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Drivers and barriers to DSS adoption in European crop protection: insights from a machine learning analysis of farmer and advisor surveys

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Integrated pest management (IPM) prioritizes non-chemical alternatives for managing pests and/or diseases, reserving chemicals as last solution, when economically and environmentally justified. The holistic consideration of the agroecosystem makes decision-making in crop protection more complex, as it requires selecting the most appropriate action at the right time. Decision support systems (DSS) for IPM help manage the risks of pests and diseases affecting crops by predicting potential threats and suggesting suitable control measures. However, their adoption remains modest among farmers, despite demonstrated benefits. An anonymous online survey was conducted among farmers, advisors, and other agricultural stakeholders to investigate factors influencing DSS uptake, or lack thereof. The survey distinguished between DSS users and non-users, enabling targeted questions on different aspects of DSS use and adoption. In total, 78 respondents were classified as *DSS users* and 29 as *DSS non-users*. Data were analyzed through clustering, followed by statistical validation of clusters and induction of a classification tree, to identify the most influential features shaping cluster formation among both *DSS users* and *DSS non-users*. The analysis identified four clusters in the *DSS users'* dataset and two clusters in the *DSS non-users'* dataset. For *DSS users*, DSS output reliability and usefulness were identified as the most influential features. Membership in a farmers' network and DSS ease of use also contributed to cluster separation. For *DSS non-users*, DSS availability for different cropping systems was the most important attribute determining cluster separation. The results indicate that farmer involvement in DSS development and calibration may enhance trust and, therefore, adoption. Moreover, the need for user-friendly systems providing simple and clear information was highlighted. Although the lack of DSS tailored to specific cropping systems emerged as the main barrier, limited awareness and concerns about costs were also important obstacles. The applied methodological approach presents a reproducible and robust AI-based framework, built on open-source tools, to analyze stakeholders' perceptions of IPM DSS and extract knowledge from complex survey data. This study provides valuable insights to facilitate DSS adoption for more sustainable crop protection and underscores the importance of both DSS technical performance and end-user needs.

KEYWORDS
AI-based analysis, decision tools, DSS uptake, pathways and obstacles to DSS use, questionnaire

1 Introduction

Diseases and insect pests can significantly threaten agricultural production, often resulting in severe yield losses (Walker, 1983). Pests are defined as any species, strain, or biotype of plant, insect, animal, or pathogen that damages plants or plant products (Bajwa and Kogan, 2002; IPPC Secretariat, 2024). Effective pest management is therefore essential for achieving adequate yields in both quantity and quality, as well as for farm profitability (Ramsden et al., 2017). One of the most commonly used approaches to pest management is the use of plant protection products (PPPs) (EPPO, 2004), which provide reliable pest control (Lamichhane et al., 2016). However, indiscriminate and excessive use of chemical pesticides has led to the development of resistant pest populations (Lucas et al., 2015; Lamichhane et al., 2016; Begum et al., 2017) while also imposing substantial environmental burdens and increasing risks to human health. These include contamination of soil, water, and air, and harm to non-target and beneficial organisms, such as pollinators and natural enemies (Rossi et al., 2012; Begum et al., 2017). There is increasing pressure from policymakers, consumers, and stakeholders to reduce the use of chemical pesticides in agriculture and to produce safer, healthier food (Möhring et al., 2020). The European Union (2009) (EU) addressed this concern through the Sustainable Use Directive (SUD, Directive 2009/128/EC), promoting the adoption of Integrated Pest Management (IPM) strategies and alternative solutions to chemical pesticides. These practices became compulsory for EU farmers in 2014. In addition, the European Green Deal has set ambitious targets for the agricultural sector to make it more sustainable, including a 50% reduction in the use of pesticides—especially the most hazardous substances—by 2030 (European Commission, 2019). Although these goals seem very challenging to achieve, several techniques and technologies have already been developed to support the transition to more sustainable crop protection strategies and to minimize chemical pesticide applications (Singh et al., 2024; Damos, 2015). The IPM principles consider the crop system as a whole, which should be managed according to a holistic approach, emphasizing the integration of all the available practices to prevent the onset and development of pests (Barzman et al., 2015; Rossi et al., 2019).

However, the adoption of IPM strategies clearly increases the complexity of the decision-making process (Hernandez et al., 2017). To address this, various decision tools, including models and decision support systems (DSSs), have been developed to assist farmers not only in the optimization and adoption of alternative strategies, but also in the improvement of pesticides application (Rossi et al., 2012, 2019). DSSs are systems that combine sensors and tools for data collection, databases to store and organize data, and tools for data analysis, providing data interpretation to support farmers in decision making (Rossi et al., 2019). The core of DSS are prediction models that are developed based on mathematical relationships that aim to describe the patho-system (Rossi et al., 2010). These relationships are implemented through various computational approaches such as artificial neural networks, fuzzy logic systems, machine learning, expert systems, Bayesian networks, decision trees, and/or simulation models (Rossi et al., 2014, 2015; González-Domínguez et al., 2023; Eze et al., 2025; Sweidan et al., 2025).

In crop protection, the main model categories are empirical or data-based models, which are developed from the existing relationships derived from field data under specific environmental conditions, without considering cause-effect relationships between variables, and mechanistic or process-based models that are based on the detailed analysis of factors affecting each step of the pest life-cycle and the external influencing variables (Rossi et al., 2019; Caffi et al., 2007; Caffi and Rossi, 2018). Empirical and mechanistic models differ in complexity, robustness, accuracy, and reliability (Caffi and Rossi, 2018). Additionally, more complex DSSs combine disease or pest models, crop growth models and fungicide models to provide suggestions to farmers for making informed decisions (Caffi and Rossi, 2018; Fedele et al., 2024).

In addition to these technologies, recent studies are integrating Artificial Intelligence (AI) systems into agriculture to improve crop protection. Systems combining AI, sensors and IoT technologies have been tested for automatic recognition of insect pests and foliar disease symptoms, enabling more timely and targeted interventions (Ahmed et al., 2024; Ibrahim et al., 2025; Deng et al., 2025). While these AI-based systems still represent future solutions, at present, DSSs are already established tools to support farmers in decision-making.

The primary aim of DSS is to forecast pest occurrence and predict crop risk, enabling timely and informed interventions. These technologies are designed to support farmers in decision-making, helping to avoid unnecessary treatments and shift from routine calendar-based applications to targeted treatments applied only when needed (Damos, 2015; Rossi et al., 2014; Lázaro et al., 2021; Eze et al., 2025). Numerous studies have shown the benefits of DSS in reducing the number of treatments without compromising the effectiveness of pest control across different crops and agricultural environments (Delière et al., 2015; Caffi et al., 2010; Schepers, 2004; Prahl et al., 2022; Lázaro et al., 2021). Caffi et al. (2010) reported that by following DSS recommendations, the number of sprays was potentially reduced by 36 and 75%, in the control of grapevine powdery mildew. In addition, Rossi et al. (2014) reported a similar reduction (24%) in the control of downy mildew on grapevine. Meno et al. (2024) compared NegFry DSS to routine farmers' practice, revealing a potential reduction in the number of sprays up to 56% for the control of potato late blight. Similarly, Prahl et al. (2022) described a potential reduction in fungicide application up to 50% in wheat. Furthermore, Rossi et al. (2014) reported an example from organic vineyards where the introduction of DSS enabled a reduction in plant protection costs of EUR 195/ha per year due to the lower number of treatments and the lower dose, indicating a potential economic advantage of using DSS. Nevertheless, the uptake of DSS among farmers remains modest (Rossi et al., 2019; Perez et al., 2023; Gent et al., 2013; Marinko et al., 2023), due to both technical and socio-economic reasons, such as a perceived lack of credibility, accuracy and accessibility of tools (Matthews et al., 2008; Gent et al., 2011; Ara et al., 2021; Rossi et al., 2012), a perception that DSS substitute rather than support farmers in decision-making (Rossi et al., 2019; Hochman and Carberry, 2011; Ara et al., 2021), and varying levels of risk aversion among individual farmers in following DSS suggestions (Gent et al., 2011; Lázaro et al., 2021; Akaka et al., 2024). However, the use of DSS by farmers may be underestimated due to indirect use by advisors (Perez et al., 2023; Rossi et al., 2019; Gent et al., 2013).

Several EU Horizon projects have been launched to accelerate the transition towards sustainable agriculture in Europe. For example, the IPMWORKS (grant agreement No. 101000339; https://ipmworks.net/) and IPM Decisions (grant agreement No. 81761; https://www.ipmdecisions.net/) projects aimed to promote and facilitate IPM adoption. During the IPM Decisions project, a free online DSS platform[1] was developed to provide farmers, farm advisors, and researchers with access to several existing IPM DSSs (Debeljak et al., 2021; Jørgensen, 2020). In addition, the IPMWORKS project established hubs for farmers to test new pest management techniques and to demonstrate the cost-effectiveness of IPM strategies. As part of the IPMWORKS project, farmers participated in DSS trials on their own farms. Despite these efforts, the use of DSS in Europe remains generally low (Rossi et al., 2019; Perez et al., 2023; Gent et al., 2013; Marinko et al., 2023). To better understand the drivers and barriers to DSS adoption, a survey was conducted among European farmers. Surveys have been widely used as a valid method to collect information from farmers about their knowledge, attitudes and opinions, as well as to identify knowledge gaps to guide new research (Escalada and Heong, 1997).

This study aims to identify the key pathways and barriers to DSS adoption in IPM. Based on these findings, we propose strategies to improve the dissemination and adoption of IPM DSS in Europe in particular and to promote sustainable pest management in general. Furthermore, the present study provides a detailed description of a machine learning method to analyze survey data, by implementing the method described by Marinko et al. (2023, 2025).

2 Materials and methods

The survey of farmers, farm advisors, technicians, researchers, and others (Section 2.1) was conducted between November 2024 and April 2025. No personal data were collected. The short online questionnaire was created using Google Forms. It was distributed through IPMWORKS hub coaches, IPMWORKS partners, social media channels, and private contacts. Within IPMWORKS, hub coaches are IPM experts appointed to coordinate groups of farmers in specific regions of Europe to facilitate the dissemination and adoption of IPM practices. Invitees were also asked to further share the survey with their own contacts. The survey was translated into Danish, Dutch, English, Finnish, French, German, Italian, Portuguese, Serbian, Slovenian, and Spanish to make it accessible to farmers and farm advisors in their native languages. Participation was voluntary, free of charge, and participants were not compensated for completing the questionnaire. The sampling strategy combined elements of convenience and snowball sampling, as the survey was disseminated through IPMWORKS hub coaches, partners, social media, and personal contacts. Although this approach enabled broad participation across different countries and contexts, it does not represent a random sample, and the results may not be statistically representative of all European farmers. Nevertheless, the strategy ensured a diversity of responses and provided valuable information on the adoption of DSS and the associated barriers.

2.1 Survey

The survey was primarily aimed at farmers and advisors, but was open to all stakeholders in the agricultural sector, including researchers, technicians, DSS developers, and students. It was structured to allow differentiation between DSS users and non-users, enabling the creation of two separate datasets for subsequent analysis.

The survey comprised seven sections, containing closed-ended, multiple choice, open-ended, and 5-point Likert-scale questions. The first section included questions on general demographic and socio-economic characteristics (e.g., country, job) as well as participation in networks for sharing knowledge and information. The final question in this section concerned experiences with using DSS, and the questionnaire was branched according to respondents' answers. Respondents who had already used a DSS were directed to the section intended for *DSS users* and were later categorized as such. Those who indicated they had not yet used a DSS were directed to the section for *non-users* and were later categorized accordingly. No technical questions about the DSS were included; therefore, respondents did not specify the technology underlying the DSS. This approach was adopted because users often do not know such details, mainly due to a lack of strong and detailed communication and knowledge exchange between researchers and farmers (Cruz et al., 2022).

Respondents categorized as *DSS users* were asked in the next two sections (2 and 3), whether they used the IPM Decisions platform, which provides the results of multiple DSSs for different crops free of charge (Marinko et al., 2024) or which DSS they normally use. The users then proceeded to section 6, where they rated a series of statements about DSS on a scale from 1 to 5, according to how much they agreed with each statement. Those identified as *DSS non-users* were given a different set of questions, including whether they usually consult the local crop protection bulletin to plan treatments or whether their advisor uses a DSS or a model (4). In section 5, an open question asked for the main reason why they do not use these tools. In the final section of the survey (7), respondents again rated a series of statements about DSS on a 1–5 scale, according to their level of agreement. The questions in each section are listed in Supplementary Table S1. The questionnaire was completed by 107 respondents; 78 (73%) were categorized as *DSS users* and 29 (27%) as *DSS non-users*. The respondents were from 20 different countries. As part of data preprocessing before analysis, the countries were grouped according to the European geographical region classification (Annex 1 Reg. 2009/1107/EC, European Union, 2009) as follows: Northern Europe, Central Europe, Southern Europe, while other countries were labelled as non-European countries. Similarly, respondents' main jobs were grouped into five categories: farmers, farm advisors, technicians (including crop technicians, commercial technicians, agrochemical technicians, experimenter technicians, etc.), researchers (including researchers, DSS developers or providers), and others (including students, teachers, employees, representatives of the agricultural ministry or agricultural cooperatives). The numbers of respondents, *DSS users,* and *DSS non-users*, classified by geographical region and job group, are reported in Table 1.

1 https://www.platform.ipmdecisions.net/

TABLE 1 Distribution of respondents by geographical regions and job group for both *DSS users* and *DSS non-users*, and total.

Category	*DSS users*	*DSS non-users*	Total
Geographical regions			
Northern Europe	14 (18%)	1 (3%)	15 (14%)
Central Europe	20 (26%)	6 (21%)	26 (24%)
Southern Europe	41 (52%)	20 (69%)	61 (57%)
Non-European countries	3 (4%)	2 (7%)	5 (5%)
Job group			
Farmers	18 (23%)	7 (24%)	25 (23%)
Farm advisors	36 (46%)	3 (10%)	39 (36%)
Technicians	6 (8%)	6 (21%)	12 (11%)
Researchers	6 (8%)	2 (7%)	8 (8%)
Other job	12 (15%)	11 (38%)	23 (22%)
Total	78 (100%)	29 (100%)	107 (100%)

2.2 Analysis of survey data

Our approach to analyzing survey data implements and extends the methodology described by Marinko et al. (2023, 2025). It comprises the following steps: (1) data preprocessing, (2) dimensionality reduction, (3) clustering, (4) statistical validation of clustering, (5) training classification models, and (6) interpretation of feature contributions in classification models. The approach is exploratory in nature and designed for structured survey datasets of moderate size. Our objective is to identify consistent patterns within the sampled respondents. Emphasis is placed on stability, interpretability, and reproducibility rather than model complexity. The approach was implemented in the Python programming language in an interactive notebook using the scikit-learn machine learning library (Pedregosa et al., 2011). The implementation is open-source and available on GitHub (see Data availability statement).

2.2.1 Data preprocessing

Data preprocessing is a crucial step that ensures the input attributes are consistent, comparable, and in a machine-readable form, which is essential for the accuracy, stability, and interpretability of the subsequent steps of the methodology. In this study, each original survey question was treated as a raw variable (referred to as an attribute), and the corresponding answer of the respondent represented the attribute value. During data preprocessing, these attributes were converted into numerical representations called features, and this terminology is used throughout the paper. The dataset consists of a set of attributes that describe each survey response, whose values are numerical, categorical, or binary; therefore, different attribute preprocessing techniques were applied. Numerical attributes were standardized using z-score normalization by subtracting the mean and dividing by the standard deviation. Categorical attributes were transformed via one-hot encoding to represent each category as a separate binary indicator. Binary attributes were ordinarily encoded as 0 or 1. These transformations convert the values of the original attributes (survey responses) into a uniform, all-numeric feature matrix that was then used for further analysis, including dimensionality reduction, clustering, and classification.

2.2.2 Dimensionality reduction

Dimensionality reduction is a technique widely used in statistics and machine learning to simplify high-dimensional datasets by projecting them into a lower-dimensional space. The aim is to retain as much relevant structure and variation in the data as possible while removing noise and redundant features. This makes the data more interpretable and suitable for several tasks such as clustering and visualization. PCA, t-SNE and UMAP are three well known methods for dimensionality reduction (Géron, 2022).

Before clustering, dimensionality reduction was performed using UMAP (Uniform Manifold Approximation and Projection; McInnes et al., 2018). This method offers several benefits: (a) it reduces noise, (b) dense regions become more compact and well-separated, (c) it decreases the memory consumption of clustering, and (d) it enables data visualization when the target number of dimensions is 2 or 3. We selected 2 target dimensions to ensure a clear visualization of the data and clusters. Although using more dimensions might improve clustering, it would reduce interpretability because the data used for visualization would differ from that used for clustering. In addition, due to the small number of instances, the default value of the parameter *n_neighbours* was reduced from 15 to 10.

UMAP is a non-deterministic method; therefore, repeatability and statistical significance of experiments require careful consideration. To address this, two approaches are commonly used: (1) fixing the random seed to ensure deterministic behavior, and (2) presenting a randomly selected result as a typical example. Both approaches have limitations. Fixing the random seed ensures repeatability, but results can change significantly when the random seed is altered, invalidating related claims and explanations. Conversely, a randomly selected result is rarely truly random, as the algorithm is usually run multiple times and the best result is chosen, thus introducing bias.

Our approach ensures statistical significance by repeating the dimensionality reduction and clustering steps multiple times. The final clustering is performed on the distance matrix $D = 1 - C$ where C is a normalized co-association matrix obtained by merging intermediate clustering results (Fred and Jain, 2005). The final visualization is obtained by taking the mean of individual UMAP results, aligned using Generalized Procrustes Analysis (Gower, 1975). This method filters out variability due to rotation, translation, and scaling, allowing for consistent and robust results.

2.2.3 Clustering

Clustering is an unsupervised approach that groups similar data points. The goal is to discover natural groupings and structures that may exist in the data. Each cluster represents a subset of data points that are more similar to each other than to points in other clusters, according to the underlying definition of similarity or density. Several clustering algorithms are available, differing in the shapes of clusters they can discover, noise handling, soft probability assignment, and whether the number of clusters is predefined, among other factors (Xu and Wunsch, 2005).

Density-based methods such as DBSCAN and HDBSCAN are most suitable for our clustering task, as they do not require a predefined number of clusters, can detect clusters of any shape, and accommodate outliers and soft probabilistic assignment. They also do not require large sample sizes to identify stable dense regions. For our analysis, we selected the HDBSCAN clustering algorithm (McInnes et al., 2017), which was applied multiple times to the two-dimensional UMAP-reduced data. The pairwise products of soft cluster probability assignments were then stored in a co-association matrix for further analysis. Due to the relatively small number of instances, we set the parameter defining the minimum cluster size to 5. The final clustering resulted from HDBSCAN clustering of the distance matrix obtained from the co-association matrix, which further reduced the impact of sampling variability. Clustering results can be visualized on the mean-aligned UMAP embedding, where colors indicate clusters and optical (alpha) reflects cluster membership probability.

2.2.4 Statistical validation of clustering

Since clustering algorithms can partition data even when no real structure exists, statistical validation is crucial for determining whether the identified clusters represent real patterns or are merely artefacts. As clustering is unsupervised, validation concerns robustness, quality, and significance of the groupings, rather than accuracy. Several approaches to statistical validation exist, including measures of compactness and separation, stability analysis, significance testing, and external validation against known groupings (Hastie et al., 2009).

To determine whether clusters differed in their response patterns, non-parametric statistical tests were applied to Likert-scale questions to assess differences in response distributions across clusters. For each Likert-scale question, the null hypothesis was that the distribution of responses was identical across all clusters. When there were two clusters, the Mann–Whitney U test was used. For more than two clusters, the Kruskal–Wallis H-test was applied, followed by Dunn's *post hoc* test to identify specific pairwise differences. All p-values were corrected for multiple testing using the Benjamini–Hochberg and Holm–Bonferroni correction procedures to control the false discovery rate for questions and comparisons. In the case of more than two clusters, the null hypothesis of the *post hoc* test was that there was no difference in the response distribution between any pair of clusters for the selected question. In this case, the results are presented as one heatmap per question comparing all clusters, enabling easy visual comparison and detection of significant differences.

2.2.5 Training of classification models

Classification is a supervised machine learning technique that predicts a target (class) variable from input data. It learns patterns from labelled examples and then applies these patterns to assign new observations to one of the predefined classes. In this study, cluster assignments served as the target variable for training classification models to explain and predict cluster membership. There is a wide range of classification algorithms, each with different strengths and interpretability characteristics (Hastie et al., 2009). Classification using classification trees is a classical and widely used approach that is simple, fast, and produces an interpretable model called a classification tree, which consists of a collection of partially overlapping rules and can be conveniently visualized as a tree.

To identify the key attributes that distinguish clusters, a classification tree model was trained using the CART algorithm, with the final cluster labels as the target variable and the preprocessed feature matrix as input. Unlike UMAP, numerical attributes were left unscaled, as classification trees do not require feature scaling, which also facilitates interpretation. The performance of the classification tree was evaluated using the leave-one-out cross-validation technique, which trains the model on all observations except one and tests it on the single held-out observation, repeating the process so that each observation serves as a test case exactly once. To reduce the risk of overfitting, tree model complexity was controlled by setting a minimum of 10 samples per leaf and applying cost complexity pruning ($\alpha = 0.01$). Given the model's interpretability-oriented objective, no hyperparameter tuning to maximize predictive accuracy was performed, therefore reducing the likelihood of modelling dataset specific noise. The F1 score provided an unbiased estimate of the model's ability to generalize cluster separation patterns. A high F1 score indicates interpretable, feature-driven clusters, while a low F1 score suggests either complex boundaries or weak relationships between clusters and features.

2.2.6 Interpreting feature contributions

Understanding which features most strongly influence the classification model provides insights into the characteristics that differentiate the clusters. The SHAP method is a recent and widely adopted approach based on cooperative game theory, quantifies the contribution of each feature to the model's prediction (Lundberg and Lee, 2017). It is model-agnostic and offers various visual outputs to facilitate interpretation.

In our implementation, SHAP values were calculated for the trained classification tree. For each observation, SHAP values indicate how much each feature increases or decreases the predicted probability of belonging to a particular cluster compared to the model's baseline prediction. By aggregating these values across all observations, we obtained global feature importance measures, identifying the most influential features in distinguishing clusters. The SHAP analysis results were visualized using a SHAP summary plot, which shows both the magnitude and direction of feature effects across all samples. This enables intuitive interpretation of how specific features and their value ranges contribute to membership in different clusters. Thus, SHAP analysis complements the classification tree structure, providing a more detailed understanding of the relationships between features and clusters.

3 Results

3.1 Characteristics of the survey participants

A total of 107 responses from different stakeholders were collected. The majority of respondents were from Southern Europe (57%), followed by Central Europe (24%), with smaller proportions from Northern Europe (14%) and non-European countries (5%). A higher proportion of respondents were farm advisors (36%) and farmers (23%), followed by those in other occupations (22%), technicians (11%), and researchers (8%). Further details are provided in Table 1. Most respondents reported not being part of any farmers' or farm advisors' network (53%), while the remainder were members of IPMWORKS (37%), IPM Decisions (1%), or other networks (9%).

Based on their answers, respondents were categorized as *DSS users* and *DSS non-users*, and analyzed separately.

3.2 Clustering of responses

The clustering analysis offers an overview of the variability in opinions, expectations, and perceptions among *DSS users* and *non-users* regarding IPM DSS. Stakeholders who provided similar answers to most questions were positioned closer together in the two-dimensional UMAP plot (Figure 1). Among *DSS users*, four distinct clusters were identified (Figure 1A), with some outliers not assigned to any cluster by the HDBSCAN algorithm. In contrast, *DSS non-users* formed two clusters (Figure 1B), with no outliers detected.

3.3 Interpreting respondent clusters using classification trees

Classification trees were used to explain the clustering results, identifying the attributes and conditions that distinguish the four clusters of *DSS users* and the two clusters of *DSS non-users*. The weighted F1 score of the classification trees, determined by leave-one-out cross-validation (Hastie et al., 2009), was 84% for *DSS users* and 86% for *DSS non-users*. These results confirm that in both cases, clusters are strongly determined by attributes and features, and their structure can be accurately described by simple rule-based boundaries.

3.3.1 *DSS users*

IPM *DSS users* were grouped into four clusters (Cluster 0, 1, 2, 3) based on their survey responses.

According to the classification model structure, the most important attribute for grouping *DSS users* was the perceived reliability and usefulness of DSS outputs, followed by membership in a network of farmers or farm advisors, such as "IPMWORKS" and "IPM Decisions," and the perceived ease of using a DSS (Figure 2).

DSS users who considered DSS output reliable and useful (i.e., assigned a score of 4 or 5) were classified into Cluster 0 or Cluster 1, while those who gave a low-to-medium score (1–3) were assigned to Cluster 2 or Cluster 3. The distinction between Cluster 0 and Cluster 1 was based on the perceived ease of DSS use: Cluster 0 included users who rated DSS as easy or very easy to use (4–5), whereas Cluster 1 comprised users reporting some difficulties in using DSS (1–3). The separation between Cluster 2 and Cluster 3 was based on the attribute "network," particularly membership in "IPMWORKS." Cluster 2 consisted of more than 90% IPMWORKS members, whereas most users in Cluster 3 (70%) were not members of any network (Figure 2).

SHAP analysis identified the attributes and features that determined the classification of *DSS users* into different clusters (Figure 3). For example, a high SHAP value (red) for attribute 6.2 ("I think that DSS outputs are reliable and useful") increases the model's confidence that an observation belongs to Cluster 0, while a low SHAP value (blue) decreases that confidence and shifts probability towards other clusters (Figure 3A). Cluster 0 mainly comprises stakeholders who rate DSS output highly for reliability and ease of use (Figure 3A). In contrast, Cluster 1 consists of users who also gave high scores for DSS reliability but assigned lower scores for ease of use (Figure 3B). IPMWORKS membership has minimal influence on the identification of Clusters 0 and 1 (Figures 3A,B). In Cluster 2, the main attributes determining cluster formation were the perceived reliability and utility of DSS output, with most respondents giving low scores, and membership in the IPMWORKS network. Most users classified in Cluster 2 were part of the IPMWORKS network (Figure 3C). Similarly, Cluster 3 was characterized by low scores for DSS output reliability, but most were not part of the IPMWORKS network (Figure 3D).

Cluster 0 is the largest group ($n = 31$), mostly comprising stakeholders from Southern Europe (63%), with farm advisors (30%) and

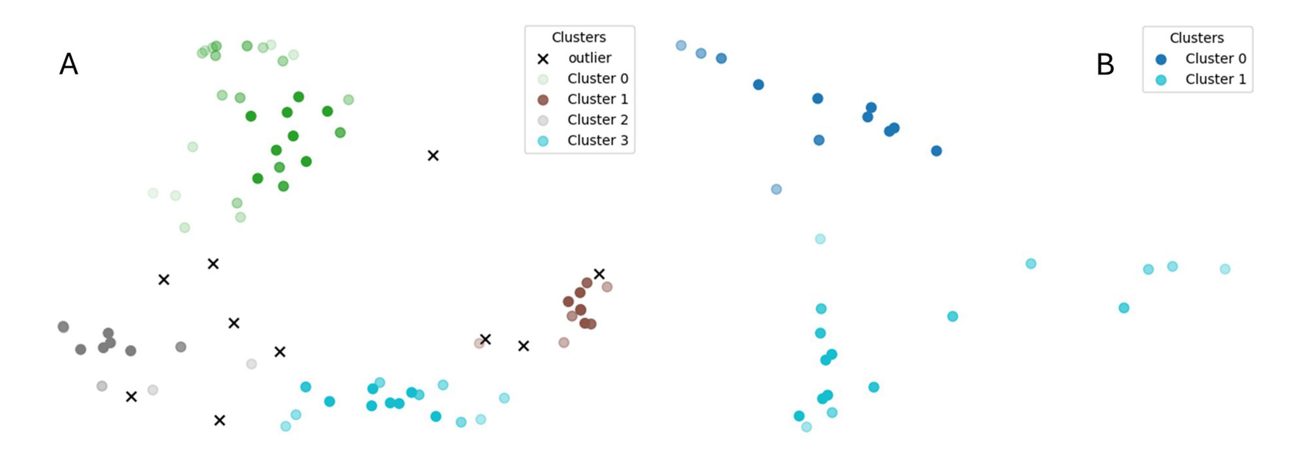

FIGURE 1
Positions of *DSS users* **(A)** and *DSS non-users* **(B)** in a two-dimensional UMAP plot, grouped into clusters. Clustering was performed using HDBSCAN with a minimum of five points per cluster. Colors indicate clusters, opacity reflects the probability of cluster membership, and 'x' marks outliers.

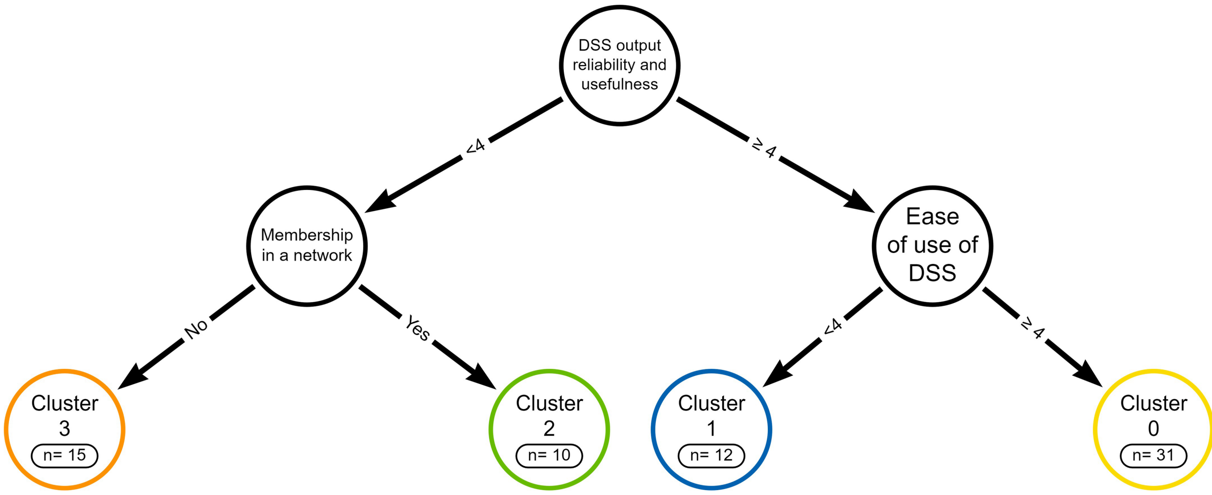

FIGURE 2
A classification tree for *DSS users* (n = 68) trained using the CART algorithm. The attribute values are reported on the arrows. Ten instances, which were labeled as outliers by the clustering algorithm, were not used in the construction of the classification tree.

farmers (23%) as the most represented job categories. A large majority (70%) were not part of any network, while 20% were affiliated with IPMWORKS and 10% with other networks. Over 80% of stakeholders in this cluster have never used the IPM Decisions platform. According to the classification tree model, users perceived DSS output as reliable and useful, and rated DSS as very easy to use, giving high scores to both aspects. They gave positive evaluations across all DSS-related questions; for example, all found DSS highly useful for their cropping systems, and, in general, 90% evaluated DSS dashboards positively in terms of clarity and intuitiveness, with scores significantly higher than those in Clusters 1 and 3 ($p < 0.001$) (data not shown). Over 90% agreed that DSS can help reduce PPP use, also showing a significant difference from the other clusters ($p < 0.05$) (Figure 4).

Cluster 1 (n = 12) consisted mainly of users from Central (54%) and Northern Europe (27%), with farm advisors representing the majority of jobs (81%). All *DSS users* in this cluster were members of a network, mainly IPMWORKS (73%), but over 90% had never used the IPM Decisions platform. They rated DSS output as reliable and useful, but reported greater difficulties in using the tools, unlike the previous cluster. This attribute distinguished Cluster 0 from Cluster 1. They also noted difficulties with DSS dashboard usability and in finding DSS for their cropping systems. Opinions on the potential reduction of PPP use through DSS adoption were mixed, showing a significant difference from Cluster 0 ($p < 0.01$) (Figure 4).

Cluster 2 comprises 10 respondents, 55% from Northern Europe and 45% from Southern Europe. Most were farm advisors (55%), with a smaller proportion being farmers (18%) and technicians (18%). Over 90% were members of the IPMWORKS network, and more than 80% had used the IPM Decisions platform. Despite this, they expressed moderate or low trust in DSS outputs, a characteristic that distinguished Clusters 1 and 0 from Clusters 2 and 3. *DSS users* in Cluster 2 expressed more variable opinions about DSS; for example, the dashboard was generally rated from acceptable to excellent for clarity and intuitiveness, while ease of use received highly variable ratings, ranging from very negative to very positive. Most (64%) expressed limited belief in the potential decrease of PPP use through DSS uptake, significantly different from Cluster 0 ($p < 0.001$) (Figure 4).

Cluster 3 (n = 15) consists mainly of Southern European (63%) users. Most participants were farm advisors (38%), farmers (31%) and researchers (25%). Almost 70% were not part of any network, and users were almost evenly split between those who had used the IPM Decisions platform and those who had not. According to the tree classification model, membership in the IPMWORKS network was the attribute that distinguished Cluster 2 from Cluster 3. As in Cluster 2, users rated the usefulness and reliability of DSS output as acceptable or negative, and they often found DSS difficult to use. The DSS dashboard evaluation ranged from acceptable to very unclear and unintuitive. Opinions about the potential reduction of PPP through DSS varied widely, from impossible to very possible.

3.3.2 *DSS non-users*

Two clusters (Cluster 0 and Cluster 1) were identified among IPM *DSS non-users* based on their survey responses. The classification tree model indicated that the most important attribute for classifying *DSS non-users* was the availability of DSS for specific cropping systems (Figure 5).

DSS non-users who perceived a lack of DSS tailored to their cropping system were classified in Cluster 1, whereas Cluster 0 includes those who believe that DSS are readily available for specific cropping systems (Figure 5). The SHAP analysis explained the attributes contributing to cluster formation (Figure 6). Thus, Cluster 0 mainly consists of stakeholders who gave a high score to DSS availability (Figure 6A), while Cluster 1 mainly consists of *DSS non-users* who gave a low score to the same attribute (Figure 6B). A low value for attribute 7.1 ("There are no models/DSSs for my cropping system") increases the model's confidence that an observation belongs to Cluster 0, while a high value decreases confidence and shifts probability towards Cluster 1.

DSS non-users classified in Cluster 0 (n = 14) were mostly from Southern Europe (75%), with the remaining 25% from Central Europe and non-European countries. This group includes farmers (33%), researchers (17%), technicians (17%), and stakeholders in other occupations (33%). Almost all participants were not affiliated with the IPMWORKS network (91%). Cluster 1 (n = 15) comprised a majority

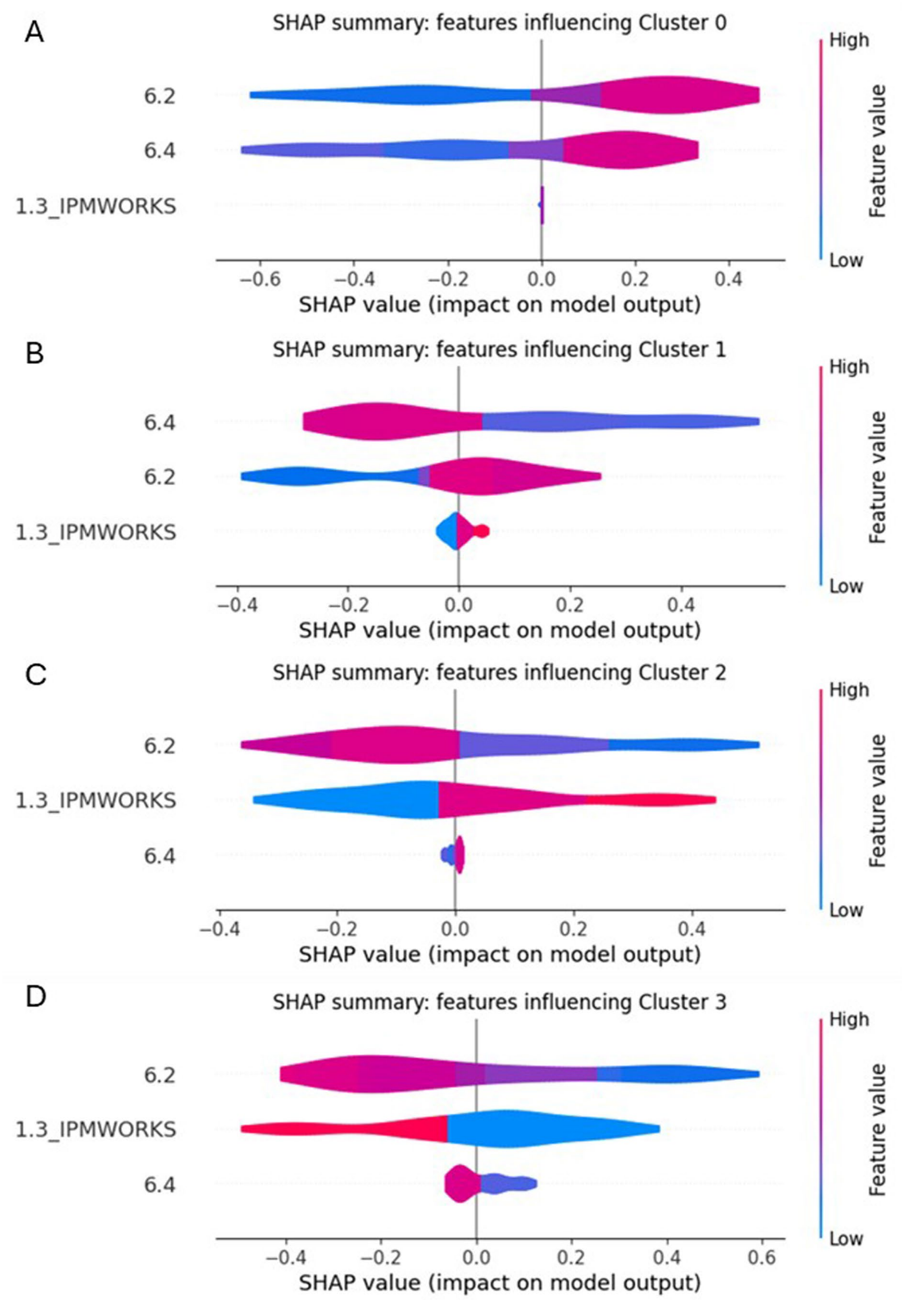

FIGURE 3
SHAP summary analysis of attributes and features determining the classification of *DSS users* in **(A)** Cluster 0; **(B)** Cluster 1; **(C)** Cluster 2; **(D)** Cluster 3. The attributes and features on the vertical axis in each plot are sorted in descending order of importance. The horizontal axis reports SHAP values, which quantify the impact of each feature on the likelihood of belonging to each cluster, with negative values reducing the likelihood and positive values increasing it. Red color denotes a high value, while blue color denotes a low value of the attribute or feature. Violin plots show the distribution (spread and density) of the impact of each attribute on the model's prediction. See Supplementary Table S1 for survey questions description.

from Southern Europe (65%), followed by Central Europe (23%), Northern Europe (6%), and non-European countries (6%). Most respondents worked in other occupations (41%) and were not part of any network; the remainder were farmers, farm advisors, and technicians.

Although classified as *DSS non-users*, stakeholders in Cluster 0 generally expressed positive opinions about DSS. Most (92%) believe that DSS are available for several cropping systems and 83% rated their outputs reliable and useful. Additionally, 58% of Cluster 0 respondents evaluated DSS dashboards as clear and user-friendly (Figure 7). In contrast, stakeholders in Cluster 1 held opposing opinions about DSS. Thus, they generally report a lack of DSS availability for several cropping systems (82%) and limited trust in DSS output (76%). While they consider the DSS platform acceptable in terms of complexity, most (94%) found the platform not user-friendly (Figure 7).

In the *DSS non-users* survey, one question asked for the reasons for not adopting DSS. In Cluster 0, the most frequent response (42%) was that participants were not farmers and therefore did not directly use the tools. In contrast, the most common reason in Cluster 1 was a lack of awareness of the tools (30%), indicating limited knowledge about DSS. Other reasons mentioned in both clusters included a lack of perceived need, limited opportunities to try the tools, the absence

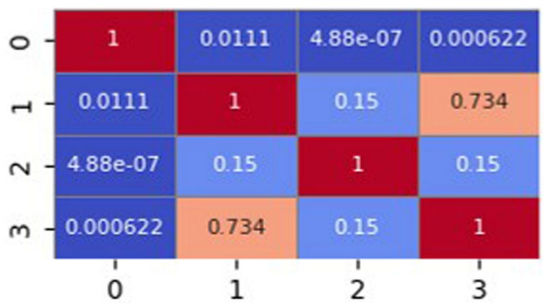

FIGURE 4
A heatmap of adjusted *p*-values from Dunn's *post hoc* test for pairwise comparisons of responses to Question 6.5 ("Would you estimate that using the DSS reduced the use of PPPs?") between clusters. Rows and columns correspond to cluster indices, and colors follow a diverging blue-red palette, with blue denoting significant differences and red denoting non-significant comparisons.

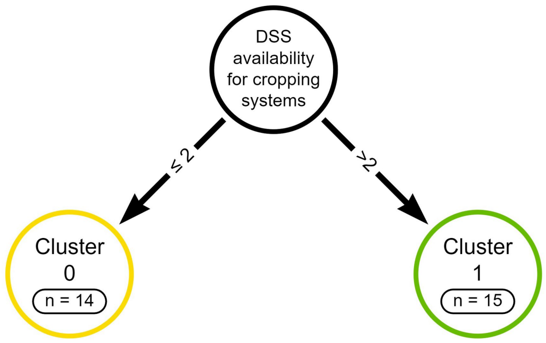

FIGURE 5
A classification tree for *DSS non-users* (n = 29) trained using the CART algorithm. The attribute values are reported on the arrows.

of DSS tailored to specific cropping systems, and the difficulty for small farms in affording DSS.

4 Discussion

This study aimed to identify the factors influencing DSS adoption in crop protection and the main barriers to their use. To minimize potential sampling biases, the survey was anonymous, voluntary, and without compensation. It was distributed through both social media channels and email, following the mixed-mode distribution strategy recommended by Vaske (2011). Participants were encouraged to share it to reduce researcher-driven sample selection (Marinko et al., 2025).

A total of 107 responses were collected, with 78 classified as *DSS users* and 29 as *DSS non-users*. The primary target audience was farmers and farm advisors, who represented 60% of the total sample, while the remaining 40% included other agricultural stakeholders, providing broad representation of the agricultural sector. Although the survey reached a wide range of participants across Europe, the use of convenience and snowball sampling may have influenced the sample composition. Notably, 57% of responses came from Southern Europe, likely due to stronger professional networks in that region, which may have led to underrepresentation of specific barriers or drivers to DSS adoption in Central and Northern Europe. However, Marinko et al. (2025) found that many barriers to DSS adoption, such as lack of trust and IT knowledge, were shared among Northern, Central and Southern European farmers, indicating similar issues in diverse contexts. Additionally, online survey distribution may underrepresent stakeholders with limited internet access or digital skills (Mergenthaler et al., 2024; Zahl-Thanem et al., 2021), often associated with age or socioeconomic status (Danie et al., 2024). Non-response bias may have occurred, particularly among farmers with little interest in digital tools. Additionally, respondents may have already held strong opinions, either positive or negative, about DSS (Mergenthaler et al., 2024), which could explain the relatively low proportion of *DSS non-users* in the dataset. The survey was also distributed through IPMWORKS hub coaches and partners, which may have further encouraged participation by farmers open to innovation and digital tools. However, even these farmers often remain reluctant to adopt DSS compared to other precision agriculture practices (Adereti et al., 2024; Caffi et al., 2025). To mitigate such biases, the survey was kept short, written in neutral language, and made available in multiple languages to encourage participation (Mergenthaler et al., 2024).

Overall, more than half of the participants evaluated DSS positively. Two key adoption drivers emerged: perceived output reliability and ease of use. A lack of confidence in DSS output has been widely recognized as a barrier to their uptake in previous studies. For example, Marinko et al. (2023) suggested involving end-users in demonstration events to build trust. Similarly, Rossi et al. (2014, 2019) and Akaka et al. (2024) showed that limited transparency in model development or in the equations underlying DSS undermines users' confidence, suggesting that enhancing transparency could foster both trust and adoption. DSS output reliability is closely linked to proper calibration and validation before market release (Lázaro et al., 2021; Rossi et al., 2019; Rossi et al., 2012; Akaka et al., 2024); inadequate validation may lead to inaccurate DSS outputs, potentially reducing yields and quality while increasing farmer skepticism (Rossi et al., 2023). Therefore, validation procedures should be tailored to the specific technology underlying DSS (Teng, 1981; Cao et al., 2012). Involving farmers and farm advisors in the development, calibration, and validation stages has been shown to enhance trust and encourage adoption (Marinko et al., 2023, 2025; Lázaro et al., 2021; Jørgensen et al., 2007; Akaka et al., 2024; Magarey et al., 2002; Rossi et al., 2023). Participatory approaches also enable developers to align tools with farmers' needs. For example, Rossi et al. (2014) reported that farmer involvement resulted in several benefits: increased awareness and ability to use DSS, first-hand testing of potential advantages, and opportunities to tailor DSS to farmers' actual needs.

A second key factor driving DSS adoption was ease of use, consistent with findings from several authors (Akaka et al., 2024; Pechlivani et al., 2023; Rossi et al., 2012, 2014, 2023; Caffi et al., 2012; Rose et al., 2016; Adereti et al., 2024; Marinko et al., 2023). Farmers prefer user-friendly systems that provide simple, clear, non-redundant information. For example, Rose et al. (2016) and Rossi et al. (2019, 2023) reported a general preference for visual outputs such as images or symbols, rather than complex written text. Additionally, Tonle et al. (2024) highlighted the importance of intuitive, multilingual interfaces that are accessible offline, thereby broadening potential adoption. However, technological barriers persist, including limited or perceived limited IT skills among end-users (Marinko et al., 2023; Adereti et al., 2024) and poor internet connectivity in rural areas (Marinko et al., 2025; Tonle et al., 2024; Rossi et al., 2012).

Interestingly, the two main drivers of DSS adoption closely align with the Technology Acceptance Model (TAM) described by Davis

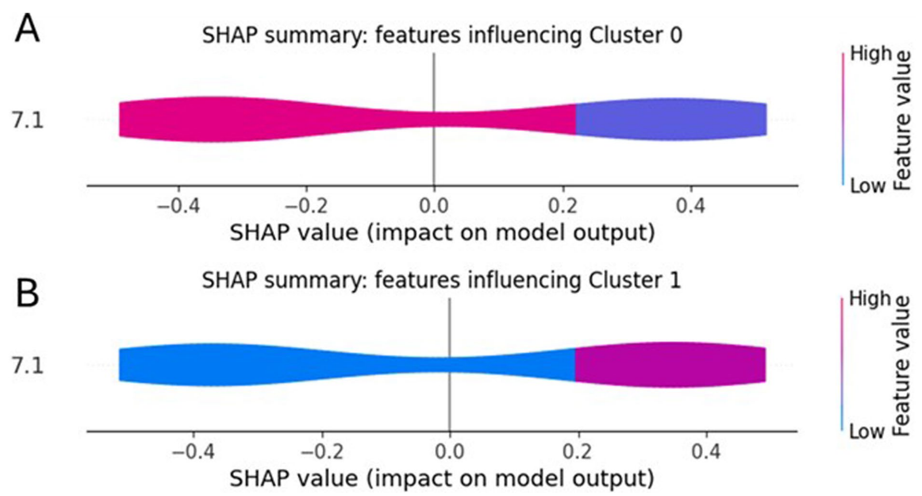

FIGURE 6
SHAP summary analysis of attribute determining the classification of *DSS non-users* in **(A)** Cluster 0, and **(B)** Cluster 1. The attributes and features on the vertical axis in each plot are sorted in descending order of importance. The horizontal axis reports SHAP values, which quantify the impact of each feature on the likelihood of belonging to each cluster, with negative values reducing the likelihood and positive values increasing it. Red color denotes a high value, while blue color denotes a low value of the attribute or feature. Violin plots show the distribution (spread and density) of the impact of each attribute on the model's prediction. See Supplementary Table S1 for survey questions description.

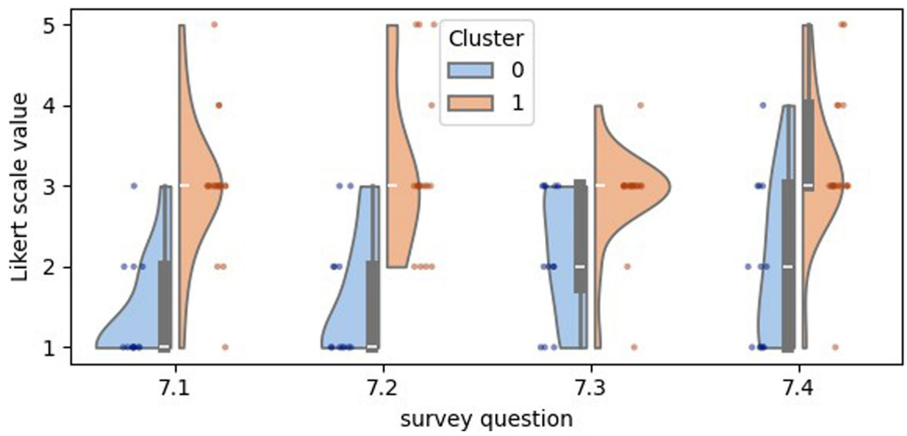

FIGURE 7
Violin plots of the distributions of Likert-scale responses to questions 7.1–7.4 for the two clusters found in the *DSS non-users* survey data. The dots indicate data points. The violins show both the spread and shape of the response distributions. The distribution of responses for all four survey questions is significantly different between clusters ($p < 0.05$). See Supplementary Table S1 for survey questions description.

(1989), who stated that a new technology is adopted primarily based on perceived usefulness, the extent to which a technology can improve work performance—and secondarily on perceived ease of use, meaning the degree of effort required to use it. Subsequent extensions of TAM, TAM2 and TAM3 emphasize additional factors: TAM2 highlights job relevance and output quality as key drivers of perceived usefulness (Venkatesh and Davis, 2000), which is particularly relevant to our study, as DSS should provide reliable and relevant output for the agricultural context. TAM3 further underlines the importance of IT skills and user experience in perceived ease of use (Venkatesh and Bala, 2008). These factors represent significant barriers to DSS adoption, although training, demonstration and experience can gradually enhance usability perception and foster adoption. Finally, the Unified Theory of Acceptance and Use of Technology (UTAUT) indicates the importance of facilitating conditions for technology adoption, such as technical infrastructure (Venkatesh et al., 2003). For example, the availability of internet connection, weather stations, validated models, or DSS for specific crops are crucial aspects for farmers adoption. Furthermore, our analysis shows that users who rated DSS most positively emphasized their potential to reduce PPP use, indicating a positive experience with DSS, as demonstrated in previous studies. For example, Lázaro et al. (2021) reported a 43% reduction in fungicide use compared with calendar-based applications; Kanatas et al. (2020) observed herbicide reductions of up to 40%, and Johnen and Meier (2000) halved insecticide applications following DSS recommendations. These positive experiences reinforced trust and satisfaction, as also observed by Akaka et al. (2024) and Marinko et al. (2023). Conversely, users who encounter difficulties may benefit from training, workshops, and demonstration events, which promote peer-to-peer learning (Cooreman et al., 2018; Marinko et al., 2023; Rose et al., 2016). Marinko et al. (2023) also proposed integrating DSS training into agricultural curricula, while Brugler et al. (2024) emphasized the need for stronger collaboration and communication between companies and educational institutions to train qualified DSS users.

Although farmer networks are often expected to facilitate the diffusion of innovation through peer-learning and shared experiences (Cooreman et al., 2018), our results suggest that membership alone does not automatically lead to greater trust or adoption of DSS. In fact, respondents affiliated with IPMWORKS did not consistently report higher levels of confidence or usability than those outside the network. A plausible explanation is that, during the project period, the DSS available within the platform were limited in number, focused on a narrow range of crops and pests, and were not always validated beyond their original development areas. In such circumstances, being part of a network may facilitate exposure, but it cannot compensate for the technical shortcomings of the tools themselves. This finding highlights an important nuance: networks can provide the social infrastructure for dissemination, but without robust, well-calibrated DSS ready for broad use (Rossi et al., 2019), membership alone is unlikely to drive adoption. Future initiatives should therefore integrate strong peer-learning frameworks with timely access to reliable, crop-specific DSS, ensuring that social capital and technical performance reinforce rather than substitute for each other.

According to responses from *DSS non-users*, the limited availability of DSS tailored to specific cropping systems was frequently cited as a barrier to DSS uptake. Crop type has already been identified as a key factor influencing adoption, with arable crop growers and their advisors more likely to use DSS than livestock farmers (Akaka et al., 2024; Marinko et al., 2023; Rose et al., 2016). Similarly, Fedele et al. (2022) reviewed published disease models, highlighting a much greater number of models focusing on cereals and fruit crops such as apples and grapes. Other crops, such as legumes, maize or rice, remain underrepresented, even though they are economically important worldwide. Therefore, DSS adoption cannot be considered independent of crop type, production system, or local context. For example, the geographical area may play a role, as DSS performance depends on model validation, data availability, weather stations, and/or internet connection (Rossi et al., 2014; Magarey et al., 2002). Furthermore, Lázaro et al. (2021) highlighted the increasing importance of DSS in both conventional and organic agriculture, noting that DSS could be even more crucial in organic production where few PPP are allowed (Reg. 834/2007/EC, European Union, 2007) and these often show a lower efficacy. These findings underline that DSS adoption is context-dependent and there is a need for tailored or adaptable DSS for specific farm-crop system conditions. In addition, many DSS address only single pests or diseases rather than integrating the multiple issues that farmers must manage (Rossi et al., 2012, 2023; Magarey et al., 2002). A multi-model approach, incorporating disease, crop, and pesticide models, has been suggested to provide more practical decision support (Caffi and Rossi, 2018; Fedele et al., 2024), as fragmented DSS can increase farmer workload and reduce the perceived value of decision tools.

Other barriers identified in the survey include a lack of awareness and a perceived lack of necessity. Communication and demonstration efforts appear more effective than online materials in promoting adoption (Jones et al., 2010; Rose et al., 2016; Cooreman et al., 2018; Marinko et al., 2023). Opportunities for hands-on trials are also important, with free or open-access versions suggested as entry points (Rose et al., 2016; Brugler et al., 2024). While many farmers prefer free DSS, experienced users often perceive low-cost tools as lower quality (Akaka et al., 2024). Willingness to pay tends to increase with trust and experience (Marinko et al., 2025; Rossi et al., 2014). Nevertheless, costs remain a critical barrier, particularly for small farms. Larger farms are generally more willing and able to invest in new technologies (Marinko et al., 2025; Rose et al., 2016; Akaka et al., 2024), while smaller farms often cannot afford to (Adereti et al., 2024; Brugler et al., 2024). Suggested solutions include shared DSS access among groups of small farmers to split costs (Brugler et al., 2024). Tailored marketing strategies should emphasize profitability for large farmers and cost savings for small farmers (Caffi et al., 2012; Akaka et al., 2024). Subsidies at the national or European level have also been proposed to facilitate uptake (Marinko et al., 2023). Past projects, such as IPMWORKS and MoDeM_IVM, have demonstrated that participatory approaches and evidence of reduced pesticide use can support broader adoption (Caffi et al., 2025; European Commission, 2013; Rossi et al., 2014).

While the empirical results highlight key barriers and drivers for the adoption of DSS, this study also makes a significant methodological contribution. IPM and sustainable agriculture depend on understanding farmers' perceptions, expectations and decision-making processes, but such 'soft data' is inherently complex and difficult to analyze using conventional statistical methods. By applying a combination of dimensionality reduction (UMAP), density-based clustering (HDBSCAN), statistical validation and interpretable classification trees, we uncovered hidden patterns in farmers' and advisors' perceptions of DSS. This methodological framework goes beyond descriptive statistics by identifying subgroups of users and non-users with distinct characteristics and highlighting the attributes that explain these differences. Importantly, the approach is reproducible, based on open-source implementations and robust enough to handle the heterogeneous datasets typical of agricultural surveys. It should also be noted that the survey was based on a combination of convenience and snowball sampling, rather than randomized sampling. Although this limits statistical representativeness, it enabled the inclusion of diverse perspectives from multiple countries and professional backgrounds. Therefore, the results should be interpreted as indicative within the sampled network rather than as population-level estimates. The dataset provides valuable insights into the dynamics of DSS adoption and highlights structurally consistent patterns across stakeholder groups. Finally, advanced AI-based methods offer a powerful complement to traditional tools and enable agricultural researchers to better capture the diversity of stakeholder perspectives that facilitate the adoption of IPM practices and digital innovations in agriculture.

5 Conclusion

This study highlights the main factors influencing DSS adoption in crop protection and the main barriers hindering broader use. Two key drivers emerged: the perceived reliability of DSS outputs and ease of use. Strategies to increase trust are discussed, such as enhancing model transparency and involving end-users during DSS development and validation, through participatory approaches. DSS should also be simple, providing clear information for practical use. Conversely, barriers continue to limit adoption. In this study, the limited availability of DSS tailored to specific cropping systems was the main obstacle, but additional reasons were identified, including a lack of DSS awareness and costs that are too high relative to farm size. In summary, our findings highlight three concrete levers for strengthening DSS adoption: building trust through transparent and validated outputs, ensuring ease of use through clear and intuitive interfaces, and expanding availability across diverse cropping systems. Importantly, our analysis shows that social networks alone are insufficient unless these technical foundations are in place. By aligning DSS development with farmers' real needs and IPM objectives, future initiatives can move beyond pilot use towards broader, long-term adoption. Although the survey was based on convenience and snowball sampling rather than random sampling, it was still able to capture a variety of perspectives across countries and stakeholder groups, providing valuable insights into DSS adoption. Finally, this study provides an open-source, reproducible and robust implementation of an AI-based survey analysis method, paving the way for a unified and transparent approach to extracting knowledge from complex perception-based datasets.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found at: https://eur03.safelinks.protection.outlook.com/?url=https%3A%2F%2Fgithub.com%2Fvpodpecan%2Fsurvey_analysis%2Ftree%2Fmain%2Fdata&data=05%7C02%7Cmargherita.furiosi%40unicatt.it%7C4741ed719e284d04140608ddf69710dc%7Cb94f7d7481ff44a9b5886682acc85779%7C0%7C0%7C638937850872226979%7CUnknown%7CTWFpbGZsb3d8eyJFbXB0eU1hcGkiOnRydWUsIlYiOiIwLjAuMDAwMCIsIlAiOiJXaW4zMiIsIkFOIjoiTWFpbCIsIldUIjoyfQ%3D%3D%7C0%7C%7C%7C&sdata=235N3gsj4frGuk2tohrJnkAKokB9YFNbx9hqi8shCS4%3D&reserved=0.

Author contributions

MF: Writing – original draft, Writing – review & editing. JM: Writing – original draft, Writing – review & editing, Conceptualization. VP: Formal analysis, Methodology, Writing – original draft, Writing – review & editing, Visualization. MD: Methodology, Supervision, Writing – review & editing. GF: Writing – review & editing, Conceptualization, Supervision. TC: Writing – review & editing, Conceptualization, Funding acquisition, Supervision.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that Generative AI was used in the creation of this manuscript. We used ChatGPT (OpenAI) for English language editing (clarity, grammar, and wording). All scientific content, analyses, and conclusions are the authors' sole responsibility.

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2026.1711425/full#supplementary-material

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