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Exploring socio-psychological factors to the adoption of decision support systems and meteorological stations in agriculture: The case of peach orchards in Greece

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ABSTRACT

Digital farming innovations, like decision support systems (DSSs) enabled with information from meteorological stations, can mitigate the impact of crop pests that leads to yield and quality decrease. Although their benefits are known, their adoption by farmers is still at a low level. In this paper, we explore the socio-psychological drivers to adoption of decision support systems, combined with the use of meteorological stations, in peach orchards in Greece. Additionally, we investigate the barriers that peach farmers face when it comes to adoption of technologies in agriculture. We find that "openness to innovation" has the highest positive impact on the adoption of DSSs, followed by "general attitudes" and farmers' "concerns" on pests-related problems. On the contrary, lack of financial support, cost, and lack of technical training and information are identified as the key barriers for technology adoption.

1. Introduction

Technological advancements, and particularly digital farming innovations[1] have the potential to improve agricultural management [2] in various fields of agricultural production, like arable, horticulture and greenhouses [3]. Examples include the use of smart sensors for soil health monitoring, irrigation management, leaf disease identification, yield improvements, and post-harvest activities [4]. Additionally, unarmed aerial vehicles (UAVs), e.g., drones, can be used for weed mapping and management, vegetation growth monitoring and yield estimation, vegetation health monitoring and diseases detection, irrigation management, and crops spraying [5,6].

Crop pest control is an important aspect of agricultural practices. Improper pest management can lead to over- or under-applications of pesticides, yield and quality decrease, increased costs, environmental pollution and health problems [7]. Digital farming innovations can contribute on sustainable pest management. For instance, precision agriculture allows for efficient use of inputs (e.g., fertilizers, pesticides, herbicides, irrigation, etc.), without the loss of crop yield [7,8]. Similarly, sensors can identify those trees that require special pest management, reducing in such a way the use of pesticides [9], and robots can be used to identify weeds and remove them mechanically, (perfectly) substituting the use of herbicides [10,11]. In this article, we focus on the adoption of decision support systems (DSSs) and weather monitoring and forecasting systems, such as meteorological stations. The rationale is the following. First, DSSs can effectively predict pest and disease outbreaks [12,13], while also enhancing the efficiency of farming equipment, such as sprayers [14,15]. Additionally, DSSs analyze climatic data alongside other factors, such as insect counts from smart traps [16], and water and nutrient requirements [17], to provide crucial insights for farmers and support the development of predictive models. As a result, weather monitoring and forecasting systems are typically integrated into these systems. Second, the use of DSSs can generate economic, environmental and health benefits. For instance, Louka et al. [18] point that the use of a DSS can result in up to 25 % reduction in pesticide costs. Similarly, Marimon et al. [19] found that using DSS can lead to 33 % reduction in fungicide in peach. Finally, DSSs can be less expensive than other digital farming innovations, like

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[1] In this article, (i) georeferencing and location technologies, (ii) diagnostic tools, (iii) applicative tools, (iv) automatized and autonomous processes, machinery and farming systems, (v) networks, information and communication are collectively referred as 'digital farming innovations' [1].

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variable rate spraying equipment [7,20].

Furthermore, in this article we target farmers that are specialized in the cultivation of peaches. Peach crop is the second most important fruit crop after apple with China being the largest producer globally accounting for 61.12 % (15.02 million tons) of global peach production in 2020 and Greece ranking fourth with a peach production of 0.89 million tons [21,22]. However, peach fruits are highly susceptible to damage from insects [23] and diseases [21] due to their soft skin compared to other tree crops [24]. Thus, peach crop has many harmful insects [25] and diseases [26] making pest control a cornerstone for the optimal production. Indeed, peach plantation can receive up to 8kg/ha of insecticides per ha to manage >10 different insect species in a crop season [23]. This can be interpreted to the use of up to 5 different insecticides [27]. Similarly for disease control, up to 7 fungicide applications can be conducted during a crop season [28].

Even though these benefits, farmer adoption of DSS remains low. Understanding the complex farmer behavior is important to increase adoption and to enable the design and implementation of tailor-made strategy and policy interventions to meet their national and European environmental targets, like those that are set in the Farm-to-Fork strategy [29] and the Biodiversity strategy [30] for the reduction of chemical pesticides by 50 % and the reduction of hazardous pesticides by 50 % by 2030.

Previous research has identified a number of factors affecting adoption like farm structural characteristics (e.g., farm size, land tenure), farmer's demographic characteristics (e.g., gender, age, education, farming experience), financial factors (e.g., off-farm income, access to credit), systemic factors (e.g., extension and advisory services, lack of infrastructures), and policy regimes (e.g., legal frameworks and bureaucracy) [31–35]. However, past research has mainly focused on non-sociopsychological factors, hence neglecting the significant impact they may have on adoption of sustainable agricultural practices [36] and technologies [34]. Furthermore, while most of the studies on technology adoption have focused on countries like Austria, Czech Republic, France, Italy, Spain, Switzerland [35,37–39], Greek farmers behavior remains underexplored (e.g., Kakkavou et al. [40]). Thus, an additional objective of this article is to contribute to the current literature on farmers' behavior by understanding how sociological and psychological factors shape behavior for Greek farmers.

The structure of this article is as follow. Section 2 presents our theoretical model, while in Section 3 we present the main study area and the characteristics of the questionnaire been used. In Section 4 we present our main analysis, while Section 5 discusses and concludes.

2. Theoretical framework

In this article, we are mostly interested in how sociological and psychological factors affect Greek peach farmers' intentions to adopt a DSS, combined with the use of meteorological stations. Currently, there is not a unique model to explain farmers' behavioral intentions to adopt technological innovations in agriculture [41]. For instance, some studies employ the technology acceptance model (TAM) [42] to study farmers' intentions on the use of precision agriculture and irrigation technologies [40,43], whereas others employ the unified theory of acceptance and use of technology (UTAUT) [44] to study behavioral intentions on the adoption of smartphone applications and information technologies in farm management [45–47].

Nevertheless, one of the most prominent theories that has been employed to study farmers' behavior is the Theory of Planned Behavior (TPB) [48], a revised framework of the theory of reasoned action (TRA) [49], in which attitudes, perceived behavioral control and subjective social norms drive farmers' intentions [50–53]. However, it has been suggested that adding more variables will increase the predictive ability of the TPB [54–58]. To this end, our model is built around the TPB, extended by constructs that try to capture farmers' concerns regarding current and future environmental conditions (environmental concern), data privacy concerns and the degree of which farmers face severe problems with pests (pest concerns). Additionally, we include "openness to innovation" as a potential explanatory construct. Fig. 1 illustrates the extended model of the theory of planned behavior.

2.1. Basic variables

2.1.1. Attitudes

Attitudes towards adoption of a particular behavior can be defined as "a psychological tendency that is expressed by evaluating a particular entity with some degree of favor or disfavor" [59]. In a similar context, Fishbein and Ajzen [49] state that attitudes are positive or negative evaluations toward performing a behavior under consideration. Generally, individuals' positive attitude toward a behavior can lead to greater intention of performing that behavior. Farmers intention to adopt DSS will be higher if they believe that using those technologies is useful and beneficial to them [55]. Indeed, in their meta-analysis, Kim and Hunter [60] found a strong link between attitudes and intentions. Therefore, our first hypothesis is formulated as follows:

H1: Attitudes towards the use DSSs, combined with data from meteorological stations, have a positive impact on farmers' intentions to adopt them.

2.1.2. Subjective social norms

Norms can be a powerful determinant of pro-environmental behavior [61,62].[2] Conceptually, the TPB refers to subjective social norms as the product of descriptive norms (i.e., what others do) and injunctive norms (i.e., what others expect from us to do) [48]. Specifically, people's beliefs on the approval of a specific behavior by important others (e.g., friends and family, peers, etc.) can facilitate intentions on the adoption of that behavior [65,66]. The work of Li et al. [67] and Nor Diana et al. [68] support this view on farmers' intentions to technology adoption in agriculture and hence, our second hypothesis is formulated as follows:

H2: Subjective social norms have a positive impact on farmers' intentions to adopt a DSS, combined with data from meteorological stations.

2.1.3. Perceived behavioral control

Perceived behavioral control refers to the degree that someone's believe that they are capable of performing a certain behavior [48].[3] This perception is shaped by various aspects related to performing a certain behavior, like skills, time, money, and support [69]. Previous research illustrates that farmers exhibit stronger intentions to adopt environmentally friendly farming practices [36,70–72] and technologies [45,73,74] when they perceive that they have more control on the adoption processes. Therefore, our next hypothesis is:

H3: Perceived behavioral control has a positive impact on farmers' intentions to adopt a DSS, combined with data from meteorological stations.

2.2. Additional variables

SubSections 2.2.1 – 2.2.4 cover the additional variables that we included in our extended model of the TPB. Specifically, farmers may exhibit various concerns prior to the choice of the farming practice they implement [75,76]. Furthermore, farmers may be skeptical regarding new and innovative technologies [77]. Thus, by including such variables in our analysis we can get a more representative picture on the factors that influence technology adoption in agriculture.

[2] Thøgersen [63] provides an extended taxonomy of norms and their influence of pro-environmental behavior. Additionally, the impact of different types of norms on (different types of) conservation behavior is also explored by Niemiec et al. [64].

[3] Sometimes, perceived behavioral control is coincide with self-efficacy. However, operational differences may exist when measuring each construct [69].

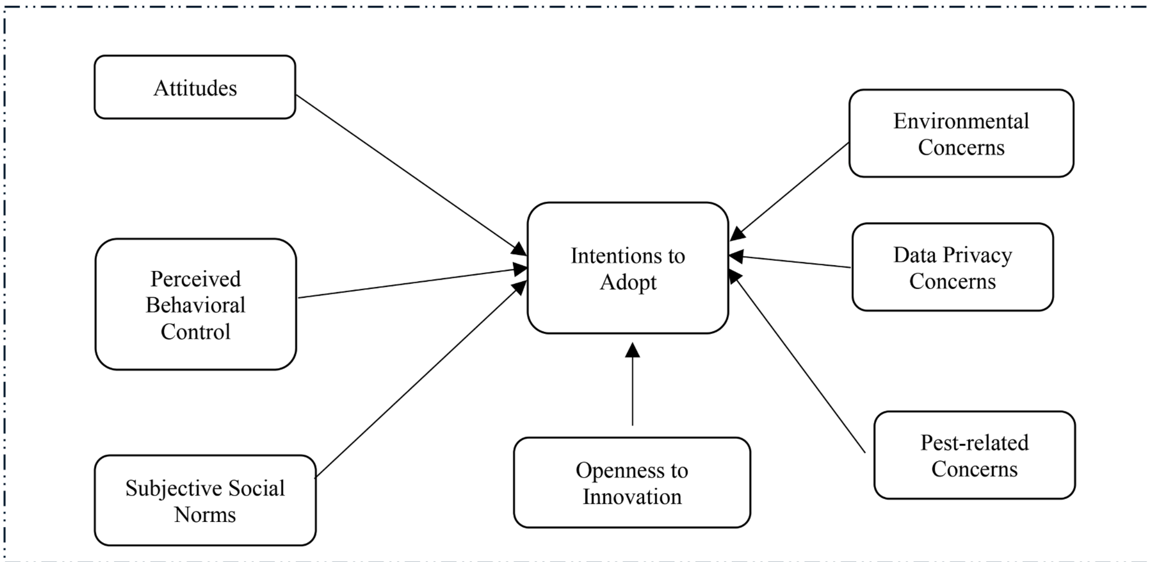

Fig. 1. Structural representation of the extended model of the TPB.

2.2.1. Environmental concerns

Dessart et al. [72] argue that environmental concern can be a determinable factor on shaping farmers' behavior. For instance, farmers may be concerned on the impact of climate change on the local environment (e.g., reduction of natural resources reserves) and consequently, on the financial viability of their farm. Additionally, farmers may be concerned on how the use of chemical fertilizers alter the local environment. Moreover, Toma and Mathijs [75], and Best [78] observed that environmental concern plays a crucial role on farmers' willingness to adopt organic farming. Furthermore, it is suggested that after years of agricultural interventions, shades of green become apparent in farmers' behavior [79].

Previous research indicates that the use of a DSS can provide environmental benefits, like reduction of fungicide [19] and efficient irrigation management [17]. Thus, we formulate the next hypothesis as follows:

H4(a): Environmental concerns have a positive impact on farmers' intentions to adopt a DSS, combined with data from meteorological stations.

2.2.2. Data privacy concerns

In many situations, the use of digital technologies requires the collection of data that can be accessible not only by farmers, but also by other stakeholders [80]. Wiseman et al. [81] explored the influence of various data attributes, like ownership, portability and privacy, on farmers' willingness to share agricultural data. Particularly, Sullivan et al. [82] found that data sovereignty, and data privacy and security concerns were important barriers for farmers to share their data with other stakeholders. A similar result was found by Drewry et al. [83] when they explored adoption of digital technologies by dairy and livestock farmers.

Fig. 2

Furthermore, previous research shows that such concerns influence farmers' intentions to adopt a DSS [84,85]. Thus, we formulate the next hypothesis as follows:

H4(b): Data concerns have a negative impact on farmers' intentions to adopt a DSS, combined with meteorological stations.

2.2.3. Pest concerns

In this article, we consider another type of concern, namely the degree at which farmers dealing with severe problems with pests and plant diseases [86]. As we mentioned in the introduction, DSSs can effectively predict pest and disease outbreaks [12,13], while also enhancing the efficiency of farming equipment, such as sprayers [14,15]. Additionally, DSSs analyze climatic data alongside other factors, such as insect counts from smart traps [16] and so, they can inform the farmer on the optimal time and the optimal amount of pesticides to be used [87]. Thus, we hypothesize:

H4(c): Pest concerns have a positive impact on farmers' intentions to adopt a DSS, combined with data from meteorological stations.

2.2.4. Openness to innovation

Openness to innovation can be interpreted as someone's interest in learning and understanding new things, welcoming innovative problem-solving approaches, and adopting state-of-the-art technologies [88]. Various factors can determine how open someone is. For instance, Saef et al. [89] argue that people embrace new (or innovative) technologies at a different level due to their diverse backgrounds and life experiences.

In the context of pro-environmental behavior, Soutter et al. [90] highlight that openness, among the 'Big Five' personality traits,[4] has the strongest influence on behavior. Furthermore, He and Veronesi [92] found a positive correlation between openness and farmers' intentions to use biogas. A similar result between openness (to experience) and farmers' willingness to participate in organic schemes is highlighted by Schröter and Mergenthaler [93]. Based on these findings, we state our last hypothesis as follows:

H5: Openness to innovation positively affects farmers' intentions to adopt a DSS, combined with data from meteorological stations.

3. Study area and questionnaire design

3.1. Study area

This study was carried out in the regions of Imathia and Pella, both of which are located in Central Macedonia in Greece. The climate in both regions is continental.

Agriculture plays a crucial role in the local economy in both regions. In 2022, the Gross Added Value (GAV) was estimated to be approximately 432 and 619 million euros (in current prices) for Imathia and Pella, respectively. Specifically, approximately 34.25 % (582.988 km^2) of Imathia was conserved for cultivation for agricultural goods.

[4] The 'Big Five' personality traits are extraversion, openness (to experience, intelligence, etc.), conscientiousness, stability (emotional), and agreeableness [91].

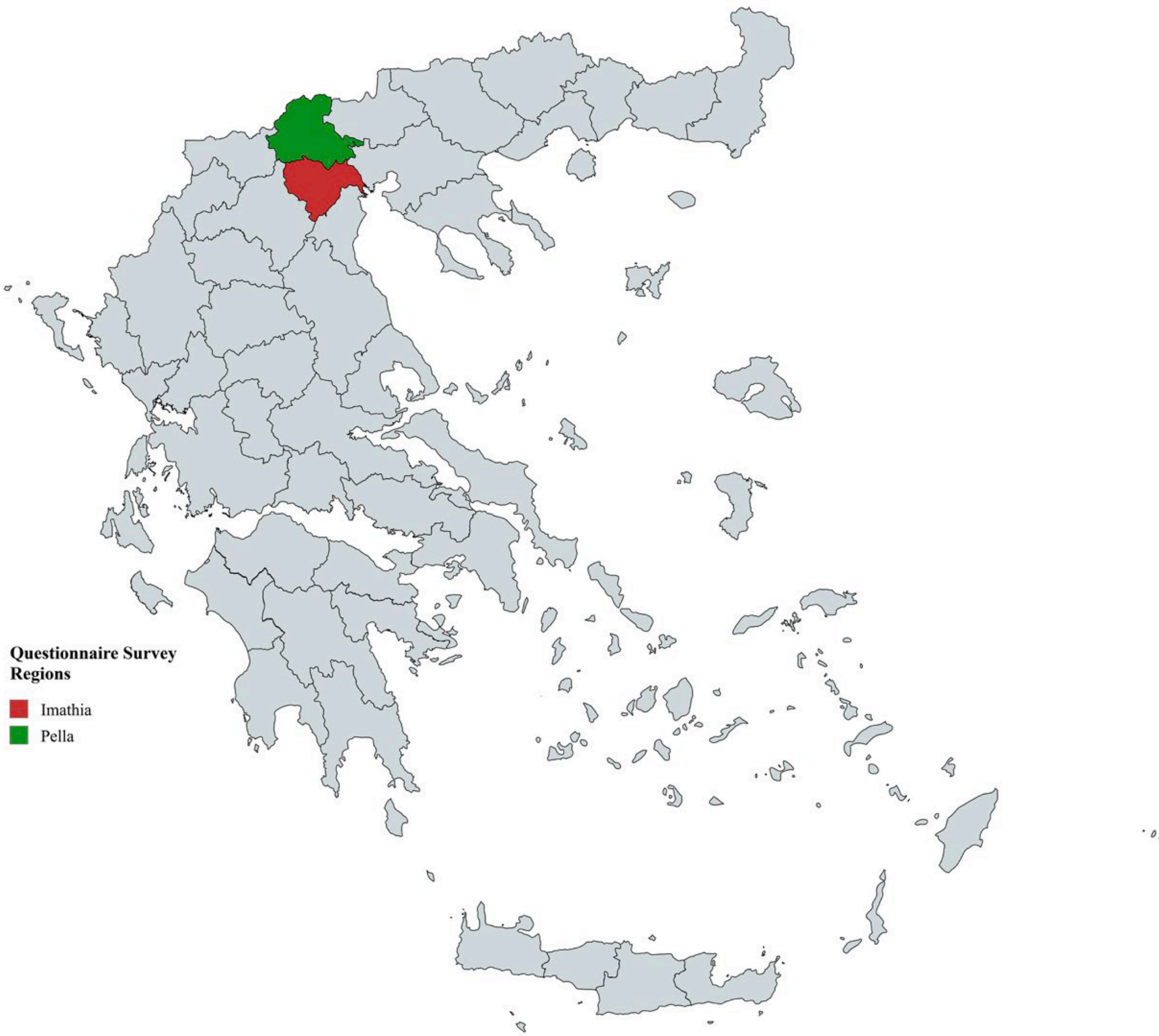

Fig. 2. Main questionnaire survey regions in Greece (created with mapchart.net).

Particularly, the 37.32 % (217.569 km^2) of the total agricultural land was used for tree crops, with stone fruit trees to account for the biggest share (77.66 % or 168.973 km^2). Peaches and nectarines constituted the main type of stone fruit trees (85.30 % or 144.127 km^2). Similarly, agriculture is an important activity in the region of Pella, as well, where the majority of the agricultural land to be dedicated to the cultivation of peaches and nectarines. Specifically, in 2022, approximately 31.80 % (797.018 km^2) of Pella was conserved for cultivation for agricultural goods. The 48.28 % (384.826 km^2) of the total agricultural land was used for tree crops, with stone fruit trees to account for the biggest share (82.90 % or 319.012 km^2). Particularly, peaches and nectarines constituted the main type of stone fruit trees (51.70 % or 164.934 km^2).

3.2. Questionnaire design

The main objective of this study was to use an extended version of the TPB in order to explore the influence of socio-psychological factors on farmers' intentions to adopt agricultural technologies, namely a decision support system combined with data from meteorological stations. Additionally, we were interested in determining the profile of Greek farmers in terms of their demographics and farm characteristics.

The questionnaire initially tries to elicit farmers' knowledge and use of various smart technologies that are used in agriculture, like UAVs, sensors (e.g., smart traps), DSSs, etc. After that, a brief description on the use and benefits of a DSS was provided to secure that every responder has (at least) the same knowledge of the technologies under consideration. The thematic areas of the questionnaire included (1) farmers' demographic characteristics, (2) farm characteristics, (3) behavioral and sociological factors that affect adoption, (4) intentions to adopt meteorological stations and DSSs, and (5) self-reported barriers for adoption.

Attitudes, perceived behavioral control, subjective social norms, openness to innovation and concerns were our main independent variables, whereas intentions to adopt was the dependent variable (see Fig. 1). Both independent and dependent variables (constructs) were measured by using multi-items [94]. Each item was expressed in a statement format, where agreement or disagreement with each statement was measured on a 5-point Likert scale, ranging from "strongly disagree" (coded with 1) to "strongly agree" (coded with 5). Statements were adopted from the literature [40,54,58,73,95,96], and they were adapted to the context of DSSs and meteorological stations. Finally, we observed a very small number of nonresponses (coded with 0). To handle these missing data, we used item mean replacement [97].

4. Analysis and results

4.1. Analysis

The data were collected during November 2024. In total, 105 questionnaires were gathered and used for further analysis. The administration of the questionnaire was made mainly by the local agricultural cooperations, which they organized either face-to-face interviews or they distributed the questionnaire directly to farmers (self-reporting). Additionally, the research team, with the help of local private agronomists, organized both face-to-face interviews and interviews through telephone by following the snowballing technique. Specifically, 26 (24.76 %) questionnaires were collected through face-to-face interviews, 10 (9.52 %) through telephone, and 69 (65.71 %) through self-reporting.

To identify the influence of independent variables on farmers' intentions to adopt meteorological stations and DSSs, the partial least square structural equation modeling (PLS-SEM) was employed [98]. The rationale of using PLS-SEM over "traditional" covariance-based structural equation modeling (CB-SEM) is that PLS-SEM does not rely on the normality of the data (or any other distribution), and hence, it is considered to be more flexible compared to CB-SEM [98]. Furthermore, Hair et al. [99] suggest it as the preferred method in situations where the sample size is small, and when multiple constructs and complex relationships among them exist on the model structure. Finally, PLS-SEM can be useful when extensions of existing theoretical frameworks are tested [100], and the objective of the analysis is to provide recommendations for policymakers [101]. Investigation of (socio-psychological) factors that affect acceptance of artificial intelligence technologies [73], the use of sustainable digital fertilization methods [102], the adoption of mixed cropping systems [103], and the intentions to adopt spot spraying for weed control [58] are some examples of the application of PLS-SEM to technology adoption in agriculture.

In PLS-SEM, the "10-times rule" is usually used to determine the minimum sample size [104]. However, previous research argues that this "rule of thumb" can lead to inaccurate estimations of path coefficients [105,106]. Therefore, in this article we used the inverse square root method proposed by Kock and Hadaya [107], which can result in more appropriate estimates compared to the standard (i.e., "10-times rule") approach [108]. According to this method, the minimum sample size (N_{min}) is the closest integer that satisfies the inequality:

$$N > \left(\frac{z_{0.95} + z_{0.80}}{|\beta|_{min}}\right)^2 \Rightarrow N > \left(\frac{2.486}{|\beta|_{min}}\right)^2 \quad (1)$$

where z-scores referred to a statistical power of 80 % ($z_{0.80}$) and significance level at 5 % ($z_{0.95}$). Hence, for a minimum path coefficient ($|\beta|_{min}$) that ranges from 0.25 to 0.3, this method requires a minimum sample size of 69 ($|\beta|_{min} = 0.3$) to 99 ($|\beta|_{min} = 0.25$) observations (i.e., questionnaires), which is below what we achieved. Finally, we used Microsoft Excel (v16.94) for performing descriptive statistics, and SmartPLS [109] for analyzing our measurement and structural model.

4.2. Results

4.2.1. Descriptive statistics

In our sample, most of the farmers were located in Imathia (85 out of 105, or 80.95 %), followed by farmers located in Pella (20 out of 105, or 19.05 %). Tables 1–3 present descriptive statistics on farmers' profile (Table 1), farm characteristics and financial indicators (Table 2), and on the statements that were used to measure each construct (Table 3).

Table 1 highlights that in our sample, most farmers are men, they have completed high school education, and they are at least 46 years old. Notably, most of them have not attended any agricultural training program, whereas more than half of them (52.38 %) reported having >20 years of experience with farming activities. These observations are consistent with previous findings that indicate that men, overaged, less educated with many years of agricultural experience is the usual profile of Greek farmers (Koutridi et al., 2018; Lianou and Fthenakis, 2021).

Table 1
Farmers' sociodemographic characteristics.

Characteristic	Frequency	Percentage
Gender		
■ Male	89	84.76 %
■ Female	16	15.24 %
Age (years)		
■ Below 25	0	0 %
■ 25 – 35	14	13.33 %
■ 36 – 45	27	25.71 %
■ 46 – 55	39	37.14 %
■ 56 and above	25	23.81 %
Education		
■ Elementary school	5	4.76 %
■ Middle school	19	18.10 %
■ High school	54	51.43 %
■ Undergraduate Degree	22	20.95 %
■ Postgraduate Degree	3	2.86 %
Agricultural training		
■ Yes	50	47.62 %
■ No	53	50.48 %
■ Don't know/Don't answer	2	1.90 %
Farming experience (years)		
■ Up to 10	18	17.14 %
■ 11 – 20	32	30.48 %
■ 21 – 30	24	22.86 %
■ 31 – 40	29	27.62 %
■ 41 and above	2	1.90 %
Membership		
■ Agricultural cooperation	90	85.71 %
■ Team of producers	84	80 %
■ None	11	10.48 %

Number of interviewed farmers = 105.

Table 2 presents useful information on farms' characteristics and, particularly, on the farmland, production and farm profitability. In our sample, most farmers own at least 1.1 ha of land, and additionally, they rent from others up to 1 ha. Furthermore, they conserve their land (both owned and rented) for peach production, whereas secondary fruits are usually kiwis, apricots, and persimmon, and cotton. Moreover, approximately half of the farmers in our sample (50.47 %) reported that during the last three years they produced, on average, up to 90 tons of peaches, whereas the majority of them did not exceed, on average, the 60 tons. Additionally, in our sample, almost 64 % of the responders reported that they cultivate peaches conventionally, whereas only approximately 30 % of them implement integrated pest management approaches. Finally, Table 2 shows that agricultural income contributes at least 51 % of farmers' total income for approximately 82 % of the responders. Most importantly, farmers reported that their net agricultural income ranges from low (from 4000 to 15,000 euros) to medium (from 15,000 to 25,000 euros).

Table 3 indicates that farmers' intentions to adopt a decision support system, combined with data from a meteorological station, are, on average, "low to medium" (ranging from 2.68 to 3.57). However, farmers' general attitudes on the use of such technologies range, on average, from 3.47 to 3.82, which can be perceived as "medium to high". In other words, on average, farmers value positively the use of a DSS, combined with the use of meteorological stations. Furthermore, items on perceived behavioral control and subjective social norms indicate that farmers, on average, believe that they lack the necessary skills and (technical and/or economic) support to implement such technologies (ranging from 2.27 to 2.85) and also, that the society does not expect from them to use a DSS for managing their farm (ranging from 2.77 to 3.45). Moreover, they don't perceive themselves, on average, as open-

Table 2
Farm characteristics and financial indicators.

Characteristic	Frequency	Percentage
Farmland		
■ Owned (Rented) (ha)	8 (58)	7.62 % (55.24 %)
○ Up to 1,0	30 (26)	28.57 % (24.76 %)
○ 1,1 – 3,0	38 (12)	36.19 % (11.43 %)
○ 3,1 – 6,0	19 (1)	18.10 % (0.95 %)
○ 6,1 – 9,9	9 (7)	8.57 % (6.67 %)
○ 10,0 – 25,0	1 (1)	0.95 % (0.95 %)
○ 25,1 and above	12	11.43 %
■ Conserved for peach production (%)	14	13.33 %
○ Up to 25	26	24.76 %
○ 26 – 50	53	50.48 %
○ 51 – 75		
○ 76 - 100		
3-years average production (tons)[a]		
■ Up to 20	6	5.71 %
■ 21 – 60	31	29.52 %
■ 31 – 90	16	15.24 %
■ 91 – 120	16	15.24 %
■ 121 – 200	28	26.67 %
■ 201 and above	8	7.62 %
Type of production		
■ Conventional	67	63.81 %
■ Integrated Pest Management (IPM)	31	29.52 %
■ Don't know/Don't answer	7	6.67 %
Farm income (%)		
■ Up to 25	5	4.76 %
■ 26 – 50	13	12.38 %
■ 51 – 75	8	7.62 %
■ 76 – 100	78	74.29 %
■ Don't know/Don't answer	1	0.95 %
Net agricultural (household) income (euros)[b]		
■ Below 4.000	2 (2)	1.90 % (1.90 %)
■ 4.000 – 15.000	39 (19)	37.14 % (18.10 %)
■ 15.000 – 25.000	34 (43)	32.38 % (40.95 %)
■ 25.000 – 50.000	13 (21)	12.38 % (20 %)
■ 50.000 and above	15 (18)	14.29 % (17.14 %)
■ Don't know/Don't answer	1 (2)	0.95 % (1.90 %)

[a] Production levels concern the years 2021, 2022 and 2023.
[b] Net agricultural and net household income concerns the fiscal year of 2023. Net household income includes income from both agricultural and non-agricultural activities of all household members.
Number of interviewed farmers = 105.

minded to new technologies ("low to medium", ranging from 2.6 to 3.66). On the contrary, farmers in this sample exhibit, on average, strong concerns regarding the environment and its impact on biodiversity and their farm (economic) viability (ranging from 4.16 to 4.43). They also exhibit, on average, "medium" concerns on dealing with pests (ranging from 3.48 to 3.86). Interestingly, farmers report not having, on average, serious concerns regarding data privacy (mean values range from 2.34 to 2.44). This observation can be justified by the fact that farmers are familiar with digital applications, like mobile services, in which the risk of data bleaching is higher compared to smart farming applications, like a DSS.

Finally, it is worth noting that the standard deviation in all items is low, indicating a high level of consistency in respondents' beliefs.

4.2.2. Assessing the quality of the measurement model

Tables 3–5 present various criteria used in PLS-SEM to assess the quality of the measurement model. For acceptable item reliability, Hair et al. [99] recommend indicator loadings (i.e., how much an item correlates with a factor) exceeding the value of 0.708. Except for DATA_4 and PBC_3, Table 3 shows that all the other items are significant ($p < 0.01$) and above this threshold.[5]

[5] One should note that by removing both DATA_4 and PBC_3 the main conclusion on the influence of sociopsychological constructs on farmers' intentions remain unchanged.

Table 3
Descriptive statistics on the statements been used for measuring constructs.

Construct	Item/Statement	Mean (SD)	Loading[a] (VIF)
Intentions to adopt			
INT_1	I will use a DSS in the future.	3.567 (1.04)	0.848*** (1.537)
INT_2	I am willing to install or rent a meteorological station within the next 5 years.	2.875 (1.021)	0.864*** (1.868)
INT_3	I am planning to use a DSS this year.	2.680 (1.062)	0.798*** (1.628)
Attitudes (The use of a DSS and the data been collected from a meteorological station will)			
ATT_1	Increase my productivity.	3.638 (0.917)	0.877*** (2.794)
ATT_2	Decrease production costs.	3.467 (0.927)	0.782*** (2.304)
ATT_3	Contribute to the preservation of natural resources.	3.695 (0.852)	0.832*** (2.386)
ATT_4	Contribute to efficient pest management.	3.629 (0.808)	0.807*** (1.981)
ATT_5	Overall, it has a positive impact on farm management.	3.819 (0.826)	0.859*** (2.490)
Perceived Behavioral Control			
PBC_1	I have the technical knowledge and skills to use a DSS for pest management.	2.848 (1.021)	0.894*** (1.505)
PBC_2	I have the financial resources to buy or rent a meteorological station.	2.267 (0.831)	0.759*** (1.338)
PBC_3	I have all the technical assistance in the use of a DSS.	2.629 (1.017)	0.701*** (1.359)
Subjective Social Norms			
SUB_2	Other farmers expect from me to use a DSS for pest control.	2.923 (0.891)	0.767*** (1.275)
SUB_3	Consumers expect from me to manage my inputs effectively.	3.447 (1.102)	0.879*** (1.628)
SUB_4	The local authorities expect from me to use a DSS for pest management.	2.772 (1.094)	0.730*** (1.494)
Openness to Innovation			
OI_1	I like to use new and innovative technologies and practices in agriculture.	3.657 (0.934)	0.877*** (2.238)
OI_2	I use state-of-the-art technologies in agriculture.	2.702 (1.022)	0.838*** (2.123)
OI_3	I am not opposed to new technologies, even when their use is outside of my daily routine.	3.221 (1.051)	0.883*** (2.435)
OI_4	I am innovator.	2.590 (0.957)	0.777*** (1.822)
Pest concerns (I face severe problems with:)			
PEST_1	Plant diseases.	3.857 (0.856)	0.926*** (2.319)
PEST_2	Insects.	3.857 (0.856)	0.913*** (2.743)
PEST_3	Weeds.	3.476 (1.015)	0.712*** (1.552)
Environmental concerns (I am concerned with:)			
ENV_1	Natural resources reserves (e.g., water).	4.429 (0.583)	0.821*** (1.668)
ENV_2	The impact of chemical fertilizers on the local biodiversity.	4.162 (0.745)	0.796*** (1.733)
ENV_3	The impact of climate change on the (financial) viability of my farm.	4.400 (0.725)	0.900*** (1.731)
Data privacy concerns			
DATA_2	The data that a DSS collects violate my privacy.	2.337 (0.759)	0.786** (1.422)
DATA_3	In general, I believe that my personal data is exposed when I use digital applications in agriculture.	2.441 (0.812)	0.946*** (2.110)
DATA_4	I believe that the use of a DSS will give unauthorized access to third parties on my private information.	2.402 (0.725)	0.595* (1.649)

[a] Significance codes: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Secondly, Table 4 presents different statistics that are commonly used to assess the internal consistency of the measurement model (i.e., the degree to which items in a survey measure the same construct), namely Cronbach's alpha and composite reliability [110]. Specifically, for acceptable levels Nunnally [111] recommends a Cronbach's alpha

Table 4
Assessing internal consistency reliability and convergent validity.

	Cronbach's alpha (α)	Composite reliability (ρ_C)	Average variance extracted (AVE)
Attitudes	0.890	0.918	0.692
Data Concerns	0.746	0.827	0.623
Environmental Concerns	0.800	0.878	0.706
Intentions	0.788	0.875	0.701
Openness to Innovation	0.867	0.909	0.714
Perceived Behavioral Control	0.707	0.830	0.622
Pest Concerns	0.824	0.890	0.733
Subjective Social Norms	0.715	0.836	0.631

Threshold levels: $\alpha \geq 0.70$, $0.7 \leq \rho_C < 0.95$, and AVE ≥ 0.50.

coefficient of 0.70 or higher, whereas Hair et al. [99] suggest the composite reliability coefficient to be at least 0.70. However, values equal to or higher than 0.95 can be problematic, as well, because they indicate either that indicators (i.e., statements) are redundant [94] or straight lining response may exist [99].

Furthermore, convergent validity (i.e., the degree at which items measuring the same construct correlate with each other) was assessed by using the average variance extracted coefficient, with a threshold value of 0.50 [99]. Additionally, discriminant validity (i.e., the degree at which constructs are empirically distinct from each other) was tested via the heterotrait-monotrait ratio [112]. For conceptually different constructs, Hair et al. [99] recommend the ratio to be lower than 0.85. Table 5 illustrates that such recommendation is met for all constructs.

Summing up, the above statistics indicate that items (a) exhibit high factor loading, (b) measure the same construct (internal consistency), and (c) correlate with each other (convergent validity). Furthermore, constructs were found to be empirically distinct from each other (discriminant validity). Thus, we can state that the quality of our measurement model is good, and so we can proceed with the assessment of our structural model.

4.2.3. Structural model assessment

The first step in the structural model assessment is to investigate the existence of multicollinearity between endogenous variables. For this purpose, we use the variance inflation factor (VIF) criterion, according to which values below 5 (ideally, VIF should be lower than 3 [99]) indicate a "low to moderate" presence of multicollinearity. Tables 3 and 6 show that multicollinearity is not an issue in our sample.

The second step is to derive path coefficients and their associated confidence intervals. One should recall that PLS-SEM does not make any specific assumption about the distribution of the data. Thus, it is recommended to use bootstrapping, ideally with 10,000 iterations [98]. Table 7 presents path coefficients, the lower and upper boundaries of the 95 % confidence interval, and p-values, where bootstrapping with 10, 000 iterations was applied.

Valuable insights emanate from Table 7. First, our path analysis indicates that "Openness to Innovation" has the strongest positive and significant ($p < 0.01$) impact on farmers' intentions to use a DSS, combined with data from meteorological stations, followed by farmers' attitudes on the use of such technologies ($p < 0.01$). In other words, the more open-minded farmers are to new technologies, and the more positive they value the use of such technologies, the more willing they will be to adopt them. Thus, we have strong reasons to accept both H1 and H5 hypotheses.

Second, the positive effect of "Perceived Behavioral Control" is significant at the 5 % significance level ($p < 0.05$), and its impact on farmers' intentions ranges from small to moderate (CI = [0.037, 0.294]). Notably, our analysis highlights that the positive impact of 'Subjective Social Norms" is insignificant, ($p > 0.10$). In other words, this observation emphasizes that farmers do not care enough about societal demands on technology adoption, and decisions on the technologies being used are likely to be driven by "selfish" factors. Thus, we reject H2, but we accept H3.

Hypotheses H4(a) – H4(c) capture the impact of environmental concerns (H4(a)), concerns with pests and diseases (H4(c)), and data

Table 6
Collinearity statistics: structural model VIF values.

	Intentions
Attitudes	1.361
Data Concerns	1.049
Environmental Concerns	1.248
Openness to Innovation	1.800
Perceived Behavioral Control	1.308
Pest Concerns	1.365
Subjective Social Norms	1.481

Threshold value: VIF < 5.

Table 7
Path analysis: Standardized path coefficients, confidence intervals and p-values.

	Path Coefficients	Confidence Intervals	P-values
Attitudes → Intentions	0.320	[0.165, 0.445]	0.000
Data Concerns → Intentions	0.047	[−0.087, 0.159]	0.268
Environmental Concerns → Intentions	0.091	[−0.011, 0.207]	0.088
Openness to Innovation → Intentions	0.461	[0.321, 0.579]	0.000
Perceived Behavioral Control → Intentions	0.154	[0.037, 0.294]	0.025
Pest Concerns →Intentions	0.177	[0.066, 0.294]	0.005
Subjective Social Norms → Intentions	0.069	[−0.063, 0.204]	0.198

Bootstrapping with 10,000 iterations.

Table 5
Assessing discriminant validity: Heterotrait-Monotrait ratio (HTMT).

	Att	DataC	EnvC	Int	OpenI	PeBeC	PestC	SubSoN
Att								
DataC	0.240							
EnvC	0.210	0.132						
Int	0.564	0.116	0.373					
OpenI	0.171	0.162	0.312	0.740				
PeBeC	0.165	0.165	0.147	0.442	0.517			
PestC	0.505	0.166	0.313	0.374	0.117	0.296		
SubSoN	0.256	0.171	0.138	0.535	0.678	0.344	0.192	

Threshold level: HTMT < 0.85.
Att = Attitudes, DataC = Data Concerns, EnvC = Environmental Concerns, Int = Intentions to adopt, OpenI = Openness to Innovation, PeBeC = Perceived Behavioral Control, PestC = Pest Concerns, SubSoN = Subjective Social Norms.

privacy concerns (H4(b)). Among them, problems with pests have the strongest positive and significant ($p < 0.01$) impact on farmers' intentions, indicating that the more severe the problems that farmers face, the more willing they become to adopt a DSS system for pest control and farm management. Environmental concerns also have a positive impact, but at the 10 % significance level ($p < 0.10$). Finally, the positive influence of data privacy concerns on farmers' intentions is probably a product of chance ($p = 0.268 > 0.10$). Particularly, the lower bound of the confidence interval shows a very small negative effect, indicating that in cases where data privacy concerns exist, even by chance, their effect on farmers' intentions is negligible. Therefore, we accept hypotheses H4(a) and H4(c), whereas we reject H4(b).

4.2.3. Goodness-of-fit and model comparison

In this article, in-sample-predictive power and out-of-sample relevance were assessed via adjusted R^2 and Q^2, respectively. Specifically, the value of adjusted R^2 equals 0.589, indicating that the model explains a moderate to strong amount of variance in farmers' intentions. Furthermore, the value of Q^2 was obtained by following a blindfolding procedure with an omission distance of ten [113]. This method generates a value of 0.544, indicating a good out-of-sample predictive accuracy [99].

Moreover, a common approach for testing goodness-of-fit is to use the standardized root mean square residual (SRMR) [53,58,114]. In this study, SRMR equals 0.091, a value that suggests an acceptable fit [115]. However, Hair et al. [99] argue that this statistic should be interpreted with caution in PLS-SEM analyses. Therefore, as an additional measure of model fit we tested whether the geodesic discrepancy (dG) [116] is lower than the bootstrapping 95 % quantile [117]. Our analysis confirms that such a condition is satisfied (dG $= 1.326 < 1.392$), indicating an acceptable fit. Esparza et al. [118], Sarma et al. [114] and Martinez-Falco et al. [119]. are few examples of prior studies that use dG on their model's goodness-of-fit assessment. Alternatively, we could use the unweighted least squares discrepancy (dULS) [116]. However, when testing overall model fit with employing the bootstrapping procedure the dG outperforms the dULS in terms of Type-I error control [120]. Based on both SRMR and dG, we can conclude that our extended model of planned behavior has a good model fit.

Finally, in order to further explore the predictive power of our model, we tested the extended model of planned behavior in Fig. 1 (thereafter, Model 1) against the basic model of planned behavior, labeling as Model 2 (see Fig. 1), and a model where farmers' concerns affect their intentions indirectly through attitudes, labeling as Model 3 (see Fig. 3). For model comparison, we employed the cross-validated predictive ability test (CVPAT) [121]. For instance, Mathieson [122] uses the CVPAT test to compare the predictive power of the TAM and TPB models regarding individuals' intentions to adopt information technologies, whereas Osrof et al. [123] use the CVPAT to compare two reflective-formative second-order constructs on farmers' intentions to adopt smart farming technologies. Additionally, to enhance the assessment of predictive performance of our model (i.e., compare predictive errors) we report both the root mean square error (RMSE) and the mean absolute error (MAE) values as it recommended by Shmueli et al. [113]. Table 8 present the values for these metrics for Models 1–3.

Table 8 provides useful insights between these three models. First, Model 1 has the smallest value of CVPAT. Importantly, we found the difference of CVPAT values between Model 1 and Model 2 to be significant at the 5 % significance level, indicating that our extended model of planned behavior has better predictive power compared to the basic one. Furthermore, both RMSE and MAE capture the difference between actual and predicted values of the statements that were used to measure farmers' intention. These metrics reveal that Model 1 performs better than Model 2, because Model 1′s RMSE and MAE values are lower. Thus, the predictive power and performance of Mode 1 outperforms the standard model of planned behavior (Model 2).

Second, a comparison between Models 1 and 3 shows that RMSE values of Model 1 are lower for INT1 and INT2 statements but not for INT3. However, their difference is negligible ($\Delta RMSE_{1,3} = 0.017$) and thus, we cannot say that the use of Model 3 provides substantial improvements on understanding farmers' intentions. Similarly, the MAE values of Model 1 are equal to or lower than those of Model 3. Finally, the value of CVPAT of Model 1 is lower to that of Model 3. However, their difference is not statistically significant ($p > 0.05$), indicating that Model 1 and Model 3 perform similarly well. For this reason, we compared the values of adjusted R^2 and Q^2 between these two models. Our analysis shows that the value of the adjusted R^2 of Model 1 and Model 3 is 0.589 and 0.560, respectively, whereas the value of the Q^2 of Model 1 and Model 3 is 0.544 and 0.444, respectively. These two statistics show that Model 1 has a slightly better both in-sample and out-of-sample predictive power than Model 3. Thus, we can conclude that overall, Model 1 is marginally preferable to Model 3.

Table 8
Model comparison.

	CVPAT	RMSE			MAE		
		INT1	INT2	INT3	INT1	INT2	INT3
Model 1 (extended TPB, excluding indirect effects)	0.699	0.751	0.816	0.931	0.597	0.672	0.753
Model 2 (basic TPB)	0.847	0.845	0.914	0.995	0.621	0.768	0.810
Model 3 (extended TPB, including indirect effects)	0.765	0.855	0.853	0.914	0.667	0.712	0.753

INTj, with $j = 1,2,3$, refers to the statement been used for measuring farmers' intentions (see Table 3).

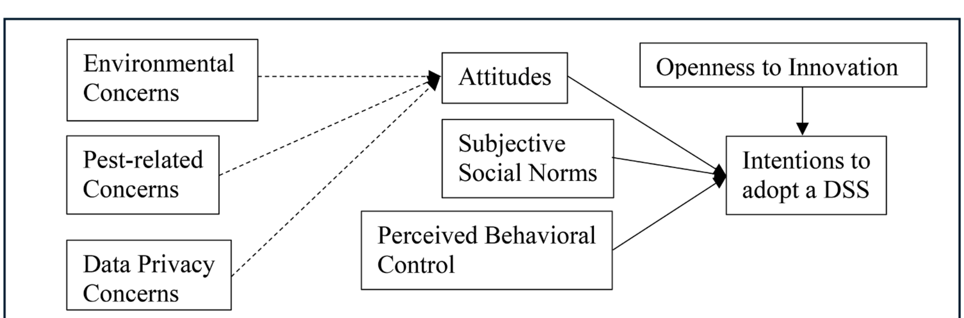

Fig. 3. Structural representation of the Model 3.

4.3. Barriers

The primary objective of this study is to investigate the influence of sociological and psychological factors on farmers' intentions to adopt technologies in pest management, namely meteorological stations and a decision support system. However, a variety of factors may prevent them from adopting such technology. Table 9 presents farmers' self-reporting valuation of various barriers, where each barrier was assessed on a 5-point Likert scale ranging from "very unimportant" (coded with 1) to "very important" (coded with 5). Responses that indicated no preference for a barrier were coded with 0.

Table 9 provides potential areas for policy interventions to support the adoption of these technologies by farmers. Specifically, "Lack of financial support", "Cost", and "Lack of technical training and information" were found to be the three main barriers to adoption. Additionally, "Lack of successful application" was also mentioned as an important barrier, followed by "Uncertainty". Interestingly, whether other farmers adopt similar technologies seems to be a low to moderate barrier, whereas data privacy and security, and access to the necessary equipment/software seems to be, on average, of a minor importance.

5. Discussion and conclusion

5.1. Discussion

In this article, we employed an extended model of the Theory of Planned Behavior to explore how sociological and psychological constructs, namely attitudes, subjective social norms, perceived behavioral control, openness to innovation and concerns (environmental, pest-related, data privacy), affect farmers' intentions to adopt a decision support system (DSS), combined with data from meteorological stations, for pest control and farm management.

Our PLS-SEM analysis shows that "attitudes" and "perceived behavioral control" significantly influence farmers' intentions to adopt a DSS, an observation that it is consistent with the current literature [7,34,55,72–74]. On the contrary, we also found that "subjective social norms" do not have a significant impact on farmers' intentions, indicating that farmers' decisions are likely to be driven by more self-centered factors. This finding contradicts previous research that indicate a strong and significant influence of important others (e.g., family and friends, peers, local authorities) on farmers' behavior [36,65,67,68]. A potential justification is that most farmers in our sample report to have many years of experience in agricultural activities. Thus, they may not feel a societal pressure [124] on how to manage their farms and deal with pests and plant diseases, but instead they rely on their own knowledge and expertise.

Furthermore, whether farmers appraise new and innovative technologies (i.e., are open to innovation) has the strongest and significance impact on their intentions to adopt a DSS, combined with data from meteorological stations. This result aligns with the work of Tohidyan Far and Rezaei-Moghaddam [125], Araujo et al. [126], and Spurk et al. [127] who also observed a strong a significant link between farmers' personal innovativeness and intentions to adopt smart technologies in agriculture. Moreover, pest-related concerns were also found to positively and significantly affect farmers' intentions to adopt a DSS. This is in accordance with Meng et al. [128] who indicated that farmers with high knowledge about the prevalence of pests and diseases in their orchards presented increased willingness to adopt precision pesticide technologies. Moreover, environmental concerns were found to have a weak but statistically significant, though practically negligible, influence on farmers' intentions. This finding aligns with the observation of Feisthauer et al. [58], who noted that small -and in their case, insignificant-effects of pro-environmental concerns may stem from the use of overly generic statements to measure this construct. So, farmers may believe that such technologies cannot mitigate general environmental problems, like climate change.

Interestingly, we found that the impact of data privacy concerns on farmers' intentions to adopt a DSS is insignificant. This finding contradicts the work of Jakku et al. [84], Gardezi and Stock [85], and Sullivan et al. [82] who noted that data privacy and security concerns may prevent farmers for sharing their data and/or adopt a decision support system in agriculture. One possible explanation may be the way that data privacy concerns are formulated. For instance, when the Model 3 (extended theory of planned behavior with indirect effects, see Fig. 3) is used instead, we observed that this type of concern has a weak significant negative impact on farmers' intention (coefficient $= -0.069$, $p = 0.051 < 0.10$), via its impact on "attitudes" (coefficient $= -0.168$, $p = 0.041 < 0.05$). Thus, data privacy concerns may work as a mediator on farmers' attitudes towards adoption of smart technologies.

5.2. Conclusion

Overall, our analysis shows that the extended model that we use in this study outperforms the standard model of the theory of planned behavior, both in terms of in-sample and out-of-sample predictive power. Moreover, our model was found to be marginally preferable to an extended version of the theory of planned behavior with indirect effects, which is also better than the standard one. Thus, in this study, we show that policymakers can benefit more by using extended models (either with indirect or without indirect effects) to understand how farmers make their choices.

Specifically, some policy recommendations emanate from our analysis. First, the observation that pest-related concerns enhance farmers' intentions to adopt a DSS indicate that policymakers should promote the use of such technologies especially to farmers that cultivate crops that are quite sensitive to pests and plant diseases or are in areas where severe problems with pests exist.

Second, our analysis identifies "Lack of financial support" and "Cost" as the main barriers for adoption which is in accordance with Anastasiou et al. [7]. Based on these observations, one potential area of intervention is the introduction of programs that financing technology adoption, either at an individual level, or collectively through agricultural organization and producers teams (e.g., cost-sharing programs between members), given that the majority of the responders reported to be a member of either an agricultural organization or in a team of producers or both (see Table 1).

Third, "Lack of technical training and information" also mentioned by farmers as a potential barrier for adoption. Educational and training programs are likely to have multiple, nonlinear effects on farmers behavior. For instance, by increasing farmers' perceived behavioral control [129], and by reducing any skepticism (i.e., improve their openness) towards innovation, enhancing in such a way their intentions to adopt smart technologies, like a DSS. Particularly, policymakers could advance the work and educational activities of agricultural extensionists and/or the activities organized by agricultural cooperations. Previous research notes that policymakers could benefit by financing exhibitions on the successful application of smart farming technologies organized by

Table 9
Barriers to adoption.

Barrier	Mean (SD)
Lack of financial support	4.04 (0.88)
Cost	3.97 (1.10)
Lack of technical training and information	3.59 (1.00)
Lack of successful application of these technologies	3.49 (0.92)
Inability to find specialized workforce	3.39 (0.93)
Uncertainty	3.30 (0.97)
Low adoption rate by other farmers	3.12 (1.03)
Increased time on the farm	2.98 (1.02)
Data privacy	2.98 (1.09)
Inability to find the necessary equipment/software	2.88 (1.01)

Number of responses = 105.

agricultural cooperations [26]. The rationale is that agricultural cooperatives are familiar with farmers' needs, because farmers usually contact them for advice on pest management and cultivation. Thus, farmers may express higher willingness to participate in a program (or activity) organized by them compared to programs (or activities) that are organized by other public organizations, like universities and/or research institutes.

However, some limitations of this study should be noted. First, the sample size is relatively small compared to other studies that employ larger datasets, even when PLS-SEM is used instead of the traditional Covariance-Based SEM (CB-SEM). Therefore, the results should be interpreted with caution. Second, institutional factors may significantly influence adoption behaviors, which could limit the generalizability of our findings. Finally, trust and habitual behavior may also play an important role in shaping farmers' decisions. These areas merit further investigation by policymakers and future research.

Ethical statement

I hereby affirm that the work presented in this article was carried out in accordance with ethical standards and integrity. All sources of information have been properly acknowledged and referenced. The research was conducted with honesty and respect for intellectual property, and no part of this work has been plagiarized.

Where applicable, informed consent was obtained from participants, and their privacy and confidentiality were protected in accordance with ethical guidelines. No data was fabricated, falsified, or misrepresented.

CRediT authorship contribution statement

Giorgos N. Diakoulakis: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Irene Tzouramani:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Funding acquisition, Conceptualization. **Marilena Gemtou:** Writing – review & editing, Writing – original draft, Methodology. **Evangelos Anastasiou:** Writing – review & editing, Writing – original draft, Methodology.

Declaration of competing interest

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Data availability

Data will be made available on request.

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