Digital Technology Adoption Among Italian Farmers: An Extended Technology Acceptance Model Approach in the Horticultural Sector

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Highlights

- A structured survey conducted with 251 Italian horticultural farmers
- The extended TAM3 explains 18% of the variance in the behaviour (the adoption of water-smart technologies), and 65% of the variance in intention
- Behavioural intention is a significant predictor of the behaviour
- Perceived usefulness and social norms have a significant effect on adoption intention
- Perceived ease of use has no influence on adoption intentions

Abstract

The adoption of digital technologies in agriculture is essential for enhancing sustainability, productivity, and resource efficiency. This study investigates the factors influencing Italian horticultural farmers' adoption of innovative water-smart agricultural technologies using an extended Technology Acceptance Model (TAM3). The research employs a structured survey conducted with 251 Italian farmers, analysing their perceptions of technology usefulness, ease of use, social norms, and sustainability outcomes. Structural equation modelling (SEM) confirms that perceived usefulness significantly influences adoption intentions, while perceived ease of use plays a limited role. Social norms and sustainability-related benefits also emerge as critical determinants. Results also indicate the impact of farm size and workforce on adoption behaviour. These findings highlight the need for targeted policies, training programs, and financial incentives to overcome adoption barriers. The study provides insights for policymakers, technology developers, and agricultural stakeholders to foster digital innovation in the horticultural sector, contributing to sustainable water management practices.

Keywords: Digital Agriculture; Farmer adoption; Technology Acceptance Model (TAM); Horticultural Sector; Water-Smart Sustainable Farming.

1. Introduction

The agricultural sector is facing many unprecedented challenges. Given the increasing pressure on agricultural systems, effective measures are needed to reduce agriculture's impact on natural resources, in line with the European Green Deal and the United Nations 2030 Agenda (Montanarella and Panagos, 2021). In this context, digital technologies and smart solutions are key to improving efficiency, productivity, and sustainability in agriculture (Yigezu et al., 2018), with irrigation practices playing a particularly important role (Asadi et al., 2020). Water scarcity and drought are now recognised as a global problem of the utmost importance (Ermolieva et al., 2022; Ungureanu et al., 2020), exacerbated by climate change (Kapsdorferová, 2024). Smart water technologies offer a double benefit: help to save water and use it more efficiently; and reduce operating costs and improve productivity by maximising output per unit of water consumed (Gemtou et al., 2024). Innovations such as soil moisture sensors, automatic irrigation systems and predictive modelling can effectively address the challenges of water scarcity and climate variability (Adeyemi et al., 2017), as well as energy savings (Patle et al., 2019). A major challenge in smallholder agriculture is the limited adoption of innovative technologies, resulting in low overall technology penetration in the sector (Senyolo et al., 2018).

Indeed, despite efforts to promote a fair transition to digital agriculture, the adoption of smart technologies remains uneven, shaped by a complex mix of individual, technological, and contextual factors (Shang et al., 2021). Previous studies have shown that there are significant differences in adoption rates among farmers (Paustian and Theuvsen, 2017). Farmers' decision-making processes is shaped by perceived benefits, ease of use and external pressures, making it a key factor in understanding the adoption landscape (Cimino et al., 2024; Schulze Schwering et al., 2022). Given the limited technological penetration of the agricultural sector and the potential benefits offered by digital technologies, it is crucial to investigate the farmers' behaviour, their willingness to adopt smart solutions, the determinants of smart technology adoption and identifying strategies to promote broader adoption of water technologies (Gemtou et al., 2024).

Although prior research has examined farmers' adoption patterns, it has often focused on large-scale farms or specific regions with advanced technological infrastructures (Paustian and Theuvsen, 2017). Additionally, studies have highlighted barriers such as limited digital literacy, financial constraints, and a lack of institutional support for small and medium-sized farms (Senyolo et al., 2018; Shang et al., 2021). Despite the increasing research on technology adoption in agriculture, there are still notable gaps. Firstly, little attention has been paid to the adoption of water-saving technologies in the horticultural sector, which is crucial for sustainable agriculture, in contrast to the more commonly studied large-scale cereal production (Adeyemi et al., 2017). Secondly, while factors like such as farm size and socio-demographic characteristics have been investigated, the influence of sustainability motivations and social norms on technology adoption has not yet been sufficiently researched (Gemtou et al., 2024). Finally, the adoption of digital technologies in Italian agriculture, which is characterised by fragmented land ownership, regional diversity and varying levels of technological readiness, has been insufficiently studied (Baldoni et al., 2018).

This study aims to fill these gaps by analysing the factors that influence Italian farmers in adopting digital technologies for better water management and the barriers they face, with a focus on horticultural crops. Horticulture has been considered for some reasons: first, because of the importance of this sector in the Italian agricultural system; secondly, for the relevance of the irrigation in this cropping system (Patle et al., 2019); third because of the relevance of smart precision in horticulture (Adeyemi et al., 2017). The technologies studied relate to smart water management through a three-stage technology complexity: the first (basic) stage is represented by the introduction of soil moisture sensors, which proceeds to a system that combines sensors with an automatic irrigation system, and in the last stage the sensors are connected to an automated system, which in turn is connected to and dialogs with predictive models[1]. Understanding farmers' perceptions and adoption of water-efficient innovations is essential for shaping targeted policies and effective incentives, offering valuable insights for policymakers and stakeholders aiming to promote sustainable agriculture.

2. Literature review and theoretical background

As the existing literature shows, the process of adopting new technologies is inherently complex and dynamic (Montes de Oca Munguia et al., 2021). In particular, the decision-making process is influenced by various factors that affect the rate of technology adoption by farmers (Gemtou

[1] Specifically, automatic irrigation systems are connected to sensors that monitor soil moisture and activate valves wirelessly; instead, predictive modelling integrates the first two solutions (soil moisture sensors and automatic irrigation systems) into predictive models that merge real-time data with historical data, analyse it, and make autonomous irrigation decisions thanks to water delivery schedules that optimize dosing based on specific crop requirements and environmental conditions.

et al., 2024; Osrof et al., 2023). Although the existing literature has explored the mechanisms of innovation diffusion, there does not seem to be a unified set of theories or models that could explain the phenomenon. Some authors have highlighted the specificity of theories in modelling different aspects of the technology adoption process (Dissanayake et al., 2022; Osrof et al., 2023), while others have expressed doubts about the generalist ability of theories to represent different technologies and practices (Montes de Oca Munguia et al., 2021). Indeed, there is still confusion about the methods of analysis and the choice of explanatory variables that should be used to model the adoption process (de Oca Munguia and Llewellyn, 2020). To illustrate, Shang et al. (2021) argue that the mechanisms of adoption and diffusion of digital agricultural technologies need to be understood at both the farm level and the system level. They also suggest that the focus in determining technology diffusion should be on system interactions in combination with individual characteristics. Given the evidence presented in the literature, it can be assumed that the categories of individual, technological, social and economic factors influencing technology adoption can describe the entire decision-making process (Dissanayake et al., 2022). There is a clear lack of convergence and consistency in the results regarding the impact and statistical significance of the individual factors assessed in the adoption models (de Oca Munguia and Llewellyn, 2020). This discrepancy can be attributed to the fact that most adoption studies do not include variables on technologies or practices. It is recognized that the use of multiple paradigms in modelling technology adoption and diffusion can increase the explanatory power of the models. However, it is important to consider the factors and their interactions in a way that is consistent with the objectives and context of the study within a specific food system (Dentoni et al., 2023).

Literature offers a large range of theoretical frames exploring the intention to adopt; among others the Theory of Planned Behaviour (TPB) (Ajzen, 1991; Fishbein and Ajzen, 2010), the Social Cognitive Theory (Bandura, 1986), and the Unified Theory of Acceptance and Use of Technology (UTAUT) and its further extensions (Venkatesh et al., 2003). In the present work we applied the Technology Acceptance Model (TAM) (Davis, 1989) for measuring the intention of Italian farmers to adopt innovative smart technologies. The TAM model has been chosen for designing the model since this theory was precisely conceived focusing on technological solutions, hereby offering the ideal setting to place the research. The other theories might be adapted to a technology frame, whereas the TAM, being already tailored on the observed object of the analysis, better suits the purpose of the current investigation. According to the TAM paradigm, two dispositions towards a new technology (perceived usefulness and ease of use) determine a person's attitude towards using that technology and influence their desire to use it. Perceived usefulness is the extent to which a person believes that job performance can be enhanced by using the new technology, whereas perceived ease of use is the extent to which a person believes that using the new technology is effortless. Some extensions of the original TAM conceptualization have been proposed, such as the TAM3 version (Venkatesh and Bala, 2008). The TAM3 extension introduces new constructs and determinants that affect the core variable perceived ease of use and proposes new relationships between the constructs. The factors influencing perceived ease of use in the TAM3 version are computer self-efficacy, perception of external control, computer anxiety, computer playfulness, perceived enjoyment, and objective usability, whereas perceived usefulness is affected by subjective norm, image, relevance to work, output quality and demonstrability of results. Other innovations introduced by this extension include: (i) the correlation between perceived ease of use and perceived usefulness, (ii) the correlation between perceived ease of use and intention, and (iii) the concept of anxiety. The latter factor, which expresses the degree of emotional fear, apprehension, nervousness, or stress experienced when interacting with a new technology, is supposed to negatively affect the perceived ease of use. The more anxiety a person feels, the less likely they are to perceive the technology as easy to use.

The TAM3 conceptualization was adopted since flexible adjustments to context specific needs compared to the original TAM version are possible. Indeed, Venkatesh and Bala (2008) added some constructs (i.e. experience, subjective norm, and image) which resulted to be key factors in the exploratory phase: farmers decision rely on peer recommendation as well as on previous experience on digital tools. Therefore, only an extended version of the very first conceptualization could confirm or not these clues. Furthermore, in order to comprise some small adjustments to the basic model (like the sustainability dimension), an extended version with more variables seemed to be more appropriate than the earliest edition. Minor adjustments were made to the original TAM3 version by Venkatesh and Bala (2008) to better suit the purpose and context of the analysis. First, all constructs were considered in the context-specific environment, i.e. the adoption of new water-smart agricultural technologies by Italian horticultural farms. Moreover, some aspects were evaluated as very important and emerged explicitly from the exploratory phase with the participants, such as technology self-efficacy and quality of outcomes. Other TAM3 characteristics, such as (computer) playfulness or perceived enjoyment, do not apply to the context of the current research and were therefore excluded from the model design. Then, the need to include sustainability dimensions when dealing with digital technologies in the agri-food sector is pressing (Alexandrova-Stefanova et al., 2024; Gemtou et al., 2024; Khanna, 2021; McFadden, 2022). Consequently, a category based on with the Sustainability Assessment of Food and Agriculture Systems (SAFA) aspects (FAO, 2014) was included in the model since this method represents a comprehensive and international reference for assessing sustainability along agri-food value chains. More specifically, the themes inspired by the SAFA indicators, were (i) the reduced water-used thanks to the optimization of the irrigation system, (ii) the improved skills the employees and the holder/farmer need to reach to use the technology, and (iii) new employees recruited thanks to their technological skills.

Therefore, we tested the following main hypotheses on the factors influencing the adoption of new water-smart agricultural technologies by Italian horticultural farms (Figure 1):

H1: perceived usefulness is positively affected by output quality (H1a), by sustainability outcomes measured by SAFA indicators (H1b), and by subjective norms (H1c);

H2: perceived ease of use is positively affected by technology self-efficacy (H2a), and is negatively affected by anxiety (H2b);

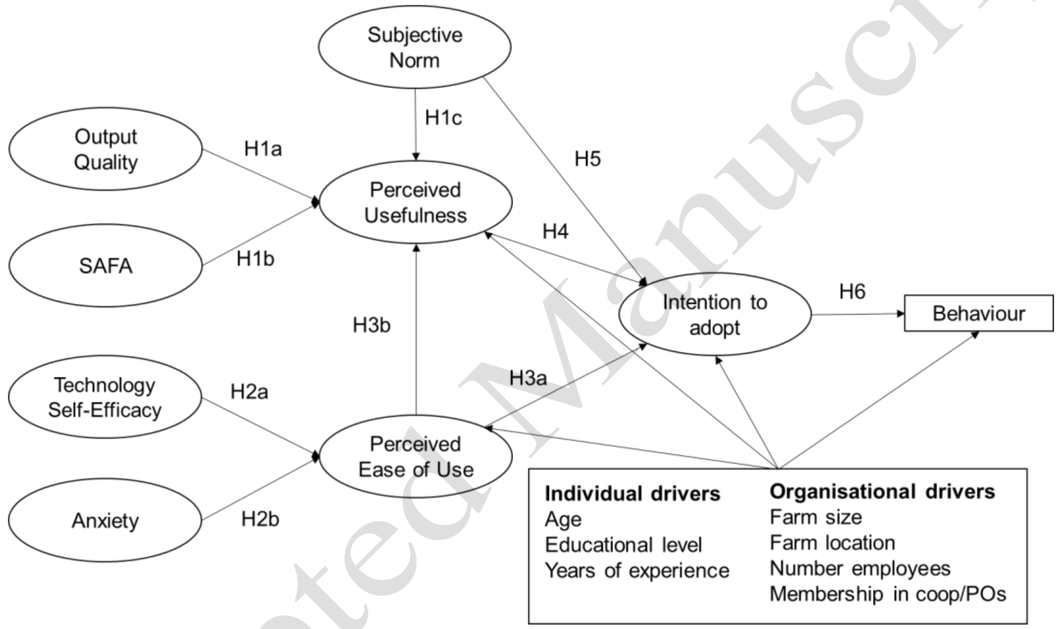
H3: perceived ease of use has a positive impact on farmers' intention to adopt new technologies (H3a), and is positively affecting the perceived usefulness of new technologies (H3b);

H4: perceived usefulness has a positive impact on farmers' intention to adopt new technologies;

H5: subjective norms have a positive impact on farmers' intention to adopt new technologies;

H6: the farmers' intention to adopt new technologies is positively affecting the behaviour, i.e. the new technology adoption.

Figure 1. Model testing the factors affecting the adoption of water-smart agricultural new technologies by Italian horticulture farms.



Moreover, individual factors, such as socio-demographic and organizational characteristics, which determine the natural and structural conditions of the farm, have been found to correlate with farmers' decisions. In particular, farmers' education level, gender, age, technology literacy, were among the individual drivers more frequently included in studies investigating the smart farming technologies adoption (Osrof et al., 2023). Farmers differentiate for their level of human capital (i.e. experience, education, and other relevant training) (Huffman, 2001; Okoye et al., 2025). These individual-level differences shape their technology adoption: the higher the human capital, the more likely the technologies are adopted (McFadden, 2022). Farm size, mostly expressed in total acreage farmland, is a prominent factor among the organizational ones, since larger farm size is consistently seen as pivotal for achieving economies of scale when adopting smart farming technologies (Okoye et al., 2025). Farm income is another key element, as farmers with a higher income are more willing to invest in new technologies (Osrof et al., 2023). Farm location is also a notable barrier within this theme, showing mixed effects in past studies. Some research indicates that it might negatively affects farmers' motivation to adopt smart technology, particularly if farms face unfavourable climate conditions or soil quality (Paxton et al., 2011). In Italy, farms in the northern regions are generally more competitive, due to larger farm sizes, advanced mechanisation, and stronger market integration. In contrast, farms located in central and southern regions often face structural constraints, including smaller farms and lower productivity (Baldoni et al., 2018; Okoye et al., 2025). Other studies emphasize the importance of social factors and access to information for the adopting of innovative smart technologies (Blasch et al., 2022). In this context, being a member of a farmers' associations or a producer organizations (POs), where knowledge transfer is one of the main objectives, might facilitate adoption (Okoye et al., 2025). Therefore, we controlled the main endogenous variables of the model, i.e. perceived usefulness, adoption intention and behaviour, with individual factors, namely farmers' age, education level and years of experience in the agricultural sector, and organizational ones, including farm size, farm location (expressed by the latitude of the province where the farm is located), number of employees, and membership in a cooperative or a producer organization (Figure 1).

3. Data and Method

3.1. Data collection

The data collection consisted in two phases: first we conducted a preliminary exploratory phase with qualitative, unstructured interviews. We interviewed 10 stakeholders, including agronomists, technicians from Producer Organizations (POs), representatives of the Tomato Interbranch Organization (OI Pomodoro Nord Italia), farmers, and vegetable/tomato producers. The aim of the exploratory interviews was to identify relevant aspects to be included in the final model and to highlight those that could be omitted. In this way, relevant points such as the output quality and self-efficacy were included in the final surveys. The questions focused on previous experience with smart technologies, skills in using them, public financial support for the adoption of technical solutions and the farm structure, as well as farmers' previous personal background. In the second phase, we conducted a survey among a sample of Italian horticultural farms. An initial pilot phase (n=21 interviews) was carried out to test the questionnaire. In this pilot phase the model was tested on 21 farms equally distributed in the country (10 in Centre and Southern Italy, 11 in the Northern regions). Most of them cultivate tomatoes, while a smaller group (n=4) grows only other fresh vegetables, such as pumpkin, celery, fell, broccoli, etc. The majority of the farms interviewed do not use any kind of technology; only a few rely on autonomous driving systems (n=3 farms), drones (n=1 farm), and sensors (n= 4 farms). Word-of-mouth, peer recommendations, and previous experience are the preferential ways the technologies are adopted.

Once the pilot phase was completed, the main study was conducted in the period from October to November 2024 by an international market research company using the CATI (Computer Assisted Telephone Interview) method. The survey lasted approximately 30 minutes. The final sample consisted of 251 Italian farmers. It included both tomato growers (50% from northern Italy and 50% from the south) and farmers cultivating other fresh vegetables, such as carrots, peppers, eggplants, lettuce, etc., distributed across northern, central and southern Italy (30%, 17%, and 53%, respectively). The geographical distribution was designed to be representative of horticultural farms, based on data from the Italian National Institute of Statistics (ISTAT). The inclusion of multiple administrative regions across the country ensures a comprehensive understanding of cultivation practices and highlights the heterogeneity of technological adoption.

3.2. Measures

Together with the socio-demographic information and the descriptive indicators, the questionnaire was designed to test the model hypotheses. Overall, it included 14 constructs, with a total of 45 items. The constructs included in the final model (Figure 1) were aimed to understand the drivers for the adoption of innovative water-smart agricultural technologies by Italian horticultural farms. All TAM3 items were measured on a 7-point scale (from 'strongly disagree' to 'strongly agree') (see Annex Table A1).

Subjective norm was assessed by three items (e.g., "Many producers I know have already adopted this innovation") and was adapted by Fishbein and Ajzen (2010). This construct refers to the perceived social pressure to perform or not perform a particular behavior. These social influences shape intentions and actions, and, in this study, the construct was explored considering peer adoption, which could lead to direct recommendations or serve as a concrete example (Kutter et al., 2011). The same construct considered also the customers' perception, which is more and more important, especially if linked to sustainability issues (such as water saving practices).

We measured the perceived usefulness with four items (e.g., "This innovation could improve my productivity") and perceived ease of use with two items (e.g., "This technology should be easy to use") (Davis, 1989). Output quality, i.e. the perception of the quality of the technology in performing the task, was measured by four items (e.g., "Using this technology will improve the quality of my products"), each adapted from Venkatesh and Bala (2008). SAFA-based aspects (i.e. the sustainability-related outcomes of the new technology adoption) were assessed by four items (e.g., "By using this innovation, I could help reduce water consumption"). Technology self-efficacy, i.e. the belief in how well someone can perform actions to achieve performance outcomes, was measured by three items (e.g., "I would use this innovation easily if I had technical support"), whereas anxiety was assessed by three items (e.g., "New technologies make me feel uncomfortable"). All these latter items were adapted from Venkatesh and Bala (2008). Finally, we used three items to assess behavioural intention (e.g., "I intend to use this technology in the near future") (Fishbein and Ajzen, 2010).

The study focused on the three levels of water-smart technologies described above: Level 1) – soil moisture sensors, Level 2) – a system combining sensors with an automatic irrigation system, and Level 3) – sensors connected to an automated system, which in turn is connected to and interacts with predictive models. If a farmer indicated they have adopted a certain level of the technology, the items were framed for the next level. For instance, if a respondent have already adopted soil moisture sensors, we asked about the intention to adopt the sensors connected to an automated system. If no adoption was reported, we asked about their intention to adopt soil moisture sensors (Level 1), whereas when they reported the highest level of adoption, we asked about the intention to adopt more advanced predictive models. Thus, the behaviour was assessed with a single item, ranging from 1 to 4, considering the different adoption levels (1=no technology; 2=Level 1; 3=Level 2; 4=Level 3). We acknowledge that in TAM3 formulations intention and behaviour typically refer to the same "future-oriented" action (Venkatesh and Bala, 2008). Given the cross-sectional nature of our study, we adopted a graduated behavioural scale to capture the level of adoption by farmers of increasingly sophisticated water-smart technologies. This decision was necessary given the multi-stage nature of the technology adoption in precision agriculture (Finger, 2023), including smart-water management technologies. Indeed, in many cases farmers adopt these solutions incrementally, in a progression from basic systems (in our case, soil moisture sensors) to more complex systems (such as predictive models). Accordingly, behavioural intention was framed toward the next logical step in technology adoption, while behaviour captured the current level of adoption. Therefore, the intention-behaviour link in this study, tested in H6 (Figure 1), should be interpreted as a sequential progression in the adoption pathway, as measured by the behavioural scale, and not as a direct action-intention relation.

3.3. Data analysis

We performed the statistical analysis using SPSS v.29.0 and AMOS v.29.0 statistical software (IBM Corporation, Armonk, NY, USA). Means, standard deviations, median and interquartile range (IQR) were calculated for each questionnaire item and its related construct. Structural equation modelling (SEM) was used to test hypotheses H1–H6 and the theoretical framework in Figure 1. SEM allows models to be specified with both latent (e.g., perceived usefulness) and observed variables (e.g., farm size) (Kline, 2016).

To improve our understanding of farm-level attitude and structural variables, we have considered two models using the same dataset: in Model 1 we included only the variables of the extended-TAM3 model, i.e. behaviour, behavioural intention, subjective norm, perceived usefulness, perceived ease of use, output quality, sustainability-related constructs (SAFA), technology self-efficacy and anxiety. Then, we controlled for the effects of individual factors (i.e., farmers' age, educational level, and years of experience in the agricultural sector) and organizational factors (i.e., farm size, farm location, number of employees, membership in a cooperative or a producer organization) on the endogenous variables (i.e., perceived usefulness, behavioural intention, and behaviour), building a second model, which is an extension of Model 1. The full model, containing all factors and their interactions, was fitted to the data; then, the least significant parameters were removed through a backwards deletion method, using Akaike's Information Criterion (AIC) for assessing the improvement in model fit (Power et al., 2013). In general, the AIC declines as the model fit increases (Kline, 2016). Where the model fit was not significantly improved by the removal of a parameter, it remained in the final model. This process was repeated until only two significant variables remained in the Model 2: number of employees and farm size (expressed in hectares of utilised agricultural area, UAA). These additions are theoretically relevant and empirically meaningful for explaining farmers' digital adoption behaviour in a real-world context (McFadden, 2022; Okoye et al., 2025; Osrof et al., 2023).

Convergent validity of the model variables was assessed using average variance extracted (AVE), Cronbach's α coefficient, and composite reliability (CR). Discriminant validity was tested by comparing the square root of the AVE of each construct with the inter-construct correlation (Bagozzi and Yi, 2012). The goodness-of-fit of the models was assessed using the χ^2 and their degrees of freedom (df), the Tucker-Lewis Index (TLI), the comparative fit index (CFI), the root mean square error of approximation (RMSEA) with a 90% confidence interval, and the standardised root mean square residual (SRMR) (Kline, 2016). Since Model 1 and Model 2 are not nested, due to additional parameters, we evaluated their relative performance using multiple comparative indicators, as recommended in the SEM literature, such as CFI, TLI, RMSEA, and AIC. The coefficient of determination (R^2) was used to measure the explained variance of the endogenous variables. We applied the Maximum Likelihood estimation routine (Byrne, 2010).

4. Results

4.1. Descriptive statistics

The overall sample consisted of 251 respondents who were responsible for farm's decisions (78% always, 14% often, and 8% sometimes). Most respondents were male (92%), had completed upper secondary education (53%), had an average age of 53 years, and a median of 30 years of experience in the agricultural sector (Table 1). Most farms were located in southern Italy and on the islands (51.4), had a median utilised agricultural area (UAA) of 15 ha, employed less than 10 people (68%), with a median turnover of €200.000. The most frequently cultivated vegetables were tomatoes, both for fresh consumption (44%) and for the processing industry (41%), followed by peppers (16%) and zucchinis (11%).

Most of the sampled farmers had not yet adopted any of the proposed technologies (n=175, 69.7%). Those who have deployed any of these technologies relied on Level 1 (i.e. soil moisture sensors, n=43, 17.1%), and a few were already using automated irrigation systems (Level 2) or predictive models (Level 3), accounting for 6.4% (n=16) and 6.8% (n=17) respectively (Table 1). In light of these findings, it is important to understand the motivation for the adoption of new technologies and the factors that hamper their introduction.

Table 1. Description of the sample: farms characteristics and socio-demographics data of farmers (n=251).

Variables	**Sample**	
	N	**%**
Age of the respondent		
Age (years, mean and SD)	52.8 (11.9)	
Gender		
Male	231	92.0
Female	20	8.0
Others or prefer not to answer	0	0.0
Educational level		

Primary	8	3.2
Secondary lower	57	22.7
Secondary higher	132	52.6
Tertiary	54	21.5
Geographical area of the farm		
North-West	28	11.2
North-East	66	26.3
Center	28	11.2
South and Islands	129	51.4
Farm size		
UAA (ha, median and IQR)	15.0 (4.0-60.0)	
Farms by UAA classes		
< 2 ha	20	8.0
2 – 4.99 ha	47	18.7
5 – 19.99 ha	69	27.5
20 – 49.99 ha	45	17.9
> 50 ha	70	27.9
Most cultivated vegetables		
Tomato (for fresh consumption)	110	43.8
Tomato (for the processed industry)	104	41.4
Peppers	40	15.9
Zucchinis	27	10.8
Eggplants	13	5.2
Lettuce	13	5.2
Potatoes	12	4.8
Melons	9	3.6
Cauliflowers	8	3.2
Enterprise n. employee category		
Micro (1-9 employees)	171	68.1
Small (10-49)	64	25.5
Medium 1 (50-99)	12	4.8
Medium 2 (100-249)	4	1.6
Large (≥250)	0	0.0
Farm's turnover		
Turnover (.000 euro, median and IQR)	200 (90-650)	
Farmer's years of experience in agriculture		
Years of experience (median and IQR)	30 (20-40)	
Levels of water-smart technologies [a]		
No technological innovation	175	69.7
Level 1	43	17.1
Level 2	16	6.4
Level 3	17	6.8

Notes: Data are presented as the mean (SD) for continuous variables for which the hypothesis of normal distribution cannot be rejected at $p<0.05$, as median (IQR) otherwise, or as number (%) for nominal variables. SD = Standard Deviation. IQR = Interquartile Range. UAA = Utilised Agricultural Area. [a] Levels of water-smart technologies: Level 1) – soil moisture sensors, Level 2) – a system combining sensors with an automatic irrigation system, and Level 3) – sensors connected to an automated system, which in turn is connected to and interacts with predictive models.

Table 2 shows the descriptive statistics of the latent and observable variables, as well as the tests conducted on the constructs. The factor loadings of the variable items (λ) exceeded 0.50, the Cronbach's α and CR values were above 0.70, and the AVE values exceeded 0.50; these results, with the only exception of perceived ease of use, demonstrated strong reliability, as well as convergent and discriminant validity of all factors in the measurement model. We opted to retain the perceived ease of use construct, first, because the construct is grounded in the TAM, where plays a fundamental role. Secondly, while the Cronbach's alpha is slightly low, the construct shows acceptable composite reliability and standardized factor loadings. The AVE is slightly below the conventional 0.50 threshold, but is still within an acceptable range, particularly when supported by theoretical significance and other reliability indicators. Discriminant validity was further confirmed by verifying that the square root of the AVE for each construct, as shown in Table 3, was greater than the correlations between the constructs (Bagozzi and Yi, 2012).

Overall, the results in Table 2 show a moderately positive perceived usefulness of water-smart agricultural new technologies (mean score: 4.81), which means in particular that farmers moderately agree that by using this technology they could reduce water consumption and improve productivity by using this technology. The results also show a moderately positive perceived ease of use (4.69) and output quality (4.59). Furthermore, important others had no significant influence (3.63), and there was relatively low anxiety about applying new technologies (3.16). The results indicated a positive evaluation of the sustainability aspects related to the new technology (e.g., reduced water consumption, enhanced technical skills, etc., mean score: 5.03), as well as positive technology self-efficacy (5.12). In particular, respondents stated that they would use this innovation easily if they had technical support. Furthermore, farmers exhibited a moderately positive intention to adopt innovative water-smart agricultural technologies (4.58).

Table 2. Mean values (standard deviation, SD) and median values (interquartile range, IQR) of single items and constructs, factor loadings (λ), composite reliability (CR), average variance extracted (AVE) and Cronbach's α of the sample (n=251).

	Mean (SD)	**Median (IQR)**	**λ**	**CR**	**AVE**	**α**
Perceived Usefulness	4.81 (1.06)	5.00 (4.25-5.25)		0.84	0.56	0.84
PU1	4.80 (1.25)	5.00 (4.00-5.00)	0.78			
PU2	4.61 (1.34)	5.00 (4.00-5.00)	0.75			
PU3	4.86 (1.20)	5.00 (4.00-5.00)	0.79			
PU4	4.95 (1.37)	5.00 (4.00-6.00)	0.67			
Perceived Ease of Use	4.69 (0.92)	4.50 (4.00-5.00)		0.61	0.45	0.61
PEU1	4.98 (1.06)	5.00 (4.00-5.00)	0.59			
PEU2	4.40 (1.10)	5.00 (3.00-5.00)	0.75			
Output Quality	4.59 (0.98)	4.75 (4.00-5.00)		0.83	0.56	0.84
OQ1	4.57 (1.15)	5.00 (4.00-5.00)	0.70			
OQ2	4.52 (1.25)	5.00 (4.00-5.00)	0.78			
OQ3	4.80 (1.16)	5.00 (4.00-5.00)	0.85			

OQ4	4.48 (1.20)	5.00 (4.00-5.00)	0.64			
SAFA	5.03 (1.00)	5.00 (4.67-5.67)		0.78	0.55	0.79
SAFA1	5.12 (1.21)	5.00 (5.00-6.00)	0.68			
SAFA2	4.87 (1.17)	5.00 (4.00-5.00)	0.72			
SAFA3	5.10 (1.20)	5.00 (5.00-6.00)	0.81			
Anxiety	3.16 (1.18)	3.00 (2.67-3.67)		0.85	0.66	0.85
ANX1	3.28 (1.33)	3.00 (3.00-4.00)	0.74			
ANX2	3.10 (1.33)	3.00 (2.00-3.00)	0.88			
ANX3	3.10 (1.37)	3.00 (2.00-3.00)	0.81			
Technology Self-Efficacy	5.12 (1.11)	5.00 (4.67-6.00)		0.92	0.80	0.92
TSE1	5.07 (1.22)	5.00 (5.00-6.00)	0.87			
TSE2	5.20 (1.18)	5.00 (5.00-6.00)	0.93			
TSE3	5.08 (1.18)	5.00 (5.00-6.00)	0.88			
Subjective Norms	3.63 (1.09)	3.67 (3.00-4.33)		0.76	0.53	0.74
SN1	3.84 (1.31)	4.00 (3.00-5.00)	0.84			
SN2	3.52 (1.41)	3.00 (3.00-5.00)	0.51			
SN3	3.53 (1.31)	3.00 (3.00-5.00)	0.78			
Behavioural Intention	4.58 (1.35)	4.67 (4.00-5.33)		0.91	0.77	0.91
BI1	4.41 (1.51)	5.00 (4.00-5.00)	0.93			
BI2	4.54 (1.47)	5.00 (4.00-5.00)	0.89			
BI3	4.80 (1.41)	5.00 (4.00-6.00)	0.80			
Behaviour [a]	1.50 (0.89)	1.00 (1.00-2.00)				

Note: All items were measured on a 7-point scale (from 'strongly disagree' to 'strongly agree'), where median value 4 indicates 'neither agree or disagree'. [a] Levels of water-smart technologies: Level 1) – soil moisture sensors, Level 2) – a system combining sensors with an automatic irrigation system, and Level 3) – sensors connected to an automated system, which in turn is connected to and interacts with predictive models.

4.2. Drivers of digital innovation

Model 1 showed a good fit with the collected data: χ^2 (df) = 461.975 (280), CFI = 0.950, RMSEA = 0.051 (90%CI 0.043 – 0.059), TLI = 0.942 and SRMR = 0.054. The standardized path coefficients and their significance levels are shown in Table 4, whereas the unstandardized coefficients and standard errors are shown in the Appendix Table A2.

Table 3. Spearman's rank-order correlations (ρ) between the constructs including the squared root of the AVE of each construct (reported in bold on the main diagonal).

	PU	PEU	OQ	SAFA	ANX	TSE	SN	BI	BEH
PU	**0.75**	0.31***	0.63***	0.52***	–0.28***	0.40***	0.36***	0.57***	0.36***
PEU		**0.67**	0.24***	0.31***	–0.17**	0.34***	0.14*	0.28***	0.15*
OQ			**0.75**	0.46***	–0.21***	0.34***	0.43***	0.60***	0.35***
SAFA				**0.74**	–0.23***	0.63***	0.16*	0.39***	0.19**
ANX					**0.81**	–0.16**	–0.15*	–0.29***	–0.17**
TSE						**0.89**	n.s.	0.39***	n.s.
SN							**0.73**	0.44***	0.36***
BI								**0.88**	0.40***

Note: PU = Perceived Usefulness; PEU = Perceived Ease of Use; OQ = Output Quality; SAFA = Sustainability Assessment of Food and Agriculture Systems; ANX = Anxiety; TSE = Technology Self-Efficacy; SN = subjective norms; BI = Behavioural Intentions; BEH = behaviour; Sign.: *** p<0.001, ** p<0.01, * p<0.01, n.s. = not significant.

Overall, Model 1 shows R^2 values of 0.65 for the intention and 0.16 for the behaviour in adopting a new water-smart technology. This means that, respectively, 65.1% of the variance in intention and 16.4% of the variance in behaviour can be explained by the tested variables. The results suggest that the intention to adopt an innovative water-smart technology significantly influences the actual behaviour (i.e., the adoption of the technology itself), as postulated by H6 (p<0.001). Behavioural intention, in turn, is positively influenced by perceived usefulness with $p<0.001$, which is one of the two core variables of the TAM3 (H4 accepted).

Table 4. TAM3-extended models: coefficient of determination (R^2), standardised coefficients (β), p-values, research hypotheses and model fit indices (n=251).

	Model 1				Model 2			
	R^2	β	p	Hypotheses	R^2	β	p	Hypotheses
PU	0.791				0.822			
PEU → PU		0.133	0.044	H3b accepted		0.121	0.060	H3b accepted
OQ → PU		0.658	<0.001	H1a accepted		0.708	<0.001	H1a accepted
SAFA → PU		0.199	0.027	H1b accepted		0.152	0.081	H1b accepted
SN → PU		0.045	0.512	H1c rejected		0.035	0.607	H1c rejected
EMP → PU						0.183	<0.001	
UAA → PU						0.040	0.351	
PEU	0.305				0.303			
TSE → PEU		0.487	<0.001	H2a accepted		0.488	<0.001	H2a accepted
ANX → PEU		–0.169	0.041	H2b accepted		–0.163	0.048	H2b accepted
BI	0.651				0.652			
PU → BI		0.601	<0.001	H4 accepted		0.602	<0.001	H4 accepted
PEU → BI		0.069	0.295	H3a rejected		0.060	0.351	H3a rejected
SN → BI		0.278	<0.001	H5 accepted		0.268	<0.001	H5 accepted
EMP → BI						0.034	0.473	
UAA → BI						0.086	0.065	
BEH	0.164				0.179			
BI → BEH		0.404	<0.001	H6 accepted		0.370	<0.001	H6 accepted
EMP → BEH						0.037	0.534	
UAA → BEH						0.153	0.009	
Model fit indices								
χ^2 (df)	461.975 (280)				500.298 (323)			
CFI	0.950				0.952			
TLI	0.942				0.944			
AIC	657.561				722.298			

RMSEA (90% C.I.)	0.051 (0.043 – 0.059)	0.047 (0.039 – 0.055)
SRMR	0.054	0.058

Note: PU = Perceived Usefulness; PEU = Perceived Ease of Use; OQ = Output Quality; SAFA = Sustainability Assessment of Food and Agriculture Systems; ANX = Anxiety; TSE = Technology Self-Efficacy; SN = subjective norms; BI = Behavioural Intentions; EMP = number of employees; UAA = average farm size (Utilised agricultural area); BEH = Behaviour.

Perceived ease of use does not significantly affect the intention to adopt technologies, therefore not supporting H3a; however, it positively affects perceived usefulness of new technologies with $p<0.05$, confirming H3b. H5 is also supported since subjective norm has a positive effect on the intention to adopt a technology ($p<0.001$), showing that perceived social pressure has an influence on the farmers' motivation to adopt a new technology. The construct of anxiety shows a negative effect on the perceived ease of use ($p<0.05$, H2b accepted), a property that is stimulating and that could open up new ways of designing and conceptualizing modern technologies. Perceived ease of use, on the other hand, is positively influenced by the self-efficacy of the technology, with $p<0.001$, supporting H2a. In turn, perceived usefulness is influenced by the quality of the output (i.e., the perceived quality of the outcomes achieved through the use of the technology, $p<0.001$) and by the SAFA indicators ($p<0.05$), thereby supporting H1a and H1b, respectively. However, H1c is not supported, as the effect of subjective norms on perceived usefulness is not significant.

Overall, Model 2 shows good fit with the data (χ^2 (df) = 500.298 (323), CFI = 0.952, RMSEA = 0.047 (90%CI 0.039 – 0.055), TLI = 0.944 and SRMR = 0.058). Despite a higher AIC for Model 2 as compared to Model 1, due to the additional parameters, the extended model shows slight improvements in global fit (CFI, TLI, RMSEA), while also improving the explained variance of dependent variables, in particular behavioural outcome (up to 17.8%) (Table 4). The overall path and the tested hypotheses are confirmed, and the inclusion of structural variables adds value to the explanatory power of the model without substantially compromising parsimony. In particular, the number of employees positively influences respondents' perceived usefulness ($p<0.001$), indicating that decision-makers in larger farms, in terms of workforce, find the innovative technology capable of enhancing farm performance. In turn, the average farm size in UAA positively influences the behaviour ($p<0.001$) and behavioural intentions ($p<0.10$). In other words, respondents working in larger farms are more willing to adopt the new technologies or have already adopted them.

5. Discussion

This study provides empirical evidence on the factors influencing the intention and behaviour of Italian farmers to adopt digital water-saving technologies, with a focus on the horticultural sector. The results show that about 70% of the farmers surveyed have not adopted any of the proposed technologies, emphasising the persistent gap between technological innovation and practical implementation in the field. This finding confirms the limited uptake of smart farming solutions in Italy and emphasises the importance of understanding the barriers to adoption and the enablers of adoption. This is in line with previous research highlighting the slow pace of digitalisation in Italian agriculture compared to other European countries (Addorisio, Spadoni, et al., 2025; Cimino et al., 2024; Okoye et al., 2025; Timpanaro et al., 2024).

Using the extended TAM3 model, the study explains about 18% of the variance in the actual adoption of water-smart technologies, and 65% in adoption intention. As expected, behavioural intention is a significant predictor of the behaviour, indicating that farmers motivation in adopting the innovative technologies affect the actual adoption. The applied model further assumes that the effect of other variables (e.g., self-efficacy) on behavioural intention is mediated by perceived usefulness and perceived ease of use. Consistent with prior research (Davis, 1989; Venkatesh and Davis, 2000) perceived usefulness proved to be a key factor in willingness to adopt, emphasising the importance farmers attach to tangible benefits such as improved efficiency, performance or sustainability. Consistent with other studies, which suggest that perceived usefulness significantly influences technology adoption when it does not significantly increase production costs (Pierpaoli et al., 2013), our results show that economic viability remains a key concern, especially in a sector dominated by small to medium sized farms with limited investment capacity. The importance of perceived benefits is also supported by studies of adoption in agriculture across Europe, including those by Paustian and Theuvsen (2017) and Shang et al. (2021), who argue that demonstrable improvements in performance are essential to overcome innovation scepticism. In general and specifically in the Italian context, where high input costs and fragmented land ownership remain systemic barriers to modernisation, benefits are often associated not only with profitability, but also with the ability to ensure compliance with environmental standards and receive subsidies under the EU's Common Agricultural Policy (CAP). The perceived benefits of digital tools by farmers are therefore determined by a complex interplay of market incentives, legal requirements and evolving sustainability expectations.

Furthermore, in horticulture, a labour-intensive and water-dependent sub-sector, the perceived benefits of smart technologies are particularly relevant. With climate change exacerbating water scarcity in regions such as southern Italy, precision irrigation and monitoring systems are increasingly recognised as essential climate adaptation tools (Lakhiar et al., 2024). However, despite their potential, the perceived benefits of these tools often depend on farmers' ability to access relevant knowledge, trust the data provided and integrate new practises into existing routines – all factors mediated by the socio-cultural and institutional dynamics of the Italian agricultural landscape (Addorisio, Casolani, et al., 2025).

In contrast to the predictions of the original TAM3 model (Venkatesh and Bala, 2008), including those of its specific application (Kühnemund and Recke, 2025), this study found that perceived ease of use did not significantly influence Italian farmers' intention to adopt digital water-smart technologies. This deviation from theoretical expectations can be explained by the structural and cultural characteristics of Italian agriculture. The sector is dominated by small family farms, many of which, especially in the southern regions, face a pronounced digital divide due to limited access to broadband infrastructure, digital skills and technical training (Addorisio, Casolani, et al., 2025). Similar findings have been found in other studies (for an overview, see Osrof et al., 2023), including research on the Italian fruit and wine sector, where ease of use was also found to be insignificant (Canavari et al., 2021). As suggested by Schulze Schwering et al. (2022), perceived ease of use may play a minor role when farmers rely more on external support or adopt collaborative practises, suggesting that social norms may override ease of use concerns. Indeed, social norms had a significant influence on adoption intentions in this study, mirroring the findings of Senyolo et al. (2018) and Dissanayake et al. (2022). These findings suggest that peer influence and visibility of successful cases may help to foster a culture of innovation and support wider adoption.

The study also shows that sustainability-related factors — such as improved water management and skills development— increase perceived usefulness. This supports the arguments of Montes de Oca Munguia et al. (2021), who emphasise that the integration of sustainability goals can increase the perceived value of smart technologies. This is particularly relevant in the Italian Mediterranean climate context, where water scarcity, soil degradation and the effects of climate change pose an acute challenge to horticultural productivity and environmental resilience. The perceived alignment of digital technologies with sustainability goals therefore not only improves acceptance, but also strengthens farmers' motivation by linking environmental benefits with economic performance (Paustian and Theuvsen, 2017). This last point is thought-provoking when it comes to examining the role of farmers and their commitment to sustainability, as well as their awareness of the use of smart devices to promote more sustainable practices. In the face of climate change and the pressure that agriculture is putting on environmental resources, only the direct and committed involvement of farmers can promote a more conscious and widespread use of smart technologies with the aim of reaping their benefits (Menozzi et al., 2015). Linking sustainability to usefulness may also increase perceived profitability, which strengthens farmers' interest in adoption.

Technology self-efficacy was found to have a significant effect on perceived ease of use, suggesting that farmers who have confidence in their technical abilities are more likely to perceive smart technologies as manageable. This supports previous findings highlighting the relevance of perceived behavioural control for the adoption of sustainable practises (Menozzi et al., 2015). In the Italian context, where a significant part of the agricultural population consists of small farmers or ageing operators with limited participation in formal ICT training, self-efficacy becomes a crucial factor for the adoption of digital practises. Italian agriculture is characterised by a dual structure: on the one hand, there are highly mechanised and export-oriented companies, and on the other, traditional small farms that often lack digital infrastructure. Therefore, strengthening the confidence and skills of farmers through training is crucial to bridging this technological gap. The results also shed light on important barriers, including limited digital skills and poor access to information, which are in line with the findings of other studies (Osrof et al., 2023; Sabbagh and Gutierrez, 2023; Yigezu et al., 2018). The negative correlation between anxiety and perceived ease of use further underscores the need for user-friendly technologies that reduce cognitive and operational complexity. Targeted training initiatives and inclusive measures are needed to address these barriers, especially for farmers with limited resources.

The structural model also examined the influence of individual and organizational characteristics. Among these, only farm size and number of employees significantly affected the model’s endogenous variables, while other factors such as education level, age, and farm location showed no consistent impact. These findings reflect the mixed evidence in the literature

(Osrof et al., 2023) and may be partially explained by the evolving role of education and age in farming. For instance, highly educated individuals may pursue careers outside agriculture (Michels et al., 2020), while smart technologies are increasingly designed to be accessible regardless of users' educational background (Wachenheim et al., 2021). Similarly, although older age is often associated with lower adoption rates, several studies have shown no significant age effect (García-Jiménez et al., 2022). Larger farms—measured by UAA acreage—were more likely to adopt or intend to adopt digital water-smart solutions. This confirms the role of scale economies in overcoming the high investment costs associated with advanced technologies (Osrof et al., 2023). The significant effect of the number of employees on perceived usefulness may be interpreted in two ways: first, these technologies may be seen as reducing labour needs and costs; second, they may be valued for their potential to enhance employees' technical capabilities and improve workforce productivity. The latter interpretation aligns more closely with the observed positive relationship between sustainability orientation and perceived usefulness.

In summary, this study contributes to the understanding of digital technology adoption in Italian agriculture by validating core constructs of the TAM3 model while highlighting context-specific dynamics. This study not only confirms existing theoretical frameworks, but also highlights the importance of adapting digital transformation strategies to the Italian agricultural reality, characterized by structural constraints, strong social networks and a growing, yet uneven, momentum towards sustainable innovation. By identifying key drivers and barriers to adoption, the findings provide valuable guidance for the development of tailored policies, training programs, and user-oriented technologies that can support the digital transformation of the horticultural sector. Promoting the integration of sustainability goals, addressing capacity gaps, and leveraging social norms can collectively enhance adoption and support the transition toward a more sustainable and resilient agricultural system.

6. Conclusion

The adoption of digital technologies in the Italian horticultural sector is a multifaceted challenge influenced by a variety of individual, technological, social and contextual factors. These same factors are of utmost importance for policy makers that needs to design appropriate measures for promoting the adoption of water-saving solutions. Identifying both the motivations and the barriers to innovation might indeed inform policies by suggesting models that are suited to the challenges faced by farmers. Likewise, these findings can inform all interested stakeholders — from solution and technology developers to producer organizations — about the key aspects needed to promote the adoption of digital technologies within the agricultural sector.

This study shows that individual intention is an important determinant of the actual adoption of innovative water-saving technologies and highlights the crucial role of farmer motivation in decision-making. Perceived usefulness of these technologies has a significant effect on adoption intention, while perceived ease of use requires further investigation due to its limited relevance in the current context. Social norms were identified as an important determinant of farmers' intentions, highlighting the importance of community influence and external support in promoting the adoption of digital technologies. To close the observed adoption gap, targeted interventions should be developed to address barriers such as digital literacy, infrastructure and accessibility of technology. Furthermore, the regional and culture-specific nuances observed in this study should be taken into account when developing customised strategies.

The results highlight important policy and business implications, suggesting that government agencies, agricultural cooperatives, and technology developers should emphasize the economic and environmental benefits of digital irrigation technologies. The identification of appropriate measures, such as the creation of networks, outreach activities, knowledge-sharing initiatives and technical assistance, can also accelerate adoption. By addressing these research and knowledge gaps, this study contributes to both the academic literature and practical policy making. It provides a refined theoretical model to understand technology adoption in small- and medium-sized farms and offers practical insights to promote sustainable and efficient water management in agriculture. Further exploration of constructs that have negative correlates, such as anxiety, could lead to more user-centred technology design that reduces barriers to technology adoption and improves usability. Policy, and in particular the Agricultural Knowledge and Innovation Systems (AKIS) under the CAP, can play a crucial role in addressing these aspects by facilitating multi-actor collaborations between farmers, researchers, advisors, and technology developers, as well as strengthening the dissemination of best practices and provide continuous support (Esposti, 2012).

Some limitations of this study should be mentioned. First, the study reflects not only a specific context, such as the horticultural sector, but also national characteristics, which can vary greatly from country to country due to different regulatory and incentive frameworks, cultural practises and, most importantly, technological infrastructures. Nevertheless, the sample is not representative of Italian farmers. This must be taken into account when interpreting the results and deriving consequences for corporate management. An extension of the sample and a repetition of the study in other countries could therefore be interesting to test the validity of all the hypotheses put forward in the original theory. Extending the analysis to other crops farming, as well as to livestock farming, and expanding the sample size could provide more accurate insights over the phenomenon. EU Cross-regional studies might also be very interesting to point out differences in the adoption rate to be linked to cultural specificities, but also to normative, political and infrastructural settings. The results might in this way serve policy makers and institutions to design *ad hoc* policies to meet the desired technology level.

Second, we did not consider prospective behaviour, i.e., we did not measure actual behaviour in the future (i.e., future adoption of the innovative technologies), but only current behaviour. Although this approach is quite common in similar cross-sectional studies (see, e.g., (Li et al., 2023) on smart agricultural technology adoption), it might have limited the compatibility of behaviour with its antecedents (Fishbein and Ajzen, 2010). For instance, it has been noticed that relations between intention and behaviour might be stronger for studies measuring concurrent behaviour than those measuring behaviour prospectively (McEachan et al., 2011). However, we decided to use this multiple-level measurement of behaviour in order to capture, better than a binary variable, the progressive adoption from basic systems (in our case soil moisture sensors) to more complex systems (such as predictive ones). Thus, the intention-behaviour link in this study should be interpreted as a sequential progression in the adoption pathway, rather than a direct action-intention relation. Future studies employing longitudinal data collection could better report this linkage between intention and prospective adoption. Finally, this study used self-report measures about the behaviour which may be subject to response biases. However, the CATI method can help with complex or sensitive questions by allowing the interviewer to clarify questions and guide the respondent, thus reducing misinterpretation and encouraging more accurate responses (Dillman et al., 2014).

Despite these limitations, this study is, to our knowledge, one of the first aimed at investigating the relative importance of behavioural precursors in explaining the intention to adopt innovative water-smart technologies in Italian horticultural farms.

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Appendices

Table A1. Constructs and Items.

Codes	*Items*
	Perceived Usefulness
PU1	This innovation would make my work easier
PU2	This technology would make my work faster
PU3	This innovation could improve my productivity
PU4	By using this technology, I could reduce water consumption in my company
	Perceived Ease of Use
PEU1	This technology should be easy to use
PEU2	Using this technology will not require much effort
	Output Quality
OQ1	I expect that the results of using this technology will be excellent
OQ2	Using this technology will improve the quality of my products
OQ3	By using this system, I would increase the efficiency of my work
OQ4	By using this innovation, I would increase the quantity of product in the field
	SAFA
SAFA1	By using this innovation, I could help reduce water consumption
SAFA2	With the introduction of this technology, employees could receive training and enhance their knowledge and technical skills
SAFA3	By introducing this innovation, I could receive training and improve my technical skills
	Anxiety
ANX1	I get nervous when working with new technologies
ANX2	New technologies make me feel uncomfortable
ANX3	I am afraid of applying new technologies
	Technology Self-Efficacy
TSE1	I would use this technology easily if someone showed me how to use it
TSE2	I would use this innovation easily if I had technical support
TSE3	I would use this innovation easily if I were familiar with the system

	Subjective Norms
SN1	People whose opinions matter to me think that I should use this technology
SN2	Many producers I know have already adopted this innovation
SN3	My customers think that I should use this technology
	Behavioural Intention
BI1	I will definitely use this technology in the near future
BI2	I intend to use this technology in the near future
BI3	If there were no significant barriers, I would use this system in the near future

Note: All items were measured on a 7-point scale (from 'strongly disagree' to 'strongly agree').

Table A2. TAM3-extended model: unstandardized beta coefficients and standard errors (S.E.) (n=251).

	Model 1		Model 2	
	Beta	S.E.	Beta	S.E.
PEU → PU	0.202*	0.100	0.180#	0.096
OQ → PU	0.796***	0.136	0.848***	0.136
SAFA → PU	0.236*	0.106	0.179#	0.102
SN → PU	0.040	0.060	0.030	0.059
EMP → PU			0.267***	0.065
UAA → PU			0.000	0.000
TSE → PEU	0.308***	0.064	0.308***	0.064
ANX → PEU	-0.098*	0.048	-0.095*	0.048
PU → BI	0.862***	0.110	0.866***	0.112
PEU → BI	0.149	0.142	0.130	0.139
SN → BI	0.351***	0.082	0.334***	0.082
EMP → BI			0.072	0.101
UAA → BI			0.000#	0.000
BI → BEH	0.256***	0.039	0.235***	0.039
EMP → BEH			0.049	0.080
UAA → BEH			0.000**	0.000

Note: PU = Perceived Usefulness; PEU = Perceived Ease of Use; OQ = Output Quality; SAFA = Sustainability Assessment of Food and Agriculture Systems; ANX = Anxiety; TSE = Technology Self-Efficacy; SN = subjective norms; BI = Behavioural Intentions; EMP = number of employees; UAA = average farm size (Utilised agricultural area); BEH = Behaviour. Sign.: *** p<0.001, ** p<0.01, ** p<0.05, # p < 0.10.