Willingness to Pay for Pest Management Information: Evidence from Specialty Crop Growers

Kelvin Amon[1], Tara Wade[2], and Zhifeng Gao[3]
University of Florida

[1] Kelvin Amon, PhD student, agricultural natural resources economics, Food and Resource Economics Department, University of Florida, Gainesville; *kamon@ufl.edu*
[2] Tara Wade, assistant professor, Agricultural Natural Resources Economics, Food and Resource Economics Department, UF/IFAS Southwest Florida Research and Education Center
[3] Professor, Food and Resource Economics Department, University of Florida, Gainesville.

Abstract

Pests (insects, pathogens, and vegetation) pose significant difficulties for producers. Pre-existing issues exacerbate the impact of pests on farmers of specialty crops. Concurrently, decreasing yields and rising pest management expenditures. Consequently, biological scientists have created a tool (risk prediction model) to prevent economic loss by predicting pest pressure in the field. The risk prediction model is useful for producers before and during planting season. It is unknown, however, how much producers are willing to accept or pay for this information. Using the generalized mixed logit model, this study aims to estimate specialty crop producers' willingness to pay for risk prediction model information in a smartphone pest management application. The study utilizes primary data from a survey of specialty crop farmers across the United States. We find growers have a high preference for smartphone pest management technology. As a result, growers have significant preferences and willingness to pay for most of the technology attributes. We find specialty crop growers trust educational/research institutions regarding pest management information on their farms. We attribute these results to the education and production systems used by growers as the drivers of their willingness to pay estimates. These results highlight the primary stakeholder concerns and readiness to mitigate pests and contribute to institutional aids available to growers.

Introduction

The current climate presents farmers with formidable and multifaceted challenges. Among these, pests and diseases are particularly daunting adversaries, compounded by the effects of climate change, which exacerbate the damage they inflict on crops and increase the cost of control measures. The issue of pest management has evolved to encompass integrated pest management, organic and sustainable pest management, the role of technology, and socioeconomic and policy aspects. Researchers have focused on the adoption and policy aspects of pest management technologies to mitigate the impact of pests and diseases. However, there has been a neglect to consider the value placed on these technologies by the farmers who utilize them. Therefore, it is essential to understand the socioeconomic and policy aspects of pest management by examining the value growers place on pest management technologies.

This research examines the extent to which farmers in the U.S. specialty crop industry value pest management technologies and information from smartphone agricultural applications. The U.S. Department of Agriculture-Agricultural Marketing Service (USDA-AMS) defines specialty crops as fruits, vegetables, tree nuts, dried fruits, horticulture, and nursery crops, including floriculture (USDA-AMS). The study employs a discrete choice experiment (DCE) approach to gauge growers' willingness to adopt pest management technologies, including those for insect pests, diseases (pathogens), and weeds, made available through smartphone applications. The hypothesis is that growers will exhibit a positive attitude toward adopting pest management technologies. Furthermore, it is anticipated that specific attribute levels, such as those associated with educational/research organizations, will be considered more trustworthy by growers than by private agricultural companies and government agencies, including the USDA.

Specialty crop growers place a high preference for pest management technologies. These pest management technologies are considered normal goods. Consequently, as growers' income increases, their demand for pest management technologies increases, all things being equal. Notably, data obtained from academic, or research institutions are considered more reliable than those obtained from private agricultural companies and government agencies. Growers demonstrate a high preference for pest management technologies that leverage historical pest presence information on their farms. As well as those with high predictive accuracy.

Integrated pest management (IPM) is a human capital-based technology and has garnered significant attention over time (Harper et al., 1990). However, studies on the willingness to pay for information related to IPM typically focus on farm educational services (extension services). These studies have explored various aspects of accessing extension offices (Diekmann et al., 2012) and extension services across different regions and countries (Feder and Slade, 1986; Bindlish and Evenson, 1997; Owens et al., 2003; Ajayi, 2006; Horna et al., 2007; Van den Berg and Jiggins, 2007; Charatsari et al., 2011; Aker, 2011; Davis et al., 2012; Ozor et al., 2013; Uddin et al., 2016; Ogunmodede et al., 2022). Furthermore, other studies have also examined the effects of extension services on pesticide usage (Godtland et al., 2004; Tripp et al., 2005; Van den Berg and Jiggins, 2007; Pan et al., 2018). Additionally, other studies have considered growers' willingness to pay for specific information beyond extension services, such as soil management information (Diafas et al., 2013). Research has also been conducted on growers' willingness to pay for technologies on and off the farm. This includes technologies such as seeds, Internet broadband, animal vaccines, and pest management. Studies that have analyzed the willingness to pay estimates for these technologies include Bennett and Balcombe (2012), Channa et al. (2019), Gharib et al. (2021), Jeffcoat et al. (2012), Nyangau et al. (2022), and Shee et al. (2019).

Despite the advancements in literature by various researchers, only a few have addressed the topic of smartphone agricultural technology adoption and the related willingness to pay for crop protection (Bonke et al., 2018) and irrigation (Jaafar and Kharroubi, 2021). This study, however, examines the willingness to pay for smartphone agricultural technology and the source of information provided for pest management. The smartphone agricultural technology in this study is a comprehensive decision-support tool that predicts past and current pest infestations on farms. Furthermore, our study differs from previous research by employing the Discrete Choice Experiment (DCE) methodology to analyze adoption and willingness to pay for pest management information rather than using binary dependent variable estimators. The adoption of agricultural mobile applications in the U.S. has been slower than in other sectors. Despite the numerous advantages they offer (Xin et al., 2015). This study provides insight into this issue by concentrating on the U.S. specialty crop industry.

The remainder of the paper is organized as follows: specialty crops and pest management strategies, choice experiment survey design and survey, methodology, results, and discussion and conclusion.

Specialty crops and pest management strategies

Plants classified as specialty crops must be grown or managed for human consumption, medicinal purposes, and aesthetic gratification (USDA-AMS). According to the USDA Census of Agriculture 2017, more than 15 million acres were farmed, and more than one million people were employed in specialty crop production on 99,463 farms (USDA Census of Agriculture, 2019). The states with the most land are California, Washington, North Dakota, Montana, and Florida (USDA Census of Agriculture, 2019). The specialty crop industry accounted for one-third of U.S. crop receipts and one-sixth of all agricultural product receipts in 2017, totaling $64.7 billion (USDA-ERS, 2020). The national production of 26 estimated vegetable and melon commodities comprised 658 million cwt in 2022 (USDA-NASS, 2023). Tomatoes, onions, and sweet corn collectively accounted for 53% of total vegetable production (USDA-NASS, 2023). In addition, the total utilized production of vegetables in 2022 reached $16.5 billion, a 27% increase from the previous year (USDA-NASS, 2023). The concurrent growth in the specialty crop industry is complemented by an increase in vegetable consumption from 146.8 lbs. to 153.3 lbs. per capita from 2000 to 2019 (Lucier and Parr 2020). The increases in consumer consumption were attributed to health benefits and the government's effort to promote fruits and vegetables (Lucier and Parr 2020).

Tomatoes are regarded as one of the most essential and widely consumed vegetables in the U.S. In 2022, tomatoes are counted as the top three in acres harvested and total production (USDA-NASS, 2023). Subsequently, tomatoes also accounted for one of the highest-valued utilized production for 2022, up 27 percent from the previous year (USDA-NASS, 2023). In 2022, tomatoes were planted on 271,000 acres and harvested on 263,800 acres, 1.8 percent less than in 2021 (USDA-NASS, 2023). Despite the growth in the specialty crop industry using tomatoes as an example, like other crops, specialty crops are susceptible to pests (insect pests, diseases (pathogens), and weeds) (USDA, 2017). The tomato industry is threatened by pests and diseases such as yellow leaf curl virus (TYLCV), which is caused by whitefly insects and can lead to significant economic losses due to increased production costs and reduced crop yield (Polston and Lapidoth, 2007). The TYLCV is the most treacherous pest to tomato fields (Camara et al., 2013; Moriones and Navas-Castillo, 2000; Picó et al., 1996). Typically, symptoms are evident in infected plants after 2 to 3 weeks post-inoculation (Bian and Gao, 2020; Srinivasan et al., 2012). The observed symptoms of infected plants include curling and yellowing of leaves, mottling, and chlorotic leaf margins (Bian and Gao, 2020; Camara et al., 2013). Farmers often struggle to manage whiteflies and associated viruses effectively due to the arduous task of selecting resistant cultivars, production methods, insecticide combinations, and optimal transplant dates to minimize the risk of infection (Bian, 2020). This stems from farmers' inability to accurately estimate the whitefly population and potential disease prevalence of their properties (Bian, 2020). Therefore, controlling parasites and diseases to maximize economic gains is challenging for producers (Bian, 2020). Timely and specific pest and disease management information is critical for viral infections and disease control presented by the risk prediction model to predict pest pressure in-field, such as the whitefly population and virus incidence among crops (Anco et al., 2020).

Risk prediction models serve as a timely pest management information tool to address whitefly population and virus incidence among crops in the field (Anco et al., 2020). The technology incorporated into farm smartphone applications functions as a decision support tool (DST). The DST assists farmers with additional information for decision-making under uncertainty (Bonke et al., 2018; Shtienberg, 2013). Advancements in technology have allowed for the merging of DST with smartphones that have access to the Internet, providing farmers with flexible usage options (Bonke et al., 2018). These mobile apps cover a spectrum of activities, from the field to the market (Costopoulou et al., 2016). In total, 665 farm management mobile apps are reported by Costopoulou et al., 2016. These apps span various categories, including animal production, farm management, crops, pests and diseases, agricultural technology and innovation, agricultural machinery, spraying-related activities, and weather forecasting, among a total pool of 1140 agricultural mobile applications (Costopoulou et al., 2016). Due to the associated and potential benefits of smart-agricultural mobile applications, some researchers have investigated farmers' willingness to pay in the context of crop protection and irrigation (Bonke et al., 2018; Jaafar and Kharroubi, 2021).

In the adoption literature for smartphone agricultural technologies, previous studies have studied adoption and willingness to adopt using a binary outcome variable (Bonke et al., 2018; Jaafar & Kharroubi, 2021; Michels et al., 2020). However, there is no knowledge regarding a stated choice approach to elicit farmers' willingness to pay for agricultural mobile tools. The stated choice experiments use quantitative methodology to evaluate the relative importance of various product attributes that affect consumer decision-making. (Louviere et al., 2000). This study contributes to the literature by using a stated choice experiment to investigate the effect of specific smartphone agricultural application attributes.

Additionally, some factors affect the adoption of farm technologies. Prominent amongst them is price. The price of precision farming tools and DST has been cited as influencing the limited adoption rates (Bonke et al., 2018; Matthews et al., 2008). There are several free and paid mobile applications for farming on the market. However, paid mobile applications are more advanced in data management, timely decision-making, and usability among farm workers.

According to researchers, the awareness and attitudes of farmers, which play a crucial role in their decision to adopt new practices, are influenced by their socioeconomic characteristics (Daberkow and McBride, 2003; McBride et al., 1999; Rogers, 1995). These sociodemographic characteristics include farm size, human capital (education, technical skills, and innovative abilities), land tenure systems, and information sources (Daberkow and McBride, 2003; Feder, 1985; Feder et al., 1985; Fernandez-Cornejo et al., 2001; Khanna, 2001; Lambert et al., 2015; Larson et al., 2008; McBride and Daberkow, 2003; Schimmelpfennig and Schimmelpfennig, 2016; Walton et al., 2010). Specifically, the relationship between farm size, behavioral characteristics (risk attitude), and information-seeking behavior of farmers has been established by previous studies. (Feder et al., 1985; Fernandez-Cornejo et al., 2001).

Adopting new technologies in agriculture has been observed to follow a sequential pattern, with farmers' risk attitudes playing a significant role in this process (Khanna, 2001; Leathers and Smale, 1991). This is because technological innovation in agriculture is inherently riskier than traditional methods (Daberkow and McBride, 2003). Risk poses a barrier to adopting new techniques, and previous studies have had mixed conclusions regarding the effect of risk attitudes on technology adoption (Aimin, 2010; Chavas and Nauges, 2020). Marra et al. (2003) highlighted three components of risk that affect technology adoption: farmers' perception of the probabilities of the distribution of net returns, variance of net returns, and strength in the direction of risk attitude. However, most studies have focused on the strength of direction (risk aversion) (Canales et al., 2023). In contrast, this study differs from the directional component of risk by Marra et al. (2003) and measures farmers' variations in preferences for smartphone pest management technology using insurance uptake. Moreover, growers have become more proactive in seeking information about innovation, and this effort is directly related to the expected gain from that knowledge (Feder, 1985; Feder et al., 1985). Therefore, adopting new technologies depends on diverse information sources that may vary depending on the stage of adoption (McBride & Daberkow, 2003). To the best of our knowledge, none of the previous studies have considered the sources of information in a choice set to estimate farmers' preferences and willingness to pay estimates for these sources.

In contrast to existing studies, this paper examines the valuation of pest management technology (smartphone agricultural apps) and information by specialty crop growers regarding three main attributes: source of information, historical pest presence, and current pest prediction accuracy. The study explores the individual willingness to pay estimates of these attributes and the effects of sociodemographic characteristics on WTP outcomes. The results can provide critical policy interventions of information dissemination channels, high-range technology predictive accuracies, and the importance of past information on the current season's production.

Choice Experiment Design and Survey

We developed a choice experiment for a risk prediction model, emulating a mobile application interface. The attributes we selected were carefully chosen to reflect the essential characteristics and objectives of constructing the risk prediction model. These attributes were also designed to mirror the features of existing pest management mobile applications, such as SIRRUS, CROPX, and Climate FieldView, currently available on the market.

The risk prediction model comprises key features such as measuring past pest occurrences and the identification of pests present on the farm. Furthermore, acknowledging the importance of information in pest management, our design incorporates the source of information used to predict pest presence on the farm. To establish the cost of the risk prediction model, we consulted the subscription fees of existing applications in the market, including SIRRUS, CROPX, and Climate FieldView. The risk prediction model attributes and associated attribute levels in our choice experiment are presented in Table 1 and defined as follows:

Table 1. Risk prediction model attributes and attributes levels.

Model attributes	**Levels**
Source of information	Government agencies, education/research institutions, private agriculture companies
Historical pest	Included, not included.
Quantifying current pest (Accuracy)	77%, 85%, 92%
Price	\$16, \$25, \$34, \$42

Identifying pests accurately is the first step in formulating effective pest control strategies, and the reliability of sources such as entomologists and field guides plays a crucial role in this regard. Therefore, understanding the biological behavior of pests from a reliable source underscores the importance of information for effective management. These comprehensive sources of information offer extensive insights into pest life cycles, habitats, and timing, which are crucial for formulating precise pest management strategies. Furthermore, Integrated Pest Management (IPM), which combines multiple pest control methods to limit the impact of pests (Peshin and Dhawan, 2009), relies on information to avert the misuse of pesticides, which can result in detrimental environmental consequences (Aktar et al., 2009).

In the stated choice experiment, growers were presented with three sources of information from which the data used to develop the risk prediction model were obtained: Government agencies, education/research institutions, and private agriculture companies. Each was presented as a bundled choice along with other attributes. Historical pest presence represents the risk prediction model's use of previous farm information on pests, diseases, and weeds to predict the presence of current pests on the farm. Attribute levels were included based on actual existing market applications, thus, included or not included. Furthermore, we incorporate the predictive accuracy of pest presence on farms into our analysis. The selection of attribute levels is informed by prior research that utilized different statistical modeling tools to forecast pest presence on agricultural lands. Specifically, the studies by Ibrahim et al. (2022), Marković et al. (2021), and Shang and Zhu (2018) reported predictive accuracies of 85%, 77%, and 91%, respectively. All things being equal, the higher the predictive accuracy, the better the effectiveness of the smartphone pest management tool and information.

Finally, the price attribute represents the monthly subscription cost for utilizing the risk prediction model. The choice of monthly subscription costs was determined by referencing real market prices obtained from sources such as SIRRUS, CROPX, and Climate FieldView. The available attribute levels are $16, $25, $34, and $42.

The experimental design was created using the SAS Macro within SAS (Statistical Analysis System). The SAS Macro output produces a full factorial design, from which we can choose a minimum number of choice-sets with high D-efficiency and relative D-efficiency. To construct the stated choice experiment for our survey, we employed a fractional-factorial design of 10, achieving a D-efficiency of 100 and a relative D-efficiency of 72.57 derived from a 72 ($3 \times 2 \times 3 \times 4 = 72$) full-factorial design (Louviere et al., 2000). The 10 choice sets were blocked into two versions (5 choice sets each) and respondents were randomly assigned to one of the two blocks. Each of the choice tasks features two smartphone application interfaces (risk prediction model) alongside a status quo option, the “none” option (see Figure 1). The inclusion of the “none” option not only helps make the selection more realistic as respondents can opt out of a smartphone application interface option if they are unsatisfied with the product selection set (Gao et al., 2019), but by eliminating the pressure to select subpar options, it ensures higher-quality data collection (Johnson and Orme, 2003).

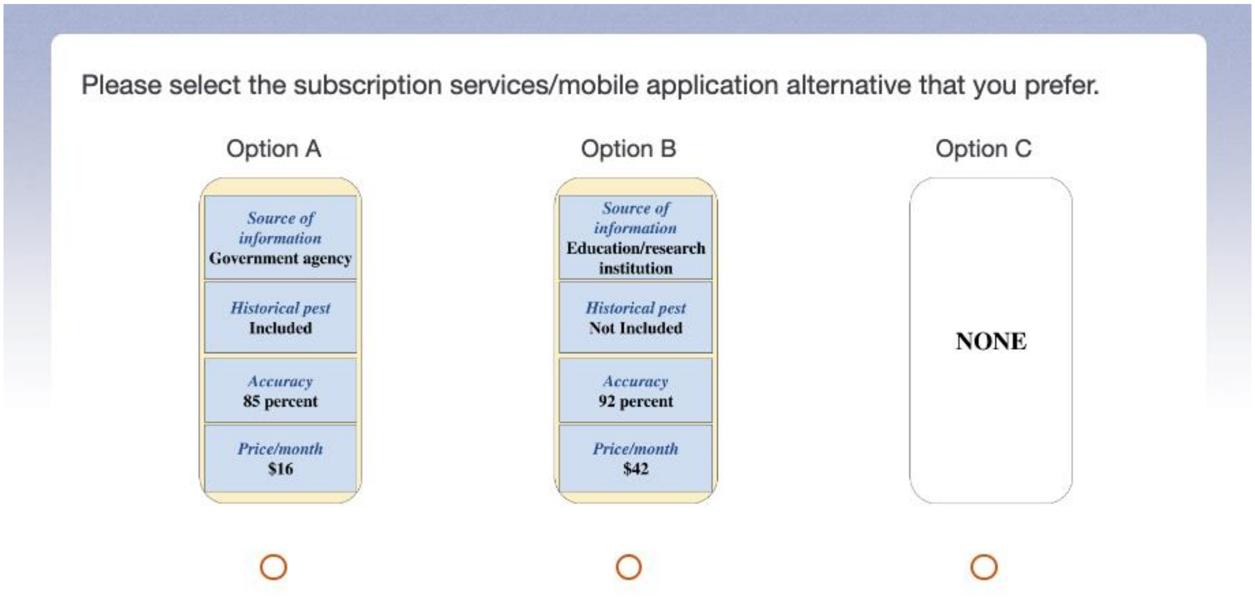

Figure 1. An example of a choice task presented to growers.

To mitigate the hypothetical bias, a statement was provided to participants indicating that their selections in each task would be considered final and binding. As depicted in Figure 1, an illustration of a choice task is provided.

The online survey was conducted by a market research firm (Qualtrics) to a panel of specialty crop growers in the United States. Our survey was tested with focus groups as suggested by Johnston et al. (2017). The focus group comprised extension agents, farmers, graduate students, and researchers with expertise in survey design for growers, to ensure comprehension of the questions posed by the survey. The survey was sampled in two parts, first, 100 samples were collected with a soft launch of 10% of the online panel. The soft launch allowed us to check the flow and consistency of our survey instruments and how respondents viewed each question. We discovered issues with the screening questions and added an extra one to allow us to sample the right group of growers. Participants were required to be, at least 18 years or older and grow vegetables and pulses or fruits and tree nuts.

After screening, respondents were asked about their specialty crop production. Acres of farm operation, specific names of specialty crops grown, production, insurance coverage, and challenges encountered in production. Respondents were asked about their use of smartphone pest management technology. Furthermore, respondents were presented with an example of a smartphone pest management technology, detailing its benefits and use. After the example, we presented attributes of the smartphone pest management technology and a cheap talk to reduce hypothetical bias before proceeding to the choice experiment (see Appendix A1). At the end of the survey, respondents reported their demographic information, such as position in the farm's production, years of farming, education, and total farm sales value from the farm in the past two years.

Methodology

Growers' preferences and willingness to pay for smartphone pest management technology and information were studied using a discrete choice modeling framework. This framework is based on Lancaster's Consumer Theory (Lancaster, 1966) and the Random Utility Theory (McFadden, 1972). The Lancaster theory considers the intrinsic complementarity of a product, which encompasses the inherent characteristics or properties appealing to the respondent. Consequently, a product comprises a set of attributes from which utilities are derived (Liu et al., 2019). The core assumption of the Random Utility Theory is that a person's utility consists of a deterministic component and an unobservable random component (Liu et al., 2019). As a result, the choice from a set of alternatives is primarily influenced by its perceived utility. In this context, the option perceived as most beneficial is likely to be chosen, as it offers the highest level of utility (McFadden, 1972). Therefore, following the random utility theory (McFadden, 2001), the farmer

k's utility from choosing the risk prediction model alternative i from a choice set of J alternatives in a choice situation t can be specified as

$$U_{kit} = V_{kit} + \varepsilon_{kit} \quad [1]$$

where V_{kit} is the deterministic component, and ε_{kit} is the random component of the utility function. The random utility model can be rewritten as

$$U_{kit} = \beta_i^* X_{kit} + \varepsilon_{kit} \quad [2]$$

where X_{kit} is the attributes of the risk prediction model, β_{kit} is a vector of unknown preferences coefficients that weigh the exogenous attributes (Chen et al., 2023). ε_{kit} is the random component of the utility, capturing the unobservable confounders affecting the utility.

Based on the distribution of the random component of the utility function and the functional form of the utility, various models can be hypothesized (Van Wezemeal et al., 2014; Bazzani et al., 2017; Liu et al., 2019; Chen et al., 2023). For example, equation [2] can be estimated using the conditional logit model (CL) and multinomial logit model (MNL), assuming homogeneity in preferences among individuals and ε_{kit} is independently and identically distributed (i.i.d.) with a Gumbel distribution (Meas et al., 2014; Liu et al., 2019; Chen et al., 2023). Previous research has emphasized the importance of heterogeneity from both methodological and empirical standpoints (Lusk, Roosen, and Fox 2003; Greene, Hensher, and Rose, 2006; Ortega et al., 2011; Greene and Hensher, 2013; Wongprawmas and Canavari 2017). The incorporation of heterogeneity can lead to biased estimates in conditional and multinomial logit models (MNL). To address this issue, Revelt and Train (1998) proposed the mixed logit model (MIXL), which accounts for varying preference coefficients across individuals (Chen et al., 2023).

Assuming respondents within the same group have similar preferences, the mixed logit model presents a choice probability as an average of logit terms, each weighted by a value from the density function. The logit terms are calculated with different values of the coefficient vector β (Chen et al., 2023). In most applications, the mixed logit model's coefficient vector weights on smartphone pest management attributes are assumed to have a multivariate normal distribution (Liu et al., 2019). However, previous studies have argued that the multivariate normal distribution used in the mixed logit model may lead to serious misspecification of the model (Louviere et al.,1999; 2002; 2008; Louviere and Eagle 2006; Louviere and Meyer 2007; Liu et al., 2019; Chen et al., 2023). Subsequently, these studies have suggested that the majority of the heterogeneity in attribute weights is caused by scale effects (Liu et al., 2019). This implies that for some farmers the scaling of the error term is weightier than others, this is described as scale heterogeneity (Liu et al., 2019; Chen et al., 2023). The introduction of scale allows researchers to account for nearly lexicographic preferences among growers (respondents), a common drawback in choice experiments (Fiebig et al., 2010; Liu et al., 2019). Therefore, the scaled multinomial logit model (S-MNL) captures scale heterogeneity (Fiebig et al., 2010). In addition to the scaled multinomial logit, Fiebig et al., 2010 developed a generalized mixed logit model that nests mixed logit and scaled multinomial logit models. Fiebig et al. (2010) found that the generalized mixed logit model demonstrated greater efficiency compared to the mixed logit model (Chen et al. (2023). In addition, Greene and Hensher (2010), concluded the improvement of the generalized mixed logit model over the standard mixed logit model (Chen et al., 2023). Modeling the generalized mixed logit model after Fiebig et al., (2010), Greene and Hensher (2010), and Greene (2012) consider the utility function as follows.

$$U_{kit} = \beta_i^* X_{kit} + \varepsilon_{kit} \quad [4]$$

where ε_{kit} is independently and identically drawn (i.i.d.) with the Gumbel distribution, and β_{kit} is specified as

$$\beta_i = \theta_i * \beta + [\gamma + \theta_i(1 + \gamma)] * L * u_i \quad [5]$$

and u_i follows a certain distribution, $0 \geq \gamma \leq 1$ and

$$\theta_i = \exp\left(-\frac{\tau^2}{2} + \tau * w_i\right), w_i \sim N(0,1) \quad [6]$$

From the generalized mixed logit model, nested mixed logit, and scaled multinomial logit models, when $\tau = 0$ and $L \neq 0$, the generalized mixed logit model converges to a mixed logit model. When $\gamma = 0$ and $L = 0$, the generalized mixed logit model results in a scaled multinomial logit model.

Empirical Framework

This analysis considers three models, *Model 1* is the mixed logit model, *Model 2* is the scaled multinomial logit model, and *Model 3* is a generalized mixed logit model. The individual farmer preferences for pest management information provided by the risk prediction model are as follows:

$$U_{kit} = None + \beta_1.Price_{kit} + \beta_2.Education\ or\ research\ Inst._{kit} + \beta_3.Private\ Ag.Company_{kit} + \beta_4.Historic\_\ Pest_{kit} + \beta_5.Egithy5_{kit} + \beta_6.Ninety2_{kit} + \varepsilon_{kit} \quad [7]$$

Where k is the individual farmer participants in the choice experiment, i represents the alternative risk prediction model in a choice scenario t. $None$ is an alternative specific constant, representing the "none" option. $Price_{kit}$ is a metric variable representing a linear relation with utility represented by four designed price levels. $Education\ or\ research\ Inst._{kit}$ and $Private\ agricultural\ company\ _{kit}$ are categorical variables that represent the source from which information provided by the risk prediction model is obtained. $Government_{kit}$ is used as a base category for the source of information. $Historic\_\ Pest_{kit}$ represents the inclusion of quantifying historical pest presence on the farm to make future predictions, with no inclusion as the base category. $Egithy5_{kit}$ and $Ninety2_{kit}$ are the predictive accuracy of the risk prediction model with $Seventy7_{kit}$ being the base category. The non-price attribute coefficients are commonly assumed to follow a normal distribution (Bazzani et al., 2017) with price and "none" option coefficients assumed fixed (Liu et al., 2019). ε_{kit} is independently and identically drawn (i.i.d.) error term.

To calculate the willingness to pay (WTP), this study utilized dummy coding for the non-price attributes. The willingness to pay (WTP) is calculated by $-\frac{\beta_\vartheta}{\beta_p}$, where β_ϑ is the coefficient of non-price attribute ϑ, and β_p is the estimated price coefficient. All three models were estimated using R studio using 1000 Halton draws for the simulations considering the panel structure of the data.

Results

Summary of Survey Response

A total of 250 growers were surveyed across the entire country. Respondents' production and demographic characteristics are presented in Table 2. The average percentage of vegetables and pluses growers represents almost 40% of our sample, almost 4% more than the national percentage reported by the 2017 census of agriculture (USDA-NASS, 2019). Regarding the size of farm production, the proportion of fewer than 1000 acres is 97.2%, larger than, 93.8% presented by the Census of Agriculture for specialty crops grown in the U.S. (see Table 2). Furthermore, our sample has a relatively larger proportion of male and white race farmers, compared to the Census of Agriculture report by 19.2% and 3.4%, respectively. Lastly, by race, our sample presents 2.8% and 3.2% of Black or African American and mixed-race growers, respectively which is higher than the 1.4% and 1.1% represented in the 2017 Census of Agriculture.

Table 2. Summary Statistics of Farmer and Farm Characteristics. (N=250)

Variable	Percentage (Mean)	2017 census of agriculture[4]
Vegetables and Pulses	39.6%	34.8%
Acres		
0-9 acres	18.4%	-
10-49 acres	13.6%	-
50-179 acres	27.2%	-
180-499 acres	22%	-
500-999 acres	16%	93.8%[5]
1000-1999 acres	2.4%	-

[4] USDA Census of Agriculture 2017 Specialty Crop
[5] Total percent of farm size below 1000 acres

Table 2. Continued

Variable	Percentage (Mean)	2017 census of agriculture[6]
2000 acres or more	0.4%	-
Sex		
Female	18.4%	37.6%
Male	81.6%	62.4%
Race		
White	90.8%	92%
American Indian or Alaska Native	0.8%	1.4%
Black/African American	2.8%	1.4%
Mixed race	3.2%	1.1%

Our sampled growers reported their main pest concern, insect pests (52.2%), diseases or pathogens (24.9%), weeds (21.3%), and others (1.6%) (see Table 4). Growers also reported previous adoption of smartphone pest management technology (68.4%) with 22.8% non-usage and 8.8% with no knowledge of a smartphone pest management technology. Scouting frequency was also reported with 50.4% and 47.5% of growers scouting always and sometimes, respectively. The rest of the growers (2.1%) rarely scout. In addition to the above, we show charts of acre proportions and systems of production untaken by our sampled growers (see Figure 2). Furthermore, in Figure 3, we explore previous app adoption and experience in farming, where growers with 8-10 years of experience have the highest adoption rate, followed by more than 20 years, and 5-7 years of experience.

[6] USDA Census of Agriculture 2017 Specialty Crop

Table 4. Main Pest concern, rate of adoption, and scouting frequency.

Variable	Obs.	Percentage (Mean)
Main Pest concern		
Other	249	1.6%
Insects	249	52.2%
Disease/Pathogens	249	24.9%
Weeds	249	21.3%
Previous App Usage		
I do not know	250	8.8%
Yes	250	68.4%
No	250	22.8%
Scouting		
Sometimes	242	47.5%
Rarely	242	2.1%
Always	242	50.4%

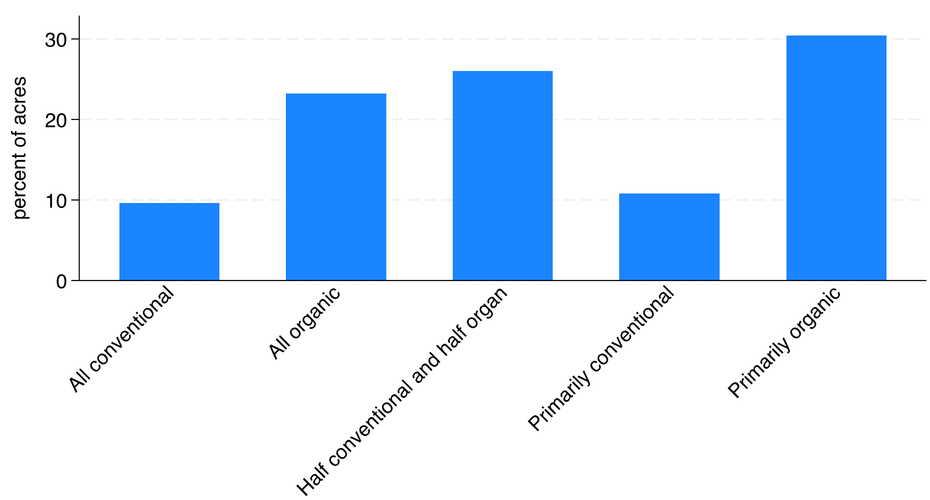

Figure 2. The share of acres by production methods.

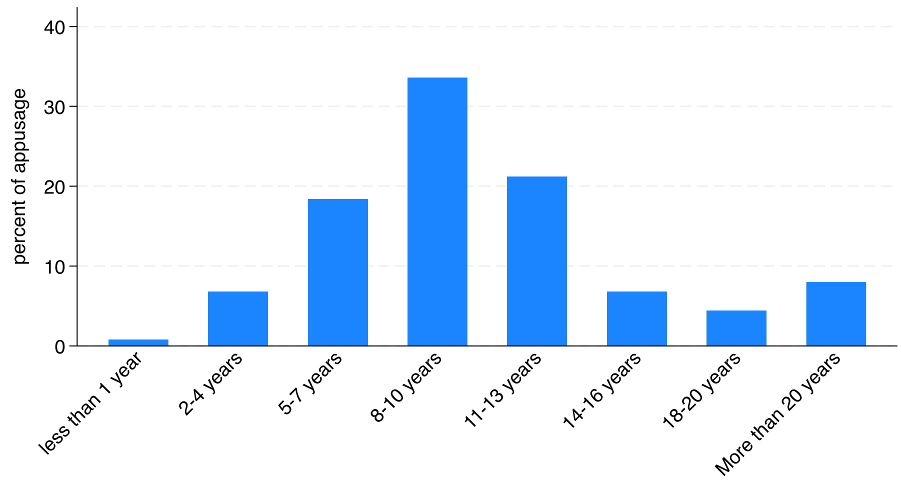

Figure 3. Rate of adoption by farming experience.

Regression results from empirical models

Table 5 reports utility/preference estimates for Model 1 (Mixed logit model), Model 2 (Scaled Multinomial logit), and Model 3 (Generalized Multinomial logit). The results from the mixed logit and generalized mixed logit models indicate that growers regard all attributes of the pest management technology as highly relevant. Consequently, the estimates were different from zero at, at least a 10% significant level. Moreover, the significance of tau, which captures the scale heterogeneity of preferences, indicates that growers weigh each attribute differently (Liu et al., 2019). Finally, the statistical and sign directions between the models (Models 1 and 3) are mostly consistent. Therefore, we discuss Model 3, the generalized mixed logit model. Model 3 presents, a better fit to the data with the highest Log Likelihood value (-889.42) and lowest Akaike Information Criterion (AIC) statistic (1808.831). Additionally, we conducted a log-likelihood ratio test that confirmed Model 3, as the best fit for the data at a 1% significance level.

The price estimate is negative and significant at the 1% level. This means that an increase in the price of a smartphone agricultural app reduces growers' utility/preference provided by the choice. Likewise, the alternative specific constant or status quo is negatively significant at 1%.

This indicates a disutility from not choosing any available smartphone app options. In contrast, the source of information used by the pest management technology, growers have a positive preference for educational/research institutions and private agricultural companies that provide data for pest presence predictions. However, growers prefer educational/research institutions (0.762) more to private agricultural companies (0.610), with government agencies as the reference attribute. Past pest presence on farms has a positive and significant coefficient, implying a higher utility/preference by growers when the historic pest feature is included in a choice. Regarding the predictive accuracy of smartphone pest management technology, growers prefer a higher predictive technology option to a lower-tier option. This is evident in the coefficient of the Ninety-two percent accuracy (1.244) which is higher than Eighty-eight percent (0.466), with seventy-seven percent as the reference point.

Table 5. Results: Preferences Estimates for Smartphone Pest Management Applications.

Variables	(1) Mixed Logit	(2) Scaled Multinomial Logit	(3) GN Mixed Logit
Price	-0.034*** (0.005)	-0.933 (2.521)	-0.0794*** (0.021)
Educational/Research Institution	0.333*** (0.113)	3.955 (8.950)	0.762*** (0.275)
Private Agricultural Company	0.265** (0.119)	1.932 (3.933)	0.610** (0.266)
Historical Pest	0.819*** (0.101)	19.458 (49.474)	1.828*** (0.444)
Accuracy: Ninety-Two	0.670*** (0.128)	7.821 (20.921)	1.244*** (0.377)
Accuracy: Eighty-Eight	0.256** (0.110)	6.182 (17.932)	0.466* (0.238)
None/Status Quo	-6.118*** (1.003)	-4381.827 (20876.664)	-14.885*** (4.148)
Tau		4.549** (1.998)	-1.146*** (0.180)

Table 5. Continued.

Variables	(1) Mixed Logit	(2) Scaled Multinomial Logit	(3) GN Mixed Logit
Gamma			-0.224**
			(0.094)
Log-Likelihood	-896.3	-970.34	-889.42
AIC	1818.607	1956.687	1808.831
BIC	1885.309	1997.734	1885.795
Observations	1250	1250	1250

Note: Standard errors in parentheses *** 1%, ** 5%, and * 10% significance level.

Since the generalized mixed logit model (Model 3) is preferred, the individual willingness to pay mean estimates are derived from Model 3, in Table 5. We used the delta method[7] approach in our estimation. Table 6 presents the individual willingness to pay estimates, illustrating that growers are willing to pay the most for past pest presence consideration ($23.025/month) in the smartphone pest management technology. Next, regarding the source of information used by the smartphone pest management technology, growers are willing to pay more for educational/research institutions ($9.605/month) compared to private agricultural companies ($7.677/month). Furthermore, regarding the predictive accuracy of the smartphone pest management technology, growers are willing to pay a premium of $9.809/month to use the highest pest-predictive accurate technology option. The outcome on the accuracy, suggests that growers place a higher value on advancement technologies that have low pest prediction uncertainties. Lastly, we report the willingness to accept/compensation due to growers when these smartphone pest management technologies are made unavailable. If the pest management technology becomes unavailable, growers have expressed their willingness to receive a monthly

[7] The delta method estimates non-linear function variances with random variables by taking the first-order Taylor series expansion around the mean of the variables and calculating the variance of the expression (Greene, 2003; Hole, 2007).

payment of $187.435. This reflects the importance placed on pest management technology by growers.

Additionally, we estimate the standard deviation of all significant attributes (see Appendix A2). The standard deviation illustrates the heterogeneity in the preferences and willingness to pay for smartphone pest management technology. Figure 4 shows the heterogeneity in the willingness to pay for past pest presence, private agricultural companies, and eighty-eight predictive accuracies.

Table 6. Results: Mean WTP Estimates Smartphone Pest Management Technology

Variables	(1) Mixed Logit	(2) Scaled Multinomial Logit	(3) GN Mixed Logit
Educational/Research Institution	9.809***	4.237	9.605***
	(3.597)	(4.705)	(2.847)
Private Agricultural Company	7.798**	2.069	7.677***
	(3.662)	(2.402)	(2.875)
Historical Pest	24.103***	20.846***	23.025***
	(3.995)	(3.776)	(3.102)
Accuracy: Ninety-Two	19.728***	8.378***	15.671***
	(4.463)	(2.607)	(3.345)
Accuracy: Eighty-Eight	7.540**	6.623**	5.862**
	(3.338)	(2.602)	(2.666)
None/Status Quo	-180.040***	-4694.310	-187.435***
	(36.650)	(9997.462)	(32.033)
Observations	250	250	250

Note: Standard errors in parentheses *** 1%, ** 5%, and * 10% significance level.

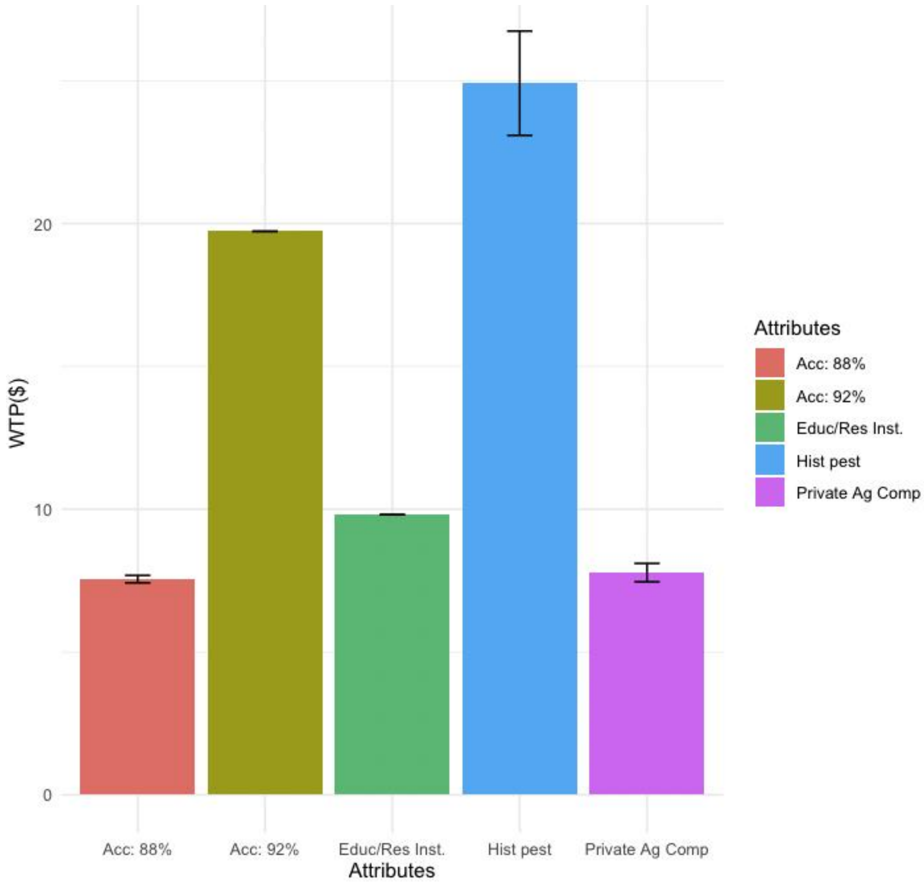

Figure 4. WTP($) for Historic Pests, Accuracy, and Source of Information.

Factors Influencing Individual WTP for Smartphone Pest Management Technology

To estimate the factors influencing individual WTP, we derived the individual-specific posterior distribution from the sequence of observed choices in the experiments (Train 2009; Chen et al., 2022). We use seemingly unrelated regressions with dependent variables, alternative specific constant (ACS), accuracy, past pest presence, and source of information used by the smartphone pest management technology. Independent variables used in the analyses include socio-demographic characteristics, main pest concern, experience with similar app usage, scouting, insurance, and production methods. Seemingly unrelated regression allows for comparison of mean individual-specific willingness to pay amongst different types of respondents while accounting for multiple correlated hypotheses since the individual-level willingness to pay is generated from the same model estimates (Chen et al., 2022). The results from the seemingly unrelated regression are presented in Table 7.

For the willingness to pay for the status quo (none) option, we find that education and primarily organic production systems prevent the nonuse of pest management technology. Likewise, the predictive accuracy of the technology, education, and organic production systems positively affects the individual willingness to pay. The main pest concerns, insects, diseases, and weeds significantly lowered the WTP for past pest presence features of the pest management tool. Similarly, growers who scout their farms have an inverse effect on the willingness to pay for past pest presence features. In contrast, all conventional, primarily organic production systems, and insured growers prefer past pest features in the smartphone pest management tool compared to all other production systems. However, male, and white race growers have an inverse effect on the individual willingness to pay for past pest features.

Regarding the source of information used by the smartphone pest management tool, the main pest concern for insects and weeds significantly lowers the willingness to pay for information from an educational/research institution while having no significant effect on the information provided by private agricultural companies. For production systems, primarily organic farming significantly affects the willingness to pay for information from education/ research institutions. On the other hand, conventional producers have a significantly reduced willingness to pay for private agricultural companies' information. Growers below the age of 64 are less willing to pay for information from education/research institutions. Again, male and white race growers also showed a low willingness to pay for information from education/research institutions.

Table 7. Results: from Seemingly Unrelated Regression on Individual WTP Estimates.

Variable	(1) Status Quo	(2) Accuracy: Ninety-Two	(3) Accuracy: Eighty-Eight	(4) Historical Pest	(5) Educ/Res Institute	(6) Private Ag company
Experience with App	-0.012 (0.086)	0.125 (1.357)	0.032 (0.507)	8.126 (6.270)	0.9207 (0.9547)	-2.031 (1.251)
Insects	0.366 (0.270)	-5.509 (4.204)	-2.023 (1.587)	-19.414** (9.232)	-5.615** (2.745)	-1.211 (2.694)
Diseases	0.214 (0.273)	-3.201 (4.235)	-1.114 (1.617)	-14.973* (8.775)	-3.758 (2.788)	-0.672 (2.631)
Weeds	0.298 (0.280)	-4.458 (4.361)	-1.60 (1.650)	-22.699** (10.053)	-5.057* (2.822)	-1.174 (2.796)
Always scouting	0 .197 (0.139)	-3.032 (2.189)	-1.134 (0.820)	-21.895** (10.355)	-2.029 (1.410)	-0.616 (1.691)
Sometimes scouting	0.159 (0.136)	-2.475 (2.144)	-0.924 (0.805)	-23.771** (10.514)	-1.563 (1.383)	0.274 (1.689)
Insurance	0.048 (0.011)	-0.821 (1.692)	-0.313 (0.641)	11.341* (6.833)	1.172 (1.101)	-1.562 (1.761)
All Conventional	-0.065 (0.125)	1.000 (1.953)	0.272 (0.734)	24.887*** (8.988)	0.811 (1.325)	-1.486 (1.420)
All Organic	-0.015 (0.087)	0.272 (1.380)	0.094 (0.533)	8.477 (5.554)	-0.259 (0.903)	0.493 (1.474)
Primarily Conventional	0.149 (0.110)	-2.337 (1.726)	-0.981 (0.648)	4.702 (6.634)	-1.168 (1.121)	-2.529* (1.416)
Primarily Organic	-0.152* (0.083)	2.407* (1.309)	0.829* (0.491)	26.247*** (5.932)	1.511* (0.880)	0.509 (1.088)
Education	-0.019* (0.909)	0.304* (0.170)	0.126* (0.064)	2.991*** (0.808)	0.177 (0.113)	-0.022 (0.126)
Age18 - 44	0.262 (0.171)	-3.986 (2.712)	-1.487 (1.01)	-7.119 (10.345)	-4.897*** (1.774)	0.660 (2.211)
Age45 - 64	0.240 (0.169)	-3.603 (2.675)	-1.348 (1.01)	-1.516 (9.254)	-4.424*** (1.706)	1.813 (2.488)
Male	0.124 (0.085)	-1.797 (1.349)	-0.808 (0.513)	-17.310*** (5.866)	-2.140** (0.837)	0.616 (1.444)

Table 7. Continued

Variable	(1) Status Quo	(2) Accuracy: Ninety-Two	(3) Accuracy: Eighty-Eight	(4) Historical Pest	(5) Educ/Res Institute	(6) Private Ag company
White	0.301	-4.432	-2.162	-22.636***	-4.793*	-0.202
	(0.234)	(3.580)	(1.615)	(8.551)	(2.461)	(2.974)
All other race	0.415	-6.344	-2.841	-20.579*	-3.980	-3.319
	(0.256)	(3.931)	(1.738)	(10.660)	(2.659)	(3.228)
Constant	-1.786***	27.413***	10.674***	29.705	22.199***	11.235**
	(0.375)	(5.896)	(2.260)	(19.981)	(3.773)	(4.996)
Chi2 p-value	0.0073	0.0087	0.0090	0.000	0.0003	0.2457
R-squared	0.106	0.102	0.109	0.215	0.138	0.066
Obs.	250	250	250	250	250	250

Note: Standard errors in parentheses *** 1%, ** 5%, and * 10% significance level.

Discussion and Conclusion

The 2017 Census of Agriculture reported a total of 435,610 specialty crop growers (USDA-NASS, 2019). The willingness to pay estimates from our representative sample reveals that growers place a high value on past pest presence, the source of information used by the app, and the accuracy of the pest prediction component of the app. The total individual willingness to pay for past pest presence is $10.03 million/month[8] and 120.4 million per year. This contextualizes the valuation and concern for information on past pest presence in analyzing future pests.

Likewise, regarding the source of information used by the app, the total willingness to pay for information from an educational/research institution is approximately $4.2 million/month ($50.2 million/year). The total individual willingness to pay for information from private

[8] This value is obtained by multiplying the willingness to pay estimates by the number of specialty crop producers reported by the 2017 Census of Agriculture.

agricultural companies is approximately $3.3 million/month and $40.1 million/year. The differences in the premium paid between these two attributes emphasize the degrees of trust growers place in information and the source from which it is obtained. The presence of extension workers from educational institutions such as land grant universities can explain the value placed on information from these institutions. However, the literature presents a mixed record of success for agricultural extension programs (Pan et al., 2018). A significant achievement of extension programs has been the outcome of field school research on pesticide knowledge and adoption (Godtland et al., 2004; Tripp, Wijeratne, and Piyadasa 2005; Van den Berg and Jiggins 2007; Pan et al., 2018). Despite the mixed success, decentralized models have argued that information flows from researchers to extension agents, and from extension agents to contact farmers (Kondylis et al., 2017). The decentralized information flow indicates contacts with farmers by researchers through extension agents, hence a level of trust between these groups, evident by almost a $1 million/month difference between educational/research institutions and private agricultural companies' total willingness to pay.

Regarding the predictive accuracy for pests, the total individual willingness to pay is approximately $6.8 million/month and $2.5 million/month for ninety-two and eighty-eight percent, respectively. The difference in the total willingness to pay and the lack of heterogeneity towards ninety-two percent predictive accuracy proves agricultural producers' homogenous preference for a high-quality technology in pest management.

The USDA has since 2009 funded projects under the Plant Protection Act’s Section 7721 as part of a national program to strengthen infrastructure for pest detection, surveillance, and mitigation (USDA-APHIS, 2023). Over a 15-year period (2009-2023), $809 million has been invested, averaging $53.93 million annually (USDA-APHIS, 2023). The yearly funding includes plant and animal health pest detection (USDA-APHIS, 2023). Despite the annual investment, it is less than what specialty crop farmers are willing to pay annually for past pest presence information on their farms ($120.4 million). Our results reveal producers support accurate, reliable, and trustworthy information for pest management.

The effect of education on technology adoption has been studied extensively across the literature (Harper et al., 1990; Khanna, 2001; Walton et al., 2010; Watcharaanantapong et al., 2013; Lambert et al., 2015; Schimmelpfennig and Schimmelpfennig, 2016). Likewise, we measure the effect of education on technology adoption using the alternative specific constant (status/none). Education an integral part of the human capital increases adoption of the smartphone pest technology; educated growers value the benefits these smartphone pest management brings to their farms. This conclusion is in line with Khanna 2001 and reduces the timing of adoption as concluded by Watcharaanantapong et al., 2013. In addition, education increases the willingness to pay for other attributes of the technology, improving the significance of education in adopting pest management technologies.

Similarly, organic growers, regard smartphone pest management technology as highly beneficial on their farms. Again, organic growers increase the willingness to pay for most of the smartphone pest management technology attributes. The reason for this can be explained by the definition of organic farming by Lampkin (1994), "to create integrated, humane, environmentally and economically sustainable production systems, which maximize reliance on farm-derived renewable resources and the management of ecological and biological processes and interactions, to provide acceptable levels of the crop, livestock, and human nutrition, protection from pests and disease, and an appropriate return to the human and other resources". The highlight of protection from pests and diseases increases the importance of smartphone pest management technology by organic growers to maximize farm-derived renewable resources for crop output. Finally, the socio-demographic characteristics of growers play a significant role in the willingness to pay for some smartphone pest management technology options. Age (-), male (-), white (-), and all other races (-). These demographic outcomes indicate a negative effect of demographics on willingness to pay levels.

Conclusion

We study the willingness to pay for pest management information using a smartphone pest management technology. The results suggest that growers prefer to have a technology that helps and provides information regarding pests (insects, diseases (pathogens), and weeds) on their farms. Therefore, past pest presence options in their toolkit and reliance on information produced by educational and research institutions with high predictive accuracy. Organic specialty crop farming increases the preferences and willingness to pay for specific pest management features compared to all other production systems. Similarly, education increases growers' adoption and willingness to pay for pest management technology. Although most of our sampled growers have had experience with a similar tool described for pest management, we realized that experience with technology did not significantly affect the adoption and willingness to pay for technology features.

Additionally, scouting for pests decreased growers' concern for past pest presence on their farms. This is explained by the frequency of data received from scouting on their farms compared to growers who do not regularly scout. Demographic effects on information sources and past pest presence on farms are worth highlighting to understand how preference for technology varies across growers.

In summary, we highlight the significance of pest management tools for specialty crop production, an expanding and increasingly significant sector within the U.S. economy. The growers' estimated valuations are more than government-provided support towards pests. The total willingness to pay highlights the importance of addressing the issue of pests in farm production, influencing productivity and farm profit of growers. Despite the conclusions raised by the study, future research can investigate crop-specific grower preferences and willingness to pay. The crop-specific analyses can be scaled nationally to understand growers' preferences using the farm resource region designated by the USDA-ERS. Again, to capture the crop-specific grower preferences and willingness to pay. The regional approach invites the use of weather and climate variables' effects on smartphone pest management technology adoption and attributes.

Appendices

A1: Survey Cheap Talk.

N8

In this survey pests refer to insects, pathogens (diseases), and weeds.

For the subscription services/mobile applications the characteristics are described as follows:

Source of information: This is where information provided by the risk prediction model is obtained. These sources could be **government agencies, education/research institutes, and private agriculture companies.**

Historical pest: The risk prediction model uses past pests presence on your farm to predict current pest presence on your farm. **This feature maybe included or not included.**

Accuracy (Quantify current pest): This feature represents the accuracy (percentage) of the risk prediction model to predict current pest (insect, pathogens (diseases), and weeds) presence on your farm. **There are three different types of accuracy, 92 percent, 85 percent, and 77 percent.**

Price: This is the value of the subscription service/mobile application you want to purchase. The price is range between **$16 per month, $25 per month, $34 per month, and $42 per month.**

When you make choices, please assume all other characteristics of the mobile applications are the same other than the characteristics mentioned above. It is important that your decision in the following questions is the same as if you were actually willing to do it in a real production scenario.

Studies have shown that most people do not answer surveys truthfully, as they would in reality. Please follow these options and respond as you would in reality.

A2

Table A2. Mean WTP Standard Deviation for Smartphone Pest Management Technology

Variables	**Models**	
	Mixed Logit	**GN Mixed Logit**
Sd. Educational/Research Institution	0.011 (166.448)	6.067 (6.571)
Sd. Private Agricultural Company	15.631*** (9.697)	9.915* (6.003)
Sd. Historical Pest	39.326*** (6.410)	33.393*** (4.466)
Sd. Accuracy: Ninety-Two	1.046 (98.298)	0.961 (17.551)
Sd. Accuracy: Eighty-Eight	9.373 (13.247)	0.919 (10.422)
Sd. None/Status Quo	171.373*** (37.268)	-205.986*** (38.080)

Note: Standard errors in parentheses *** 1%, ** 5%, and * 10% significance level.

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