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Smart farming technology adoption and perceived impacts: Evidence from Italian farms

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ABSTRACT

While a growing body of literature highlights the potential of smart farming technologies (SFTs) to improve farm yield, efficiency, and sustainability, existing evidence remains largely focused on perceived drivers, barriers, and intentions to adopt, rather than observed outcomes among actual adopters. Moreover, little attention has been given to whether these technologies deliver economic and resource-related impacts under real farming conditions. This study addresses these gaps by providing a national-level assessment of smart farming adoption and perceived impacts in Italy, focusing on identifying determinants of adoption, quantifying perceived economic and resource-saving impacts, and examining heterogeneity across technologies and regions.

Using survey data from 345 farms and applying descriptive analysis alongside Probit and Heckman selection models, we examine the adoption of seven categories of SFTs and their impacts on revenue, costs, water, labour, fertiliser, and pesticide use. Results indicate that adoption is primarily determined by farmers' digital knowledge, cooperative membership, gender, and arable cropping area, while formal education and age play more limited roles. Among SFTs, robotics and autonomous vehicles, decision support systems (DSS), and data collection technologies consistently showed the highest mean impacts, whereas management-oriented tools such as farm management information systems (FMIS) and cloud platforms show more modest gains. Although adoption is higher in the northern and central regions, farms in the South and the Islands report significantly greater revenue growth, cost reductions, and input savings. Overall, the findings suggest that SFTs primarily function as a mechanism for narrowing performance gaps by delivering the largest marginal benefits where constraints are most severe.

1. Introduction

The fourth industrial revolution, known as Industry 4.0, is transforming industries worldwide, including agriculture. This shift is mainly driven by advances in technological innovations such as the Internet of Things (IoT), which connects devices and generates vast amounts of data; cloud computing, which stores and processes big data; and artificial intelligence (AI), which transforms data into meaningful insights [1, 2]. In farming, this transition, often described as "Agriculture 4.0" and sometimes referred to as "smart farming" or "smart agriculture," uses innovative digital technologies to optimise resource use, reduce agrochemical inputs, and enhance sustainability [3]. These technologies range from proximal sensors and satellite imagery to autonomous vehicles, smart machinery, and mobile management software.

Following the Agriculture 4.0 paradigm, the European Union (EU), under the Common Agricultural Policy (CAP 2023–27), promotes smart and sustainable agriculture by fostering knowledge, innovation, and digitalisation in line with its key objectives [4]. However, integration is currently hindered by high costs, skill gaps, and a lack of rural connectivity. The EU is addressing these challenges by improving rural connectivity, investing in training, and supporting collaborative on-farm innovation [4]. The market for agricultural machinery reflects this technological shift. Globally valued at €145 billion, the sector showed 32% export increase from 2017 to 2021, (€56 billion to €74 billion), with Italy ranking as the fourth largest exporter (€5.07 billion) of agricultural tools and smart technologies in 2021 [5].

Italy provides a favourable environment for the smart farming industry due to its significant role in the global food sector, diverse agricultural landscape, and strong technological base in agricultural machinery production [5]. Despite this, the performance of the Italian Agriculture 4.0 market is mixed. Between 2021 and 2024, the market value increased by approximately 44% (€1.6 billion to €2.3 billion);

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however, preliminary results indicate an 8% decline from 2023. Although 84% of farms benefited from at least one public incentive, adoption among new farms is slower. Digital maturity among surveyed farms, assessed using a digital maturity model, remains low: 8% are mature, 35% are transitioning, and 57% are inactive, with 90% of the latter having made no digital investments [6]. This contrast between strong potential and slow diffusion highlights a broader challenge: evidence on actual adoption and the magnitude of benefits reported by adopters is often unclear.

The existing literature on smart farming has primarily focused on identifying the drivers and barriers to technology adoption. Several internal factors (e.g. user awareness, perceptions of costs and benefits, and risk-bearing capacity) and external factors (e.g. regulatory policies, incentives, and infrastructure) influence technology adoption [7]. Behavioural aspects such as individual intention, perceived usefulness, and socio-cultural influences also shape adoption choices [8]. Studies show that adoption determinants operate at multiple levels, ranging from individual characteristics such as education and skills to farm and managerial capacity, technological features including complexity and compatibility, psychological factors such as social trust, and the broader external environment, including policy and connectivity [9]. These factors interact in complex ways, encompassing technical, human, and institutional elements, and generate heterogeneous effects across regions and production environments [10]. Moreover, adoption is generally higher on larger farms and progresses unevenly across technology types, with simpler diagnostic tools being adopted earlier and more widely than advanced technologies, reflecting scale constraints and uncertainty regarding financial returns [11]. Mixed findings on adoption outcomes [12] suggest that a stronger intention to adopt SFTs often depends on clear evidence of productivity, cost efficiency, and sustainability performance [13]. Studies on technology acceptance highlight that favourable intentions do not always translate into adoption behaviour, underlining the importance of using farm-level data to analyse observed adoption and post-adoption outcomes [8]. Without such evidence, farmers face uncertainty, especially smaller farms that struggle with high entry costs and limited capital [14]. Expectations of profitability also play an important role, as farmers and agricultural entrepreneurs are more likely to adopt technologies offering quicker returns, while interest may be lower for technologies whose benefits are realised in the long term [15]. Yet, there is very little attention in real-world scenarios to whether these adopted technologies are associated with economic and operational benefits. Several existing studies highlight the need to evaluate technologies beyond technical performance, considering their economic implications in farming and learning from the experiences of current adopters [16–20]. Missing this opportunity to learn from adopters weakens the feedback loop necessary for widespread and successful integration of SFTs, limiting the evidence base for policy design.

While studies highlight the potential of SFTs to improve yields, reduce costs and enhance sustainability, very few provide comprehensive, farm-specific evidence on the economic feasibility of technology adoption across diverse farm sizes (e.g. small, medium and large) and sectors (e.g. crops, livestock or integrated systems). Many studies focus on a single smart farming technology, a specific agricultural sector or a particular crop, limiting their broader applicability [21–23]. Consequently, such evidence often generalises outcomes and does not capture variations in economic performance when technologies are used across different farm structures and production environments. In addition, interactions among different technologies and existing farm practices may lead to heterogeneous effects that cannot be ignored. Systematic reviews of Agriculture 4.0 further indicate that much of the research remains focused on descriptive analysis of technologies, with comparatively less attention to the livestock sector, and uses a wide range of evaluation indicators, while empirical validation of economic and environmental benefits at farm level is limited and uneven, particularly when multiple technologies are adopted together [24]. When impacts are assessed, they are mostly evaluated through case studies in specific farm or environmental contexts, providing valuable insights but limiting the generalisation of results across broader farming systems [8]. The lack of standardisation of evaluation frameworks further reduces the usefulness of existing evidence for policy and decision-making.

Therefore, three consistent gaps emerge. First, most studies rarely analyse adoption across the full portfolio of SFTs within a single empirical framework, limiting comparison of technology adoption and spread across farm systems. Second, research assessing the impacts of smart technologies is limited, with most studies reporting hypothetical benefits rather than perceived changes in revenue, costs, water use, labour, or chemical inputs from actual adopters. Third, very few studies jointly examine adoption and impacts using appropriate econometric methods. Most do not control for differences between adopters and non-adopters in knowledge, organisation, or exposure to technology, which can bias results. Only a small number of studies use models such as Probit-Heckman, and almost none apply them across multiple technology categories.

This study addresses these gaps by conducting a dedicated farm-level survey across Italy, capturing the adoption of seven SFT categories and six key impact indicators (revenue growth, cost savings, water savings, labour savings, fertiliser savings, pesticide savings). This allows us to provide a national-level understanding of who adopts smart technologies, the impacts associated with adoption, and how technologies differ in adoption and perceived benefits. The main objective of this paper is to examine the determinants of adoption and impact outcomes of smart agricultural technologies in Italy to address three major research questions:

1. *RQ1: Which farmer, farm, and organizational characteristics determine whether a farm adopts at least one smart farming technology?*
2. *RQ2: What economic impacts on revenue, cost savings, and water, labour, fertiliser, and pesticide savings are perceived and associated with adopting smart farming technologies?*
3. *RQ3: How do smart farming technologies differ in adoption patterns and perceived impacts?*

To address these research questions, the study estimates a standard Probit adoption model, using a binary variable equal to one if the farm has adopted at least one smart farming technology. Additionally, to analyse the impact outcomes while correcting for non-random selection, Heckman two-step selection models are subsequently applied. This is one of the first national studies to jointly analyse adoption and impacts across multiple SFT categories.

This study provides a national perspective that has been largely missing from the literature. It advances research on Smart Farming Technologies (SFTs) by moving beyond adoption intentions and perceived barriers to provide real-world evidence on farmers' perceived post-adoption outcomes. The study evaluates whether these technologies are associated with the expected benefits in economic performance, resource use, and sustainability. Notably, it is not limited to a single technology, crop, or farming system, but examines a systematically classified range of SFTs across diverse farms and sectors.

2. Materials and methods

2.1. Study design and sampling

The study is based on a cross-sectional farm-level survey conducted nationwide in Italy. A structured questionnaire was developed between April and June, followed by pre-testing in July with a small group of farmers. Data collection took place from August to October 2025.

A non-probability convenience sample, supported by network-based dissemination, was used to reach farms across multiple regions and production systems. The questionnaire was disseminated via Agriliv's platform and subsequently through Edagricole, the main publisher in agricultural topics in Italy, with several leading technical journals widely read by farmers and agricultural advisors. The survey was further promoted through its associated editorial and digital platforms linked to a professional database of over 23,000 contacts. This figure reflects the size of the addressable database rather than a controlled distribution of surveys to individual recipients. A total of 859 responses were recorded, corresponding to an approximate response rate of 3.7% relative to the database size. Among those received, 345 complete responses were retained after excluding partial entries and those lacking core variables. Participants were selected using a combination of random and snowball distribution. Participation was voluntary and anonymous, and both adopters and non-adopters of smart farming technology were included to capture variations in current use, future use, perceived barriers, and other comparative differences.

2.2. Data collection

The data collection tool was an online questionnaire developed using the Qualtrics platform. Each participant received information about the project objectives and the survey, as well as a brief introduction to smart farming technologies. The questionnaire was divided into sections, with each question coded to collect specific information relevant to the study's purpose. After obtaining participant consent, the questionnaire collected information in three main categories: i) smart farming technology use, ownership, and support status; ii) technical information on perceived economic and resource-saving impacts; and iii) socio-demographic and farm structure characteristics.

The survey covered seven categories of smart farming technologies based on their functional roles, reflecting the main technologies identified in the smart and precision farming literature and enabling comparative analysis across clear technological layers, rather than focusing on individual technologies or tools.

1. Data collection systems (proximal sensors, weather stations, satellite imagery)
2. Autonomous vehicles (AV) and robotics (drones, robotic equipment)
3. Smart and connected machinery (intelligent tractors, automated steering)
4. Mobile and portable devices (smartphones, tablets, farm apps)
5. Decision Support Systems (DSS crop protection, irrigation forecasting, risk models)
6. Farm Management Information Systems (FMIS and digital farm records)
7. Cloud digital infrastructure (remote storage, data processing)

These categories were maintained to collect the most crucial information on the six perceived impacts of their adoption: revenue growth, cost savings, water savings, labour savings, fertiliser savings, and pesticide savings. The questionnaire included several multiple-choice questions to gain insights into the various dimensions of adoption and its impacts, such as:

- Binary (yes/no) questions for current adoption, future intention to adopt (to ensure a clear and unambiguous adoption decision), cooperative membership, and whether funding and training support were received.
- Five-point Likert scale questions (from completely disagree to completely agree) for the social and environmental sustainability of the technologies (e.g. reduced drudgery, improved working conditions, lower emissions, reduced pollution).
- Multiple choice and multiple response categorical questions include an ' other (specify)' option for ownership status (owned, leased, shared, contracted), operational uses on farms (soil preparation, sowing, monitoring, irrigation, fertilisation, plant protection, harvesting, post-harvest, livestock management, logistics, labour management), reasons for non-adoption among non-users, and production type (crop, livestock, mixed, permanent grassland).
- Percentage range categories are used to quantify perceived impacts on revenue, costs, and resource savings (water, labour, fertiliser, pesticides).
- Numeric entry fields for continuous variables such as farm size and the farmer's age.
- Nominal categorical item for gender and ordinal categorical scales for education level, knowledge of digital technologies (ranging from none to highly specialised), and the share of agricultural income in total household income (from 0–20% to 80–100%).
- Dropdown selection for province and farm location.
- Open-ended questions to collect insights on any other positive impacts, disadvantages and barriers to technology adoption.

All the impact variables are based on farmers' self-reported assessments following adoption and therefore reflect perceived impacts. Table A1 in Annex provides description of the sections and questions used in survey.

2.3. Model estimation

Data were screened for completeness and checked for missing values. Only fully completed responses with all core variables ($n = 345$) were included in the analysis. The Nomenclature of Territorial Units for Statistics (NUTS-1) macroregion was treated as a categorical variable. Continuous variables (e.g. farm size, farmers' age) were retained in numeric form, ordinal variables (e.g. education, knowledge level) were coded in ascending ranks, and binary variables (e.g. gender, yes/no responses) were coded accordingly.

Descriptive statistics were used to summarize farm and farmer characteristics, socio-economic conditions, ownership, funding, and training. Open-ended responses were reviewed and integrated with the main data. Adoption and impact levels were compared regionally according to the NUTS-1 macro-regional classification (North-West, North-East, Centre, South, and Islands). Technology portfolios were analysed in terms of adoption intensity, technology combinations, and distributions, while production type, technology application fields, and reasons for non-adoption were summarised using frequency and percentage distributions.

The econometric framework comprises a Probit model for technology adoption and a Heckman two-step selection model to estimate post-adoption impacts while correcting for potential sample selection bias. A Probit model is suitable for analysing binary adoption decisions, where the probability of adoption is modelled as a function of explanatory variables [25]. Probit models are widely used in empirical research on smart or digital agriculture technology adoption [12,26–28], validating their suitability for modelling farmer decision-making and post-adoption studies.

Our study relies on several key assumptions of the econometric models. The probit model assumes a parametric relationship between explanatory variables and a binary outcome, deriving probabilities by applying a transformation to a linear index through the cumulative normal distribution function [29]. It also assumes that the error term follows a standard normal distribution, observations are sampled independently and at random from the population, and regressors remain exogenous to guarantee consistent estimation [25]. The model also assumes that there is a nonlinear relationship between the explanatory variables and the probability of the outcome. This means that the probability function has an S-shape and is between zero and one [30].

Adoption was defined using a binary variable indicating whether a farm has adopted at least one of the smart farming technologies (AnyTech = 1), and subsequently for each technology category. Here, AnyTech_i^* denotes an unobserved adoption index, while the observed adoption outcome AnyTech_i takes the value one when $\text{AnyTech}_i^* > 0$ and zero otherwise.

$$\text{AnyTech}_i^* = X_i\beta + u_i \tag{1}$$

$$\text{AnyTech}_i = \begin{cases} 1 \text{ if } AnyTech_i^* > 0 \\ 0 \text{ if } AnyTech_i^* \leq 0 \end{cases} \tag{2}$$

Then the model takes the form:

$$P(\text{AnyTech}_i = 1|X_i) = \Phi(X_i\beta) \tag{3}$$

where in the above equations, P(.) is the probability of adoption by farm i, and Φ denotes the cumulative distribution function of a standard normal random distribution [31]. β is the vector of parameters to be estimated, and u_i is an error term. The vector X_i includes farmer characteristics (age, gender, education, knowledge), farm characteristics (farm area, arable area, livestock presence, household income share from farming), organisational characteristics (cooperative membership), and regional dummy variables as explanatory variables.

To provide a more intuitive interpretation of the Probit results, marginal effects are derived to measure the responsiveness of the adoption probability to changes in the explanatory variables (Eq. (4)) [32].

$$\frac{\partial P(\text{AnyTech}_i = 1|X_i)}{\partial x_{ik}} = \phi(X_i\beta)\beta_k \tag{4}$$

Where ϕ denotes the standard normal probability density function, x_{ik} represents the k-th explanatory variable for farm i, and β_k is the corresponding coefficient.

Average marginal effects are then obtained by calculating these effects for each observation and taking their sample mean, providing a representative measure at the sample level.

To evaluate post-adoption impacts, Heckman two-step selection models were estimated for each of the six impact indicators reported to assess adoption outcomes while correcting for the potential selection bias.

Selection bias arises when the sample of observed outcomes is not randomly selected. Certain unobserved factors that drive a farmer's decision to adopt a technology may also influence the eventual outcomes, creating a hidden link between the two. Sample selection bias is a specification issue that arises from non-random selection and is comparable to an omitted variable problem [33].

In this context, adoption and its impacts can be seen as a two-stage process, where post-adoption outcomes are observed only for adopters, creating a non-random sample. This non-random selection could result from unobserved factors influencing adoption, such as farmers' risk preferences or innate managerial ability, which could also influence the outcome variables, leading to biased estimates in conventional models.

The Heckman selection model posits that sample selection is potentially non-random and corrects this by jointly modeling both the selection and the outcome processes. It assumes that the error terms of the selection and outcome equations follow a joint normal distribution, and their correlation captures the presence of selection bias [33]. Additionally, the model assumes the availability of valid exclusion restrictions for robust identification; however, in their absence, identification is based on the nonlinearity of the inverse Mills ratio obtained from the selection equation [34].

To address this issue, the Heckman model incorporates the inverse Mills ratio (IMR) as a specialised regressor in the second-stage outcome equation. Derived from the first-stage Probit selection model, the IMR serves as a mathematical proxy for previously omitted unobserved factors [33]. The inverse Mills ratio is computed for each observation based on the predicted values from the Probit model and is defined as the ratio of the standard normal probability density function to its cumulative distribution function [35]. By accounting for the correlation between the error terms of the selection and outcome equations, this approach corrects for sample selection bias [25,33]. Ultimately, the IMR serves as a diagnostic test; a non-significant coefficient on the IMR indicates that the selection process does not systematically bias the outcome estimates. In such cases, the results provide consistent and robust estimates of the impacts across the sampled observations.

In the first stage, we use the Probit adoption model and then compute the inverse Mills ratio (Eq. (5)). In the second stage (Eq. (6)), we estimate the post-adoption impacts following Heckman framework as follows [25,33,36]:

$$\lambda_i = \varphi(X_i\beta)/\Phi(X_i\beta) \tag{5}$$

$$\text{Impact}_i = Z_i\delta + \rho\sigma\lambda_i + \varepsilon_i \tag{6}$$

where, λ_i denotes the inverse Mills ratio, φ(.) and Φ(.) are the standard normal probability density function and cumulative distribution function, respectively. Z_i is the vector of determinants of perceived impact, δ is the corresponding parameter vector, ε_i is an error term and ρσ captures the sample selection bias.

Another essential assumption for regression-based models is that there is no significant multicollinearity between explanatory variables. This was assessed using generalized variance inflation factors (GVIF) for all covariates, including those that are conceptually related, such as education level and digital knowledge. The adjusted values (GVIF^(1/(2·Df))) were all substantially lower than the generally accepted threshold of 5, suggesting that there is no evidence of problematic multicollinearity [37].

Finally, R software was used for both descriptive and inferential statistics from the models.

3. Results

3.1. Smart farming technology adoption pattern

3.1.1. Descriptive statistics

The sample included 345 Italian farms, with the highest number of responses from the North-East (35.4%) and South (22.6%), followed by the North-West (18.6%), Centre (15.1%) and Islands (8.4%). Respondents were predominantly male (69.9%), with 16.0% female, 2.6% identifying as other, and around 11.6% preferring not to disclose their gender.

Regarding digital literacy, intermediate knowledge (40.6%) and basic knowledge (32.5%) were more common, while 20.3% reported advanced or highly specialised knowledge, and only a small proportion reported no digital knowledge (6.7%). Education levels among respondents were relatively high, with over half (52.1%) holding a university degree or higher, 35.9% having a high school diploma, and fewer than 9.3% reporting only basic schooling. Additionally, 2.6% of respondents did not report their education level.

Farm size distribution showed that 32.8% manage farms smaller than 10 ha, 37.5% operate farms of 10–50 ha, and 27.0% manage farms larger than 50 ha, while 2.9% did not report. Average farm size ranged from about 41 ha in the South to 101 ha in the Centre, with the Northern regions showing intermediate values (60–69 ha). Regarding production type, across the full sample, farming was predominantly crop-arable based (80.3%), with the North-East (34%) and the South (25%) accounting for the largest shares, followed by mixed farming (11%), permanent crops (4.3%), and livestock-only farms (3.5%). Most mixed farms were concentrated in the North-East (45%) and North-West (32%), with similar patterns observed for permanent pastures. Although livestock farms represented the smallest production group, they were scattered across all regions, with 14.5% of all farms having livestock.

A total of 42.3% of farms reported cooperative membership, while 57.1% were not affiliated, and very few did not report. Agricultural activities accounted for at least 60% of total household income for

37.9% of respondents, including about 26.5% who were nearly fully dependent on agriculture (81–100%), while about 21.2% chose not to provide income information. Full regional socio-demographic distributions are provided in Annex Table A2.

Adoption patterns varied significantly across Italy. Regional differences were pronounced, with the highest adoption rates consistently found in the North-East and Centre for most technologies, particularly data sensors (54% and 43%), DSS (37% and 34%), and FMIS (37% and 39%). Smart machinery adoption ranged from 33% in the North-West to 29% in the Centre but fell to 3% in the Islands. DSS and FMIS uptake was higher in the Centre and North-East (around 34–39%), while the Islands consistently reported low usage across all categories (≤10% in most cases). Robotics/AV and cloud platform adoption remained underdeveloped nationally, with regional levels for robotics/AV between 12 and 18%, highest in the North-East and almost no uptake in the Islands, while cloud adoption remained low nationwide and minimal in the Islands (3%) (Table 1).

The future intention to adopt remained substantially higher across all categories, demonstrating strong demand for SFTs. Among the SFTs, mobile and portable technologies generated the greatest interest (90%), followed by FMIS (83%), data sensors (81%), and DSS (77%). Even advanced technologies such as smart machinery and robotics/AV showed higher levels of interest, with over 60% of respondents indicating an intention to adopt (Fig. 1).

3.1.2. Technology portfolio and intensity

Among adopters, Fig. A1 shows lower intensity, defined as the number of SFTs adopted by each farm. The distribution indicates decreasing adoption intensity as the number of technologies increases, with most farms adopting one (22.2%), two (22.6%), or three (20.6%) technology combinations. Only 17.3% of farms adopted technologies from four categories, and adoption intensity was limited, with 11.7% using five technologies and a significant drop for six (3.6%) and all seven (2.0%) technologies. The portfolio analysis showed strong intensity in the use of mobile/portable tools and data sensors, frequently complemented by DSS and FMIS. Other technologies, such as robotics/AV, cloud, and smart machinery, appeared less frequently (Fig. A2).

Fig. 2 presents the results of smart farming applications across various use cases, with the highest adoption in data-intensive and input management activities, led by data analysis (14.7%), plant protection (13.1%), fertilisation (12.0%) and irrigation (10.8%). Moderate adoption is observed for sowing (9.5%), crop monitoring (9.3%) and soil preparation (7.6%), while adoption in other areas remains lower, including harvest (6.9%), labour management (3.9%), logistics (2.5%), post-harvest (1.9%) and livestock management (1.8%). This suggests a current prioritisation of precision input management and decision support over post-production processes.

3.1.3. Ownership, funding and training support

Ownership models varied greatly across technology categories. Nationally, full ownership was most common (60.6%), followed by shared ownership (21.8%), renting or leasing (12.4%), and outsourced or contracted services (5.2%). Full ownership was highest for mobile and portable devices and data sensors across all macroregions, while robotics/AV, DSS, FMIS, and cloud platforms showed more varied ownership models.

In terms of structural support for training and funding received, data sensors, mobile and portable technologies, and smart machinery – especially in the North-East – showed consistently strong participation. DSS, FMIS, robotics/AV, and cloud platforms showed lower and more uneven support, while the South and especially the Islands consistently recorded the lowest levels of both funding and training across all technologies and regions (Table A3). Additionally, training was consistently higher than funding received across technologies and macroregions.

3.1.4. Barriers to adoption

Non-adoption of smart farming technologies was found to be mainly driven by higher investment costs and the perceived irrelevance of these technologies to farm size or goals, followed by limited technical knowledge and uncertainty about associated costs and benefits. Other barriers, such as risks of system failure and connectivity issues, were reported less frequently (Fig. 3).

3.2. Determinants of adoption

3.2.1. Any tech model

Table 2 presents Probit estimates and average marginal effects for the adoption of at least one smart farming technology. The probit model for any smart technology adoption identified several significant predictors. Adoption was significantly associated with farmer knowledge, cooperative membership, gender, and arable cropping area.

Farmers' level of knowledge emerged as the strongest driver of adoption. Farmers with higher digital knowledge had about a 34 percentage point higher probability of adopting at least one smart farming technology compared to those with low knowledge, while medium knowledge was associated with a 19 percentage point increase. In contrast, formal education is not statistically significant in the Any Tech model, although it became relevant in technology-specific models (Table A4).

Being a member of an agricultural cooperative was another important and positive factor, with members 22 percentage points more likely to adopt. Similarly, female farm managers were significantly more likely than males to adopt smart technologies, with a 19 percentage point higher likelihood. Additional area (ha) under arable cropping increased the probability of adoption, while total farm area had a small negative effect, though this was not statistically significant. Farms with livestock showed a negative coefficient, but this effect was also not statistically significant. Age had a slightly negative effect, suggesting older farmers were less likely to adopt, but this was not a significant determinant when other factors were considered. Regional differences were not significant, although there was a positive coefficient and higher adoption in the Northern regions.

The model demonstrates a good overall fit, with a McFadden's R^2 of 0.266—a value indicating a substantial improvement over the null model and within the range considered to represent a good model fit [38]. The adjusted McFadden R^2 also remains acceptable, suggesting that model performance is not driven by overfitting. Consistent results are obtained using alternative pseudo-R^2 measures, with Cox–Snell and Nagelkerke R^2 values of 0.27 and 0.39, respectively. The model correctly classifies about 77% of observations, indicating good predictive

Table 1
Smart farming technology adoption by technology type and region (%).

NUTS Macroregion	Data Sensors	Robotics/AV	Smart Machinery	Mobile/Portable	DSS	FMIS	Cloud
Centre	54	12	29	65	37	37	27
Islands	10	0	3	28	7	10	3
North-East	43	18	31	60	34	39	19
North-West	42	13	33	56	17	30	8
South	32	14	17	54	36	24	13
Grand Total	39	14	26	56	30	31	15

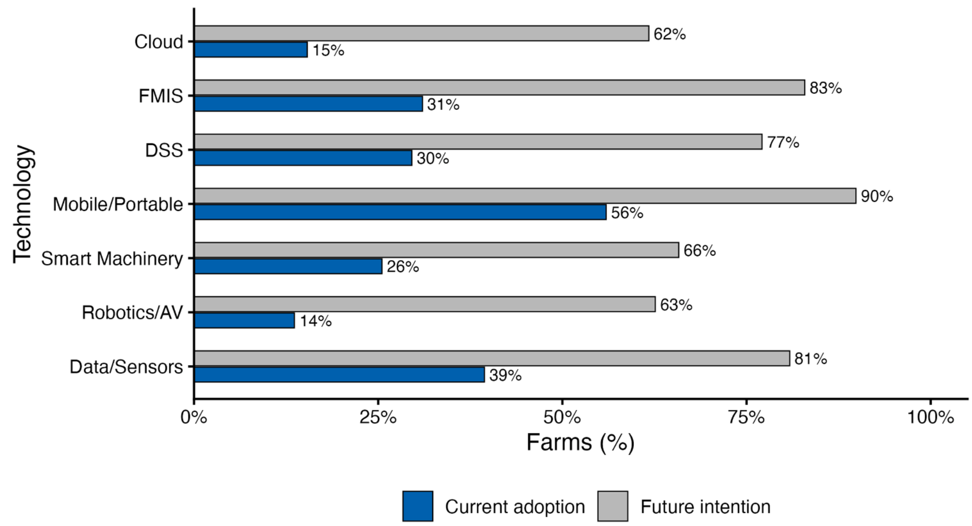

Fig. 1. Current adoption and future intention to adopt SFTs among Italian farms.

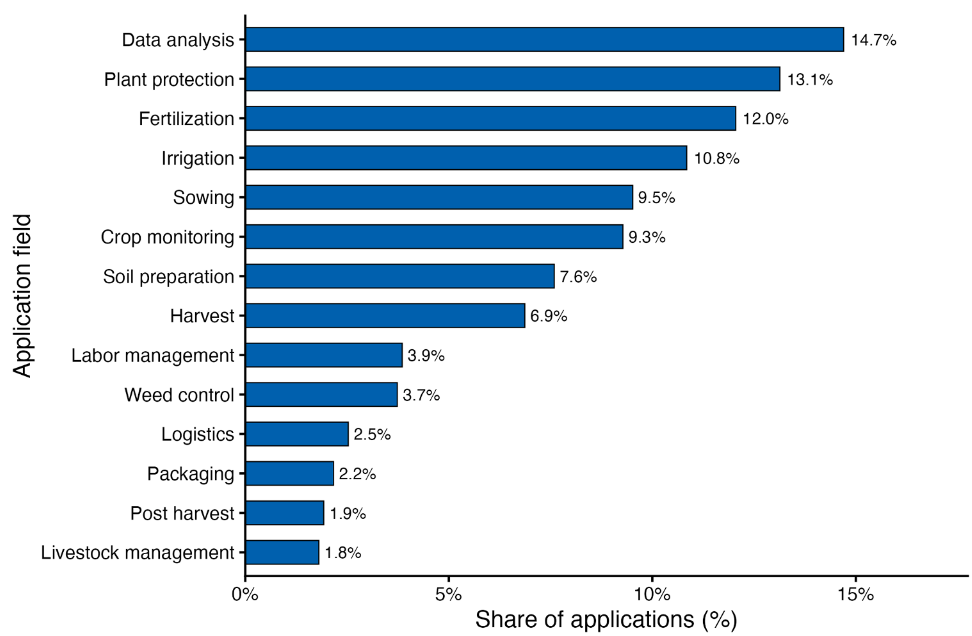

Fig. 2. Fields of smart farming technology adoption in Italian farms.

accuracy for technology adoption decisions.

Such values are consistent with broader social science literature in which lower goodness of fit values are considered acceptable when key predictors are statistically significant [39], including similar probit-based studies reporting comparable levels of model fit [26,40,41].These relatively moderate values may reflect the complexity of technology adoption decisions, data limitations arising from unobserved factors (e.g., weather, prices, and management practices) and measurement constraints, indicating scope for improving model fit in future research through more detailed farm-level variables and improved measurement of factors relevant to technology adoption.

3.2.2. *Tech by tech model*

Adoption drivers varied substantially across technology categories (Table A4), although digital knowledge was consistently the strongest determinant, as in the Any Tech model. Formal education had a positive effect for more complex technologies, as medium and high education significantly increased adoption of data sensors, robotics/AV, and cloud platforms, but showed no significant effects for smart machinery, DSS, or FMIS.

Cooperative membership significantly increased the adoption of most technologies, except for data sensors and cloud platforms. Female farm managers were more likely to adopt mobile technologies and DSS, while gender effects were insignificant for other technologies. The presence of livestock reduced the adoption of data sensors, DSS, and FMIS, whereas a larger arable cropping area was positively associated with the adoption of data sensors, smart machinery, and FMIS. Regional effects were generally weak, with significantly lower adoption of data sensors and robotics/AV in the Islands, and significantly lower cloud adoption in the North-West.

3.3. *Impacts of adoption*

3.3.1. *Descriptive impact patterns*

Fig. 4 presents assessments by adopters of the social and environmental sustainability effects of smart farming technologies. Across all

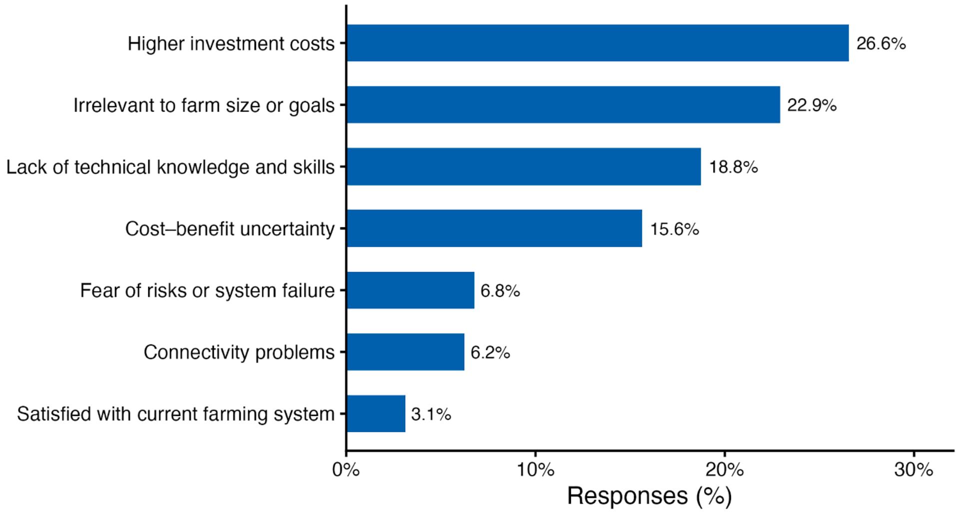

Fig. 3. Barriers to adoption of smart farming technologies.

Table 2
Probit estimates and marginal effects for any technology adoption.

Variable	Coefficient	Standard Error (coef)	Marginal Effects	SE (AME)
(Intercept)	−0.845	0.794	-	-
Age	−0.007	0.009	−0.002	0.002
Gender (Female)	0.893***	0.336	0.191***	0.058
Education (ref. Low)				
Medium	0.439	0.413	0.117	0.114
High	0.656	0.441	0.170	0.118
Knowledge (ref. Low)				
Medium	0.678***	0.231	0.195***	0.065
High	1.397***	0.361	0.337***	0.069
Farm Structure				
Total Farm Area	−0.007	0.004	−0.002	0.001
Crop Area	0.013**	0.006	0.003**	0.001
Has Livestock	−0.365	0.457	−0.093	0.12
Member Cooperative	0.865***	0.232	0.220***	0.056
Share of HH Income Agri.	0.003	0.004	0.001	0.001
Region (ref. Centre)				
North-East	0.125	0.353	0.031	0.088
North-West	0.534	0.418	0.121	0.094
South	−0.207	0.358	−0.054	0.092
Islands	−0.489	0.516	−0.132	0.141
McFadden R2	0.26582571			
McFadden Adj R2	0.145520298			
Cox-Snell R2	0.273807918			
Nagelkerke R2	0.391221168			
Classification accuracy	0.769230769			

***, **, * Indicate significance at 1%, 5% and 10% levels.

technology categories, most farmers agreed with statements indicating positive effects on environmental sustainability indicators, such as reduced emissions and improved pollution control, and on social sustainability indicators, such as reduced physical fatigue and better working conditions. Overall, responses were dominated by strong or moderate agreement. Strong agreement was most frequently observed for robotics/AV, smart machinery, data sensors, and DSS, while FMIS and cloud platforms showed comparatively lower, though still predominantly positive, evaluations, largely characterised by moderate agreement.

Figs. 5 and 6 show significant variation in the perceived impacts of smart farming technologies across impact indicators and macroregions.

Robotics/AV, DSS, and data collection systems consistently produced the highest mean impacts, while FMIS showed the lowest values across all indicators. Among the technologies, revenue growth was highest for robotics/AV (10.11%), followed by data collection systems/sensors (9.93%), DSS (9.67%), and cloud platforms (9.49%). Lower mean revenue effects were observed for smart machinery (8.13%) and mobile tools (7.02%), with FMIS showing the smallest revenue gains (4.64%). A similar pattern was seen for cost savings, with robotics/AV (11.52%) and DSS (10.92%) showing the largest savings, followed by cloud platforms (9.44%), smart machinery (9.27%), and data sensors (9.04%). Mobile/portable technologies showed moderate cost savings (8.98%), while FMIS again accounted for comparatively lower effects (5.16%).

The perceived impacts on resource-saving varied more noticeably among the technologies. Water savings were highest for DSS (11.67%), data sensors (10.86%) and robotics/AV (10.38%), followed by mobile/portable technologies (8.70%) and cloud platforms (7.30%), while smart machinery (4.23%) and FMIS (4.30%) showed lower savings. For labour savings, robotics/AV led (14.22%), followed by data sensors (10.41%), DSS (9.31%), cloud platforms (8.77%) and mobile/portable tools (7.56%), with smart machinery (7.25%) and FMIS (4.52%) reporting smaller impacts. Fertiliser savings were highest for data sensors (9.87%), robotics/AV (9.64%), smart machinery (9.05%) and DSS (8.76%), with lower performance from cloud platforms (7.60%), mobile/portable tools (7.51%) and FMIS (4.94%). Pesticide savings were greatest for robotics/AV (13.43%) and DSS (13.19%), followed by data sensors (10.93%), smart machinery (8.63%), cloud platforms (8.13%) and mobile/portable tools (8.08%), with FMIS showing the lowest mean reduction (5.04%).

Spatial heterogeneity was observed in the perceived impact levels of technologies. The most consistently high impacts across indicators by technology and microregion were found in the South, including revenue growth (data sensors 18.62%, DSS 17.38%, cloud platforms 16.15%), cost savings (DSS 18.07%, cloud platforms 15.45%), labour reductions (robotics/AV 21.77%, DSS 18.16%), and pesticide savings (DSS 21.89%, cloud platforms 20.05%). The North-West region showed strong performance, especially for robotics/AV in pesticide reductions (24.0%) and cost savings (15.0%), while data sensors were associated with revenue growth (10.44%) and pesticide reductions (12.06%). In contrast, the Centre and North-East displayed more moderate impacts, with lower revenue growth and limited resource savings.

In the Islands, technologies exhibited greater variation across the perceived impact dimensions. Higher impacts were noted especially for cloud platforms, DSS, and smart machinery, while other technologies

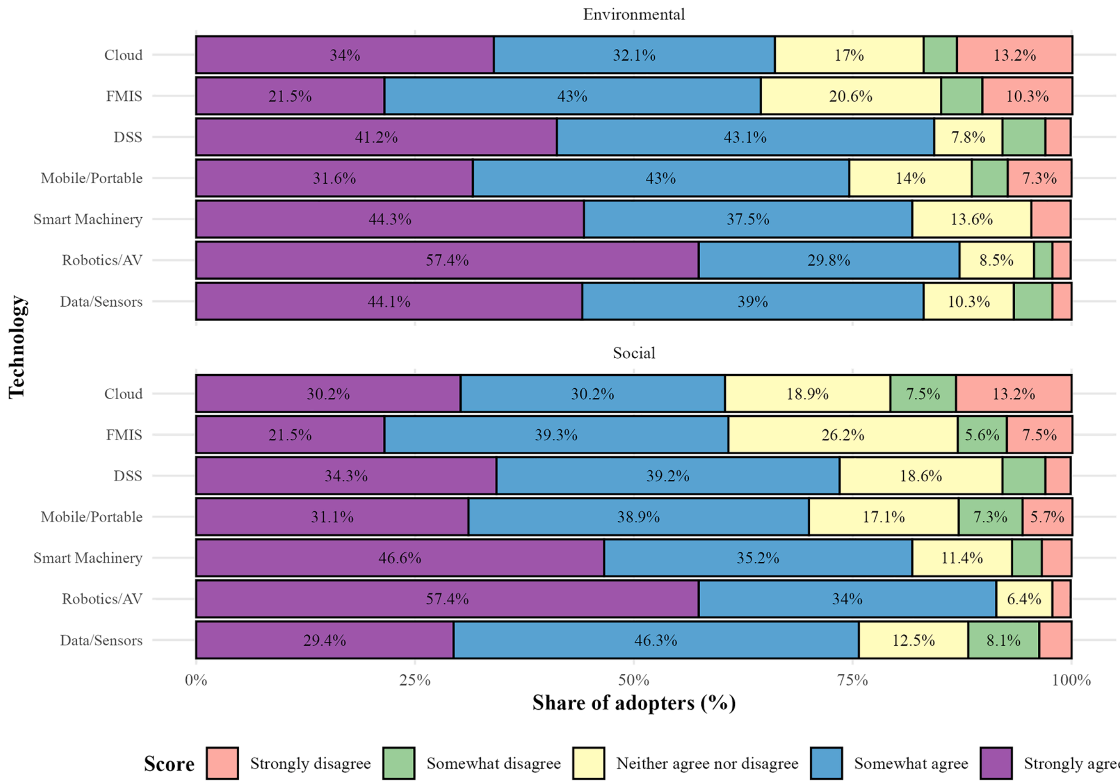

Fig. 4. Perceived social and environmental sustainability impacts of smart farming technologies.

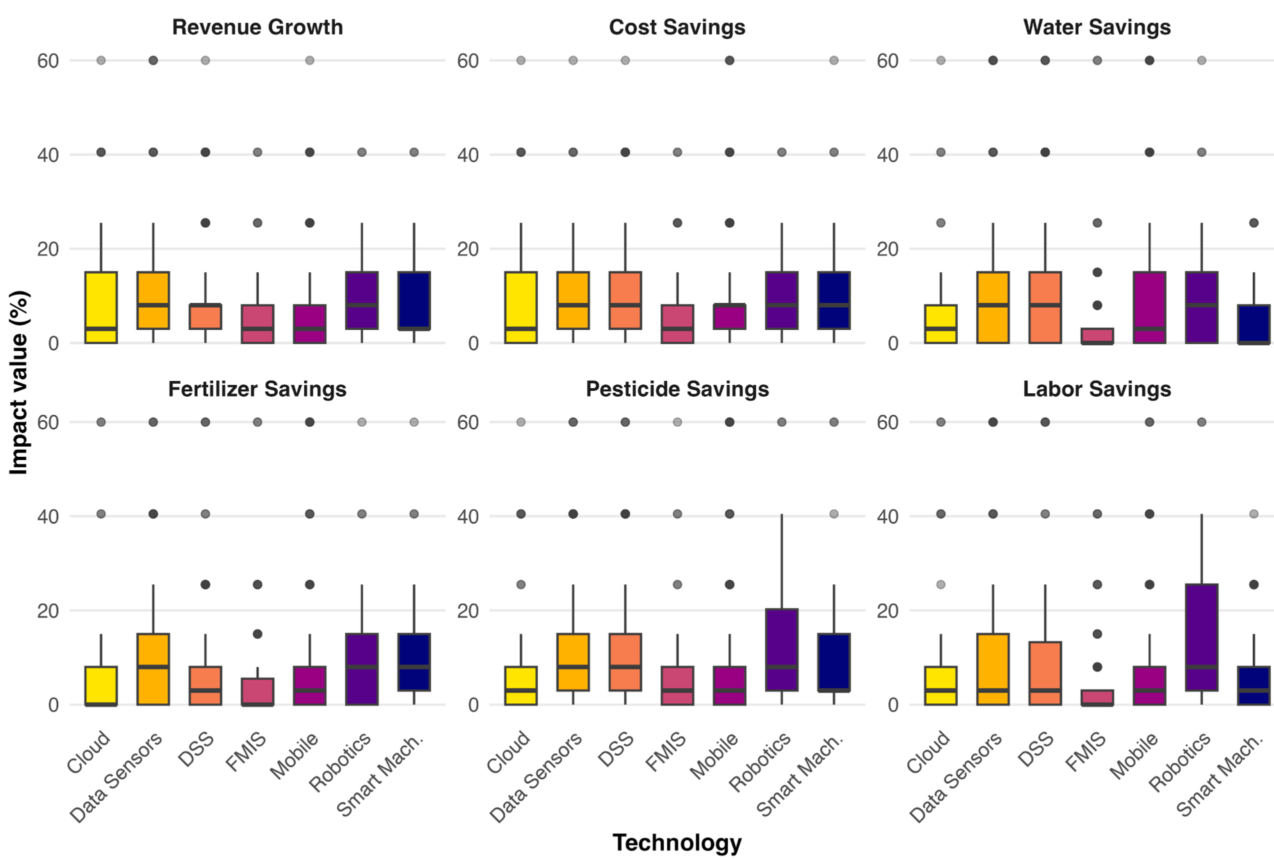

Fig. 5. Distribution of economic and resource-use impacts of SFTs (box and whisker plots).

such as FMIS showed limited effects.

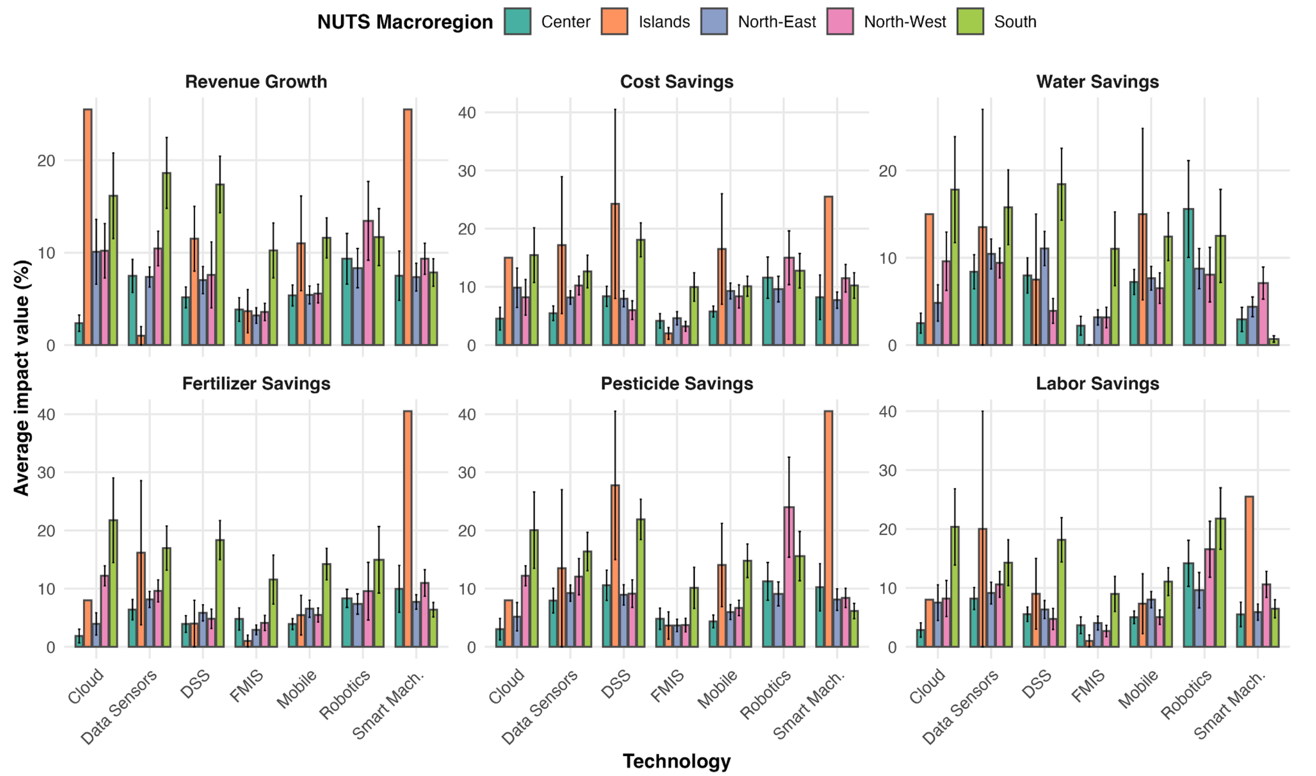

Fig. 6. Regional differences in the impacts of SFTs across Italian macro-regions.

3.3.2. Heckman two-step estimates for technology adoption and impacts

The results from the Heckman selection equation confirmed those of the AnyTech probit model, with adoption significantly influenced by farmers' digital knowledge, cooperative membership, and arable cropping area (Table 3). The inverse Mills ratio was statistically insignificant in all outcome equations, indicating no sample selection bias.

Results from the outcome equation showed that, upon adoption, the perceived impacts varied systematically with farm and farmer characteristics and regional context. Consistent with the adoption results, digital knowledge significantly enhances the performance of the technologies: medium knowledge increases the perception of cost savings and labour reductions, while high knowledge increases the perception of labour and pesticide savings. Total farm area has a positive and statistically significant association with revenue growth, whereas the arable cropping share of the farm shows a small but statistically significant negative association with revenue growth. Furthermore, the presence of livestock increases the perception of cost savings while significantly reducing the perception of water and pesticide savings.

Regional effects were noticeable at the impact levels. Although regional effects in adoption selection were insignificant, farms in the South and Islands reported significantly higher and positive impacts. Across all impact indicators, the South was highly positive and showed significant effects, while the Islands were positive and significant for revenue growth and cost savings, and highly positive but insignificant for pesticide savings.

4. Discussion

4.1. Determinants of smart farming technology adoption

The adoption of smart farming technologies in our study is far from uniform, showing clear heterogeneity across regions, farm types, and technology categories. The findings reveal that adoption is primarily driven by capabilities rather than scale. Digital knowledge consistently emerges as the most essential enabling factor, highlighting that smart farming requires not only access to technology but also perceived

Table 3
Heckman two-step estimates for any technology adoption (selection) and impacts (outcomes).

Predictor	Selection	Outcome					
		Revenue Growth	Cost Savings	Water Savings	Labor Savings	Fert. Savings	Pest. Savings
Gender (F)	0.893**	−0.631	7.348	2.495	2.053	0.308	0.364
Knowledge -Medium	0.678***	2.548	4.122**	2.941	6.620***	3.154	3.764
Knowledge -High	1.397***	1.841	0.478	2.314	5.360*	4.002	6.484**
Education -High	0.656	0.856	0.222	−6.528*	1.274	−3.246	−1.355
Member Cooperative	0.865***	−0.234	−1.882	−0.210	0.996	−0.176	1.759
Total Farm Area	−0.007	0.053**	0.024	−0.006	−0.026	−0.024	−0.037
Crop Area	0.013**	−0.051**	−0.019	0.001	0.029	0.028	0.039
Has Livestock	−0.365	2.375	4.299*	−4.584*	0.927	−3.064	−4.551*
NUTS -Islands	−0.489	7.496*	8.830**	0.952	−0.686	−0.960	7.721
NUTS -South	−0.207	6.029***	5.072**	5.177*	4.32*	8.602***	5.999**

Approximate pseudo-R^2 values ranged between 0.10 and 0.19.
***, **, * Indicates significance at 1%, 5% and 10% levels.

familiarity and confidence in using digital tools within farm management. Farmers with at least intermediate digital knowledge were much more likely to adopt smart farming solutions, as confirmed by our adoption model.

This suggests that the adoption process depends more on practical knowledge and learning than on obtaining an educational degree. This aligns with evidence of inequalities in digital literacy and limited access to training programmes, which hinder farmers from effectively using technology and perpetuate the digital divide [42,43]. Nearly 25% of farms report a lack of knowledge, and 34% cite insufficient information as key barriers to adoption [44]. In this context, education and training programmes are equally important, as positive perceptions and clear awareness of benefits strongly influence adoption [45].

Adoption is also influenced by organisational characteristics. The role of collective institutions in promoting technology exposure, risk sharing, and access to complementary services is strengthened by cooperative membership, which reduces informational and coordination obstacles, thereby lowering barriers to innovation. In regions such as the North-East, where cooperative networks and contributions are stronger, this results in greater diffusion of innovations. This aligns with evidence that cooperatives facilitate peer learning among farmers from the experiences of fellow adopters, reducing uncertainty [46] and embedding adoption within social and institutional networks rather than in isolation at the individual farm level [47–49].

Adoption varies depending on the type of technology. We found that relatively accessible digital tools, such as FMIS and cloud platforms, are more widely accepted by farmers than more complex and capital-intensive innovations like robotics and autonomous vehicles, which remain niche. The influence of cost and complexity leads to a decline in farmers' willingness to adopt these technologies as the level of automation increases [50]. This further supports our tech-by-tech model results, where formal education is more relevant to automated technologies, suggesting that improving digital literacy through training and education is vital for expanding the user base.

Interestingly, female-managed farms in Italy are not lagging in adoption rates; however, we found that they prefer accessible information and decision-oriented technologies to support farm management, planning, and daily operations. Similar studies suggest that targeted digital literacy initiatives help reduce gender gaps, supporting more inclusive involvement in farming [51]. While age is not a statistically significant determinant, younger farm managers tend to be more open to adopting new technologies, most likely due to their comfort with smart devices and willingness to experiment.

The type of farming system plays a key role in determining both the likelihood of adoption and the type of smart farming technologies adopted. Farms specialising in crop-based arable production has the highest adoption rates, reflecting a stronger alignment between available technologies and crop management needs for input optimisation, monitoring, and decision support. In contrast, livestock-based farms show lower adoption, particularly for data sensors, DSS, and FMIS, indicating a weaker perceived fit between these technologies and livestock management practices. This is consistent with the idea that uniform technology strategies are unlikely to be effective [52], as smaller farms may benefit more from affordable and shared digital tools, while larger farms are better positioned to adopt integrated, data-driven systems that align with farmers' greater willingness to pay for technologies that increase returns or reduce labour, followed by water savings [53].

Furthermore, our study revealed significant regional differences in adoption. The Northern and Central regions, supported by higher digital skills, better access to funding and training, a greater density of service providers, and more favourable enabling environments, all contributed to higher technology uptake. In contrast, lower adoption rates and fewer technologies in the South and Islands may be attributed to structural limitations rather than a lack of interest. This is supported by a study showing that Southern regions have distinctly lower innovation capacity and economic size than Northern regions, while the Islands occupy an intermediate position [54]. This regional divide may result from better capitalisation and benefits in the North, stemming from stronger agribusiness networks and innovation infrastructures that enable quicker diffusion of new technologies.

A supportive regional context can increase adoption beyond what farm-level factors alone would predict, consistent with studies identifying limited access to finance and credit as persistent structural barriers to smart farming adoption across diverse contexts [55,56]. At a broader spatial scale, the persistence of these regional gaps aligns with evidence that Italy is part of a Mediterranean digitalisation lag, where weak positive spatial spillovers limit the spread of smart farming technologies and maintain regional disparities [57]. Thus, our study clearly finds that the interplay between micro-level determinants (such as knowledge and skills) and macro-level conditions (such as regional initiatives and infrastructure) is critical.

4.2. Economic and resource impacts

Our study shows that adopting SFTs is associated with perceived improvements in both farm economic performance and resource use efficiency. However, rather than producing uniform impacts, SFTs appear to create value by addressing specific production constraints. The scale of the perceived impacts therefore depends less on adoption itself and more on whether the adopted technology effectively addresses challenges related to input use or reduces pressures on resources. It is important to distinguish between smart tools that mainly support farm management and record keeping (e.g. FMIS and cloud platforms) and those that directly affect production processes (e.g. sensors, robotics, smart machinery, and DSS). While both types of tools are essential, their ability to be associated with immediate economic and resource use benefits differs.

Firstly, we found a strong differentiation in economic impacts across technology categories, with robotics and autonomous vehicles, DSS, and data collection and sensing technologies consistently outperforming others in both perceived revenue growth and cost savings. Consistent with our findings, technologies that are automated or support real-time, informed decision-making are associated with farms achieving tangible economic returns because actions occur at the right time (irrigating, spraying, harvesting, allocating labour), allowing farms to save money, reduce waste, and increase earnings. In contrast, tools such as FMIS and cloud platforms mainly support managerial and organisational functions, which appear to be associated with benefits that are more incremental, indirect, or realised over longer time horizons. Our economic impacts align more closely with EU-level evidence in 2024, where agricultural digitalisation resulted in overall productivity and efficiency gains, with higher gross value (4.4%) and cost savings for inputs (5.7%) [58].

Furthermore, the greatest perceived benefits were reported by farms where technology helps reduce their main costs, especially labour. The greatest labour savings are associated with the adoption of robotics/AV, followed by data sensors and DSS, indicating that automation is most beneficial for farms facing high labour costs or shortages, while its economic returns are more limited where labour is readily available. Other resource-saving impacts in our study follow a similar pattern. Technologies operating directly in field processes, particularly DSS, data sensors, and robotics/AV, are associated with the largest perceived reductions in water use, fertiliser application, and pesticide use, while other technologies show comparatively weaker effects.

On average, water savings are especially notable for DSS and data sensor technologies, while pesticide reductions are greatest for robotics/AV and DSS. A DSS-based pilot project in Italian vineyards showed significant efficiency gains, including a 33.4% reduction in greenhouse gas emissions and a 7.6% reduction in pesticide use [59]. Consistent with these results, SFTs appear to create value by helping correct inefficient input and labour use. This is supported by studies from Southern Italy, where digitalisation has been linked to improvement in productivity, input efficiency, and the ability to cope with labour shortages, as demonstrated by experiences in Calabria [60,61]. Economically, this input saving is even more important in the current context of rising input prices, such as nitrogen fertiliser, which increased by about 176% between January 2020 and December 2022 following the COVID-19 pandemic and the Russia-Ukraine war, making precision and DSS-based nutrient management particularly valuable for fertiliser saving and farm profitability [62].

A key finding of this study is that perceived impact levels do not align with adoption levels across regions. Although adoption is more prevalent in the Northern and Central regions, farms in the South and the Islands report greater impacts once adoption occurs. In the South, revenue gains are 18.62% for data sensors and 17.38% for DSS, while labour reductions are 21% for robotics/AV and pesticide savings are 22% for DSS. The Islands also show significant revenue gains and cost savings for cloud platforms and DSS, even though fewer farms adopt these technologies. This is consistent with the census-based study using ISTAT (Italian National Institute of Statistics) 2020 data, which highlights a wider North-South divide in farm sustainability and digitalisation: the North-West has 64.2% sustainable farms compared with only 34.6% in the South [54], and Northern regions such as Trento and Bolzano are far more digitalised than Central and Southern Italy [63]. Thus, contrary to what adoption patterns alone might suggest, the South and the Islands, which combine lower baseline efficiency with younger farmers and larger farm sizes but weaker digital penetration and computerization [64], appear to offer greater potential for large marginal gains when smart farming technologies are introduced [65]. For example, in the South and the Islands, where water scarcity is a critical limitation, DSS and sensor-based irrigation technologies significantly improve water use efficiency and drought resilience compared to other regions. These differences are evident from the large variations across Italy in baseline irrigation infrastructure, digitalisation, and agrometeorological support [66].

A pressing situation with ongoing Mediterranean drought, Sicily declaring a natural disaster, reservoirs falling in Sardinia, and water shortages spreading to parts of Central and Northern Italy [66,67], along with climate projections indicating a decline in durum wheat yields of up to 30% by the end of the century [68] in large parts of Central and Southern Italy, explains why DSS and other water-saving technologies have shown greater perceived impact in climate-vulnerable regions.

In addition to the realised economic and resource impacts, adopters often report positive perceptions of the social and environmental sustainability outcomes associated with SFTs. There is strong consensus for robotics/AV, smart machinery, data sensors, and DSS, particularly regarding reduced fatigue, improved working conditions, and environmental benefits such as emission reductions and pollution management. FMIS and cloud platforms receive comparatively moderate, yet still favourable, evaluations. These perceptions align with evidence showing that 76% of European farmers expect economic gains from digitalisation, 72% expect environmental benefits, and 67% anticipate social improvements [69].

Lastly, our econometric results confirm that perceived impacts depend not only on technology adoption but also on its effective use. Digital knowledge significantly improves resource-saving outcomes, especially for labour, fertiliser, and pesticide savings, highlighting the importance of skills and learning ability in converting adoption into benefits. At the same time, farms in the South and the Islands report significantly higher impacts once they adopt, even though their adoption rates are lower.

5. Conclusion, implications and policy recommendations

This study provides the first integrated evidence for Italy on how smart farming technologies are adopted and how they are associated with farm performance, resource use, and sustainability across the country. By combining descriptive analysis with econometric modelling, we show that the adoption and perceived impacts of smart farming technologies in Italy are highly heterogeneous across farmers, technologies, and regions.

Importantly, the spatial pattern of adoption does not correspond to the same pattern of impacts. Smart farming technologies appear to reduce performance gaps by delivering the greatest perceived benefits where constraints and inefficiencies are most pronounced, such as in the South and the Islands. Technologies that act directly on production processes, particularly DSS, data sensors, and robotics, are associated with the largest gains in economic and resource savings, whereas management-oriented tools such as cloud platforms and FMIS are associated with more modest returns. Overall, smart farming technologies should not be seen as uniform productivity or performance-enhancing solutions; rather, their perceived economic and environmental impacts are essentially context-dependent, linked to local constraints, production efficiency, existing environmental pressures, and user capabilities. The key challenge for Italy is therefore not only to expand adoption but also to ensure that high-impact tools reach the farms and regions where marginal gains are greatest.

Our survey evidence indicates that smart farming in Italy remains at an early stage of digitalisation, primarily focused on optimising input use and data-driven decision-making. Advanced, fully automated, and AI (artificial intelligence)-enabled systems are still relatively rare and unevenly distributed across farms and regions. This is understandable given the ownership structures of SFT applications currently in use. We found that simple, low-cost technologies, such as mobile or portable tools and data sensors, are predominantly fully owned by farms, whereas more complex and capital-intensive technologies, such as robotics, autonomous vehicles, and decision support systems, are more often subject to shared ownership, leasing, or outsourcing.

This ownership pattern is consistent with the barriers reported by non-adopters. Higher investment costs and uncertainty about economic benefits discourage farmers from full ownership of advanced technologies, while limited technical knowledge and perceived irrelevance to farm size or production goals reduce their willingness to commit to long-term investments. As a result, farmers tend to rely on shared, leased, or outsourced arrangements for technology use to reduce financial risks and technical complexities. In the regional context, particularly in the South and the Islands, where farmers reported the lowest levels of training and funding support, these barriers strongly reflect the lower adoption rates despite the greater potential gains.

A closer look at where SFTs are primarily used in farming operations further clarifies the nature of this early stage of digitalisation. Adoption is concentrated in data analysis and core input management, such as fertilisation, irrigation, plant protection, and crop monitoring, while logistics, post-harvest handling, and livestock management remain much less digitised. Consequently, the perceived impacts are strongest in these input-intensive and decision-dependent areas, where SFTs directly influence timing, precision, and resource allocation. Ownership arrangements, application, and adoption barriers together create a situation in which low-risk smart tools spread widely, but technologies with the greatest transformative potential remain concentrated among a smaller group of farms and regions able to overcome financial and capability constraints.

Public policy should therefore adopt a two-step approach: first, promote farmers' familiarity with digital technologies and their ability to evaluate potential benefits; then, strengthen their capacity to use and integrate these tools effectively through training, advisory services, and cooperative-based mobilisation. Finally, integrating smart irrigation, fertilisation, and pest management tools into water, climate, and agri-environmental policies will improve farm profitability, resilience, and socio-environmental performance, while addressing the digital divide between lagging and advanced regions.

6. Limitations and future research

This study is not without limitations. Although we have a rich dataset on adoption and post-adoption outcomes reported by farmers, the results may still be affected by recall errors, subjective evaluation, and performance influenced by weather, prices, or management practices not fully observed in the data or controlled for in the models. The voluntary nature of the survey introduces self-selection, which may have resulted in an over-representation of more highly educated farmers and may have limited our ability to clearly disentangle the effects of education in the models. In addition, the survey relies on a non-probability sample and is therefore not statistically representative of the entire farming population. No ex ante stratification by geographic region or farm size was applied due to the nature of the dissemination approach; however, it captures substantial heterogeneity across regions, farm sizes, and production systems, which is essential for analysing adoption-impact relationships. Some technologies (FMIS, cloud) may deliver benefits over a long time horizon that our data may not have captured, considering the initial stage of digitalisation, as the survey does not capture the duration of technology use. Although the Probit and Heckman two-step models help to identify important patterns, some unobserved factors such as managerial ability or agronomic skills may simultaneously influence both adoption and the perceived impacts. Moreover, the analysis of technology categories represents average effects, potentially masking the effects of individual technologies within each category. The use of a binary (yes/no) measure for future adoption intention simplifies respondents' choices and may not fully capture intermediate or uncertain attitudes towards adoption. Future research could incorporate more nuanced scales to better reflect varying degrees of adoption intention. In addition, the lack of precise georeferenced farm coordinates limits the ability to conduct spatially explicit analyses of adoption patterns and impacts, which could provide deeper insights into local heterogeneity in future studies.

Future research should therefore combine longitudinal farm-level data and experimental trials to complement the reported evidence, strengthen inference, and better understand when impacts materialise and how they evolve over time. Integrating remote sensing and detailed cost-benefit analysis per farm would allow more precise measurement of economic and socio-environmental outcomes over time. Future studies could incorporate spatial data to enable the application of spatial econometric models and better capture localised heterogeneity in technology adoption and perceived impacts. In addition, the application of count models could be explored to better understand the determinants of adoption intensity. In addition, disaggregating technology categories into individual tools (e.g. irrigation DSS, yield monitors, variable rate sprayers) would help identify which components drive the observed impacts, while investigating the connections among different technologies could be the next step.

Ethics statement

This study involved a voluntary survey of farmers. Participation was anonymous and informed consent was obtained from all respondents prior to data collection. No personal or sensitive data were collected, and all data were treated confidentially in accordance with applicable ethical standards for survey-based research.

CRediT authorship contribution statement

Yogendra Katuwal: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Giulia Maesano:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Data curation, Conceptualization. **Davide Viaggi:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Annex

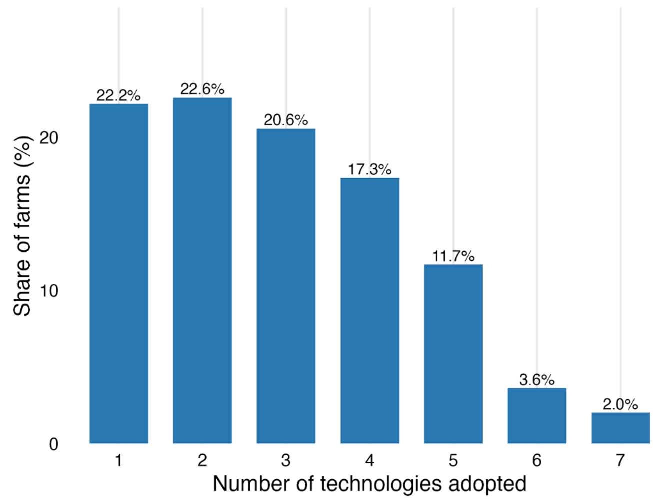

Fig. A1. Adoption intensity of SFTs among adopter farms.

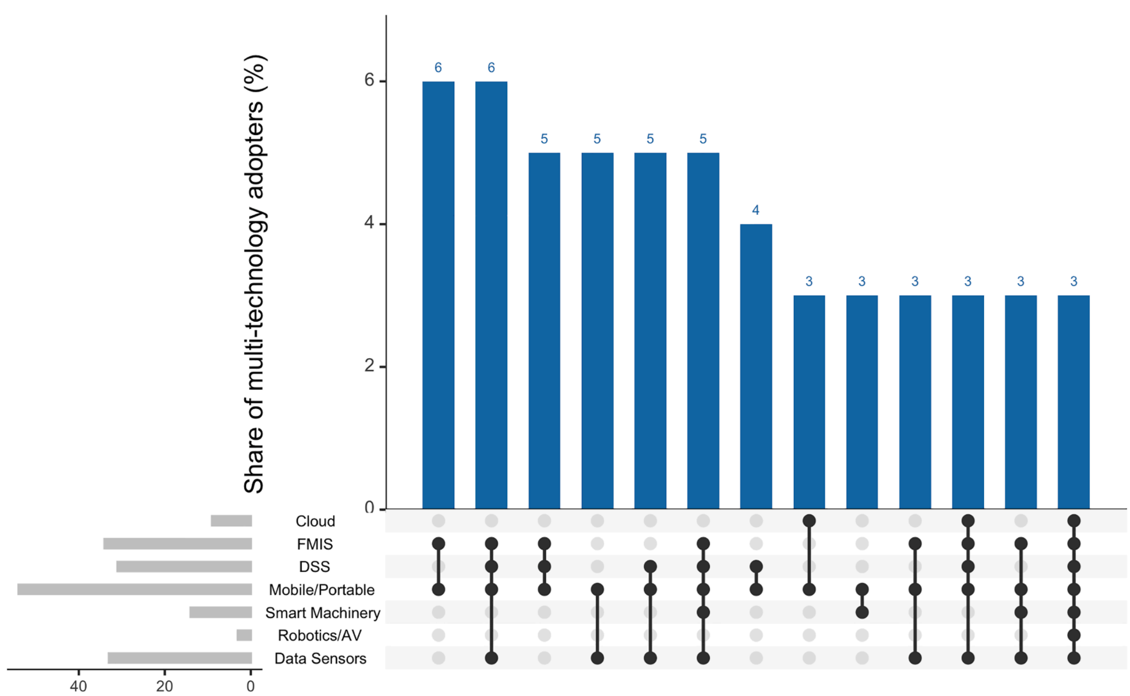

Fig. A2. Most frequently observed combinations of SFTs used by farms.

Table A1
Survey questionnaire.

Code	Question	Response options
1.0	Digital knowledge level for agricultural management	None; Basic; Intermediate; Advanced; Highly specialized
1.1.1–1.7.1	Current use of the technology	Yes; No
1.1.2–1.7.2	Planned future use of the technology	Yes; No
1.1.3–1.7.3	Technology ownership status	Owned; Shared; Rented/leased; Outsourced/contracted
1.1.4–1.7.4	Financial support received	Yes; No
1.1.5–1.7.5	Technical training received	Yes; No
1.1.6–1.7.6	Revenue increase	Percentage (%)
1.1.7–1.7.7	Operating cost reduction	Percentage (%)
1.1.8–1.7.8	Water savings	Percentage (%)
1.1.9–1.7.9	Labour savings	Percentage (%)
1.1.10–1.7.10	Fertiliser savings	Percentage (%)
1.1.11–1.7.11	Plant protection product savings	Percentage (%)

(continued on next page)

Table A1 (*continued*)

Code	Question	Response options
1.1.12–1.7.12	Other effects	Open-ended
1.1.13–1.7.13	Social sustainability effects	Strongly disagree; Disagree; Neutral; Agree; Strongly agree
1.1.14–1.7.14	Environmental sustainability effects	Strongly disagree; Disagree; Neutral; Agree; Strongly agree
1.8.1	Application areas of SFTs	Soil preparation; …; Data analysis; …
1.8.2	Any disadvantages of the technology used	Yes; No; Open-ended (if yes)
2.1	Farm size	Numeric (hectares)
2.2	Main production type	Arable/crop production; Livestock production; Mixed; Permanent/pasture
2.2.1	Crop production area	Numeric (hectares)
2.3.1–2.3.2	Province; Municipality	Categorical
2.3.3	Cooperative membership	Yes; No
2.4.1	Gender	Male; Female; Other; Prefer not to say
2.4.2	Age	Numeric (years)
2.4.3	Education level	No formal education; Primary; Lower secondary; Upper secondary; University degree or higher
2.4.4	Share of agricultural income in household income	<20%; 21–40%; 41–60%; 61–80%; 81–100%
3.0	Reasons for non-adoption of SFTs	High investment costs; …; Lack of technical knowledge and skills; …

Note: Technology groups 1.1–1.7 correspond respectively to the following SFTs categories: (1.1) Data collection systems; (1.2) Autonomous vehicles and robotics; (1.3) Smart and connected machinery; (1.4) Mobile and portable devices; (1.5) Decision Support Systems; (1.6) Farm Management Information Systems; (1.7) Cloud digital infrastructure.

Table A2
Socio-demographic characteristics of the surveyed farms (n = 345).

Variable	Category	North-East (n = 122)	North-West (n = 64)	Centre (n = 52)	South (n = 78)	Islands (n = 29)	Total (n = 345)
Gender	Male	80 (65.6)	44 (68.8)	29 (55.8)	65 (83.3)	23 (79.3)	241 (69.9)
	Female	24 (19.7)	10 (15.6)	12 (23.1)	8 (10.3)	1 (3.4)	55 (16.0)
	Other	5 (4.1)	1 (1.6)	2 (3.8)	0 (0.0)	1 (3.4)	9 (2.6)
	NA	13 (10.7)	9 (14.1)	9 (17.3)	5 (6.4)	4 (13.8)	40 (11.6)
Age	< 40	18 (14.8)	12 (18.8)	9 (17.3)	12 (15.4)	5 (17.2)	56 (16.2)
	40–60	44 (36.1)	24 (37.5)	23 (44.2)	31 (39.7)	12 (41.4)	134 (38.8)
	> 60	59 (48.4)	27 (42.2)	19 (36.5)	34 (43.6)	12 (41.4)	151 (43.8)
	NA	1 (0.8)	1 (1.6)	1 (1.9)	1 (1.3)	0 (0.0)	4 (1.2)
Education	Primary	3 (2.5)	1 (1.6)	1 (1.9)	2 (2.6)	1 (3.4)	8 (2.3)
	Middle school	14 (11.5)	4 (6.3)	3 (5.8)	2 (2.6)	1 (3.4)	24 (7.0)
	High school diploma	44 (36.1)	27 (42.2)	16 (30.8)	26 (33.3)	11 (37.9)	124 (35.9)
	Bachelor's degree	22 (18.0)	12 (18.8)	11 (21.2)	24 (30.8)	6 (20.7)	75 (21.7)
	Master's degree	24 (19.7)	13 (20.3)	11 (21.2)	15 (19.2)	7 (24.1)	70 (20.3)
	Postgraduate	11 (9.0)	5 (7.8)	8 (15.4)	9 (11.5)	2 (6.9)	35 (10.1)
	NA	4 (3.3)	2 (3.1)	2 (3.8)	0 (0.0)	1 (3.4)	9 (2.6)
Knowledge level	None	9 (7.4)	5 (7.8)	2 (3.8)	5 (6.4)	2 (6.9)	23 (6.7)
	Basic	43 (35.2)	20 (31.3)	15 (28.8)	23 (29.5)	11 (37.9)	112 (32.5)
	Intermediate	49 (40.2)	25 (39.1)	20 (38.5)	31 (39.7)	15 (51.7)	140 (40.6)
	Advanced	19 (15.6)	11 (17.2)	13 (25.0)	17 (21.8)	1 (3.4)	61 (17.7)
	Highly specialised	2 (1.6)	3 (4.7)	2 (3.8)	2 (2.6)	0 (0.0)	9 (2.6)
Cooperative membership	Yes	67 (54.9)	16 (25.0)	23 (44.2)	31 (39.7)	9 (31.0)	146 (42.3)
	No	54 (44.3)	48 (75.0)	29 (55.8)	46 (59.0)	20 (69.0)	197 (57.1)
	NA	1 (0.8)	0 (0.0)	0 (0.0)	1 (1.3)	0 (0.0)	2 (0.6)
HH income from Agri.	0–20%	21 (17.2)	17 (26.6)	14 (26.9)	18 (23.1)	7 (24.1)	77 (22.3)
	21–40%	18 (14.8)	9 (14.1)	6 (11.5)	12 (15.4)	1 (3.4)	46 (13.3)
	41–60%	17 (13.9)	7 (10.9)	5 (9.6)	12 (15.4)	5 (17.2)	46 (13.3)
	61–80%	13 (10.7)	4 (6.3)	5 (9.6)	8 (10.3)	1 (3.4)	31 (9.0)
	81–100%	29 (23.8)	14 (21.9)	12 (23.1)	13 (16.7)	4 (13.8)	72 (20.9)
	NA	24 (19.7)	13 (20.3)	10 (19.2)	15 (19.2)	11 (37.9)	73 (21.2)
Farm size (ha)	< 10 ha	33 (27.0)	16 (25.0)	16 (30.8)	30 (38.5)	18 (62.1)	113 (32.8)
	10–50 ha	52 (42.6)	30 (46.9)	15 (28.8)	25 (32.1)	5 (17.2)	129 (37.4)
	> 50 ha	34 (27.9)	15 (23.4)	18 (34.6)	20 (25.6)	6 (20.7)	93 (26.9)
	NA	3 (2.5)	3 (4.7)	1 (1.9)	3 (3.8)	0 (0.0)	10 (2.9)

Note: Counts with percentages in parentheses. NA = missing or prefer not to answer.

Table A3
Ownership, training and funding status of smart farming technology adoption.

Technology	Macroregion	Contract	Owner	Lease	Shared	Funding	Training
Data Sensors	Centre	3	12	2	11	9	20
Data Sensors	Islands	1	0	0	2	2	1
Data Sensors	North-East	2	31	3	17	23	41
Data Sensors	North-West	1	10	7	9	9	15
Data Sensors	South	2	17	3	3	8	12
Robotics/AV	Centre	0	2	0	4	2	6
Robotics/AV	Islands	0	0	0	0	0	0
Robotics/AV	North-East	1	12	1	8	11	15
Robotics/AV	North-West	0	4	2	2	6	6

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Table A3 (*continued*)

Technology	Macroregion	Contract	Owner	Lease	Shared	Funding	Training
Robotics/AV	South	1	8	0	2	4	5
Smart Machinery	Centre	2	11	0	2	11	7
Smart Machinery	Islands	1	0	0	0	0	0
Smart Machinery	North-East	4	32	0	2	22	23
Smart Machinery	North-West	2	16	2	1	16	11
Smart Machinery	South	3	7	0	3	5	6
Mobile Portable	Centre	0	24	3	7	8	16
Mobile Portable	Islands	0	5	1	2	2	1
Mobile Portable	North-East	2	58	2	11	16	41
Mobile Portable	North-West	1	29	5	1	7	15
Mobile Portable	South	1	34	2	5	5	12
DSS	Centre	2	6	6	5	7	12
DSS	Islands	0	1	0	1	1	1
DSS	North-East	0	20	6	16	11	32
DSS	North-West	0	5	1	5	4	9
DSS	South	3	10	8	7	5	14
FMIS	Centre	0	8	5	6	5	11
FMIS	Islands	0	1	1	1	0	0
FMIS	North-East	1	21	9	16	5	31
FMIS	North-West	1	12	5	1	5	13
FMIS	South	2	10	4	3	1	9
Cloud	Centre	0	8	4	2	3	5
Cloud	Islands	0	1	0	0	0	1
Cloud	North-East	1	16	4	2	5	9
Cloud	North-West	0	4	1	0	0	3
Cloud	South	1	5	3	1	2	5

Table A4
Technology specific probit regression estimates.

Model	Variable	Coef. (SE)	SE (coef)	AME	SE (AME)
Data Sensors	(Intercept)	−1.494*	0.8		
Data Sensors	Age	−0.011	0.008	−0.003	0.002
Data Sensors	Gender (F)	−0.127	0.279	−0.034	0.074
Data Sensors	Education Medium	0.887*	0.495	0.208**	0.093
Data Sensors	Education High	1.138**	0.511	0.278***	0.101
Data Sensors	Knowledge Medium	0.795***	0.24	0.221***	0.063
Data Sensors	Knowledge High	1.614***	0.289	0.479***	0.074
Data Sensors	Total Farm Area	−0.005	0.004	−0.001	0.001
Data Sensors	Crop Area	0.01*	0.005	0.003*	0.001
Data Sensors	Has Livestock	−1.115***	0.395	−0.257***	0.069
Data Sensors	Member Cooperative	0.11	0.214	0.03	0.058
Data Sensors	Share HH Income Agri.	0.002	0.004	0.0	0.001
Data Sensors	NUTS Islands	−7.144	201.5	−0.405**	0.173
Data Sensors	NUTS North-East	0.225	0.309	0.066	0.089
Data Sensors	NUTS North-West	0.236	0.372	0.069	0.107
Data Sensors	NUTS South	−0.422	0.331	−0.114	0.091
Robotics/AV	(Intercept)	−7.504	336.717		
Robotics/AV	Age	0.0	0.009	0.0	0.002
Robotics/AV	Gender (F)	−0.275	0.348	−0.046	0.053
Robotics/AV	Education Medium	5.314	336.716	0.122***	0.027
Robotics/AV	Education High	5.656	336.716	0.193***	0.046
Robotics/AV	Knowledge Medium	0.541*	0.314	0.079*	0.043
Robotics/AV	Knowledge High	1.025***	0.345	0.194***	0.066
Robotics/AV	Total Farm Area	−0.002	0.004	−0.0	0.001
Robotics/AV	Crop Area	0.002	0.004	0.0	0.001
Robotics/AV	Has Livestock	0.367	0.393	0.076	0.091
Robotics/AV	Member Cooperative	0.468*	0.26	0.085*	0.046
Robotics/AV	Share HH Income Agri.	−0.003	0.004	−0.001	0.001
Robotics/AV	NUTS Islands	−4.211	426.723	−0.078*	0.044
Robotics/AV	NUTS North-East	0.368	0.4	0.057	0.057
Robotics/AV	NUTS North-West	0.719	0.459	0.134	0.083
Robotics/AV	NUTS South	0.421	0.424	0.068	0.064
Smart Machinery	(Intercept)	−1.657**	0.834		
Smart Machinery	Age	−0.005	0.009	−0.001	0.002
Smart Machinery	Gender (F)	−0.077	0.297	−0.018	0.068
Smart Machinery	Education Medium	−0.077	0.435	−0.018	0.103
Smart Machinery	Education High	0.019	0.46	0.005	0.11
Smart Machinery	Knowledge Medium	0.234	0.262	0.05	0.056
Smart Machinery	Knowledge High	0.944***	0.291	0.245***	0.075
Smart Machinery	Total Farm Area	−0.007	0.004	−0.002	0.001

(*continued on next page*)

Table A4 (*continued*)

Model	Variable	Coef. (SE)	SE (coef)	AME	SE (AME)
Smart Machinery	Crop Area	0.015***	0.005	0.004***	0.001
Smart Machinery	Has Livestock	−0.479	0.384	−0.099	0.069
Smart Machinery	Member Cooperative	0.703***	0.232	0.168***	0.054
Smart Machinery	Share HH Income Agri.	0.004	0.004	0.001	0.001
Smart Machinery	NUTS Islands	−8.486	202.846	−0.257	0.371
Smart Machinery	NUTS North-East	0.16	0.338	0.039	0.08
Smart Machinery	NUTS North-West	0.431	0.401	0.111	0.101
Smart Machinery	NUTS South	−0.182	0.369	−0.04	0.083
Mobile Portable	(Intercept)	−1.667**	0.746		
Mobile Portable	Age	0.003	0.008	0.001	0.002
Mobile Portable	Gender (F)	0.875***	0.294	0.256***	0.076
Mobile Portable	Education Medium	0.57	0.408	0.169	0.115
Mobile Portable	Education High	0.716*	0.433	0.213*	0.123
Mobile Portable	Knowledge Medium	0.44**	0.214	0.151**	0.073
Mobile Portable	Knowledge High	1.589***	0.315	0.482***	0.076
Mobile Portable	Total Farm Area	−0.004	0.004	−0.001	0.001
Mobile Portable	Crop Area	0.004	0.004	0.001	0.001
Mobile Portable	Has Livestock	0.35	0.395	0.106	0.118
Mobile Portable	Member Cooperative	0.575***	0.205	0.18***	0.064
Mobile Portable	Share HH Income Agri.	0.004	0.003	0.001	0.001
Mobile Portable	NUTS Islands	−0.44	0.494	−0.133	0.149
Mobile Portable	NUTS North-East	0.014	0.314	0.004	0.095
Mobile Portable	NUTS North-West	0.05	0.365	0.015	0.111
Mobile Portable	NUTS South	−0.288	0.328	−0.088	0.1
DSS	(Intercept)	−2.398***	0.794		
DSS	Age	0.002	0.008	0.0	0.002
DSS	Gender (F)	0.56**	0.276	0.164**	0.082
DSS	Education Medium	0.269	0.451	0.07	0.111
DSS	Education High	0.483	0.468	0.131	0.118
DSS	Knowledge Medium	0.989***	0.258	0.255***	0.06
DSS	Knowledge High	1.602***	0.294	0.473***	0.079
DSS	Total Farm Area	−0.003	0.004	−0.001	0.001
DSS	Crop Area	0.003	0.004	0.001	0.001
DSS	Has Livestock	−0.736*	0.387	−0.178**	0.077
DSS	Member Cooperative	0.406*	0.21	0.114*	0.059
DSS	Share HH Income Agri.	0.003	0.004	0.001	0.001
DSS	NUTS Islands	−0.047	0.553	−0.012	0.139
DSS	NUTS North-East	0.407	0.311	0.114	0.082
DSS	NUTS North-West	−0.23	0.394	−0.056	0.095
DSS	NUTS South	0.378	0.331	0.105	0.089
FMIS	(Intercept)	−1.289*	0.736		
FMIS	Age	−0.003	0.008	−0.001	0.002
FMIS	Gender (F)	0.377	0.267	0.114	0.083
FMIS	Education Medium	−0.084	0.398	−0.025	0.121
FMIS	Education High	−0.336	0.423	−0.097	0.126
FMIS	Knowledge Medium	0.737***	0.241	0.204***	0.063
FMIS	Knowledge High	1.22***	0.277	0.373***	0.082
FMIS	Total Farm Area	−0.007*	0.004	−0.002*	0.001
FMIS	Crop Area	0.008*	0.004	0.002*	0.001
FMIS	Has Livestock	−0.682*	0.376	−0.173**	0.079
FMIS	Member Cooperative	0.449**	0.205	0.134**	0.061
FMIS	Share HH Income Agri.	0.006*	0.003	0.002*	0.001
FMIS	NUTS Islands	−0.857	0.629	−0.207	0.127
FMIS	NUTS North-East	0.147	0.299	0.045	0.091
FMIS	NUTS North-West	−0.118	0.362	−0.035	0.107
FMIS	NUTS South	−0.163	0.322	−0.048	0.095
Cloud	(Intercept)	−5.96	230.584		
Cloud	Age	−0.001	0.009	−0.0	0.002
Cloud	Gender (F)	−0.203	0.337	−0.035	0.054
Cloud	Education Medium	4.654	230.583	0.132***	0.028
Cloud	Education High	4.839	230.583	0.17***	0.044
Cloud	Knowledge Medium	0.466	0.312	0.071	0.045
Cloud	Knowledge High	0.868**	0.348	0.164**	0.067
Cloud	Total Farm Area	0.005	0.004	0.001	0.001
Cloud	Crop Area	−0.004	0.004	−0.001	0.001
Cloud	Has Livestock	−0.018	0.471	−0.003	0.085
Cloud	Member Cooperative	0.091	0.251	0.017	0.046
Cloud	Share HH Income Agri.	−0.003	0.004	−0.0	0.001
Cloud	NUTS Islands	−0.369	0.62	−0.072	0.111
Cloud	NUTS North-East	0.086	0.329	0.021	0.077
Cloud	NUTS North-West	−1.051*	0.562	−0.145**	0.071
Cloud	NUTS South	−0.419	0.378	−0.08	0.076

***, **, * Indicates significance at 1%, 5% and 10% levels.

Data availability

Data will be made available on request.

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