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Drivers of Precision Agriculture Adoption in Italian Viticulture

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ABSTRACT

This study examines the main drivers influencing the adoption of two types of precision farming technologies in the viticultural sector: Decision Support Systems (DSSs) and Variable Rate Technologies (VRTs). We apply a partial proportional odds model and find that socio-demographic characteristics are not significant determinants of adoption, whereas farm structural features and a general positive attitude toward technology significantly increase the likelihood of uptake. Environmental concern plays a role only with respect to the intention to adopt, but not in explaining actual adoption behavior. Moreover, farmers' perceptions of the usefulness of digital technologies and the difficulties associated with their use emerge as key factors shaping adoption intentions among non-adopters. These results suggest that targeted training initiatives and strengthened advisory services could play a crucial role in fostering the diffusion of precision farming technologies in viticulture.

JEL Classification: Q12Q15

1 | Introduction

Precision agriculture (PA) has emerged in response to the global challenge of feeding a growing population while preserving natural resources and minimizing the environmental impact of agriculture (Ruder et al. 2026). The underlying problem stems from the limitations of conventional management practices, which apply inputs such as fertilizers and pesticides at uniform rates based on average field and weather conditions and generic crop characteristics (Khanna 2021). This approach neglects the spatial and temporal heterogeneity of soils. For instance, fixed-rate fertilization may result in insufficient nutrient supply in certain areas, thereby constraining potential yields, while excessive applications in other areas lead to economic inefficiencies and environmental pollution due to nutrient leaching into groundwater.

Furthermore, in the European Union, agricultural productivity in the medium term is entering a new phase, in which crop yield growth is expected to slow down and production levels to stagnate. This trend is driven by several factors, including climate change, the increasing frequency of extreme weather events, and the reduced use of plant protection products and synthetic fertilizers (European Commission 2022). In this context, the integration of advanced digital technologies—such as artificial intelligence—together with data generated by the Internet of Things (IoT) and other sources has the potential to substantially improve agricultural operations, foster innovation, and transform food production systems while simultaneously addressing environmental sustainability, climate challenges, and societal well-being (European Commission 2025).

Originally developed in the 1980s, PA is defined as a "management strategy that gathers, processes and analyses temporal, spatial and individual data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production" (ISPA 2024).

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The development of digital technologies has enhanced the capacity to identify, quantify, and implement site-specific management practices that optimize input application rates according to specific soil conditions and timing requirements (Wolfert et al. 2017; Khanna 2021). In this regard, the viticulture sector represents a particularly promising field of application for PA, as vineyards are characterized by a high degree of heterogeneity due to structural factors that require differentiated agronomic management (Matese and Di Gennaro 2015). In this context, Precision Viticulture faces several inherent challenges, particularly its reliance on accurate real-time meteorological and environmental data, as well as the carbon footprint associated with vineyard management practices (Sofia et al. 2025).

Although not a strategic sector for human feeding, viticulture plays a fundamental role worldwide by generating income, shaping landscapes, supporting rural development, and contributing to cultural identity (Grella 2022). This is particularly true for Italy, which in 2024 ranked first globally in wine exports in terms of quantity (21.7 million hectoliters) and second, after France, in terms of sales value (8.1 billion euros) (Area Studi Mediobanca 2025).

Despite the increasing scientific effort devoted to digital technologies in agriculture over recent decades, only a limited share of the literature on PA focuses specifically on viticulture. It is estimated that approximately 5% of PA-related publications concern viticultural applications (Ferro and Catania 2023). Empirical studies on the adoption of precision viticulture technologies remain relatively scarce (Dressler and Paunovic 2021; Bastard and Chaillet 2023; Boyer and Touzard 2021; Muscio et al. 2017), as research has largely focused on sustainability practices in broader terms (Merli et al. 2018). Only a small number of studies investigate the adoption of PA by explicitly accounting for the attributes of different technologies (Barnes et al. 2019; Blasch et al. 2022).

The existing literature has largely focused on adopters and on the broader farming context, while devoting limited attention to the performance characteristics of the technologies themselves (de Oca Munguia and Llewellyn 2020). Moreover, few studies compare the adoption of technologies characterized by different levels of automation. Only recent research has explicitly examined the adoption of smart water management technologies in the Italian horticultural sector by classifying technologies according to increasing levels of complexity (Cozzi et al. 2025). Although a substantial body of literature investigates the determinants of technology adoption in agriculture (Kroupová et al. 2025), most studies do not clearly distinguish between intention to adopt and actual adoption. In a seminal contribution, Pierpaoli et al. (2013) frame this distinction in terms of ex ante versus ex post adoption studies. Ex post studies focus on the factors that have encouraged farmers to adopt new PA technologies, while ex ante studies analyze the acceptance of new technologies by potential adopters prior to their introduction.

Against this background, this study aims to investigate the main drivers of adoption, as well as the intention to adopt two precision farming technologies—namely Decision Support Systems (DSSs) and Variable Rate Technologies (VRTs)—in the Italian viticulture sector. Following Blasch et al. (2022), DSS are classified as non-automated technologies, such as systems that use satellite imagery to generate field data maps accessible via personal computers or mobile devices, in which the operator remains central to the interpretation of biometric information. By contrast, VRTS are classified as fully automated technologies, such as spreaders equipped with built-in real-time sensors. Although both technologies are commercially available, the adoption of VRT remains limited (Tardaguila et al. 2021).

Among the factors that may influence adoption and adoption intention, this study considers farm and farmer characteristics, as well as farmers' attitudes toward environmental issues and technology use. In addition, we test whether the factors typically included in the Technology Acceptance Model (TAM) (Davis et al. 1989; Cozzi et al. 2025) are relevant in explaining the intention to adopt the two technologies under analysis. The TAM framework is particularly relevant in this context given the different degrees of automation embedded in DSS and VRT, which imply varying levels of user engagement and technical skills and may therefore affect perceived ease of use.

We collected 219 responses through an online questionnaire administered to Italian viticultural farmers. The empirical analysis is conducted by adapting the Trans-Theoretical Model of Adoption (TTMA) (Lemken et al. 2017; Michels et al. 2020; Ha et al. 2024) to the objectives of this study. The TTMA allows for the analysis of the gradual adoption process by identifying the probability that a farmer belongs to a specific stage of adoption, ranging from non-adoption to full adoption, as well as the drivers that facilitate transitions between stages. Compared to a binary classification of adoption versus non-adoption, this approach captures intermediate stages and provides more detailed insights into the dynamics of technology adoption. The analysis is carried out separately for DSS and VRT.

2 | Literature Review

Agricultural management is often conceptualized as a “gray box”, consisting of controllable inputs (fertilizers, seeds, pesticides) and uncontrollable factors (e.g., pests, rainfall), combined with incomplete knowledge of the relationships between them (Cook and Bramley 1998). PA aims to address these gaps through the use of technologies such as Global Navigation Satellite Systems (GNSS), yield monitoring, soil mapping, and variable-rate applications for seeding, fertilizers, and pesticides (Nowak 2021; Ruder et al. 2026). Technological advancements have progressively enhanced local adaptability and operational precision (Lowenberg-DeBoer and Erickson 2019), while the Agriculture 4.0 paradigm introduces autonomous operations and decision-making systems (Fragomeli et al. 2024; Santos Valle and Kienzle 2020).

Digital transformation constitutes the essential backdrop against which the European agri-food system is expected to develop in the coming years (Reinhardt 2023). At the international level, precision technologies have been adopted more rapidly in Europe and North America, particularly by large, export-oriented enterprises, whereas adoption has been slower in regions characterized by fragmented landholdings and small family farms, such as much of the Mediterranean basin (González-Vivar et al. 2025). Nevertheless, the emerging empirical evidence points to a rapid adoption of GNSS guidance systems alongside a slower uptake of VRTs (Khanna 2021). Farmers also tend to remain within the same bundle of technologies, although transitions between different technology bundles have been observed (Miller et al. 2017; Barnes et al. 2019; DeLay and Comstock 2021).

In the literature, barriers to the adoption of PA technologies are commonly classified as economic, technical, cultural, and structural obstacles. The acquisition of precision farming technologies entails substantial costs; therefore, financial constraints represent a major limitation to their adoption within agricultural enterprises. The high initial investment required may exceed the financial capacity of many farmers and agricultural entrepreneurs (Alka et al. 2024). Furthermore, many farmers lack the necessary skills to effectively use digital technologies and to correctly interpret the complex data generated by digital systems (Alka et al. 2024; Bono et al. 2025). It is expected that artificial intelligence will play an increasingly important role in the detection and management of spatial variability through autonomous approaches (Ferro and Catania 2023). More generally, a widespread concern toward innovation persists, largely due to the perceived risks associated with shifting from traditional farming practices to more technologically advanced approaches (Alka et al. 2024). A further critical issue relates to generational transition within family-owned wineries, which constitute the majority of the Italian wine sector. In this context, the main challenge is the limited interest of heirs in continuing the family business (Sarri et al. 2020). Moreover, bureaucratic constraints (De Steur et al. 2020) and uncertainty regarding return on investment (Vecchio et al. 2020) further reinforce a cautious attitude toward the adoption of precision farming technologies.

Despite these challenges, several factors encourage agricultural entrepreneurs to pursue digitalization. First, digital technologies enable the optimization of resource allocation and the improvement of both yields and the quality of final products (Bono et al. 2025; Ammoniaci et al. 2021). Second, market pressure and increasing consumer ecological awareness act as pull factors, driving farmers to adopt digital technologies in order to communicate their sustainable identity in a credible and transparent manner (Flores 2018; Muscio et al. 2017). However, previous studies on innovation adoption in agriculture have not sufficiently emphasized the role of farmers' motivation toward environmental sustainability (Blasch et al. 2022; Barnes et al. 2019). Passarelli et al. (2023) find a positive effect of behavioral attitudes toward environmental and economic sustainability on the intention to adopt digital innovations. In the Italian wine sector, environmental sustainability drivers of innovation adoption have been found to generally score higher than economic drivers (De Steur et al. 2020).

Finally, difficulties in finding qualified seasonal workers, combined with an aging workforce, are accelerating the adoption of robotic and automated solutions (Moganapathi et al. 2025). According to Sarri et al. (2020), although the Italian wine sector has access to a wide range of investment and financing opportunities, it lacks the human, territorial, and organizational resources necessary for the successful adoption of technological innovations. This results in a relatively low adoption rate, particularly with respect to VRT (Ammoniaci et al. 2021). As reported by Sofia et al. (2025), only 11% of Italian farms made at least one investment in precision farming between 2018 and 2020.

In our study, we analyze two attitudinal dimensions—namely, attitude toward the environment and general attitude toward technology—and their effects on the adoption of the two technologies analyzed (DSS and VRT). The most widely used scale to investigate environmental attitudes is the revised New Environmental Paradigm (NEP) scale (Dunlap et al. 2000), which consists of 15 statements and has been extensively validated as an accurate measure of environmental values. In the wine industry, environmental perceptions measured through the NEP scale have been predominantly investigated from a consumer perspective (Kemp et al. 2022; Palmieri et al. 2023), while very few studies have adopted the NEP scale to assess farmers' environmental attitudes. One exception is Jobin-Poirier et al. (2019), who find that Canadian winegrowers exhibit a pro-ecological worldview. Among European winegrowers, perceptions of climate change impacts have led to growing interest in adaptation technologies, combined with a demand for additional information (Battaglini et al. 2009).

With regard to general attitudes toward technology, previous studies show that demographic attributes—such as age, education, and farm size—affect technological attitudes (Marescotti et al. 2021). A specific scale in this area is the Technophobia and Technophilia Questionnaire (TTQ), developed and validated by Martínez-Córcoles et al. (2017). The relationship between technological and environmental attitudes has also been examined. Gardezi and Arbuckle (2020) corroborate the negative relationship identified in the literature between techno-optimism and climate change, showing that a perceived high technical capacity to support pro-environmental actions may promote decision-delay responses to climate-related threats.

3 | Methodology

We adapt the Trans-Theoretical Model of Adoption (TTMA) to analyze the adoption process of DSSs and VRTs. The TTMA is derived from the Trans-Theoretical Model of Behavioral Change introduced in psychology by Prochaska and Velicer (1997) and subsequently adapted to the agricultural context to study the adoption of farming practices (Lemken et al. 2017) and technologies (Michels et al. 2020).

We apply the model to investigate the determinants of gradual changes in PA technology adoption behavior within the viticultural sector. Unlike binary models, in which adoption can only take the values "yes" (i.e., adoption) or "no" (i.e., non-adoption), the TTMA also identifies intermediate stages of adoption, which encompass farmers' intentions to modify established behaviors. As such, it provides more detailed insights into both the adoption process and the drivers associated with being in a specific stage of adoption.

Partially building on the literature on agricultural technologies (Lemken et al. 2017; Michels et al. 2020),[1] the adoption process has been operationalized into three phases: (1). Precontemplation ("I am not willing to adopt this technology on my farm"); (2). Contemplation ("I am principally willing to try out the application of this technology on my farm") or ("I have concrete plans to use this technology on my farm"); (3). Action ("I already use this technology on my farm"). This model is particularly suitable for our study because one of the two technologies, that is, the VRT, is still barely adopted in agriculture and therefore the small number of adopters may hinder the estimation of meaningful parameters. Therefore, splitting the adoption in a more articulated process than the binary one helps to gain insights on the gradual change toward adoption. This modeling framework is particularly suitable for the present study because one of the two technologies analyzed—namely VRT—is still scarcely adopted in agriculture, and the limited number of adopters may hinder the estimation of meaningful parameters in a binary framework. Therefore, modeling adoption as a more articulated process than a simple binary outcome allows for a better understanding of the gradual transition toward adoption.

The econometric model we apply is a partial proportional odds model, where the dependent variable is an ordinal variable indicating one of the three stages of technology adoption. The true underlying process of gradual adoption is represented by:

$$y^* = \boldsymbol{x}'\boldsymbol{B}^{\boldsymbol{s}} + \boldsymbol{z}'\boldsymbol{\gamma} + \varepsilon \tag{1}$$

where $y^*$is a latent variable, $\boldsymbol{x}'$ is a vector of factors affecting technology adoption through the coefficient vector $\boldsymbol{B}^{\boldsymbol{s}}$, which is different for each stage of adoption $\boldsymbol{s}$. $\boldsymbol{z}'$ is a vector of factors affecting technology adoption through the coefficient vector $\boldsymbol{\gamma}$, which is the same across the three stages of adoption, and ε is the error term with a logistic distribution.

To test whether a coefficient associated with a variable is the same across all the different adoption stages or not, we apply the Brant test (Brant 1990), and for those variables failing the Brant test, we allow the related coefficients to vary with the stage of adoption ($\boldsymbol{B}^{\boldsymbol{s}}$).

As the true y^* driving the adoption process is unobserved, what we actually observe is y, the ordinal dependent variable which represents the stage of the adoption ranging from 1 (Precontemplation) to 3 (Action):

$$\mathrm{y} = \begin{Bmatrix} 0 \; if \, y^* \le \mu_1 \\ 1 \; if \, \mu_1 < y^* \le \mu_2 \\ 2 \; if \, \mu_2 < y^* \le \mu_3 \\ 3 \; if \, y^* > \mu_3 \end{Bmatrix} \tag{2}$$

where μ_{j} are the cut points of the adoption stages. We perform this estimation procedure separately for each technology (DSS and VRT).

Our empirical model takes the following form:

$$\begin{aligned} y_{iT} = {} & B_{1T} male_i + B_{2T} age\_less\_40_i + B_{3T} degree_i \\ & + B_{4T} education\_agriculture_i + B_5 North_i \\ & + B_6 organic_i + B_7 Farm\ size_i + B_8 \%own\ land_i \\ & + B_{9T} hill\_mountain_i + B_{10T} environmental\ attitude_i \\ & + B_{11T} technological\ attitude_i \end{aligned} \tag{3}$$

where $T=1$, 2 indicate the technology considered (*1*=DSS, *2*=VRT), *i* indicates the farmer, *male*, *age_less_40*, *degree*, *education_agriculture*, *North*, *organic*, *hill_mountain* are coded as dummy variables and take value 1 respectively for farmers that are male, younger than 40 years old, having a university degree, having an education in the agricultural field, having the farm located in Northern Italy, having the farm in a hilly or mountain area. *Farm size* is the size of farmland in hectares, *% own land* indicates the share of farmland owned by the respondent. *Environmental attitude* and *technological attitude* are indexes measuring the attitudes toward the environment (Dunlap et al. 2000) and toward technology (Martínez-Córcoles et al. 2017), and are computed as means of several statements measured on a five-point Likert scale. Details of scales are provided in Section 4.1. Before calculating the mean, the scores for each scale are reversed for the opposite statements, such that a higher mean environmental attitude score indicates a more positive attitude toward the environment, and a higher mean technological attitude score indicates a more positive attitude toward technology.

We estimate one additional model for each of the two technologies, where we exclude the farmers belonging to Stage 3 and we include two TAM questions.[2] This additional model uses the same variables as in Equation (3) and it adds two additional variables taken from the TAM (*perceived usefulness* and *perceived difficulty to use*). By excluding Stage 3, this model collapses to a binary model that measures the intention to adopt each technology.

4 | Data

Our target population is Italian winegrowers with different farm sizes and production methods. To achieve our research objective, we developed a questionnaire to collect information on multiple aspects. First, we assessed the participants' familiarity with the two technologies (DSS and VRT), followed by a brief presentation of their mechanisms and goals. We then identified which of the three stages of adoption for each technology the farmer belongs to, asking about the reasons behind adoption or non-adoption, and we explored the potential drivers and enablers for behavioral change in case of non-adoption. The survey also includes a section aimed at obtaining demographic information and farm characteristics. Finally, the last section was dedicated to assessing participants' attitudes toward the environment, technological innovation, and the farmers' perception of the usefulness and the difficulty of using the technologies under study, measured by scales validated in the literature. In the following subsection, we detail the scales used along with the TAM questions included.

The intention to adopt PA technologies has been largely investigated through the TAM (Davis et al. 1989), predicting the use of technologies according to attitudes (Michels et al. 2020; Mohr and Kühl 2021). The TAM consists of two factors that predict the intention to use a technology. First, it positively depends on the extent to which a person believes that it will help them perform a better job (perceived usefulness), and second, on the belief that the technology is not too difficult to use and that the benefits in terms of performance outweigh the efforts required to use the application (perceived ease of use) (Davis et al. 1989).

4.1 | Attitudinal Scales

The farmers' concerns toward the environment are retrieved through the NEP scale (Dunlap et al. 2000). To keep the length of the survey within a reasonable time limit and to avoid the use of outdated statements (Whitmarsh 2008), we select five out of the fifteen original statements, following the work of Pierce et al. (1987) who proposed and validated a reduced version of the original NEP scale.

The farmer's general attitude toward technology has been investigated by a reduced version of the TTQ developed and validated by Martínez-Córcoles et al. (2017). The TTQ consists of a technophobia component defined as a single-factor structure (i.e., an irrational fear caused by using technological devices) and a technophilia component defined by three sub-constructs: *enthusiasm*, *dependency*, and *technoreputation*.

We also include two questions taken from the TAM framework (specifically "The use of this technology would be of great importance for the different operations on my farm", "I am not the kind of farmer who knows how to work with this technology") to elicit the perceived usefulness and the difficulty of using the two analyzed technologies by farmers.

Table 1 displays the statements from NEP, TTQ, and TAM used in the survey. Participants were asked to evaluate them on a five-point Likert scale (1 = I strongly disagree; 2 = I disagree; 3 = I do neither agree nor disagree; 4 = I agree; 5 = I strongly agree).

A pilot survey was conducted to ensure participants' understanding of the functioning and aims of the questionnaire. To reach our target and guarantee a geographically representative sample, we employed three channels: (1) a mailing list of about 3000 winegrowers distributed throughout Italy; (2) the FIVI's (*Federazione Italiana Vignaioli Indipendenti*) mailing list of about 1500 winegrowers; (3) the *Confagricoltura*'s list of about 4000 wine producers. An email containing the link to the survey was sent to winegrowers through these channels. The data collection process began in early March 2024 and concluded at the end of May 2024.

TABLE 1 | Statements used in the survey for each scale (1–5 points Likert scale).

Scale	Statement
NEP	We are approaching the limit of the number of people the Earth can support
	Plants and animals have as much right as humans to exist
	The balance of nature is very delicate and easily upset
	Human ingenuity will ensure that we do not make the Earth unlivable
	Humans are seriously abusing the environment
TTQ	I feel uncomfortable when I use new equipment or technology
	I am excited for new equipment or technology
	I find it very difficult to learn how to use new technologies
	I'm afraid of being left behind if I cannot use the latest equipment or technology
	I feel inexperienced in using new equipment or technology
	Lately, I have been using new equipment or technology too often
TAM	The use of this technology would be of great importance for the different operations on my farm
	I am not the kind of farmer who knows how to work with this technology

4.2 | Sample Description

Out of the emails sent to farmers, 352 opened the link to the survey. After the data-cleaning process, the final dataset comprises 220 observations. As is common in online surveys targeting farmers, the response rate is low. This may imply a self-selected sample, but it also helps explain some of the farmer characteristics we discuss below. Table 2 reports the descriptive statistics for the variables included in the two models and shows the main farmer and farm characteristics. Figure 1 further illustrates the distribution of respondents by farm size classes.

AdoptionDSS and *AdoptionVRT* measure the stage of adoption of DSS and VRT by farmers on a scale from 1 (Precontemplation phase) to 3 (Action phase), where a higher score indicates being in a later stage of adoption. Most respondents are positioned at Stage 2 for both technologies (56% for DSS and 62% for VRT), that is, the Contemplation phase, indicating they are interested in evaluating their adoption. The shares of farmers at Stage 3 are largely different between the two technologies (27% for DSS vs. 6% for VRT). Furthermore, the higher share of farmers at Stage 1 for VRT (32%) compared to that for DSS (16%) indicates greater reluctance toward VRT. This suggests that DSS may be perceived as either more beneficial or easier to implement. Another reason is that farmers are generally more familiar with DSS than with VRT: 56% of our sample was unaware of the existence of VRT, while DSS was known by 72% of participants.

Regarding participants' demographic characteristics, 72% of the respondents are male, reflecting the national gender distribution of agricultural employment,[3] where 69% of farmers are men (ISTAT 2022). Conversely, 33% of participants are under 40 years old, which does not fully capture the real share of Italian farmers under 40, which is 9% (ISTAT, 2022). Regarding education, 60% of winegrowers in the sample have a higher education degree. This does not reflect the real population data, as only 19% of young farmers and 9% of those over 40 hold a university degree (ISTAT 2022). Differences with national data also emerge in terms of educational background in agriculture: 57% of farmers in our sample declared having attended an agricultural specialization course. This is higher compared to national data, where this share is 47% among farmers under 40 and drops to 27% for older farmers

TABLE 2 | Descriptive statistics of variables included in the models.

Variable	Description	Mean	S.d.	Min	Max
AdoptionDSS	Stages of adoption process of DSS				
Stage 1	Do not want to use DSS	16.43%	\		
Stage 2	Open to consider the use of DSS	56.16%	\		
Stage 3	Do already use DSS	27.40%	\		
AdoptionVRT	Stages of adoption process of VRT				
Stage 1	Do not want to use VRT	31.51%	\		
Stage 2	Open to consider the use of VRT	62.10%	\		
Stage 3	Do already use VRT	6.40%	\		
Male	1 if male, 0 if female	0.72	\	0	1
AgeLess40	1 if less than 40 years old, 0 otherwise	0.33	\	0	1
Degree	1 if hold a university degree, 0 otherwise	0.60	\	0	1
EducationAgriculture	1 if hold agricultural education, 0 otherwise	0.57	\	0	1
North	1 if located in the North, 0 otherwise	0.51	\	0	1
Organic	1 if organic, 0 otherwise	0.49	\	0	1
FarmSize	Farm size in hectares	82.08	149.01	1	1200
OwnLand	Share of own land	80.37	30.15	10	100
HillMount	1 if located in hill or mountain	0.82	\	0	1
Environmental attitude	Mean of the NEP scale[a]	3.91	0.61	1.3	5
Technological attitude	Mean of the TTQ scale[a]	3.65	0.57	1.8	5
Perceived usefulness DSS	Perceived usefulness of DSS (Likert scale 1–5)	3.56	0.70	1	5
Perceived usefulness VRT	Perceived usefulness of VRT (Likert scale 1–5)	3.35	0.84	1	5
Perceived difficulty to use DSS	Perceived difficulty to use DSS (Likert scale 1–5)	2.44	0.99	1	5
Perceived difficulty to use VRT	Perceived difficulty to use VRT (Likert scale 1–5)	2.40	0.96	1	5

[a]Negative statements have been reversed such that *environmental attitude* indicates a positive attitude toward the environment and *technological attitude* indicates a positive attitude toward technology.

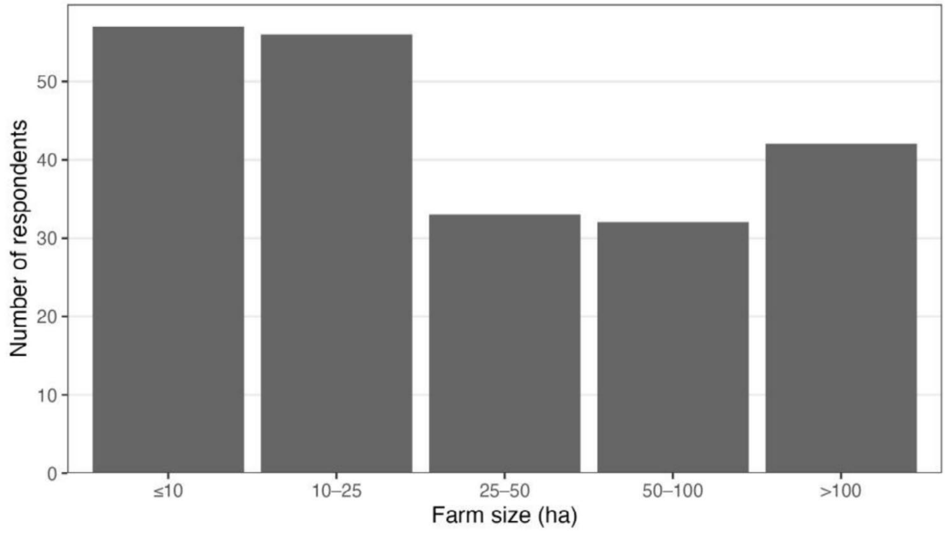

FIGURE 1 | Distribution of respondents by farm size classes.

(ISTAT 2022). These data suggest that our sample is younger and more educated compared to the Italian winegrower population, probably due to the online nature of the survey.

Concerning farm characteristics, 51% of farms in the sample are located in the Northern regions, which aligns with national data (45% are located in the North). Moreover, 49% of farmers adopt organic agriculture. It is worth noting that the sample is skewed toward organic viticulture compared to the national share of 23% organic vineyard area (SINAB 2022). In addition, our sample includes a wide range of farm sizes, with a mean of 82 ha and a standard deviation of 149. Our average farm size is much higher than the Italian average, which is 11 ha (ISTAT 2022). This reflects the strong right-skewness of the farm size distribution. Most respondents own relatively small farms (median = 25 ha). However, the presence of a relatively high number of very large farms increases the sample mean (Figure 1).

Furthermore, most farmers own a significant portion of their land (80%). Despite our sample being skewed toward larger farms and male and well-educated farmers, Michels et al. (2020) encountered similar sampling issues. In line with Michels et al. (2020), we state that our sample is representative of farmers adopting PA in Europe, and thus, we can focus on the obstacles and drivers of adoption in Italy for the targeted population of potential adopters. Finally, 82% of responding farms are located in hilly or mountainous areas, which is significantly higher than the national share of 51% (Osservatorio UIV 2023).

5 | Results

5.1 | Descriptive Statistics

Figures 2,3 show the various areas of applications of DSS and VRT, respectively, for winegrowers who have reached Stage 3 in the adoption process.

The main use of DSS, as reported by 36.2% of respondents, concerns pesticide application. This finding aligns with the technology's renowned ability to optimize pesticide use by increasing its efficacy while reducing overall usage, allowing for cost-effective pest control management. The second best-rated application is water use management, declared by 20.6% of participants. In

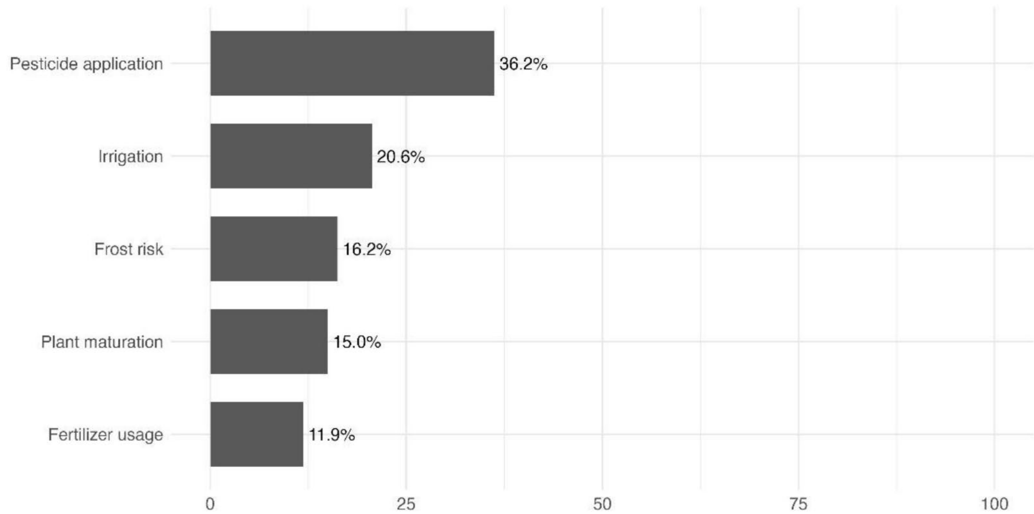

FIGURE 2 | Areas of application of decision support system ($n = 60$).

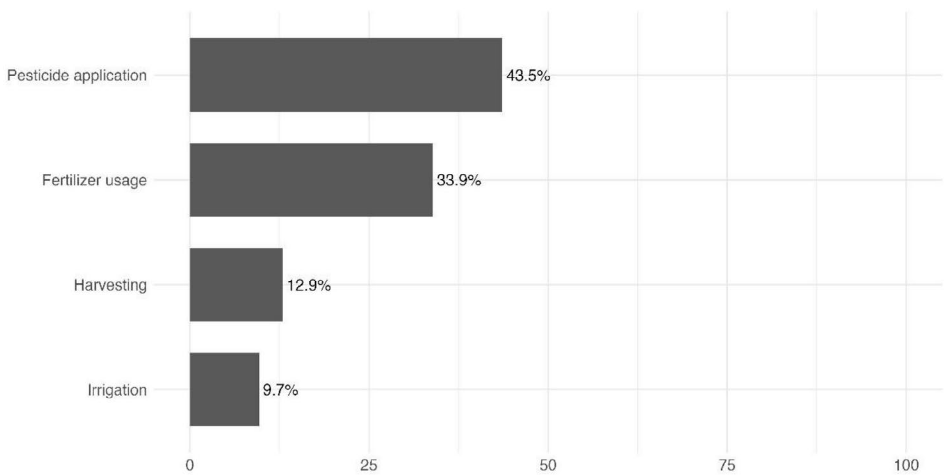

FIGURE 3 | Areas of application of variable rate technology ($n = 14$).

addition to these primary applications, 16.2% of winegrowers indicate they use DSS for frost risk reduction, which is crucial for ensuring grape yield quality.

The primary use of VRT among adopting farmers relates to pesticide application (43.5% of the adopters). This reflects VR technology's role in managing vines and controlling pests and diseases. Fertilization is the second most prevalent application, as 33.9% of the adopting winegrowers use the technology for this purpose. Harvesting and irrigation, on the other hand, are less common applications, with 12.9% and 9.7% of the respondents who adopt a VRT, respectively, indicating the relatively scarce use of the technology in these operations.

For both technologies, we asked participants who are at stage 1 and stage 2 of the adoption process to indicate the reasons why they are not using them. Figures 4,5 show the reasons for not adopting DSS and VR technology, respectively. The lack of financial resources is the main barrier to both DSS and VRT adoption (reported by 31.2% and 35.1% of participants, respectively). Not having access to detailed information was the second most significant barrier for both, although it was slightly higher for

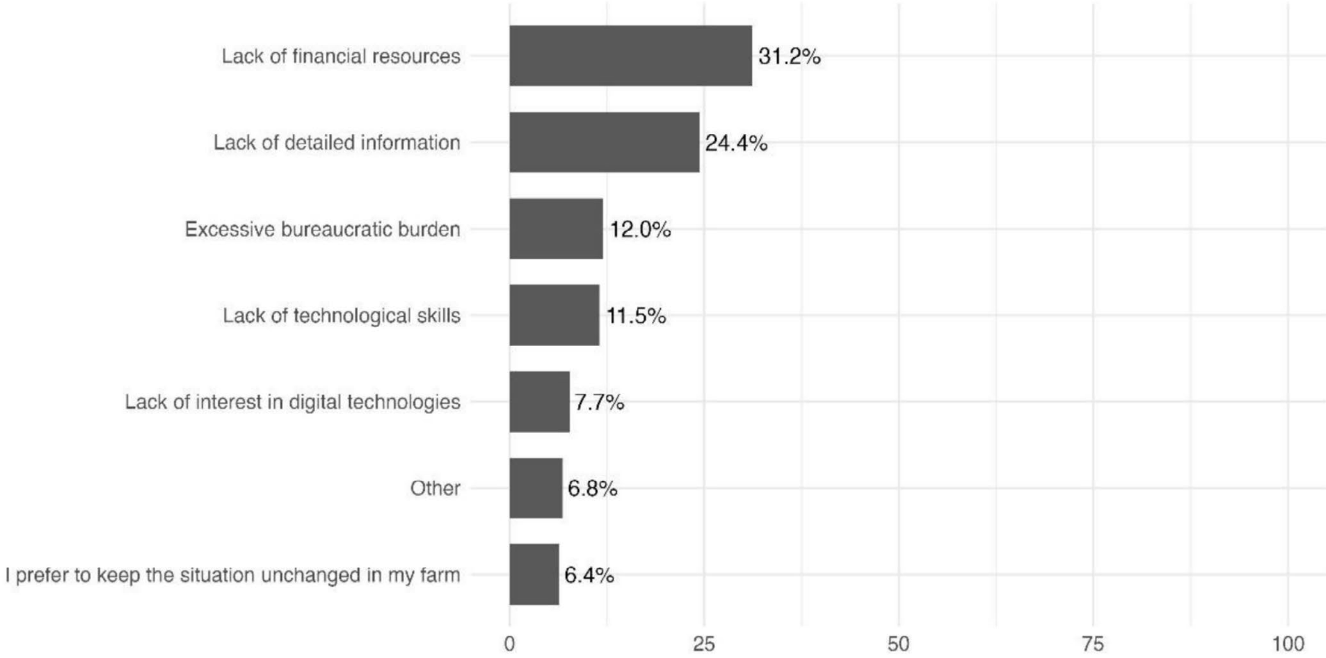

FIGURE 4 | Reasons for not adopting decision support system ($n = 151$).

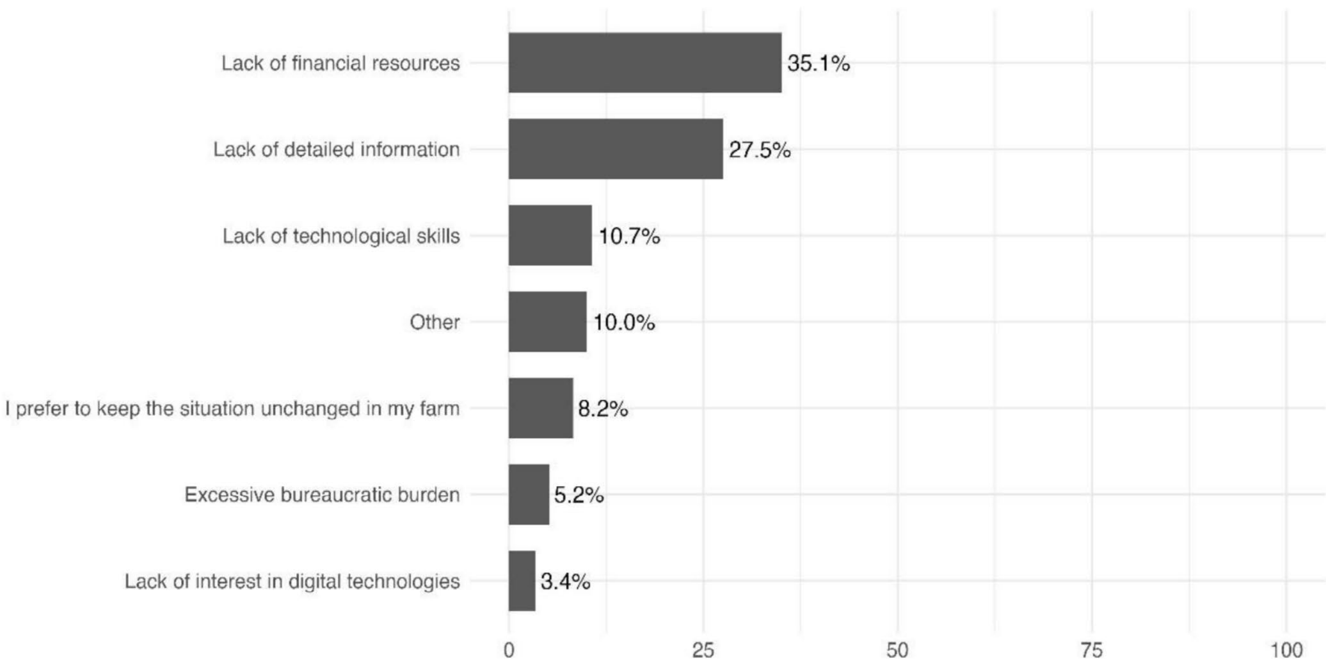

FIGURE 5 | Reasons for not adopting variable rate technology ($n = 191$).

TABLE 3 | Results of the partial proportional odds model for the DSS technology ($N = 219$).

	Odds ratio	Standard error	95% confidence interval	
			Lower	Upper
Male[b]	1.095	0.369	0.371	1.819
Age less than 40[b]	0.697	0.213	0.279	1.116
Degree[b]	0.945	0.280	0.397	1.494
Education in agricultural field[b]	1.513	0.432	0.667	2.359
North[b]	1.001	0.292	0.428	1.574
Organic[b]	1.077	0.311	0.468	1.686
Farm size (ha)	1.001	0.001	0.999	1.003
% own land	1.010	0.005	1.001	1.020
Hill or mountain area[b]	0.898	0.324	0.264	1.532
Environmental attitude (1)[a]	2.363	0.673	1.044	3.681
Environmental attitude (2)[a]	0.793	0.200	0.400	1.185
Technological attitude (Likert scale 1–5)	3.075	0.820	1.467	4.683

	Stage 1	Stage 2	Stage 3
Predicted probabilities	0.163	0.562	0.275
Log likelihood	−193.733		
Pseudo-R2	0.093		
AIC	415.465		
BIC	462.913		

[a]The environmental attitude does not follow a parallel trend. Environmental attitude (1) indicates stage 1 vs. stage 2 and stage 3. Environmental attitude (2) indicates stage 1 and stage 2 vs. stage 3.
[b]The variable is coded as a dummy variable.

TABLE 4 | Results of the partial proportional odds model for the VRT technology ($N = 219$).

	Odds ratio	Standard error	95% confidence interval	
			Lower	Upper
Male[b]	0.633	0.224	0.194	1.072
Age less than 40[b]	1.094	0.349	0.410	1.779
Degree (1)[b,a]	1.602	0.511	0.600	2.604
Degree (2)[a]	0.515	0.311	0.095	1.125
Education in agricultural field[b]	1.189	0.351	0.501	1.876
North[b]	1.132	0.345	0.456	1.807
Organic[b]	1.031	0.308	0.428	1.635
Farm size (ha)	1.005	0.001	1.002	1.007
% own land	1.006	0.005	0.996	1.015
Hill or mountain area[b]	1.172	0.439	0.311	2.033
Environmental attitude (Likert scale 1–5)	1.314	0.327	0.672	1.955
Technological attitude (Likert scale 1–5)	1.011	0.263	0.496	1.526

	Stage 1	Stage 2	Stage 3
Predicted probabilities	0.313	0.621	0.066
Log likelihood	−182.99		
Pseudo-R2	0.074		
AIC	367.031		
BIC	414.478		

[a]Degree does not follow a parallel trend. Degree (1) indicates stage 1 vs. stage 2 and stage 3. Degree (2) indicates stage 1 and stage 2 vs. stage 3.
[b]The variable is coded as a dummy variable.

VRT (27.5%) than DSS (24.4%). The lack of technological skills is perceived as a barrier by 11.5% of participants for DSS and 10.7% for VR technology.

5.2 | Regression Results

The results of the partial proportional odds model for DSS and VRT are provided in Table 3 and Table 4, respectively. We report the results in terms of odds ratios, together with the corresponding standard errors and 95% confidence intervals. In the DSS model, the variable *Environmental attitude* failed the Brant test, indicating that it does not follow parallel trends in the different stages. Thus, we allow the coefficient of this variable to change across stages. The probability of being in a later stage of adoption of the DSS technology is affected primarily by the farmer's general attitude toward technology (OR = 3.075, 95% confidence interval: 1.467–4.683) and, to a smaller extent, by the share of farmland owned by the farmer (OR = 1.010, 95% confidence interval: 1.001–1.020). A stronger environmental attitude increases the probability of moving away from stage 1 ("Precontemplation phase"), while it does not affect the probability of already adopting the technology compared to the intention to adopt.

In the VRT model, the parallel trend assumption fails for the variable *Degree*. In this case, the partial proportional odd model, however, does not show any influence of such a variable on the VRT adoption phase. In this case, the only adoption driver seems to be the farm size, although the coefficient is rather small (OR = 1.005), indicating that the farm size affects the adoption process only marginally. All the other variables do not play any role.

Predicted probabilities indicate that stage 2 is more likely to be observed for both technologies, with a probability of 56.2% for DSS and 62.1% for VRT. While the probability of being in the last stage of adoption is equal to 27.5% for DSS, it is only 6.6% for VRT, indicating that the actual adoption of such a technology is still very limited.

The results of the analysis that considers only the first two stages of adoption (thus excluding those farmers who have already adopted the technology, i.e., Stage 3) and includes in the models the two TAM variables (i.e., *perceived usefulness* and *perceived difficult to use*) are reported in Tables 5,6, respectively. In the DSS model, the variables that increase the probability of the intention to adopt the technology are the environmental attitude (OR = 2.135, 95% confidence interval 1.045–4.548) and the perceived usefulness of the technology (OR = 2.812, 95% confidence interval 1.431–5.865).

The results of the corresponding VRT model indicate that both the TAM variables explain the intention to adopt such a technology, one with a positive effect (i.e., *perceived usefulness*) and one with a negative effect (i.e., *perceived difficult to use*). Specifically, scoring one unit higher in the perceived usefulness of the VRT increases the odds of the intention to adopt the technology by 5.7 times. Conversely, a one-unit increase in the score of the difficulty to use variable leads to a decrease in the odds of the intention to adopt by 63.5%. Surprisingly, an increase in the score to the technological attitude scale reduces the probability of being open to consider the adoption of the technology.

TABLE 5 | Results of a logit model for the DSS technology excluding the stage 3 and including the TAM questions ($N = 159$).

	Odds ratio	Standard error	95% confidence interval	
			Lower	Upper
Male[a]	1.332	0.659	0.498	3.520
Age less than 40[a]	0.646	0.308	0.252	1.658
Degree[a]	0.720	0.347	0.273	1.834
Education in agricultural field[a]	1.089	0.482	0.453	2.602
North[a]	0.890	0.412	0.355	2.210
Organic[a]	0.860	0.394	0.347	2.114
Farm size (ha)	1.000	0.002	0.997	1.004
% own land	1.012	0.007	0.998	1.026
Hill or mountain area[a]	0.753	0.488	0.187	2.515
Environmental attitude (Likert scale 1–5)	2.135	0.792	1.045	4.548
Technological attitude (Likert scale 1–5)	1.284	0.573	0.532	3.096
Perceived usefulness (Likert scale 1–5)	2.812	1.001	1.431	5.865
Perceived difficulty to use (Likert scale 1–5)	0.670	0.173	0.400	1.111

	Stage 1	Stage 2
Predicted probabilities	0.226	0.774
Log likelihood	−213.641	
Pseudo-R2	0.093	
AIC	415.465	
BIC	462.915	

[a]The variable is coded as a dummy variable.

6 | Discussion and Conclusions

In the literature, socio-demographic factors tend to be important drivers of adoption of PA (Pierpaoli et al. 2013). Some studies highlight the influence of age and education on adoption behavior (Daberkow and McBride 2003; Paxton et al. 2010; Marescotti et al. 2021). Tamirat et al. (2018) found that farmers under the age of 50 years exhibit a higher propensity to adopt innovations compared to their older counterparts. However, empirical evidence has also produced conflicting results regarding demographic characteristics (Paustian and Theuvsen 2017; Tamirat et al. 2018).

Generally, young farmers have less experience and are thus more willing to use technologies for the management of their farms. Conversely, older and less educated farmers may prefer to maintain the status quo, as they are approaching retirement and do not consider the long-term economic benefits of new technologies. We found that neither age nor education or gender has a significant influence on effective adoption of PA in the viticultural sector. Having a higher education degree plays a role in the intention to adopt but not in the last phase of adoption. In our sample, the adoption of and the intention to adopt DSS and VRT are mainly driven by individual attitude or perception. Individual socio-demographic characteristics seem to play no role, while farm size and the share of land owned by the farmer play marginal roles. A positive environmental attitude increases the probability of declaring the intention to adopt DSS technology, but it does not affect actual adoption. An increase in the declared attitude toward technology is associated with an increased likelihood of being in a later stage of DSS adoption, while it seems to reduce the intention to adopt VRT technology. The TAM variable *perceived usefulness* drives the intention to adopt both technologies. Concerning the influence of farm size and owned land, our results are in line with previous studies, in which larger farms (Barnes et al. 2019; Marescotti et al. 2021) or farms that own land (Lambert et al. 2014) are more likely to adopt PA technologies.

Farmers are more inclined to innovate to ensure opportunities for preserving the long-term productivity of their owned land (Watcharaanantapong et al. 2014). Reasonably, on bigger

TABLE 6 | Results of the ordered logit model for the VRT technology excluding stage 3 and including the TAM questions ($N = 205$).

	Odds ratio	Standard error	[95% confidence interval]	
			Lower	Upper
Male[a]	0.628	0.294	0.244	1.540
Age less than 40[a]	1.168	0.488	0.518	2.689
Degree[a]	1.343	0.533	0.615	2.936
Education in agricultural field[a]	0.881	0.334	0.415	1.852
North[a]	1.223	0.483	0.566	2.681
Organic[a]	0.856	0.333	0.397	1.836
Farm size (ha)	1.001	0.002	0.997	1.005
% own land	1.001	0.007	0.988	1.013
Hill or mountain area[a]	0.634	0.315	0.231	1.640
Environmental attitude (Likert scale 1–5)	0.914	0.293	0.483	1.711
Technological attitude (Likert scale 1–5)	0.435	0.178	0.190	0.952
Perceived usefulness (Likert scale 1–5)	5.684	1.692	3.300	10.675
Perceived difficulty to use (Likert scale 1–5)	0.365	0.095	0.215	0.601

	Stage 1	Stage 2
Predicted probabilities	0.337	0.663
Log likelihood	−213.641	
Pseudo-R2	0.074	
AIC	367.031	
BIC	414.478	

[a]The variable is coded as a dummy variable.

farms, the large number of daily operations may result in the need for innovative tools, like VRT. During the preliminary interviews we conducted at wine fairs, we found that small-scale winegrowers are reluctant to adopt VRT. Due to the manageable size of their farm, they believe they can personally monitor the conditions of their parcel and intervene accordingly. In addition, some small-scale farmers reported they would rather employ their profits on alternative uses rather than purchasing digital technologies. Concerning the influence of a general positive attitude toward technology, our result for DSS is in line with Marescotti et al. (2021), who found that Italian farmers who already use smartphones for professional duties are more willing to adopt new technologies.

Notably, one-third of our sample considers financial constraints as a determining factor in their decision not to adopt. Lack of detailed information is another barrier to adoption: the existence of DSS is unknown to 28% of the sample, while 44% of respondents are not aware of VRT. Conversely, the perceived usefulness of the technology is a driver of adoption intention, in line with previous studies (Michels et al. 2021; Mohr and Kühl 2021). This suggests that more information needs to be provided to farmers, not only in terms of applications but also about the economic benefits these technologies could bring, particularly in the case of DSS.

In Italy, DSS for grapevines is commercially available starting from about 1000 euros per year.[4] A comparison between the costs and the benefits of these technologies would support farmers in their decision to adopt them. Although winegrowers consider digital technologies potentially useful, they also perceive them as difficult to use. This mixed view on technology may hinder its effective adoption. Explaining and demonstrating the use of technologies with varying levels of engagement by farmers is necessary to strengthen the belief that PA can prove beneficial and contribute to the sustainability of their operations. Long et al. (2016) found that difficulties in demonstrating the value of technological innovations by technology providers represent one of the main supply-side barriers to adoption. A well-designed information policy will be crucial for increasing the rate of adoption.

From a policy perspective, our findings are consistent with recent evidence on the implementation of the CAP Strategic Plans (European Commission 2025), which show that, despite digitalisation being a cross-cutting objective of CAP 2023–2027, the uptake of digital farming technologies remains limited and uneven across farms. This is relevant for more complex and capital-intensive technologies (such as VRT), for which CAP support is mainly provided through investments that tend to be more accessible to larger and more capitalized farms. This suggests the need for a better targeting of CAP support for digitalization. Targeting support for VRT toward farms with sufficient scale, while prioritizing less expensive and easy-to-use digital tools, such as DSS, for smaller farms, could improve policy effectiveness. Furthermore, lack of detailed information is indicated by winegrowers as the second main reason for not adopting both DSS and VRT, and many perceive these technologies as difficult to use, even when they recognize their potential. Strengthening advisory services, training activities, AKIS, and on-farm demonstrations within the CAP framework could therefore play an important role in increasing both awareness and farmers' ability to effectively use them.

One limitation of our study is the lack of representativeness of our winegrowers' sample, since it overrepresents young, educated farmers with large and organic farms. Although we acknowledge this limitation, which is common to similar studies (Michels et al. 2020) and likely due to the online administration mode, we argue that these characteristics identify the core group of PA adopters in Europe (Paustian and Theuvsen 2017; Barnes et al. 2019; Tamirat et al. 2018; Paxton et al. 2010). Thus, if we consider our target population to be those winegrowers who are more inclined to adopt PA, we state that our sample is representative of it. Conversely, if we consider the general population of winegrowers as the target population, we can interpret the results of our study as a lower bound for the attitudes of the general winegrower population.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are openly available in Open Science Framework at https://osf.io/97rvf/?view_only=ba974caea8fe4f9d9e2254d264c58a6a.

Endnotes

[1] Lemken et al. (2017) and Michels et al. (2020) identify four stages of adoption: Precontemplation ("I am not willing to adopt this technology on my farm"); 2. Contemplation ("I am principally willing to try out the application of this technology on my farm"); 3. Preparation ("I have concrete plans to use this technology on my farm"); 4. Action ("I already use this technology on my farm"). Following the suggestion of the editor and of one reviewer, we merge stages 2 and 3, as such a distinction may not be clear in the mind of the farmer.

[2] The study has received ethical approval from the German Association for Experimental Economic Research. The approval is available at this link https://gfew.de/ethik.

[3] Official national statistics are available for the farming population rather than specifically for winegrowers. These figures are therefore used as contextual benchmarks and should not be interpreted as direct population comparisons.

[4] See, for example, GrapeDSS provided by Agricolus s.r.l. or vite.net developed by Horta s.r.l.

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