan farmers. This sample size is relatively large compared to studies such as Kanovska [37] (27 semi-structured interviews), Mi et al. [12] (183 agricultural corporations), Lassoued et al.[27] (27 participants), Adimassu et al.[10] (202 households), and Harisudin et al.[11] (120 millennial farmers), but smaller than those used by Musafiri et al.[22] (300 smallholder farmers) and Giua et al.[26] (474 farmers). Given the scope of this research and the diversity of the sample, collected at a major agricultural exhibition, this sample size is considered sufficient to ensure statistical validity and meaningful generalization of the findings within the Moroccan context.

The findings of this study indicate that age has a strong negative correlation with farmers' decisions to adopt digital agriculture. Younger farmers are naturally more adaptable and open to behavioral changes within the farming sector. Similar conclusions were drawn in studies from Germany[21], Kenya[22], and Nigeria[23], where age was found to significantly influence technology adoption. In this respect, our results align well with the existing literature. However, once the technology is adopted, age does not significantly influence how extensively it is used. This suggests that factors such as crop type and risk aversion play a more decisive role in determining the intensity of smart farming use.

Moreover, the type of product cultivated by the farmer was found to significantly influence both the likelihood and extent of smart farming technology use. The results indicate that farmers engaged in livestock and fruit production are more aware of the benefits of smart agriculture compared to those cultivating cereals and vegetables. This can be attributed to the higher added value and greater water requirements associated with livestock and fruit production, which incentivize the adoption of smart technologies to manage water-related constraints better. These findings align with those of MI et al.[12], supporting the positive association between product category and the adoption of digital agriculture adoption. However, other studies have not found a strong relationship between the type of product and the level of adoption[20, 23, 24].

Risk aversion was also found to have a strong positive influence on both the adoption and the extent of digital agriculture use. This result is consistent with expectations, as smart farming technologies can be particularly appealing to risk-averse farmers seeking to mitigate potential losses. Existing literature supports this finding, with several studies, such as those by Dibbern et al.[38], Andati et al.[4], and Schukat and Heise[17], identifying risk aversion as a key determinant in the adoption of smart farming technologies. However, our findings challenge the hypothesis suggested by Musafiri et al.[22], which posits that risk-sensitive farmers tend to resist adopting agricultural innovations.

On the other hand, although previous literature has highlighted the significant influence of factors such as gender, education and experience level, farm size, ownership structure, innovativeness, perceived ease of use, and perceived usefulness and benefits[18, 20, 33], this study found no significant relationship between these variables and the adoption of smart farming technologies. This finding aligns with Sun et al.[19], who argued that the intention to adopt digital agriculture is more strongly influenced by perceived financial, time, and social costs than by expected gains. Similarly, Adimassu et al.[10] found no relationship between gender and the adoption of site-specific fertilizer recommendations, and Mashi et al.[23] reported no association between land ownership and the adoption of climate-smart agricultural technologies.

6. Conclusion

The central aim of this article was to investigate the determinants influencing both the adoption and intensity of smart farming use in the Moroccan agricultural sector. By employing a multivariate logit model and the Heckman model, this study offers robust insights into the key factors shaping farmers' decisions to adopt and utilize digital agricultural technologies.

Based on survey data from 250 Moroccan farmers, the findings support existing empirical research highlighting age as a key factor in digital agriculture adoption[21–23]. However, this variable does not significantly influence the extent of smart farming use. Additionally, this study is among the few to introduce product category as a novel and significant determinant, confirming that higher risk aversion positively influences both the likelihood and extent of smart agriculture adoption. This emphasizes the importance of farmers' risk attitudes and the presence of high-value-added crops in shaping adoption decisions. These findings corroborate, on the one hand, those of MI et al.[12], who found that crop type is a determining factor, and those of Dibbern et al.[38], Andati et al.[4], and Schukat and Heise[17], who identified risk aversion as a key determinant of digital agriculture adoption. On the other hand, this study contributes to the existing literature by identifying both crop type and risk aversion as significant factors influencing the extent of smart farming use.

Furthermore, the results reveal that variables such as risk perception, perceived ease of use, perceived usefulness, and perceived benefits do not significantly influence Moroccan farmers' decisions to adopt smart farming solutions. Similarly, no significant associations were found between digital agriculture adoption and farmers' experience, education level, land size, or ownership structure, likely due to the overriding influence of environmental concerns like drought, the traditional and low-tech nature of Moroccan agriculture, and a general mistrust of digital tools; factors such as ease of use may hold greater relevance in the context of fintech than smart farming solutions.

In conclusion, this study highlights that age, product category, and risk aversion are key determinants of smart agriculture adoption among Moroccan farmers. Additionally, product category and risk aversion significantly influence the extent of digital agriculture use, outweighing traditional demographic or perceptual factors. These findings emphasize the need for targeted policies that address irrigation and drought challenges, support high-value crop sectors, and incorporate risk management strategies to drive digital transformation in agriculture. In addition, the findings open the door for future research aimed at deepening the understanding of Moroccan farmers' behavior toward the adoption of smart agriculture and exploring the direction of causality between key variables.

Author Contributions

Conceptualization, M.A.J. and A.I.M.; methodology, M.A.J.; software, M.A.J.; validation, M.A.J. and A.I.M.; formal analysis, M.A.J.; investigation, M.A.J.; resources, M.A.J.; data curation, M.A.J.; writing—original draft preparation, M.A.J.; writing—review and editing, M.A.J. and A.I.M.; visualization, M.A.J.; supervision, A.I.M.; project administration, M.A.J. and A.I.M; funding acquisition, A.I.M. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest

The authors declare no conflict of interest. The research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Appendix A

Questionnaire:

Survey number ....
Name ....
Phone number ....

1. Basic information:

- Gender ....
- Age ....
- City of Residence ....
- Education ....
- Years of Experience ....

- Surface Area ....
- Number of Plots ....
- Crop Yield ....
- Crop Type ....
- Land Ownership ....
  - What proportion of the land you currently cultivate is owned by you (not rented or borrowed)? ....
- Turnover ....

2. Use of digital agriculture solutions:

- Do you use digital agriculture solutions to monitor your plots and intensify your production sustainably?

  ☐ Yes ☐ No
- If no, why?
  - ☐ Economical and financial conditions (cost
  - ☐ Technical knowledge
  - ☐ Concerns about security and privacy
  - ☐ Other factors ....

    ....

    ....
- You use digital agriculture solutions to:
  - ☐ Access to various indexes such as vegetation, elevation map, or weather
  - ☐ Monitor your plots to capture heterogeneity and avoid applying my inputs in a uniform manner
  - ☐ Optimize my fertilization
  - ☐ Modulate my irrigation
  - ☐ Monitor my dry matter to improve forage quality
  - ☐ Investigate from home and schedule inspection routes for my workers
- Using this service improves my financial/technical decision - making:

  ☐ Yes ☐ No
- Number of platforms used ....
- How often do you use these solutions? ....
- You find the system easy to use" or "The system is user - friendly? ....
- Do you know anyone who uses digital agriculture services?

  ☐ Yes ☐ No
- How likely are you to adopt digital agriculture services if your friends and family use them? ......

3. Corporate and environmental factors

- Do you have a computer/tablet?

  ☐ Yes ☐ No
- If so, how many computers/tablets does your startup use?

  ....
- If no, why?

  ....

  ....
- Are you equipped with Internet access?

  ☐ Yes ☐ No
- If so, what type of subscription do you use?

  ....

  ....
- Do you have a monitoring team?

  ☐ Yes ☐ No

4. Cost Security and Privacy Concerns

- What is the cost of using digital agriculture solutions?

  ....

  ....
- How concerned are you about your personal data being used by digital agriculture companies?

  ....

  ....
- Would you be willing to use fintech services if you were confident in their security?

  ....

  ....
- Do you feel your data is secure with this service?

  ....

  ....

5. Technology, risk aversion and perception factors

- Risk aversion:

  ....

  ....

  ....

  ....

  ....

  ....

  ....

- **Risk perception:**

Questions	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
a. I prefer sticking to methods that I know work, even if newer options might be more profitable					
b. Trying new technology in farming feels too risky for me.					
c. I am willing to invest in new technology, even if it's not guaranteed to work perfectly at first.					
d. When I make farming decisions, I prioritize avoiding losses more than gaining potential profits.					
e. I would be more likely to try new technology if other farmers in my area had success with it first.					

- **Perceived Ease of Use (PEOU)**

Questions	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
a. I find it relatively easy to learn how to use digital agriculture services					
b. I feel confident using digital agriculture services without needing assistance					

- **Perceived Usefulness (PU):**

Questions	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
a. Using digital agriculture services helped me manage my project more effectively					
b. I feel that digital agriculture solutions save time compared to traditional tools					
c. I think the digital agriculture services help me reach my financial goals					

- **Perceived Benefits & Behavioral Intention:**

Questions	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
a. The service helped me save money and reduce fees					
b. I am very likely to continue using the service because it has helped streamline my farm operations and improve yields					
c. I intend to use this service more frequently moving forward					
d. I recommend this digital agriculture platform to friends or family					

6. Macrolevels factors.

- How do government regulations influence your adoption of digital agriculture solutions?

  ....
  ....
  ....
  ....
  ....

- How important is access to government subsidies or financial support in your decision to adopt digital agricultural technologies?

  ....
  ....
  ....
  ....
  ....

- How users perceive the distinctiveness of digital agriculture offerings compared to traditional services?

  ....
  ....
  ....
  ....

- How often customers see new features or improvements being added?

  ....
  ....
  ....
  ....

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