FARMERS' PREFERENCE TO PRECISION AGRICULTURE DATA MANAGEMENT: A DISCRETE CHOICE EXPERIMENT

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Title

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

MASTER OF SCIENCE

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ABSTRACT

There is no legal or regulatory framework that protects a farmer's right to control the data generated from their use of precision agriculture. This may impede the adoption of new precision agricultural technologies. Using a choice experiment, we show that factors contributing to willingness to enroll in a data management contract include the discount received from a service provider, whether data ownership rights are retained, data privacy guarantees, and whether the data is transferred manually or automatically between systems.

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LIST OF ABBREVIATIONS

ATP ....Agricultural Technology Providers.

CE ....Choice Experiment.

GIS ....Geographic Information System.

GPS ....Global Positioning Systems.

HIPAA ....Health Insurance Portability and Accountability Act.

IIA ....Irrelevant and Identically Distributed.

IID ....Independently and Identically Distributed.

IRB ....Institutional Review Board.

PA ....Precision Agriculture.

PAIPAA ....Precision Agriculture Information Protection Accountability Act.

PAT ....Precision Agricultural Technologies.

PIPEDA..Personal Information Protection Electronic Document Act.

SD ....Standard Deviation.

1. INTRODUCTION

Farmers have historically made production decisions with heavy reliance on their judgment and experience. They made farm-level production decisions based on the bushels they brought to the elevator and used their own manual movements to guide their tractors (Strobel, 2014). The introduction of precision agricultural technologies has changed this for many farmers, making it one of the twentieth century's most significant technological advances in information technology (Walter, 1997).

Precision agriculture (PA) is the use of data generated from a technology-guided assessment of crop growth and conditions to guide sophisticated, computer-controlled farm equipment, enabling farmers to treat different areas within a single field differently (Kaplan, 1996). PA began with the geographic information system (GIS) and has advanced through technological development to include guidance systems and variable rate technologies. PA makes use of tools such as yield mapping and global positioning systems (GPS) through the GIS to collect data that enables farmers to make informed decisions. The first commercial manufacturer introduction was in the late 1990s when John Deere started fitting their equipment with GPS sensors to facilitate data collection and information management (Sharma et al., 2018; Strobel, 2014). Precision agriculture's computer systems are designed with precise information about an entire field and allow for synchronization with machinery and equipment that can take advantage of this data. For example, the seed drill collects data on seeding rate variations over a field. This data can then be used to variable rate apply fertilizer (Freeland, 2012).

Data created using precision agricultural technologies (PAT) is valuable not only to farmers, but also to cooperatives, firms, the government, and other organizations. And the user may not have control over how, when, and by whom the data is accessed. Once data is released to a company, in the absence of a confidentiality or privacy agreement, it can be permanently available to others (Walter, 1997). Firms and organizations may be able to access and use the data, including selling it to make profit or using it for targeted advertising (Strobel, 2014). Farmers who generate such data are recommended to have in place a privacy contract under the advice of an attorney before the data is released or otherwise available to others. The question of control arises when more than one party has access to data generated from use of PA (Russo, 2013).

Farmers must weigh the costs of and benefits associated with data sharing. One important factor presumed to be vital in influencing farmers generally to share their data is the benefit they get from doing so (Lee, 2013; Moffat & Zhang, 2014; Ward & Berno, 2011; Zhang & Jiang, 2015). Recent research conducted by Zhang et al. (2021) suggests that the willingness of farmers to share their data is positively correlated with benefits derived. Alternatively, concerns about the management of farm data include maintaining ownership rights and privacy and security of data (Keogh & Henry, 2016; Sonka, 2014; Van Der Burg et al., 2021; Wiseman et al., 2018; Wiseman et al., 2019). Many PA technology and service providers offer a guarantee to farmers that their data will remain private and not be passed on to retail customers. This is usually done in a written privacy policy that requires the client or consumer either accept or decline. Despite assurances from some technology and service providers, some have found a low level of trust among farmers that their service providers will keep their data confidential (Zhang et al., 2018; Wisemen et al., 2019). A source of distrust is that a majority of farmers know little to nothing about their data privacy agreement with service providers (Zhang et al., 2018).

1.1. Problem Statement

Farmers are facing an ever-increasing amount of data and information generated on their farms. There is promising potential for PA to increase farm productivity and help reduce environmental impact (Bronson & Knezevic, 2016; Kamilaris et al., 2017; Wolfert et al., 2017). There is a strong and growing body of literature on PA focusing on the adoption process, willingness to adopt, and the value that PA adoption can generate but still little literature addressing farmer preferences regarding the management of their data. Zhang et al. (2021) investigated farmer perceptions of data sharing. Their aim was to investigate farmers' willingness to share farm data to form a pool of aggregated data and understand who was benefitting from the sharing of the data. The results are informative but there remain questions regarding farmer preferences for data sharing and how farm data and its management affects the global food economy (Alexandratos & Bruinsma, 2012; Davis et al., 2016; Tilman et al., 2011). We address the former by investigating farmers' preferences regarding the management of their data, i.e., the use, collection, ownership, privacy, and transfer of their data. Towards this end, we conducted an online survey to identify what factors students in agribusiness classes perceive as important when their data is being managed by service providers or other stakeholders.

2. REVIEW OF LITERATURE

2.1. Introduction

This literature review focuses on the definition of precision farming and the various types of data being collected. It also includes a review of the importance of precision farming data as well as some issues regarding precision data management. Finally, it highlights an example of data privacy in the health sector.

2.1.1. Definition of Precision Farming

Precision agriculture, precision farming, and site-specific agriculture are all interchangeable terms. Essentially, the terms mean utilizing technological innovations such as satellites, sensors, and highly detailed maps to manage entire fields as small plots of land that are individually connected. A farmer can benefit from this type of management by making more efficient use of production inputs and monitoring production output on both a micro and macro scale (Walter, 1997). Within-field variability, the foundation of precision farming, was first proposed in 1929 with methods for assessing the spatial variability of soil acidity (Usery et al., 1995).

Employing PAT generates different types of data, termed precision agriculture data (Bendre et al., 2016). According to Griffin (2016), geospatial data and metadata on productivity, machinery, and environmental conditions are all types of data collected on the farm. Supporting data such as input application rates, planting depth, and cultivar selection are referred to as metadata (Whitacre et al., 2014). The use of geospatial data in precision farming includes soil and yield information specific to a particular location (Coble et al., 2018).

2.1.2. Types of Precision Farming Data

Precision farming is based on the collection of geo-referenced environmental data in order to provide relevant information for management planning (Usery et al., 1995). Precision agricultural technologies and other approaches can capture a wide range of data. Using these data, valuable insights about the farm's operations can be obtained, which can subsequently be used to make better, more informed decisions (Fulton & Port, 2018).

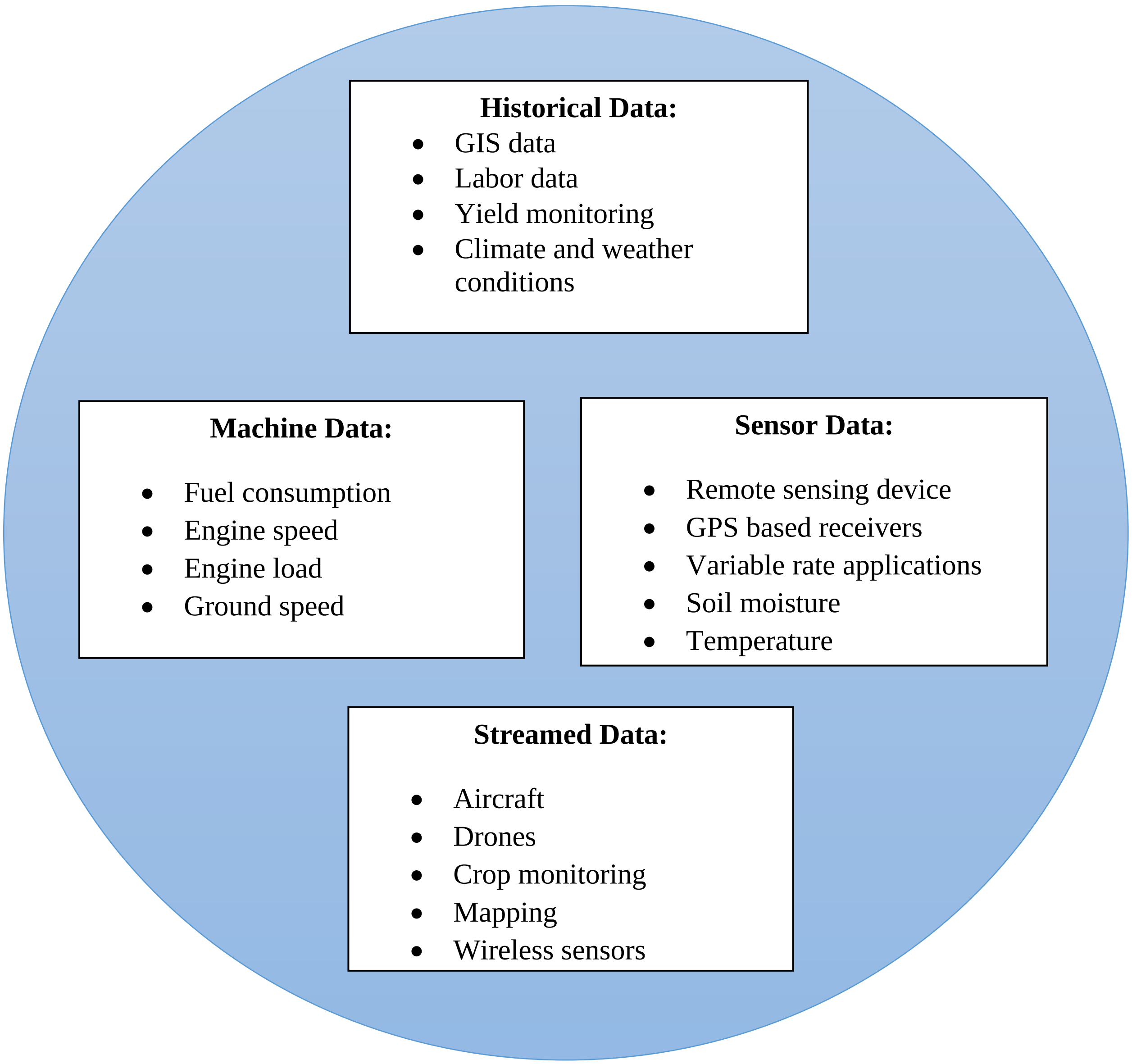
According to Bendre et al. (2016), agricultural data are collected in both structured and unstructured formats. Structured data is defined as any set of data that is unprocessed, highly organized and stored within a record file. An example is spreadsheets that help organize data into tables. Unstructured data include all datasets that cannot be categorized into a spreadsheet, examples include graphics, web pages, emails, and videos. To collect such a wide range of data, uniform and diverse sensing devices, as well as new technologies, are required.

Precision agriculture data can also be categorized as historical data, agricultural equipment data (also known as machine data), sensor data, and streamed data (Bendre et al., 2016). Historical data consist of soil testing, yield monitoring, climate conditions, weather conditions, GIS data, and labor data. Agricultural equipment or machine data includes information gleaned from farm equipment such as, fuel consumption, engine speed, engine load, and ground speed (Fulton & Port, 2018). Sensor data include that captured from remote sensing devices including GPS-based receivers, satellites, variable rate applicators, and instruments that collect soil moisture and temperature information (Bendre et al., 2016). Streamed data consists of that from crop monitoring, mapping, drones, aircraft, wireless sensors, smartphones and security surveillances.

Figure 2.1 illustrates these types of data and includes some examples of each.

Figure 2.1

Precision Farming Data Types



2.1.3. Importance of Precision Farming Data

The application of precision farming data in agriculture allows for increased sustainable and enhanced productivity, prevents and reduces the impact of agricultural activities on the environment, and can help tackle challenges of food security and sustainability (Senanayake, 1991; Zhang et al., 2021).

Precision farming technologies' data have the potential to help with prescriptive planting programs such as customized fertilizer, pesticide and seed applications, and hybrid seed selection. Also, the data can benefit society by helping with analysis of problems for public goods which may otherwise be ignored (Ellixson & Griffin, 2016). For example, it can facilitate monitoring the impact of fertilizers, herbicides and pesticides used during production to help identify ways of reducing the impact of these chemicals on the quality of both surface and groundwater. Precision farming may boost yields and enhance crop quality while also safeguarding the environment (Folnović, 2021).

Data generated from GIS are spatial data, resulting in information with specific patterns and that can be synchronized using computers. For many years, this technology has continued to grow significantly in use (Malczewski, 2006). For example, images obtained allow for the analyses of crop health and soil moisture (Jankowski, 1995; Abdelrahman et al., 2016; Montgomery et al., 2016). Some other important uses of the data include improved level of decision making for management of pesticide and fertilizer application as well as irrigation (Barnes & Baker, 2000; Méndez-Barroso et al., 2008; Hinzman et al., 1986; Lelong et al., 1998; Pal & Mather, 2003; Singh et al., 2007; Tilling et al., 2007).

One cannot neglect the value derived from the collection of farm data to service providers. For example, the data generated from a particular field can be utilized by service providers to prescribe particular treatments to said field, resulting in a better management decision for the producer (Miller et al., 2018). The service provider can also use data aggregated across fields and farms, called big data, to make an informed decision for a specific region (Kamilaris et al., 2017; Zhang et al., 2021).

2.1.4. Issues Regarding Precision Farming Data

Access to farm data by service providers and other external parties gives rise to certain concerns about how data is being used or handled. The question of whether and why farmers are willing to share agricultural data is critical and topical for precision farming research, as it mirrors broader societal concerns and disputes about the ever-increasing use and misuse of data (Wiseman et al., 2019). Zhang et al. (2021) discovered that one major factor that influences the sharing of farm data by producers is the perceived benefit, noting that farmers were willing to share their data if they received incentives. They also discovered that farmers were willing to share their data and feel comfortable doing so if the primary beneficiaries were farmers.

There is little research conducted on issues concerning precision farming data in terms of farmer's preferences. The closest work is that of Wiseman et al. (2019) which discusses the impact of law on farm data and farmer perceptions about data use. They note that service providers present lengthy and complex license agreements to farmers on how data is being managed and hence farmers do not actually know what controls or who controls their data.

A major concern in precision farming data is the issue of privacy. However, there is little doubt that precision technology will continue to be used despite the privacy risk because of its value in facilitating production efficiencies. Like other risks involved in farming (e.g., weather, price fluctuations), farmers can take measures to protect their data. For example, farmer's risk in areas such as weather and price fluctuation are being protected through various programs such as crop insurance, government subsidies, pricing contracts, and cooperative support (Strobel, 2014). Farmers could be provided protection for their data similar to the Personal Information

Protection Electronics Document Act (PIPEDA) and Health Insurance Portability and Accountability Act (HIPAA) (Strobel, 2014).

PIPEDA was adopted in Canada to prevent the exposure of private data in commercial activities with the main objective being to eliminate the problems associated with information theft on the internet and reassure consumers who are engaged in e-commerce (Willems, 1999). This act contains a code for protecting information in commercial activities and consists of ten principles that include: accountability, accuracy, identification purposes, consent, collection limitation, usage limitation, (disclosure and retention), safeguards, openness, owner's access, and challenging compliance, all being overseen by an organization to ensure compliance to these principles (Fitzgerald et al., 2010).

HIPAA is the health care act adopted in the U.S which provides an individual the ability to change or transfer health care plans when there is a loss of job, minimizes health care fraud and abuse, implements compulsory, industry-wide standards for health care information, and protects how confidential health information is being handled (Act, 1996). HIPAA consists of the following privacy rules: (1) information put in a patient's medical records by physicians, (2) conversations between doctors and nurses as well as other personnel about any care or treatment rendered to a patient, (3) a patient's information in their health insurance system, (4) billing details about a patient at the patient's clinic, and (5) other health information about a patient held by those who must follow these rules (Fitzgerald et al., 2010). HIPAA provides federal protections for personal health information held by physicians' which give certain rights to both physicians and patients with respect to the information as seen in the rules above. According to Strobel (2014), policies could also be generated to protect farmer data such as through a Precision Agriculture Information Protection Accountability Act (PAIPAA). This would be similar in providing protections as HIPAA and PIPEDA and would help close the gap of mistrust between farmers and service providers. This in turn should lead to an increase in the adoption of precision technologies thereby resulting in more effective farming practices.

3. METHODOLOGY

3.1. Data

To examine preferences for precision agriculture data management in the region, a survey was constructed. The survey collects data on respondents' characteristics, use of the technology, attitudes towards data sharing, and likelihood of enrolling in contracts with differing data management attributes. The survey was approved by the North Dakota State University Institutional Review Board (IRB) Protocol #IRB0003974, distributed online via Qualtrics to agribusiness students at North Dakota State University during the spring term, 2021. Most students grew up on a farm, had experience with farming, and/or are currently farming. The sample population was comprised of students enrolled in AGEC 246 (Agricultural Finance), AGEC 350 (Agri-sales) and AGEC 420 (Integrated Farm and Ranch Management). No identifying information was included in the survey to maintain the anonymity of respondents.

The survey consists of two sections; the first section asks questions about the farm, household characteristics, and attitudes about precision agriculture data management (past and present) and their effects on adoption of precision agriculture technology. The second section of the survey consists of a choice experiment to determine respondents' preference to how their data is managed.

3.1.1. Description of Survey Questions

The first portion of the survey asks demographic questions including gender and experience associated with farming and precision agriculture. These demographic questions allowed for grouping of respondents. For example, respondents with a significant level of farming or precision farming experience may be willing to pay more attention to their farm data and what goes on with it outside of their farm. Questions about precision agriculture technologies respondents are using or have used were asked, as were questions relating the data generated from their use for management decisions. Questions related to data and third-party management were also asked. For example, whether respondents belong to or have been involved with data service networks and have received incentives for sharing their data to third parties such as service providers or data service networks. Respondents were asked about their level of comfort with sharing their farm data with other parties, ability to transfer their data to new platforms, data security, data privacy and the use of their data by other parties for profit making. They were also asked how important different factors are in affecting their decision about whether to adopt PAT.

3.1.2. Choice Experiment

The second portion of the survey is the choice experiment (CE). The CE was used to understand the value of data contract attributes to respondents. We presented contracts with these attributes at different levels. XLSTAT (2021 version) was used to decide the number of scenarios, combinations to propose to the respondents, and the design of the experiment based on full factorial and D-optimal designs. Fifteen different combinations were generated with the option to drop scenarios wherein theory dictated a clearly superior option, for example, two options identical in all attributes except the discount. An opt-out option was included in each choice set. This allowed an individual to choose to opt-out of the service or decide not to go into a contract with a service provider. This eliminates the assumption that the presented choices represent the totality of options available to a respondent. The inclusion of this opt-out option helps improve the realism of the choice sets and thereby gives robustness in the results (Adamowicz & Boxall, 2001; Kontoleon & Yabe, 2003).

An example is illustrated in Figure 3.1.

Figure 3.1

An Example of the Choice Sets for the Choice Experiment Survey

Attributes	Choice A	Choice B	Choice C
Discount ($/acre)	3	5	Opt-out of service
Data sharing	Company choice	Anonymous	
Ownership	Retained	Retained	
Data transfer	Automatic	Manual	
Selection			

Respondents were asked to choose whichever contract they would agree to enter with a PA service provider. An additional question at the end of the choice set questions asked respondents in a matrix format the level of importance of each attribute when deciding on which contract to undertake. Figure 3.1 summarizes the attribute description and attribute levels used in the choice experiment.

Table 3.1

Attribute Descriptions, Levels and Coding Described in the Choice Experiment

Choice set attributes And the opt-out	Description	Levels	Coding
Discount	A discount from payment made by a farmer to the service provider for their services	$0 $1 $3 $5 $7	0 1 3 5 7
Data sharing	*Company Choice*: the company decides how they use a client's data without the need to make it anonymous or provide compensation	Company choice	1 or 0
	Anonymously Aggregated: data is shared with the service provider to provide the service and can be anonymously aggregated by the provider to improve their services	Anonymously aggregated	1 or 0
	Only Service: data is shared with only a service provider to provide information to the farmer	Only service	1 or 0
Ownership	*Retained Ownership*: data can be shared, accessed, and transferred by the farmer	Retained	1
	Not Retained: farmer has no ownership rights to the data	Not retained	0
Data transfer	This refers to how the data is uploaded for storage once collected	Automatic Manual	1 0
Opt-out	Decide not to sign a contract	Opt-out	2

3.2. Conceptual Framework

Respondents' decision to enroll in a particular contract given a set of contract options results from the comparison of the utility they derive from different hypothetical alternatives, with each alternative defined by its attributes and attribute levels. A discrete choice experiment framework assumes that each respondent would select the contract that provides the highest level of utility. The statistical analysis of a discrete choice experiment is based on McFadden's random utility model (McFadden, 1973). According to this theory, respondent i (where i =

1,……, n) will choose alternative j (where j = 1,……., m) in choice set C_t (where t = 1,….., T) if the alternative provides the highest level of utility among the alternatives presented in the choice set (Lancaster, 1966; McFadden, 1973). The utility is defined by an observable component determined by the attributes of the alternatives and respondent characteristics, and unobservable influences on their choices represented by error terms. Depending on assumptions regarding the distribution of error terms, different discrete choice models can be estimated. The basic discrete choice experiment model is referred to as the Conditional Logit model which is usually the starting point of many discrete choice experiment analysis. In the Conditional Logit model, it is assumed that the error terms are independently and identically distributed (IID) among alternatives and across the population and that irrelevant alternatives are independent (IIA). So, if A_{jit} is a dummy variable that takes the value of 1 if alternative j is chosen by respondent i in the choice set C_t, the probability associated to this choice according to is represented as follows:

$$\mathrm{P}\ (A_{jit} = 1) = \frac{\exp(X'_{jit}\beta)}{\sum_{m \epsilon C_t} \exp(X'_{mit}\beta)} \tag{1}$$

where X_{jit} represents the attributes of alternative *j* faced by respondent *I* and β is the vector of *k* preference parameters, which represents the average importance of each attribute of the contract on farmers' preferences (Kuhfuss, et al., 2016).

However, a conditional logit model is associated with series of restrictive assumptions that can lead to policy implication bias, especially when it comes to optimal implementation of results from a discrete choice analysis (Train, 2009). One such assumption is the IIA assumption and the premise that each respondent's preferences are homogenous. The IIA in individual choice theory sometimes referred to as Chernoff's condition states that if an alternative x is chosen from a set T, and x is also an element of a subset C of T, then x must be chosen from S.

What this means is that eliminating some of the unchosen alternatives should not have any effect when selecting x as the best option.

A model that relaxes some of these assumptions is the mixed logit model which is sometimes referred to as the random parameter logit model. It is one of the most widely used models for choice experiment analysis because it relaxes some of these assumptions. It allows for the capture of heterogeneity of farmer's preferences and allows for the accessing of the β_{ki} that are specific to each respondent and randomly distributed across the population, having a density function $f(\beta_k)$. According to (Kuhfuss et al., 2016), the conditional probability of $(A_{jit} = 1)$ on vector β_i which is the probability that a respondent *i* chooses alternative *j* in a choice set C_t is represented as:

$$\mathrm{P}\ (A_{jit} = 1 \mid \beta_i) = \frac{\exp(X'_{jit}\beta_i)}{\sum_{m\epsilon C_t}\exp(X'_{mit}\beta_i)} \tag{2}$$

The probability of observing the sequence of T choices by respondent *i* is:

$$\mathrm{P}(A_{ji1} = 1, \ldots\ldots, A_{jiT} = 1) = \int \prod_{t=1}^{T}\left(\frac{\exp\left(X'_{jit}\beta\right)}{\sum_{m\epsilon C_t}\exp\left(X'_{mit}\beta\right)}\right) f(\beta)|d\beta, \tag{3}$$

where $f(\beta)$ can be specified to be normal or lognormal: $\beta \sim N(\mu, W)$ or ln $\beta \sim N(\mu, W)$, respectively and the mean μ and covariance *W* are estimated by simulation (Train, 2009).

Because of the limitations posed by the conditional logit model, we estimated the individual-level parameters for each of the attributes using the mixed logit model as proposed by Revelt & Train (1999).

4. RESULTS

4.1. Sample Characteristics

The total number of useful responses as determined by completion of the survey and the choice experiment received was 107, which is equivalent to 4,815 observations (15 x 3 x 107). Of the total respondents, there were 25 females (23.4%) and 82 males (76.6%). That the majority of the respondents were males is expected based on the percentage of students majoring in Agricultural Economics or Agribusiness at NDSU (78.6%).

Descriptive statistics of the respondents are represented in Table 4.1. A majority of respondents have farming experience defined as experience farming or operating precision agriculture equipment.

Table 4.1

Sample and Population Characteristics

		Respondents in the sample
Gender (%)	Male	76.60
Course enrolled in (%)	AGEC 246	53.64
	AGEC 350	22.72
	AGEC 420	23.64
Experience	Have farming experience	75.45

According to the responses, 75.45% were raised on a farm/ranch, have farming experience, or have experience with precision agriculture tools while 24.55% were not raised on a farm, or do not have any experience with farming/ranching or precision agriculture.

Table 4.2 is a summary of additional responses in the survey.

Table 4.2

Summary of Technology Use

Precision Technology	Have used the technology (%)
Global positioning system	55.4
Yield monitoring and mapping	50.0
Soil sampling for management zones	31.8
Auto-steer guidance	60.0
Automatic section control	34.6
Satellite imagery	29.1
UAV or drone imagery	19.1
Variable rate seeding rate	30.0
Variable rate fertilizer/lime application	29.1
Variable rate crop protection products	15.4
Variable rate irrigation	2.7

The table above illustrates the respondents' responses to the question of precision agriculture technology use. Over 50% of the respondents make use of GPS which is a common tool that allows the user and machinery to identify their position on the farm which is essential for use of PAT. Fifty percent also make use of one of the major precision agriculture tools in the industry (yield monitoring and mapping). Sixty percent indicated they have used or are using auto-steer guidance which is a technology adapted by most precision agriculture manufacturing companies. A majority of precision agricultural equipment comes with an auto-steer guidance preinstalled. For every other precision technology reported in the survey, there was a record of low use.

Forty-four percent of respondents indicated they hire services such as custom hired drone operators to assist in collecting farm imagery or hiring a local crop scouting service to collect and analyze soil samples; 20% do not, and 36% are unsure. Another instance is where farmers can rent some of the equipment to use rather than purchasing or having them on the farm. A great example is variable rate fertilizer equipment.

Of the technologies mentioned, yield monitoring and mapping are reported to be used more for management decisions by the respondents (43.6% reported using the data for management decisions). Yield monitors help track yield histories and can be very useful in prescribing input use and practices which optimize yield for upcoming seasons. The adoption/use of these technologies found in the study were somewhat similar to a USDA survey on farm profits and adoption of precision agriculture completed in 2016 which indicated that nearly half of corn farms used yield monitors, guidance systems were the second-most frequently adopted PA technology and yield mapping was less commonly used (25 percent of corn farms) (Schimmelpfennig, 2016).

Among respondents of the study, 47.3% store data from the use of precision agriculture technologies, 16.4% do not store any data and 36.4% don't know if data is stored. Respondents who have experience farming or have experience using precision technology would have more knowledge about how their data is being stored as they make use of the technology. Very few respondents belong to any form of data service networks (9.2% belong; 18.1% do not belong, 36.4% do not know, and 36.3% did not respond to this question). Nine percent of respondents reported receiving incentives for providing their data to service providers or third parties; 22.7% have never received incentives; 31.8% were uncertain and 36.5% did not respond to the question. Nine percent of respondents also reported that third-parties other than their service providers or those authorized by them have access to their data; 21.8% did not share access; 32.7% did not know who had access; and 36.5% did not respond to the question. Few (12.7%) respondents were uncomfortable or slightly uncomfortable sharing their data with crop insurance agents; 27.3% were neutral, and 60% were comfortable or very comfortable. Twenty-nine percent of the respondents were either uncomfortable or slightly uncomfortable sharing their data with government representatives, 32.8% were comfortable or very comfortable and 38.2% were neutral. Few (10%) respondents were uncomfortable or slightly uncomfortable sharing their data with service providers; 20% were neutral, and 70% were comfortable or very comfortable. Seventy-two percent of respondents were uncomfortable or slightly uncomfortable sharing their data with third-party firms without an incentive, and 28% were either comfortable or very comfortable. Few (22%) respondents were uncomfortable or slightly uncomfortable sharing their data with third-party firms making profit if the service provider provided incentives and 78% were comfortable or very comfortable.

Ninety-eight percent of respondents indicated that the potential for data access by others has a high influence on PAT adoption. This means that data access by others has a vital role to play on the probability of PAT adoption. Most (98%) reported that the ability to transfer data from one service to another has high influence on their decision to adopt PAT. Ninety-six percent report that service providers making use of their data for profit has an influence on PAT adoption. And, finally, 98% reported that data protection from malicious activities has an influence on their adoption decision.

4.2. Empirical Results

To examine the factors that affect respondents' preferences for precision agriculture data management, a mixed logit model was used to identify factors with a significant influence on contract enrollment. We modeled first according to the attributes of the contract as sole factors of choosing a contract (Model 1) and then by introducing an interactive term (Model 2). Table 4.3 represents the results from the analysis for both models.

Table 4.3

Mixed Logit Model Estimates for the Choice Experiment

Variables	Model 1	Model 2
Discount	0.458***	0.458***
	(0.049)	(0.049)
Company choice	-1.298***	-1.316***
	(0.336)	(0.333)
Only for service	0.653***	0.649***
	(0.145)	(0.144)
Ownership	1.816***	1.791***
	(0.243)	(0.242)
Data transfer	0.341*	0.691***
	(0.147)	(0.202)
Experience * Data transfer		-0.488*
		(0.216)
SD		
Company choice	2.532	2.535
	(0.385)	(0.376)
Only for service	0.877	0.869
	(0.195)	(0.188)
Ownership	1.213	1.210
	(0.239)	(0.201)
Data transfer	0.722	0.706
	(0.128)	(0.127)
Log likelihood	-1414.856	-1412.1113
Chi^2	114.87	127.49
Observations	4815	4815
Number of respondents	107	107

Standard errors in parentheses
Significant levels: ****P* < 0.01, ***P* < 0.05, **P* < 0.1

Discount payment and the interaction variables in Model 2 are fixed while other variables are random (normally distributed). For both models, all contract attributes had a significant effect on choice. Both models show that the likelihood to participate decreases when offered the data sharing option as company choice compared to anonymously aggregated or only for service. This is expected because when compared to the base (anonymously aggregated), the company choice provides less utility (negative sign) to the respondents. In Model 2, an interactive term was introduced that considers the effect of the data transfer contract feature for those with and without experience with precision agriculture. The negative sign on the interactive term suggests that those with precision agriculture experience do not value automatic transfer as much as those without experience. This is an interesting result that begs further consideration. Those with experience and presumably experience with data transfer may value some attributes of manual transfer such as control over the data as it moves from the source of collection to the target of use. There is heterogeneity of preferences in this model because the standard deviations are quite large (far from zero).

To test the effects of a change in attributes to farmers' response to the contracts, we ran sensitivity analysis. We used scenarios where discount payments decreased or increased by 5% and 10% for both contracts.

Table 4.4

Sensitivity of Changes in Discount Payment Within Contract A: likelihood of accepting contract

	Original Margins	5% Decrease	10% Decrease	5% Increase	10% Increase
A	0.292	0.281	0.270	0.303	0.315
B	0.362	0.369	0.380	0.355	0.348
C	0.346	0.350	0.350	0.342	0.337

Result shown in Table 4.4 indicate that when discount payment in contract A is decreased, the likelihood of respondents selecting contract A decreases, and the likelihood of them selecting contract B or not taking any of the contracts increases. The reverse is the case when there is an increase in the discount payment.

Table 4.5

Sensitivity of Changes in Discount Payment Within Contract B: likelihood of accepting contract

	Original Margins	5% Decrease	10% Decrease	5% Increase	10% Increase
A	0.292	0.300	0.307	0.283	0.270
B	0.362	0.347	0.333	0.397	0.400
C	0.346	0.353	0.360	0.330	0.330

An increase in the discount payment in contract B results in an increase in the likelihood of respondents selecting the contract and a decrease in likelihood of selecting contract A or not taking any contract. A decrease in discount however has the reverse effect.

The results in Table 4.4 and Table 4.5 show that there is a significant impact of the amount farmers expect to receive for sharing their data to service providers. The higher the discount payment to the farmers, the more they are willing to sign the contracts. The other major factor that also plays an important role in farmers' decision is how data can be shared by the service provider. If the data is not used for service only or anonymously aggregated, but rather company chooses what they do with the data, they are more likely not to sign any contract.

Table 4.6

Sensitivity of Changes in Only for Service Data Sharing Option in Contract B: likelihood of accepting contract

	Original Margins	Included in B	Not included in B
A	0.292	0.235	0.342
B	0.362	0.465	0.279
C	0.346	0.300	0.379

The results in Table 4.6 illustrates that when a contract contains details of using respondents' data for providing services by service providers, the likelihood of selecting the contract increases and the likelihood decreases if the company rather chooses what to do with their data.

Table 4.7

Sensitivity of Changes in Data Ownership Attribute in Contract B: likelihood of accepting contract

	Original Margins	Retained in B	Not retained in B
A	0.292	0.125	0.435
B	0.362	0.624	0.142
C	0.346	0.251	0.423

The sensitivity results in Table 4.7 illustrate that when a contract allows for respondents to retain ownership of their data, there is an increase in the likelihood to select such contract, and a decrease if their ownership is not retained. This means that farmers are more likely to enter into precision agriculture contracts with service providers that allow them to move their data amongst various platforms.

Table 4.8

Sensitivity of Changes in Data Transferability Attribute in Contract B: likelihood of accepting contract

	Original Margins	Automatic in B	Manual in B
A	0.292	0.248	0.334
B	0.362	0.423	0.309
C	0.346	0.329	0.357

The results in Table 4.8 illustrates the sensitivity changes because of changes in data transferability in a contract. It shows that a change in data transferability from manual to automatic increases the likelihood of respondents to select such contract and decreases the likelihood of selecting other contract or not selecting any contract.

5. DISCUSSION AND CONCLUSION

5.1. Conclusions and Implications

Precision agriculture has been a major contributor to increased and improved production process over the years. The disposition of data generated from the use of this technology has been a hotly debated topic in recent times. One may wonder what farmers' perceptions are concerning their data management, what type of agreements they have when signing contracts with service providers and how true the service providers adhere to such contract agreements. This study was aimed at identifying major factors associated with data that explains farmers' decisions to sign a contract and to adopt in a precision agriculture technology.

A choice experiment survey was conducted among students in Agricultural Economics classes, a majority of whom were raised on a farm, have farming experience, and / or have experience with precision agriculture techniques. A total of 107 useful responses were received out of a total 279 students that comprised of students enrolled in courses in farm management (AGEC 420), agricultural finance (AGEC 246), and agricultural sales (AGEC 350). We selected four attributes to describe scenarios of a service provider contract including discount received from the service provider, data sharing options, ownership rights of data, and data transferability options.

All attributes considered in the choice experiment had significant effects on the likelihood of choosing a contract. The likelihood of choosing a contract decreases with a contract having data sharing option of company choice. This illustrates that farmers have more likelihood of entering a contract that does not give the service producer free reign over use of their data but rather prefer contracts where their data is used either as anonymously aggregated or used only to service the customer. The interaction of experience with data transfer also gave some interesting results that beg further consideration. Those with experience and presumably experience with data transfer may value some attributes of manual transfer such as control over the data as it moves from the source of collection to the target of use.

Another factor considered was the responsiveness of willing to engage in a contract to its attribute levels. This provides a better understanding of respondent sensitivity to attribute levels. Respondents were slightly responsive to small changes in the discount offered to them in the expected direction; higher discounts increased the utility of the contract and the likelihood they would enroll. Further, when ownership rights are retained, respondents are more likely to enter a contract. Respondents were relatively responsive to how data ownership is defined.

Implications can be drawn from these results. Firstly, when constructing a contract, service providers should take into consideration respondents' incentives, especially for their data generated on their farms as a result of using their services. Respondents in particular value ownership of their data including whether they can retain use of their data such as when they change service providers. It is useful for service providers to understand the value to customers associated with flexibility in data ownership. In other words, when developing a contract, firms should take into consideration the allowance for data ownership rights for their consumers, e.g., how data can be used on other platforms and with other service providers.

Secondly, when constructing contract terms, service providers should have clear statements about what access they have to the data generated and how the farmers can be compensated if there is ever a use of the data. Service providers have to earn the trust of respondents for respondents to engage in their farm data sharing. Wiseman et al. (2019) concluded that one key factor that hinders farmers from sharing their data is a lack of trust. They concluded that even in the presence of a contract, farmers lack trust in service providers to stay true on their agreement.

Finally, these results provide insights for policymakers. Currently there is no law that captures data privacy of farmers in the U.S. like we have in the health sector with HIPAA. Policymakers may consider development of laws that would help protect farmers data, as this may facilitate PAT adoption.

In the absence of these laws to cater for farm data privacy protections, a non-profit corporation is trying to address issues with farm data contracts and privacy. They are referred to as The Ag Data Transparency Evaluator and are backed by both farmer-led industry organizations and agricultural technology providers (ATP) such as American Farm Bureau Federation, American Soybean Association, Farmobile, John Deere, National Corn Growers Association, National Farmers Union, and Independent Data Management, among others. A project like this will help farmers understand the contracts they sign, and whether they should sign them. They will also have some trust in the providers since they are backed by some farmer organizations.

5.2. Limitations and Future Research

One limitation of the study is the respondents in the study. Respondents were students, and therefore do not well represent farmers in general. The population is specified, and it is an important population as it is comprised largely of students with direct farm experience who intend to return to agriculture (farm or ranch) or enter a closely related career (e.g., agricultural lending, service providers). They are also comprised of educated individuals who are more familiar with and likely to adopt technology. That said, they are not currently in general making the decisions on the farm operation and therefore expanding the study to include farmers throughout the region may have considerable value. Another limitation to the study was the inability to test for the independent and irrelevant alternatives in the choice experiment. One reason for this is that we did not present the scenarios of two options to the respondents before presenting an opt-out option. In the future research, we intend to fill this gap as we have data from a like-choice experiment conducted among the same population that does not present an opt-out option.

Finally, the model does not include many demographic variables. This also limited the interaction of some variables such as education level and age with the attributes presented in the choice experiment. These variables were not included in the current model because there is little variability among college students in these variables. However, they may be valuable for inclusion with a more general farmer survey. Another such characteristic not included is whether farmers are engaged in livestock production. We however intend to also fill this gap in future studies related to this topic.

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