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Farmers' willingness to adopt precision agricultural technologies to reduce mycotoxin contamination in grain: evidence from grain farmers in Spain and Lithuania

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Abstract

Purpose This study examines the willingness of Spanish and Lithuanian grain farmers to adopt a combined approach of preventive site-specific spraying (PSSS) and selective harvesting (SH), two precision agricultural technologies (below referred to as PSSS-SH) aimed at mitigating the risk of mycotoxin contamination in barley and wheat.

Methods Data were collected from 190 commercial grain farmers using a choice experimental survey. The empirical analysis relied on the estimation of mixed logit and integrated latent class models.

Results The surveyed farmers were heterogeneous in their preference for the PSSS-SH technology, with a majority (81%) reporting that they were willing to adopt and pay for the PSSS-SH technology. Furthermore, the farmers' willingness to adopt PSSS-SH technology was influenced by the trade-offs between the potential production, economic and environmental changes.

Conclusion Profit maximization is not the only motivation for a farmer's decision to adopt PSSS-SH, there are also important non-financial benefits that align with the observed choices. Furthermore, the perceived usefulness of the technology, the willingness and readiness to use the technology, and the farmer characteristics (e.g. cooperative membership, employment status, share of household income from grain production and past experience with precision farming technology) were positively associated with uptake of the PSSS-SH technology. Therefore, extension programmes should have a special focus on the perceived usefulness of the technology, the willingness and readiness of farmers to use it, and its unique characteristics.

Keywords Choice experiment · Selective harvesting · Preventive site-specific spraying · Willingness to pay · Mycotoxin contamination

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Introduction

In recent decades, precision agriculture has emerged as a modern farming management concept that uses a combination of information and communication technologies (ICT) and sensing devices to provide real-time data-driven insights to assist farm management and support farming decisions (Cisternas et al., 2020; Klerkx & Rose, 2020). Existing evidence shows that the adoption of digital agricultural technologies promotes resource efficiency, contributes to sustainable agricultural production with higher yields, enhances access to markets, promotes value-chain integration and coordination, and reduces the environmental footprint of agricultural production (e.g.Deichmann et al., 2016; Schimmelpfennig, 2018).

Within the European Union (EU), the mainstreaming of precision agriculture has been integral to achieving the targets set out in agricultural and environmental strategies, including the European Green Deal and Farm to Fork Strategy (EU Commission, 2020). The promotion of precision and sustainable agricultural practices in the EU, including precision agriculture technology (PAT), is expected to foster the production of plant and animal products with enhanced efficiency and a reduced ecological footprint (EU Commission, 2020). However, the adoption of precision agricultural technologies among EU farmers presents a challenging and "dynamic issue for farmers, extension services, agri-business and policymakers" due to a suite of technological, infrastructure, economic, local and environmental considerations (EU Commission, 2017). In addition, the uptake of precision agriculture technologies (PATs) has been low and varies significantly by the type of technology and region (Barnes et al., 2019; Soto et al., 2019), with adoption being highest in north-western European countries (Groher et al., 2020; Michels et al., 2020; Paustian & Theuvsen, 2017) where farmers have more training in the use of these technologies than in other parts of the EU. Despite this, the number of empirical studies that have examined what motivates EU farmers to choose PATs and their willingness to pay remains relatively scare (Barnes et al., 2019) compared to studies in other regions (e.g. Erickson & Widmar, 2015; Kingwell & Fuchsbichler, 2011; Miller et al., 2017). For instance, a bibliometric mapping and clustering of global research output on PATs published from 2000 to 2016 shows that the USA and China were the most active knowledge producers, collectively accounting for 35% of publications. In contrast, individual European countries had a significantly lower rate of publication, with Germany contributing the most at 6.4% of the total research output (Pallottino et al., 2018). This disparity extends to farmers' adoption of PATs. A recent review of the literature on the adoption of fast-spreading PATs (e.g. guidance systems, automatic section control and yield monitors) and slow-spreading technologies (e.g. soil mapping, variable rate fertilizing and variable rate seeding) revealed that the adoption rate was generally higher in North America (USA and Canada) than in Europe (Nowak, 2021). For instance, the results showed that, on average, 17% more North American farmers adopted fast-spreading technologies compared to European farmers (ibid). These disparities can be attributed to several factors. In particular, large-scale farming operations in North America benefit significantly from precision agriculture, driving strong demand for innovation and research. In addition, there is a robust culture of innovation and early technology adoption in North America, leading farmers and agribusinesses to be more inclined to adopt new technologies, while creating a feedback loop that promotes further research and development. Furthermore, the regulatory environment in North America is often more conducive to the development and deployment of new agricultural technologies, which in turn leads to increased research activity and publication.

The present study aims to examine the willingness of Spanish and Lithuanian grain farmers to adopt and pay for preventive site-specific spraying and selective harvesting (PSSS-SH), which is a recently developed PAT that aims to reduce the risk of mycotoxin contamination in barley and wheat (Whetton et al., 2018). We focus on Spain and Lithuania because the environmental conditions in these countries favour the growth of fusarium and mycotoxin contamination. The empirical analysis uses data collected in the two countries through a choice experimental survey among 190 commercial grain farmers conducted between September 2022 and May 2023.

We contribute to the existing literature on the uptake of precision farming technologies in the following ways. First, we account for farm heterogeneities and farmers' preferences in adoption of precision farming technologies. Recent studies show that farmers are heterogeneous in their preferences for precision farming technologies (e.g. Blasch et al., 2022; Späti et al., 2022). Specifically, we test whether farmers' preferences for precision farming technologies are driven more by farmer- and farm-specific characteristics (structural variables) or by latent attitudinal and behavioural constructs (measurement variables) based on the Theory of Planned Behavior (TPB) (Ajzen, 1991) and the Technology Acceptance Model (TAM) (Davis, 1984). We achieve this by employing an integrated latent class model, which allows us to incorporate latent constructs into the choice model framework without inherent endogeneity bias and measurement error (Mariel et al., 2015).

Furthermore, by examining factors that influence grain farmers' preferences for specific PSSS-SH characteristics and the monetary values attached to the PATs attributes, we identify policy relevant factors and strategies that could be used to incentivize the uptake of innovative and more environmentally friendly technologies. With the perceived potential of PATs to simultaneously meet the increasing demand for agri-food commodities and reduce the environmental footprint of agricultural production, the findings of this study can contribute to efforts to promote and assess the potential of precision agriculture across European farming systems. An understanding of grain farmers' preferences and the implicit monetary values attached to PATs is important for designing suitable policy support that incentivizes the adoption of PSSS-SH technology to reduce the risk of mycotoxin contamination in barley and wheat in the agri-food system.

We provide insight into the balance of benefits from PAT, namely, whether environmental or financial gains drive PSSS-SH technology adoption, or a combination of both. In addition, the adoption of a system for the detection of the infield spatial distribution of fusarium head blight (FHB) will allow the evaluation of the risk of spatial distribution of mycotoxin contamination, which is important information for maximizing output price, while minimizing the risk to human health and livestock.

Preventive site-specific spraying and selective harvesting (PSSS-SH), precision agricultural technologies for reducing mycotoxin contamination in grain

Mycotoxin contamination in grains is a significant and long-standing problem in crop production that is recognized as an unavoidable risk (USDA, 2022). Fusarium species, particularly F. graminearum and F. culmorum, are the main cause of trichothecene type B, which is associated with FHB in cereals. FHB can also cause indirect loss because the fungus contaminates grain with potent mycotoxins, especially deoxynivalenol (DON). Mycotoxin contamination of grains has been recognized as a global problem due to the toxic effects on humans and livestock, as well as the implications for trade (Gurikar et al., 2023). Mycotoxins significantly impact food and fodder safety and have significant economic impacts, for example, a direct decrease in marketable crop yields, reduced value of contaminated products in domestic markets, regulatory rejection of products by high-value markets and damage via afflicted livestock, including disease, morbidity, mortality and contamination of animal products. Mycotoxins are considered to be the most prevalent food-related health risk in EU field crops, including wheat and barley (Moretti et al., 2019). At present, producers do not have a validated methodology to determine toxin contamination levels before harvesting grain. Current plant-protection solutions to combat FHB in cereal crops include the uniform spraying of fungicide with different application occasions and rates, depending on weather conditions and crop variety. The grain is harvested with combine harvesters and stored in a single storage location without being sorted into different categories based on mycotoxin levels. This solution is outdated due to the fact that the degree of FHB infection in the field, and consequently the mycotoxin concentration, is spatially and temporally variable and depends on spatially variable factors (e.g. topography, soil attributes, crop density and microclimate conditions). A new solution is needed that takes advantage of recent advances in digital technology, ICT and automated decision making based on sensing, modelling and control.

The available literature on FHB detection in the field is limited, which may be attributed to the difficulty of detecting symptoms on ears. The limited studies that have attempted to find solutions to FHB detection in the field include Whetton et al. (2018) and Liu et al. (2020). Whetton et al. (2018) developed a line scan hyperspectral camera (HSC) system mounted on a tractor for in-field real-time FHB detection. Liu et al. (2020) proposed a new disease index for monitoring wheat FHB using Sentinel-2 data. However, these solutions do not include the mapping of FHB and correlating FHB severity with the DON mycotoxin concentration to reduce mycotoxin risk in food and fodder. Hence, a new system for detection of the infield spatial distribution of FHB and correlating FHB severity with the DON mycotoxin concentration would allow for the evaluation of the risk due to the spatial distribution of mycotoxin contamination, which is important information for maximizing yield price, while minimizing the risk to human health and livestock.

A new integrated solution based on preventive site-specific spraying and selective harvest (PSSS-SH) has been developed to minimize the risk of mycotoxin in food and fodder that originates from barley and wheat grain. This integrated solution, which combines PSSS and SH, builds on the work of Whetton et al. (2018) to predict and map FHB and reduce the risk of mycotoxin in food and fodder. In this integrated approach, HSC is used to detect FHB in the field and combines this data with forecasted FHB developments based on the synthesis of information on crop density, FHB-related crop indexes, within-canopy temperature and humidity, and soil fertility attributes. This information is used to derive georeferenced maps that divide study fields in Spain, Lithuania and Belgium into mycotoxin-contaminated, slightly/moderately-contaminated, and healthy areas.

Depending on the weather conditions, the fields are scanned around 3–4 weeks before harvest using the hyperspectral camera on one occasion. The forecasted FHB maps are used for PSSS during crop growth to reduce the probability and severity of FHB infestation in the cropping season. The predicted FHB and DON maps closer in time to crop harvest are used to deploy SH. The recommendation maps for SH are generated based on the predicted DON levels in the field. This delineation involves a classification into three distinct categories: for human consumption (< 1.25 ppm), for feed (1.25–8 ppm), and for bioenergy (> 8 ppm). This information is then used for intelligent machine route planning and in-field logistics with the aim of achieving the SH of grains in the three categories, for food (healthy), for feed (fodder) and for bioenergy (e.g. ethanol). The integrated system enables end users to access and download different data layers in addition to recommendations for PSSS and combine harvester route planning for SH. The resultant treatment maps are then uploaded to precision agriculture compatible fungicide sprayers and combine harvesters.

The PSSS technology helps farmers adjust the dosage of fungicides in response to disease forecasting models by allowing the application of full dosage where the probability of disease infection is higher and a reduced amount where the disease risk is lower (Karimzadeh et al., 2011). In turn, this enables the optimum use of inputs, reduces the environmental footprint of agrochemical agents and increases economic profitability. The SH technology can categorize the yield into different quality levels and help to deliver the best food quality to the market (Harel et al., 2022).

Conceptual framework for integrated model

The conceptual framework (Fig. 1) represents an integrated choice model that combines choice and latent variable frameworks. The latent variable component presented in Fig. 1 captures the latent constructs selected from the TPB (Ajzen, 1991) and TAM (Davis, 1984). The attitudinal and behavioural constructs pertaining to PAT usage were measured based on a number of statements obtained from the literature (e.g. Ajzen, 1991; Davis, 1989; Ezer et al., 2009; Landmann et al., 2021). TPB and TAM approaches have been used in the literature to forecast behaviour and intentions in relation to new technologies, as well as the acceptance and use of new technologies in agriculture, including precision farming technologies (e.g. Krone et al., 2016; Landmann et al., 2021; Venkatesh & Sykes, 2013; Verma & Sinha, 2016; Zeweld et al., 2017). In the present study, we measured behavioural control, attitude, subjective norm, perceived usefulness, desire, self-efficacy, farm advisors and farmer readiness. In line with TPB, behaviour control, attitude and subjective norm are key factors that influence behavioural intention (Ajzen, 1991; Landmann et al., 2021).

Thus, behavioural control reveals the apparent level of ease with which an individual performs a certain act. In the context of PAT usage among grain farmers in Spain and Lithuania, behavioural control reveals the perception of control over the functionality of PAT and its uses. Attitude indicates the degree of overall favourability assigned to the PAT from the

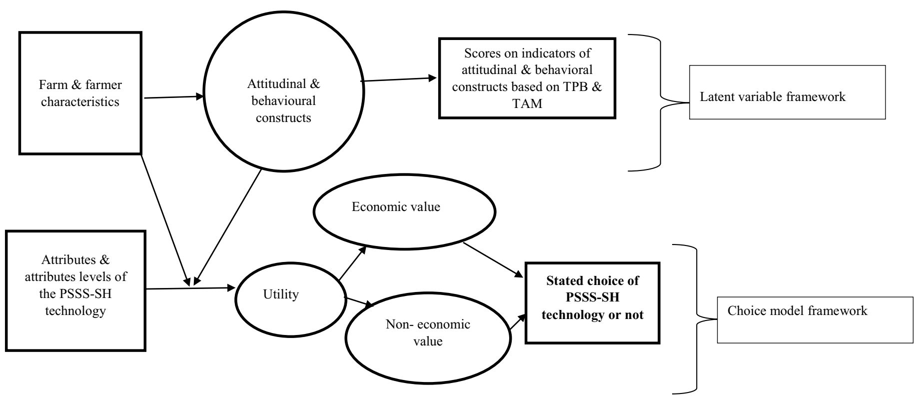

Fig. 1 Conceptual framework for integrated choice model

farmer's perspective. Subjective norm describes the role of societal pressure from the individual's network, which influences whether he or she performs a given action or not. In this study, subjective norm can be described as the grain farmer's perception of opinions on PAT usage in grain farming among other farmers in his or her societal and farming network (Ajzen, 1991). Research on TAM has identified perceived usefulness and ease of use as two key constructs that predict technology acceptance (Davis, 1989; Ezer et al., 2009).

Perceived usefulness describes the degree to which a given technology is expected to improve a potential user's performance (Davis, 1989). In the case of PAT for grain farming, a farmer may ask how the PAT will improve the farm's economic outcome, and the environment and health. Perceived ease of use is described as the amount of effort needed to effectively use the technology (Davis, 1989). For instance, perceived ease of use of PSSS-SH relates to the efforts needed by farmers to incorporate the new solution into existing farm equipment (e.g. combine harvesters). Both perceived usefulness and perceived ease of use have been used to successfully predict older adults' intention to use robots and ICT in farming (Ezer et al., 2009; Ulhaq et al., 2022). In accordance with TPB, desire describes the motivational push for behavioural intention based on the individual's awareness and acceptance of the desire to act (Davis, 1984). According to Ajzen (2002) and Cheon et al. (2012), perceived self-efficacy measures an individual's beliefs about his or her own motivation and ability to act in a certain manner, such as using PAT in grain farming. Ajzen (2002) and Cheon et al. (2012) indicate that individuals' perceptions of the prevailing beliefs among important actors in their social network are key determinants of technology acceptance. Cheon et al. (2012) highlight the readiness of advisors and other farmers as an important factor in the process of technology acceptance and knowledge generation in agriculture.

The choice model framework incorporates farm and farmer characteristics, attitudinal and behavioural constructs, attributes of the PSSS and SH and how the adoption of PSSS and SH technology affects farmers' utility. From a theoretical perspective, this model builds on a random utility framework. Grain farmers' utility from using PSSS and SH is assumed to be derived from the sum of the utilities associated with each PSSS-SH choice attribute. The overall utility can either be financial, non-financial or both (Owusu-Sekyere et al., 2022). Therefore, in this study, the motivation to use or not use PSSS-SH technology depends on the expected utility, which can either be economic, non-economic (e.g. decreased GHG emissions) or both. Thompson et al. (2019) indicate that some farmers may look beyond economic aspects when making decisions to adopt new technology. Hence, in this study, we also investigate whether farmers obtain utility from the non-financial attributes of the PSSS-SH technology (e.g. reduced greenhouse gas emissions). Existing studies show that attitudes and behaviour towards precision agricultural technologies (e.g. Adrian et al., 2005; Atkinson & Birch, 1970; Gollwitzer & Bargh, 1996), psychological factors (Chuang et al., 2020) and perceptions of the benefits of precision agriculture technologies (e.g.Adrian et al., 2005; Thompson et al., 2019) affect farmers' uptake of precision agriculture technologies. Hence, in the choice framework, attitudinal and behavioural constructs are hypothesized to affect farmer's choice of a given PSSS-SH attribute, and this translates to the utility.

Material and methods

Empirical analysis

Following the random utility theory (McFadden, 1974), grain farmers' preferences for PAT are assumed to vary based on the attributes of the PSSS-PH technology, and as such can be gauged in a utility function. A rational individual would select the alternative that offers the highest utility (Lancaster, 1966). The utility obtained by grain farmer k for choosing PAT option q in choice scenario s is specified as:

$$U_{qks} = \hbar\left(Z_{qks}, X_k, \Upsilon_k, \alpha\right) + \varepsilon_{qks} \tag{1}$$

U_{qks} is the utility obtained by the farmer; $\hbar\left(Z_{qks},\ X_k,\ \Upsilon_k,\ \alpha\right)$ is the observed systematic element of the utility function; Z_{qks} is a vector of attributes of the PAT type q; X_k represents observed personal and farm characteristics; Υ_k represents the latent variables relating to attitudinal and behavioural constructs of PAT usage; α is a vector of parameters to be estimated; and ε_{qks} is the random element of the utility, which is independent and identically distributed.

The latent class model places the sampled grain farmers into distinct classes C and the class allocation depends on distinctive utilities π_c. The allocation of an individual grain farmer to a given class depends on allocated probability, which has a logistic distribution:

$$\Phi_{k,\,c} = \frac{\exp^{\left(\theta_{o,\,c}+\gamma_C X_k\right)}}{\sum_{C=1}^{C} \exp^{\left(\theta_{o,\,c}+\gamma_C X_k\right)}} \tag{2}$$

$\Phi_{k,\,c}$ is the probability of being allocated to class c. The utility of a given class is also a function of X_k, which captures the observed farm and farmer characteristics. γ_C is vector of parameters to be estimated and θ_o a constant for class c. As shown in Eq. 2, the latent variable (Υ_k) was not included in the function. Only X_k was included, as studies have shown that the direct inclusion of behavioural and attitudinal variables in the utility function leads to measurement and endogeneity bias (Daly et al., 2012; Mariel et al., 2015; Paulssen et al., 2014). Hence, we use the integrated latent-choice method, which avoids inherent bias from the direct inclusion of perception and attitudinal variables in the utility function (Hess, 2012).

We used confirmatory factor analysis to generate eight latent factors: (i) behaviour control (ii) attitude (iii) subjective norms (iv) perceived usefulness (v) desire (vi) self-efficacy (vii) farm advisors' readiness (viii) farmer readiness. We chose to incorporate the generated factor scores derived for confirmatory factor analysis in the latent class model (Anderson & Gerbing, 1988). In this way, we obtain consistent and improved estimates (Daly et al., 2012). The consistent estimates can be obtained using either the limited information criteria (two steps, sequentially) or the full information criteria (one-step, simultaneously). In this study, we used limited information criteria (two steps, sequentially) because of convergence problems arising from multiple integrals (Bahamonde-Birke et al., 2017). For a given behavioural and attitudinal factor j for grain farmer k, we specify the i^{th} factor estimate as:

$$t_{ik} = \lambda\left(Y_{ijk}, \xi\right) + \varepsilon_{ijk} \tag{3}$$

where t_{ik} is a function of Y_{ijk} and a vector of parameters (ξ);ε_{ijk} is a random term with logistic distribution ι_k;ξ_i measures the impact of the unobserved variable (Y_k) on the attitudinal and behavioural factor t_{ik}; and Y_k is incorporated in the model via the class-specific allocated probabilities in Eq. 2. We re-specify Eq. 2 to include Y_k as:

$$\Phi_{k,c} = \frac{\exp^{\left(\theta_{o,c}+\delta_C X_k+\gamma_C Y_{ijk}\right)}}{\sum_{C=1}^{C} \exp^{\left(\theta_{o,c}+\delta_C X_k+\gamma_C Y_{ijk}\right)}} \tag{4}$$

where $\theta_{o,}$ δ_c and γ_c are parameters to be calculated. The impact of attitudinal and behavioural constructs relating to the PAT, Y_k, in elucidating the prospect of grain farmer k fitting in a particular class is shown as γ_c. The influence of the farmer and farm variables on class assignment is captured by δ_c. The impact of attitudinal and behavioural constructs is captured under the measurement component of the model, and the structural aspect contains the impact of the farm and farmer characteristics. The combined log-likelihood equation for our integrated latent class model is stated as:

$$LL(\pi, \theta, \Upsilon, \xi, \eta) = \sum_{n=1}^{N} \ln \int_{\psi} \left(P_k \prod_{i=1}^{8} T_{t_{ik}} \right) f(\psi) d\psi \tag{5}$$

The empirical analysis began with the estimation of conditional logit and mixed logit models to determine whether the sampled grain farmers are homogenous or heterogeneous in their preferences for PSSS-SH attributes. The estimates from conditional logit and mixed logit models revealed that the sampled grain farmers are heterogeneous in their preference for PSSS-SH.

Definition of variables, attributes and choice design

Table 1 presents the definition of variables and their summary statistics. As shown in Table 1, the sampled Spanish grain farmers are about five years older than the Lithuanian farmers. In both countries, most of the grain farmers are males. Most of the Lithuanian grain farmers have completed an agricultural education on the university level. Spanish grain farmers have about seven more years of grain farming experience relative to the Lithuanian grain farmers. About 51% of the Lithuanian grain farmers' household income and 35% of the Spanish grain farmers' household income is obtained from grain production. On average, Lithuanian grain farmers cultivate 43.82 hectares more than the Spanish grain farmers. The wheat yield in tonnes per hectare in Lithuania is about three tonnes higher than the yield in Spain. In terms of the use of precision farming technologies, Spanish grain farmers have about seven years of experience, whereas Lithuanian grain farmers have about six years of experience in using other precision farming technologies, such as drones, sensors, smart irrigation and GPS.

Table 2 presents the attributes and attribute levels used in the choice experiment design. While no previous study has assessed the economic and environmental impacts of PSSS-SH in the context of Spain and Lithuania, the determination of the values of different attributes in Table 2 was done in consultation with local experts from academia and other government and non-government stakeholders including grain farmers, agronomists, precision farming technology experts and companies. These attributes and their levels were explained to respondents in their local language to facilitate understanding. In addition, this was further refined and validated during the field trials and the pre-test of the questionnaire.

Table 1 Summary characteristics of variables

Variable	Definition	Spain Mean (SD)	Lithuania Mean (SD)	Mean difference
Socioeconomic variables				
Age	Age of farmer	38.60 (15.12)	32.79 (11.68)	5.82***
Gender	1 if male, 0 otherwise	0.88 (0.33)	0.79 (0.41)	0.09
Agric education	1 if farmer has agricultural education from university, 0 otherwise	0.43 (0.49)	0.79 (0.41)	−0.35***
Experience	Years in grain production	18.22 (13.03)	10.98 (7.82)	7.24***
Share of income	% of household income from grain production	35.46 (22.53)	51.48 (21.43)	−16.01***
Salary employment	1 if farmer has salary employment aside farming, 0 otherwise	0.09 (0.28)	0.33 (0.47)	−0.24***
Farm characteristics				
Land owned	Hectares of land owned	52.23 (70.92)	136.24 (166.28)	−84.00***
Land leased	Hectares of land leased	36.49 (66.72)	84.70 (129.90)	−48.21***
Land size (Grain)	Hectares of land under grain production	81.89 (92.17)	125.72 (148.09)	−43.82**
Wheat yield	Wheat yield in tonnes per hectare	3.40 (0.88)	6.60 (5.76)	−3.19***
Livestock	1 if farmer keeps livestock in addition to grain production, 0 otherwise	0.12 (0.33)	0.26 (0.44)	−0.14*
Conventional	1 if grain farm is conventional, 0 otherwise	0.71 (0.45)	0.84 (0.37)	−0.13**
PAT experience	Years of using precision farming technologies	6.82 (2.61)	5.93 (4.08)	0.89*
Institutional variables				
Extension access	1 if farmer has access to advisory services, 0 otherwise	0.95 (0.21)	0.46 (0.50)	0.49***
Cooperative membership	1 if farmer is a member of farmers' cooperative, 0 otherwise	0.60 (0.49)	0.28 (0.45)	0.32***
FBO	1 if farmer is a member of any other (not cooperative) farmer based organization	0.79 (0.40)	0.41 (0.50)	0.38***
Drought information	1 if the farmer has access to drought information, 0 otherwise	0.99 (0.09)	0.77 (0.42)	0.22***
Precision tools usage				
GPS usage	1 if the farmer uses GPS technology in farming, 0 otherwise	0.88 (0.32)	0.18 (0.39)	0.70***
Drone usage	1 if the farmer uses drones in farming, 0 otherwise	0.25 (0.43)	0.07 (0.25)	0.18***
Sensor usage	1 if the farmer uses sensor technology in farming, 0 otherwise	0.27 (0.45)	0.03 (0.18)	0.24***

Table 1 (continued)

Variable	Definition	Spain Mean (SD)	Lithuania Mean (SD)	Mean difference
Smart irrigation	1 if the farmer uses smart irrigation in farming, 0 otherwise	0.13 (0.34)	0.16 (0.37)	−0.03
Mobile application	1 if the farmer uses smartphone mobile applications in farming, 0 otherwise	0.80 (0.40)	0.10 (0.02)	0.70***

Table 2 Attributes and attribute levels used in the choice experimental survey

Attribute	Attribute levels
Reduction in fungicide application per hectare	No reduction 22% less 26% less
Reduction in greenhouse gas (GHGs)	No reduction in GHG emission 10% reduction in GHG emission 20% reduction in GHG emission
Increase in yield of wheat/barley (ton/hectare)	0.49 tons per hectare 0.54 tons per hectare 0.59 tons per hectare
Profitability of wheat/barley using SH (%)-through quantitative prediction of mycotoxin	5% increase in profit 10% increase in profit 20% increase in profit
Profitability of wheat/barley using PSSS (%)-through data fusion	5% increase in profit 10% increase in profit 20% increase in profit
Additional yearly investment by the farmer (Euro per hectare)	€13 ^{per} ha €19 ^{per} ha €25 ^{per} ha

Likewise, the six categories of variables listed in Table 2 were selected based on consultations with key informants in each country. We used a random-parameter panel-efficient design to generate two PAT alternatives (A, B), which included a "none" alternative (Choice Metrics, 2021). In the design process, which used Ngene software, we used priors from the initial pilot survey conducted in Spain (sample size = 29), using a multinomial logit model and orthogonal design in the random-parameter panel-efficient design (Choice Metrics, 2021). In addition to the D-error efficiency, we used blocking to reduce the number of choice sets assigned to a respondent. Four blocks were generated, with each block containing six choice scenarios. We randomly allocated each respondent to a block. The total number of observations of our pooled data is 3,420.

Study area and sampling

The study was conducted in Spain and Lithuania from September 2022 to May 2023. These countries were selected because environmental conditions favour the growth fusarium and mycotoxin contamination. These countries are far from each other geographically and differ in climate, production patterns, cropping seasons and farmer characteristics but face similar problems with fusarium and mycotoxin contamination. The selection of farmers to be included in the study was performed as follows. First, a sample frame consisting of grain farmers was obtained from grain producers associations in both countries. In Spain, the sample frame was obtained from Agrovegetal SA and Innovative Project for Climate-Smart Improvement of Maize Cultivation (GO-MaizSostenible). Agrovegetal SA is a public–private entity dedicated to the breeding and development of new varieties of extensive crops, as well as the production of certified seeds. Its partners include producers, cooperatives and the agricultural industry. GO-MaizSostenible consists of grain farmers spread across major grain-producing regions in Spain. We were able to connect with 80% of grain farmers through Agrovegetal and the remaining 20% through GO-MaizSostenible. We randomly selected 129 wheat farmers from a sample frame of wheat farmers. In Lithuania, the sample frame for wheat was created from the Lithuanian Grain Growers Union. The Lithuanian grain growers union consists of farmers who grow grains such as maize, oat, rye and rapeseed. The union represents a majority of grain growers in Lithuania, though there are some farmers who are not part of the union. Hence, grain farmers who are not part of the union were not included in the study. Specifically, we randomly selected 61 wheat farmers from the sample frame in Lithuania. The random selection ensured that each wheat farmer in the sample frame had an equal likelihood of being selected. In total, 190 commercial wheat farmers were sampled from both countries.

Data collection

The data were collected through face-to-face interviews using a structured questionnaire, including a discrete choice experiment. The survey instrument was reviewed and discussed with project partners to ensure that all relevant factors were captured. A key informant discussion was held online with developers from Ghent University (Belgium), University of Seville (Spain) and Vytautas Magnus University (Lithuania) to discuss the attributes and the entire questionnaire. The online meeting was held on 19 April 2022 and was led by researchers from the Swedish University of Agricultural Sciences, Uppsala, Sweden. A key informant discussion was held in Kaunas, Lithuania on 26 August 2022 to discuss the technologies' attributes and the survey instrument. The final survey instrument was pretested (sample size = 29). The items defining each of the latent factors are included in Table 7 in the Appendix. The attitudinal and behavioural constructs included were obtained from the literature (Landmann et al., 2021; Venkatesh, 2000; Venkatesh & Bala, 2008). However, the statements were modified to suit the present study. Three MSc students from the Department of Applied Economics in Agriculture, University of Seville (Spain), collected data in Spain. In Lithuania, two PhD holders and one PhD candidate from the Agronomy Department, Vytautas Magnus University Agriculture Academy were involved in the data collection.

Empirical results

Mixed logit estimates

The empirical analysis began with the log-likelihood ratio test (LR-test), Akaike information criteria (AIC) and Bayesian information criteria (BIC) to test whether the sampled grain farmers are heterogeneous or homogenous in their preferences for PAT attributes (see Table 8 in Appendix). The LR-test results from conditional logit and mixed logit models revealed that the sampled grain farmers are not homogenous in their preferences, suggesting that the sampled grain farmers are heterogeneous in their preferences for PSSS-SH technology. Following the determination of preference heterogeneity, we estimated mixed logit models for both countries, and the pooled data and the results are presented in Table 3. The mixed logit estimates are presented for both countries and were performed to ascertain how preferences for PSSS-SH attributes differ among grain farmers in Spain and Lithuania. Expectedly, and in accordance with economic theory, the results of the pooled sample show that investment cost for the PSSS-SH is negative and statistically significant

Table 3 Heterogeneous estimates of preferences for PSSS-SH attributes in Spain and Lithuania (mixed logit model)

Attributes	Levels	Pooled Coefficient	Lithuania Coefficient	Spain Coefficient
Reduction in fungicide application per hectare	22% less	–	1.919*** (0.554)†	0.433 (0.332)†
	26% less	2.207*** (0.616)	3.113* (1.597)	2.388*** (0.704)
Reduction in GHG emission	15% reduction in GHG	1.614*** (0.203)†	1.044** (0.408)	2.212*** (0.293)
	20% reduction in GHG	1.675*** (0.280)†	0.951** (0.414)†	2.512*** (0.530)†
Yield increase	0.54 tons per hectare	0.312 (0.400)†	3.116 (1.928) †	−0.372 (0.361)
	0.59 tons per hectare	0.495*** (0.166)	0.565 (0.355) †	1.060*** (0.335)
Profitability of wheat/barley using SH (%)	10% increase in profit due to quantitative prediction of mycotoxin	3.298 (2.279)†	1.647 (1.340)	2.056 (3.534)
	20% increase in profit due to quantitative prediction of mycotoxin	0.645*** (0.199)†	1.657*** (0.432)†	0.335** (0.140)†
Profitability of wheat/barley using PSSS (%)	10% increase in profit due to data fusion modelling	1.251*** (0.207)	2.382*** (0.603)†	0.754*** (0.253)
	20% increase in profit due to data fusion modelling	1.604*** (0.210)†	2.480*** (0.544)	2.041*** (0.386)†
Investment cost		−0.028** (0.011)	−0.096*** (0.033)	−0.055** (0.019)
None		259.982 (662.953)	36.643 (32.614)	2.415 (3.501)
Number of observation		3420	1098	2322
Log likelihood		−815.21	−187.85	−563.37
Pseudo-R^2		0.39	0.25	0.35
LR chi^2		193.50***	39.17***	180.40***

† indicates significant standard deviation estimate at 95% level. Standard errors are in brackets. ***, **, * show significance at 1%, 5% &10% levels

(McFadden, 1974). This implies that grain farmers are sensitive to the cost of investing in PSSS-SH technology and that a higher investment cost decreases the likelihood that farmers will adopt the technologies.

In terms of the reduction in fungicide application, the results reveal that grain farmers have positive and statistically significant preferences for the PSSS-SH if it reduces fungicide application per hectare by 26%, as shown in the pooled sample results in both the Lithuanian and Spanish samples. Lithuanian farmers still prefer the PSSS-SH technology if it can reduce fungicide application per hectare by 22%. Another interesting result related to the reduction in GHG emissions is that grain farmers in both countries have statistically significant positive preferences for reduced GHG emissions at 15% and 20%.

A potential increase in grain yield of about 0.59 tonnes per is statistically significant in influencing farmers' decision to adopt the PSSS-SH technology. However, the country specific estimates show that only Spanish farmers prefer the 0.59 tonne increment in grain yield per hectare, as shown by the statistically significant utility estimate. In terms of profitability, farmers in both countries have statistically significant and positive preferences for the technology if SH can lead to a 20% increase in profit through the quantitative prediction of mycotoxin levels. In addition, the results show that farmers in both countries have positive and statistically significant preferences for PSSS if it can increase profit by 10% to 20%. The statistically significant standard deviation estimates for different levels of the attributes confirm the existence of preference heterogeneity among the grain farmers. In addition, the statistically significant standard deviations imply that willingness to pay estimates cannot be interpreted as being representative of the entire sample. Hence, we estimated a latent class model to unpack the distinct segments of farmers within the sample, which is defined by the technology's attributes, farm and personal characteristics, and attitudinal and behavioural factors. The results are presented in the next section.

Latent class results

Log-likelihood, AIC and BIC estimates from the latent model show that there are two distinct segments of grain farmers within the entire sample. Table 4 presents the results for the two classes of grain farmers. The class probabilities show that 81% of the grain farmers belong to class one and the remaining 19% belong to class two. As expected, and in line with mixed logit results, the investment cost variable was negative and statistically significant in both classes. This means that the grain farmers are sensitive to the cost of PSSS-SH technology and that the higher the cost of investment, the lower the likelihood that grain farmers will adopt the technology.

In class one, members attain positive and statistically significantly utility from all attributes and levels, with the exception of a 10% increase in profit due to the quantitative prediction of mycotoxin levels. However, the utility estimate for the "none" option is negative and statistically significant, suggesting that grain farmers in class one obtain negative utility from the status quo option. Given this finding, the utility estimates for all the attribute levels (except the 10% increase in profit from SH) of PSSS-SH attributes are positive and statistically significant, where class one members are classified as "advocates" of PSSS-SH technology.

In class two, members attain positive and statistically significantly utilities from only a 26% reduction in fungicide application per hectare and a 20% reduction in GHG emissions, as well as from the status quo option. The utility estimates for a 22% reduction in fungicide application per hectare, 15% reduction in GHG emissions and 20% increase in profit

Table 4 Maximum likelihood estimates from the integrated latent class model (Pooled data)

Classes	Class 1		Class 2	
Class probabilities	0.81		0.19	
Utility function	Coefficient	Z	Coefficient	Z
Reduction in fungicide application				
22% less	0.432*** (0.109)	3.96	−0.442* (1.926)	−1.79
26% less	1.321** (0.635)	2.08	1.618** (0.754)	2.14
Reduction in GHG emission				
15% reduction in GHG emission	1.441*** (0.141)	10.22	−3.726** (1.463)	−2.55
20% reduction in GHG emission	1.732*** (0.143)	12.09	3.472** (1.627)	2.13
Yield increase				
0.54 tons per hectare	0.573*** (0.115)	4.99	−0.230 (1.039)	−0.22
0.59 tons per hectare	1.076*** (0.329)	3.27	0.603 (0.852)	0.71
Profitability of wheat/barley using SH (%)				
10% increase in profit due to quantitative prediction of mycotoxin	0.725 (0.560)	1.29	−1.621 (1.107)	−1.46
20% increase in profit due to quantitative prediction of mycotoxin	0.856*** (0.121)	7.10	−4.519*** (1.007)	−4.49
Profitability of wheat/barley using PSSS (%)				
10% increase in profit due to data fusion modelling	1.263*** (0.124)	10.17	1.225 (0.824)	1.49
20% increase in profit due to data fusion modelling	1.305*** (0.167)	7.79	−2.229 (1.956)	−1.14
None	−1.890*** (0.504)	−3.75	1.289*** (0.201)	6.41
Investment cost	−0.017** (0.008)	−2.20	−0.086* (0.052)	−1.65
Class allocation function				
θ_1	1.417*** (0.184)	7.70		
Diagnostic statistics				
Log likelihood	−776.48			
AIC	1594.95			

Table 4 (continued)

Classes	Class 1		Class 2	
Class probabilities	0.81		0.19	
Utility function	Coefficient	Z	Coefficient	Z
BIC	1663.03			
Parameters	21			

***, **, * show significance at 1%, 5% &10% levels respectively through the use of PSSS are negative and statistically significant, indicating that members of class two have negative preferences for these attribute levels. The class allocation function estimate is positive and statistically significant at the one percent level, suggesting that farmers with higher latent constructs have a greater likelihood of belonging to class one than class two. Therefore, the structural and measurement results pertain to class one. Based on the class allocation function, class two is set as the reference class. The results in Table 5 describe the members of class one.

Structural and measurement variables explaining the sources of grain farmers' heterogeneity

Table 5 presents the structural results for farmer and farm characteristics and measurement results relating to the behavioural and attitudinal factors that explain the heterogeneity in preferences for PSSS-SH attributes. The variables included in the structural and measurement components helped explain the sources of grain farmers' heterogeneity (Daly et al., 2012; Mariel et al., 2015; Owusu-Sekyere et al., 2022). Relative to class two, the structural results indicate that grain farmers who prefer PSSS-SH technology are less likely to be male, as shown by the negative and statistically significant estimate for the male variable.

The salary employment variable is positive and statistically significant, suggesting that grain farmers that have other salary employment in addition to grain farming are more likely to adopt PSSS-SH. The cooperative membership variable is positive and statistically significant, implying that grain farmers who prefer PSSS-SH technology are more likely to

Table 5 Hybrid Latent class structural and measurement component estimates

Variable	Coefficient	Z
Structural equations (effect of farmer & farm characteristics)		
ΥAge	0.023	1.42
ΥMale	−1.104*	−1.78
ΥAgric_Univ_Edu	0.148	0.28
ΥSalary employment	1.389*	1.65
ΥCooperative membership	0.413*	1.89
ΥFarm size	0.179	1.04
ΥShare of income from grain	1.066*	1.88
ΥOrganic system	−1.426	−1.39
ΥPast_PAT_use	0.740**	2.44
Measurement equation (effect of attitudinal &social factors)		
λ_{t1}Perceived_usefulness	0.813***	2.80
λ_{t2}Attitude	−0.491	−0.94
λ_{t3}Advisor readiness	−0.524	−1.33
λ_{t4}Farmer readiness	0.313**	2.76
λ_{t5}Subjective norm	−0.563*	−1.65
λ_{t6}Self efficacy	−0.363	−0.99
λ_{t7}Behaviour control	−0.209	−0.60
λ_{t8}Desire	0.229***	5.07

***, **, * show significance at 1%, 5% &10% levels respectively be members of cooperatives. The variable, share of income from grain farming and prior usage of other PATs (e.g. variable rate seeding, drones, smart irrigation, etc.) are positive and statistically significant, which implies that members of class two are more likely to be grain farmers who obtain a higher share of household income from grain production. These grain farmers are also more likely to have prior experience with other precision farming technologies. For the measurement results, the estimate for the perceived usefulness variable is positive and statistically significant, indicating that grain farmers who prefer the PSSS-SH technology are more likely to be associated with higher values of perceived usefulness.

Similarly, the estimates for the variables, farmer readiness and desire are positive and statistically significant, suggesting that farmers who prefer the PSSS-SH technology are more likely to be associated with higher values of farmer readiness and a desire to use PSSS-SH technology. On the other hand, the estimate of subjective norm is negative and statistically significant, meaning that grain farmers who prefer the PSSS-SH technology are less likely to be associated with higher values of subjective norm.

Implicit trade-offs and monetary valuation of the PSSS-SH attributes

As shown in Table 6, members of class one, which includes a majority of the sample, attach the highest monetary value to the technology's ability to reduce GHG emissions by 20% and 10%. This is followed by the technology's ability to reduce fungicide application per hectare by 26%, increase in profit by 20% and 10% with PSSS usage. Members of class one are willing to accept a compensation of €111 to choose the status quo alternative.

Members of class two also attach the highest monetary value to the technology's ability to reduce GHG emissions by 20%. This is followed by the technology's ability to reduce

Table 6 Implicit trade-offs and monetary valuation of the PAT attributes

Attributes	Class 1 (€)	Class 2 (€)
Reduction in fungicide application per hectare		
22% less	€25.41	€−5.14
26% less	€77.71	€18.81
Reduction in GHG emission		
15% reduction in GHG emission	€84.76	€−43.33
20% reduction in GHG emission	€101.88	€40.37
Yield increase		
0.54 tons per hectare	€33.71	NS
0.59 tons per hectare	€63.29	NS
Profitability of wheat/barley using SH (%)		
10% increase in profit due to quantitative prediction of mycotoxin	NS	NS
20% increase in profit due to quantitative prediction of mycotoxin	€50.35	€−52.55
Profitability of wheat/barley using PSSS (%)		
10% increase in profit due to data fusion modelling	€74.29	NS
20% increase in profit due to data fusion modelling	€76.76	NS
None	€−111.18	€14.99

NS not significant

fungicide application per hectare by 26%. Unlike class one, class two members attach monetary value to the status quo option. In addition, class two members need a compensation to choose 22% reduction in fungicide application per hectare, 15% reduction in GHG emissions and 20% increase in profit due to selective harvesting.

Discussion

We have investigated factors that influence grain farmers' decisions to adopt precision farming technology that combines preventive site-specific spraying and selective harvesting (PSSS-SH). The results show that grain farmers are heterogeneous in their preferences for PSSS-SH attributes. The solution grain farmers currently use to protect against FHB is the uniform spraying of fungicide on different application occasions and at different rates, depending on weather conditions and crop variety. Uniform application of fungicide on the entire field is costly, and with the new technology, farmers can minimize the cost of spraying. In reviewing the country-specific findings, we find some similarities. Specifically, both Lithuanian and Spanish grain farmers are interested in the PSSS-SH technology's ability to minimize the quantity of fungicides when applied at a higher amount (i.e. 26%). Another interesting finding concerned the reduction in GHG emissions. The findings indicate that the ability of the PSSS-SH technology to minimize GHG emissions is a feature of the technology that has a positive influence on farmers' adoption decisions in both countries. In terms of differences, Spanish grain farmers are more concerned with improvements in yield, preferring the PSSS-SH technology's ability to increase wheat yield by 0.59 tonnes per hectare. Lithuanian farmers are also interested in using the PSSS-SH technology to achieve a lower level of fungicide application per hectare, but Spanish grain farmers have no statistically significant preference for a less ambitious reduction in fungicide application.

Based on the integrated latent class findings, two distinct segments of grain farmers were identified based on their preferences for different PSSS-SH technology attributes, with a majority (81%) expressing a preference for the PSSS-SH technology. The other segment of farmers (19%) expressed a preference for the status-quo option, which is related to their current use of farming technology that does not incorporate PSSS-SH. However, farmers in this segment are interested in the ability of PSSS-SH technology to minimize GHG emissions and minimize fungicide application to a higher degree. Our findings suggest that the uptake of PSSS-SH technology is influenced by the benefits provided by the technology. The utility estimates indicate that the decision of grain farmers to use PSSS-SH technology in both segments and countries is largely dependent on the technology's ability to improve the environment. We can infer from these findings that maximizing financial utilities (i.e. utilities obtained from profit) is not the single motivating factor when grain farmers decide whether to use precision farming technologies. There are also important non-financial utilities that align with actual observed choices made by grain farmers. This is consistent with previous studies by Howley (2015), Owusu-Sekyere et al. (2022) and Thompson et al. (2019), who point out that some farmers look beyond economic factors when making decisions to adopt new technologies. This finding lends support to the notion that farmers may have non-financial motivations for adopting precision farming or smart farming technologies. One such non-financial motivation could be the reduction of greenhouse gas emissions.

Another important finding has to do with the attitudinal and behavioural constructs identified and their effects on the choices made by the grain farmers. Specifically, perceptions of the potential usefulness of the PAT may encourage grain farmers to adopt the SH and PSSS technology. A farmer's readiness to incorporate new technology into the existing farming system may encourage a grain farmer to adopt the PSSS-SH technology. Enhancing awareness of these perceived benefits is thus a key for promoting adoption. Preparing farmers for adoption of this new technology through awareness and knowledge raising efforts, as well as through training in the incorporation of the new systems into existing combine harvesters, are key measures needed to promote adoption. In this way, we can prepare farmers and reduce concerns about technical challenges that farmers expect to encounter if they adopt this new technology. This is in accordance with Späti et al. (2022), who found that perceived technical failures could discourage farmers from adopting new PATs. In addition, the inclusion of the farmers' desires and their significance is a particularly important aspect of the present study, as the results suggest that there is a certain "desire shift" in work-specific usage decisions among the grain farmers included in this study (Landmann et al., 2021). We recommend the introduction of training programmes on the use of the technology itself. Specifically, there is a need to raise awareness of the technology's positive financial, health and environmental impacts. By increasing perceived usefulness, the readiness and desire to use the technology, and access to technological knowledge support, we can increase the likelihood that SH and PSSS technologies will be adopted.

The effects of socioeconomic and farm characteristics on PAT decisions are worth considering. Relative to female farmers, male farmers are less likely to take up a new PAT that combines SH and PSSS, suggesting that there are gender disparities in the uptake of PSSS-SH technology. Cooperative membership positively correlates with preferences for new PAT that combines SH and PSSS. A recent study by Zhang et al. (2020) supports this finding. The authors found a positive association between cooperative membership and technology adoption in China. Abebaw and Haile (2013) also found a positive association between cooperative membership and technology adoption in Ethiopia, and Coydon and Molitor (2011) noted that affiliation with community-based organizations positively influences technology adoption. Cooperatives may increase the uptake of SH and PSSS technologies by, for example, actively seeking collaborations with external technology providers and including academic institutes and commercial innovation companies. This finding implies that cooperatives can act as a channel for promoting and accelerating the adoption of PSSS-SH technology in Spain and Lithuania. The adoption of precision agricultural technology is also associated with off-farm salary employment. Previous studies (e.g. Fernandez-Cornejo et al., 2007; Koundouri et al., 2006) have shown that engagement in off-farm activity offers financial resources and incentives that enable the adoption of new technologies. Fernandez-Cornejo et al. (2007) further point out that managerially intensive technologies, such as PSSS-SH technology, could reduce the time available for off-farm activities, resulting in lower off-farm income.

Prior experience with other precision agricultural technologies, such as variable rate seeding, drones, smart irrigation and GPS, is associated with a preference for PSSS-SH technology. This is not surprising, as technological progress in general, and precision agriculture in particular, may be skill-biased and since human capital rises over time, uptake of new precision agricultural technology may favour experienced farmers (Weinberg, 2004).

The SH technology can be expanded to other grain harvesting applications, for example, the selective harvest of other grains with different qualities (e.g. protein content, starch content, other biological damage than DON) over a different zone in a field. The results in this study are applicable to all European countries where wheat and barley are grown on a large scale. The results from Lithuania are applicable to the Baltic countries (e.g. Sweden, Denmark, Finland, etc.), as they have similar climatic conditions and agricultural systems. Furthermore, the results from Spain are applicable to countries (e.g. Greece, Italy, and Southern France) with similar climatic conditions and agricultural systems. However, the policy implications of this study are based specifically on data from Spain and Lithuania. Hence, future research should investigate grain farmers' willingness to adopt PSSS and SH technologies to reduce mycotoxin contamination in grain in comparable countries where environmental conditions favour the growth fusarium and mycotoxin contamination. In terms of limitations, we acknowledge that the sample size in Lithuania is small compared to the Spanish sample. However, we believe that the results presented in this study are robust and highly relevant. Additionally, while PSSS and SH technologies were developed for wheat and barley, this study focused exclusively on wheat farmers. Therefore, future research in Lithuania, Spain and other countries where environmental conditions favour the growth fusarium and mycotoxin contamination should expand the sample to include both wheat and barley farmers.

Conclusion and policy implications

We conclude that grain farmers' adoption of PAT that combines PSSS and SH is likely to be based on trade-offs between potential changes in farming practices and outcomes, and economic and environmental changes. In particular, farmers who are willing to adopt PAT have a greater concern for and assign a higher monetary value to the environmental benefits (i.e. reduced fungicide application and GHG emissions) offered by the technology. We conclude that the grain farmers surveyed are heterogeneous in their preference for PSSS-SH technology, with the majority (81%) of farmers willing to adopt and pay for the technologies. Another important conclusion is that maximizing financial utilities (i.e. utilities obtained from profit) is not the only motivation for farmers when deciding whether to adopt PSSS-SH. There are important non-financial utilities that align with actual observed choices made by grain farmers.

Drawing from our empirical findings, several policy recommendations emerge for the promotion of the adoption of SH and PSSS technologies among farmers. First, the results underscore the need for policymakers to prioritize the implementation of comprehensive strategies to encourage farmers to adopt PATs, where it is not only the economic viability of such technologies (e.g. reduced fungicide application and enhanced crop yields) that should be emphasized, but the environmental considerations and reduced ecological impact (e.g. decreased GHG emissions). This entails developing integrated support programmes that provide farmers with training, technical assistance, financial incentives and access to the resources they need to adopt the technology. These programmes could be designed to reward reductions in GHG emissions through the adoption of PSSS-SH technology, or to acknowledge substantial improvements in crop yield. Launching public awareness campaigns highlighting the environmental and productivity benefits of PSSS-SH technology could target both farmers and consumers, thus emphasizing the role of sustainable agricultural practices in mitigating climate change and ensuring higher food quality. Second, designing effective adoption-promoting strategies requires consideration for farmers' attitudinal and behavioural aspects in order to ensure that interventions are designed in a way that resonates with their needs and preferences. This requires a better understanding of farmers' attitudes, beliefs, motivations and perceptions in the adoption of new technologies, as well as recognizing the behavioural drivers and barriers that influence their decision-making processes. Third, addressing gender disparities in technology uptake will require gender-sensitive interventions to overcome barriers that prevent adoption of PSSS-SH technology among male farmers. Lastly, policymakers should recognize cooperatives as key facilitators of technology uptake and consider strategies to leverage their influence in promoting the adoption of innovative agricultural practices. This may involve providing support and resources to cooperatives to facilitate knowledge-sharing, training and access to technology among members, as well as incentivizing the participation of cooperatives in technology adoption initiatives through targeted funding opportunities or collaborative partnerships. Overall, these policy interventions should contribute to creating an environment that supports the widespread adoption of PSSS-SH technology among grain farmers, ultimately enhancing agricultural productivity, sustainability and resilience.

Appendix

See Tables 7, 8.

Supplementary equations

1. When faced with different PAT types,P_{ks}, a rational grain farmer k is assumed to choose PAT product type q in choice scenario s, if the utility of his or her choice is greater than the status quo alternative of no PAT which combines PSSS-SH, m. Thus $U_{qks} > U_{mks};\forall_r \neq q, m \in P_{ks}$.
2. For a given grain farmer k fitting in class c, his or her conditional probability (ρ_k) of selecting PAT type q from the choice set s is specified as:

$$\rho_k = \Pr(g_{ks} / C, Z_{qks}) = \prod_{s=1}^{S_k} \frac{\exp^{(\pi_C\, \mathrm{Z_{qks}})}}{\sum_{l=1}^{L} \exp^{(\pi_C\, \mathrm{Z_{qks}})}} \tag{6}$$

where g_{ks} captures how grain farmer k orders his or her choices across the choice sets S_q. Z_{qks} vector of attributes of PAT types q. Equation (6) takes the form of a multinomial logit probability outcome but we fixed one of the scale parameters for identification purposes.

3. The unlimited probability over the order of representative choices made by the grain farmers is computed by finding the expected values for every identified class, C as:

$$\rho r_k = \Pr(g_{ks} / Z_{qks}) = \sum_{c=1}^{C} \Phi_{k,c} \prod_{s=1}^{S_k} \frac{\exp^{(\pi_C\, \mathrm{Z_{qks}})}}{\sum_{l=1}^{L} \exp^{(\pi_C\, \mathrm{Z_{qks}})}} \tag{7}$$

4. We employed the ordered logit framework for the attitudinal and behavioural components $t_1 - t_r$. The probability of a given observed behavioural and attitudinal factor $t_{ik}(k = 1.....y)$ is specified as:

Table 7 Statements defining latent constructs in the measurement model

Statement	Response
Perceived usefulness	
1. I am willing to test new farming technologies in my grain production	
2. Using PAT for selective harvesting and detecting Fusarium and mycotoxin spread will save time	
3. I think using PAT for selective harvesting and detecting Fusarium and mycotoxin spread is useful	
4. I believe PAT for selective harvesting and detecting Fusarium and mycotoxin spread would be easy to use	
5. I think using PAT for selective harvesting and detecting Fusarium and mycotoxin spread would reduce the risk of mycotoxin presence in food and fodders	
6. Using PAT for selective harvesting and detecting Fusarium and mycotoxin spread could increase sales price	
7. I think using PAT would enable me to detect Fusarium and mycotoxin spread quickly	
8. Being familiar with PAT for selective harvesting and detecting Fusarium and mycotoxin spread also enables me to work with other technological innovations	
9. Using PAT for selective harvesting and detecting Fusarium and mycotoxin spread could increase my farm income	
10. Using PAT for selective harvesting and detecting Fusarium and mycotoxin spread is the most effective way to control the contamination of cereals on my farm	
11. I think using PAT for selective harvesting and detecting Fusarium and mycotoxin spread is much easier than manual sorting of grains	
12. Overall, I think that using PAT for selective harvesting and detecting Fusarium and mycotoxin spread is advantageous	
Attitude	
1. Using PAT for selective harvesting and detecting Fusarium and mycotoxin spread will be helpful	
2. I would like grain farming more if I would PAT for selective harvesting and detecting Fusarium, and mycotoxin spread	
3. Using PAT for selective harvesting and detecting Fusarium and mycotoxin spread is a wise idea	
4. Using PAT for selective harvesting and detecting Fusarium and mycotoxin spread in my grain farming would be a pleasant experience	
5. Using PAT for selective harvesting and detecting Fusarium and mycotoxin spread would make my grain more attractive	
Farm advisors readiness	
1. I think farm advisors and experts would be in favour of using PAT for selective harvesting and detecting Fusarium and mycotoxin spread	
2. I think farm advisors and experts would believe that PAT could be a useful tool in grain production	
3. I think farm advisors and experts would possess adequate technical skills to use PAT for selective harvesting and detecting Fusarium and mycotoxin spread in grain production	
4. I think farm advisors and experts would be willing to recommend the use of PAT for selective harvesting and detecting Fusarium and mycotoxin spread in wheat and barley production to other grain producers	
Farmer readiness	
1. I think other farmers would be in favour of utilising PAT for selective harvesting and detecting Fusarium and mycotoxin spread	
2. I think other farmers would believe that PAT for selective harvesting and detecting Fusarium and mycotoxin spread could be a useful technology for in their grain farming	

Table 7 (continued)

Statement	Response
3. I think other farmers would possess adequate technical skills to use PAT for selective harvesting and detecting Fusarium and mycotoxin spread in their grain farming	
Subjective norm	
1. Stakeholders I am working with think I should integrate PAT for selective harvesting and detecting Fusarium and mycotoxin spread	
2. Most people who are important to me would be in favour of using PAT for selective harvesting and detecting Fusarium and mycotoxin spread in grain farming	
3. Other farmers in my surrounding think I should take advantage of PAT for selective harvesting and detecting Fusarium and mycotoxin spread	
4. People whose opinions are valued to me expect that people like me should use PAT for selective harvesting and detecting Fusarium and mycotoxin spread	
5. I think other grain farmers would expect me to have higher willingness to adopt PAT for selective harvesting and detecting Fusarium and mycotoxin spread	
6. Generally, it is expected of me to use PAT for selective harvesting and detecting Fusarium and mycotoxin spread	
Perceived self-efficacy	
1. I am confident about using PAT for selective harvesting and detecting Fusarium and mycotoxin spread	
2. Using PAT for selective harvesting and detecting Fusarium and mycotoxin spread would not be a challenge for me	
3. I would be comfortable to use PAT for selective harvesting and detecting Fusarium and mycotoxin spread	
Behavioral control	
1. I think that I have the discipline to learn how to use PAT for selective harvesting and detecting Fusarium and mycotoxin spread	
2. I have a sufficient extent of knowledge to use PAT for selective harvesting and detecting Fusarium and mycotoxin spread	
3. My own decisions and actions are decisive whether I will use	
4. I have a sufficient extent of control to make a decision to adopt PAT for selective harvesting and detecting Fusarium and mycotoxin spread	
5. I have a sufficient extent of self-confidence to make a decision to adopt PAT for selective harvesting and detecting Fusarium, mycotoxin and rust spread	
Desire	
1. My desire for using PAT for selective harvesting and detecting Fusarium and mycotoxin spread can be described as strong	
2. I want to use PAT for selective harvesting and detecting Fusarium and mycotoxin spread	
3. I am planning to use PAT for selective harvesting (SH) and for detecting Fusarium and mycotoxin spread	
4. I will increase efforts to use PAT for selective harvesting and detecting Fusarium, and mycotoxin spread	

Please indicate your level of agreement or disagreement with the following statements pertaining to the use of Precision Agriculture Technology (PAT) for Selective Harvesting (SH) and Preventive Site Specific Spraying (PSSS) for detecting Fusarium and mycotoxin spread, on a scale of 0 to 5 (0 = not relevant for me; 1 = I strongly disagree; 2 = disagree; 3 = neutral; 4 = agree; 5 = I strongly agree).

Table 8 Log-likelihood ratio test, Akaike information criteria (AIC), and Bayesian information criteria (BIC) Test Results

Test parameters	Conditional logit (homogeneous assumption)	Mixed logit (Heterogeneous assumption)
Log likelihood	−776.48	−632.82
LR chi^2	393.14***	193.50***
Pseudo-R^2	0.16	0.39
AIC	1594.95	1373.64
BIC	1663.03	1548.69

$$T_{t_{ik}} = t_{(t_{ik}=q_1)}\left[\frac{\exp^{(\eta_{i,q_1}-\xi_i Y_k)}}{1+\exp^{(\eta_{i,q_1}-\xi_i Y_k)}}\right] + \sum_{f=1}^{F-1} t_{(t_{ik}=q_1)}\left[\frac{\exp^{(\eta_{i,f}-\xi_i Y_k)}}{1+\exp^{(\eta_{i,f}-\xi_i Y_k)}} - \frac{\exp^{(\eta_{i,(f-1)}-\xi_i Y_k)}}{1+\exp^{(\eta_{i,(f-1)}-\xi_i Y_k)}}\right]$$
$$+t_{(t_{ik}=q_G)}\left[1-\frac{\exp^{(\eta_{i,(Y-1)}-\xi_i Y_k)}}{1+\exp^{(\eta_{i,(G-1)}-\xi_i Y_k)}}\right] \tag{8}$$

5. The set of computed threshold parameters from Eq. (4) is signified by $\eta_{i,1}, \eta_{i,2} \dots \eta_{i,G-1}$. Each of $\eta_{i,1}, \eta_{i,2} \dots \eta_{i,G-1}$ are computed with ancililary parameters $\sigma_{i,1}, \sigma_{i,2} \dots \sigma_{i,(G-1)}$ in that $\eta_{i,2} = \eta_{i,1} + \sigma_{i,1}$, $\eta_{i,3} = \eta_{i,2} + \sigma_{i,2} \dots \eta_{i,G} = \eta_{i,G-1} + \sigma_{i,G-1}$ and $\sigma_{i,G} \geq 0 \forall G$. The ancillary variables are specified such that $\eta_{i,1} < \eta_{i,2} < \dots < \eta_{i,(G-1)}$.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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