# ADOPTION OF UNMANNED AERIAL SYSTEMS BY FARMERS IN TEXAS

A Thesis

by

MISTY VIDRINE MILES

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| Chair of Committee, | Tracy Rutherford |
| Committee Members, | Gary Briers |
| | Marco Palma |
| | Cristine Morgan |
| Head of Department, | Scott Schafer |

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# ABSTRACT

Though Unmanned Aerial System (UAS) technology is a promising tool that can aid farmers in production efficiency, little research has been found on the adoption/acceptance of this new technology in agriculture. The study aims to describe Texas farmers' perspectives regarding UASs and identify the attributes and applications most salient to each perspective. The study used a Q methodological approach to identify the different viewpoints held by 25 Texas crop farmers who reside in five different agricultural regions of the state. Rogers' Diffusion of Innovation theory and previous precision agriculture and UAS adoption studies were used as a conceptual framework to guide this mixed-method study. Identified perspectives include *high-tech harvesters* (innovators), *purposeful propagators* (early adopters), and *conventional cultivators* (laggards). Technical applications of detecting invasive insects and weeds and overall crop health emerged as the primary capabilities of interest for *high-tech harvesters* and *purposeful propagators,* accounting for the majority of the farmers in the study. The *conventional cultivators* showed little interest in technical applications but were interested in UASs reducing labor requirements. Findings suggest that future research and development continue to make the technology more user-friendly and economical while focusing on the application of using UASs to monitor fields proactively to prevent yield losses. Furthermore, steps should be taken to implement statewide trainings, geared towards *high-tech harvesters* and *purposeful propagators,* to educate them on this innovation in precision agriculture.

## DEDICATION

> And on the eighth day, God looked down on his planned paradise and said, "I need a caretaker." So God made a farmer.
>
> –Paul Harvey, *So God Made a Farmer*, 1978

Reflecting back on the two-and-a-half years spent on this degree, my time spent with the farmers was the most impactful and rewarding experience of all. A South Texas farmer shared with me something his father would say to him: "Our job is one of the few where you can make all the right decisions, perform on time, show up to work, stay late, put out max effort, have a great reputation, be fully informed about all the data and if God doesn't bless it with rain and good weather, it doesn't amount to anything." Then the farmer looked at me and said, "But every career you pick is just like that, it's just more obvious in ours."

This thesis is dedicated to the American farmer.

## ACKNOWLEDGEMENTS

I would first like to express my sincere gratitude to my former boss, Bob Avant. Not only did he make it possible for me to pursue this degree; he provided guidance and counsel throughout the entire process. I will forever be grateful for what he has done for me.

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# CONTRIBUTORS AND FUNDING SOURCES


## Contributors

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NOMENCLATURE

| | |
|---|---|
| ERS | Economic Research Service |
| FAA | Federal Aviation Administration |
| GCFI | Gross Cash Farm Income |
| NAS | National Airspace System |
| NASS | National Agricultural Statistics Service |
| NOTAM | Notice to Airman |
| PA | Precision Agriculture |
| UAS | Unmanned Aerial System |
| UAV | Unmanned Aerial Vehicle |
| USDA | United States Department of Agriculture |
| VRT | Variable Rate Technology |

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# CHAPTER I

# INTRODUCTION

Researchers continue to develop new technologies that promise to enhance the efficiency or productivity of agricultural production. With climate change threatening agriculture and global food security, farmers may be more accepting of new technologies in their farming operations. An agricultural management concept that is particularly open to new technologies and “offers a variety of potential benefits in profitability, productivity, sustainability, crop quality, food safety, environmental protection, on-farm quality of life, and rural economic development,” is commonly referred to as Precision Agriculture (PA) (Robert, 2002, p. 143). Pierre Robert, who is often regarded as the father of precision farming, stated that PA is not just the addition of new technologies but it is rather an information revolution, made possible by new technologies that result in a high level, a more precise farm management system” (Robert, 2002, p. 144). These technologies allow farmers to better steward their land and protect the environment by supplying them with spatial information to make informed, site and temporal-specific management decisions (Robert, 2002). Examples of PA technologies are yield-monitoring harvesters, tractor guidance systems, proximal and remote sensing instruments for soils and crops, and variable-rate application of inputs such as seeds, fertilizers, water, and chemicals (Schimmelpfennig, 2016).

Although PA technologies have been around since the 1980s and can lead to a larger return on investment when implemented, many PA technologies have had a slow rate of adoption in the U.S. (Robert, 2002; Schimmelpfennig, 2016; Tey & Brindal, 2012).

An emergent PA technology at the beginning of its diffusion process is Unmanned Aerial Systems (UASs). The term UAS includes the aircraft or unmanned aerial vehicle (UAV, commonly referred to as a drone), the ground control station, data links for communications, and sensors that detect spatial differences in the field (Braun, Friedewald, & Valkenburg, 2015; Shi, et al., 2016; Zhang & Kovacs, 2012). In comparison to other remote sensing platforms like ground vehicles, manned aircraft, and satellites, UASs have a flexible re-visit time, are more easily deployed, have a lower operation cost, can fly at lower altitudes, and collect images with higher resolution (Shafian et al., 2018; Shi, et al., 2016; Zhang & Kovacs, 2012).

A few examples of research studies using UAS technology to enhance crop production include, but are not limited to, measuring plant height and/or canopy cover and predicting yield (Jung, et al., 2018; Malambo, et al., 2017; Yu, et al. 2016). Furthermore, recent studies have used UAS technology to measure growth patterns in cotton (Chu, 2016) and sorghum (Shafian, et al., 2018), detect diseases such as sheath blight in rice (Zhang et al., 2018) and anthracnose in sorghum (Pugh, 2018), and identify different weed species in the field (Kunz, et al, 2017; Peña et al, 2013).

## Challenges

Challenges that may hinder the adoption of UASs in agriculture in the U.S. include media hype, complex data acquisition and analysis, and restrictive federal policy.

### Media hype.

In 2013, the Association of Unmanned Vehicles Systems International (AUVSI) released a U.S. economic report predicting UAVs would have an economic impact of more than $82 billion by 2025, and 80% of the commercial market would come from the agricultural sector (Jenkins & Vasigh, 2013). Furthermore, AUVSI noted, "the economic benefits to individual states would not be evenly distribute[d]" and estimated that Texas alone would account for $802 million, ranking it the third most profitable state in the U.S. (Jenkins & Vasigh, 2013, p. 3).

This economic prediction is contingent on several factors including the integration of UASs into the U.S. National Airspace System (NAS) and the overall acceptance of the technology. AUVSI stated the following regarding the acceptance of UASs:

> There are many factors that influence the rate at which new technologies are adopted and diffused into a society. We found considerable literature on this topic. The conclusion from the brief search we conducted is that new technologies are either accepted or rejected quickly. There is already a trade association that is doing outreach to the primary targets and showing products in their trade show(s). Because there is previous experience in this field, we reject

the notion that these products will not be adopted. However, it is suggested that a follow up to this study be conducted on adoption of new technology (Jenkins & Vasigh, 2013, p. 5)

Contrariwise, to AUVSI's brief search on diffusion and adoption rates, technologies are not always adopted or rejected quickly. In fact, "many innovations require a lengthy period of many years from the time when they become available to the time when they are widely adopted" (Rogers, 2003, p. 1).

Freeman and Freeland (2015) conducted a content analysis study of U.S. media reports from 2010-2014 to understand the potential, policy, and hype, or unrealistic expectations, that surround UASs in agriculture. Freeman and Freeland used the Gartner Hype Cycle as a framework to analyze 5,418 U.S. media reports and found hype was used to describe UASs in agriculture. The study noted that media often highlighted the success of UASs in countries with smaller agricultural fields than the U.S. and underestimated the cost of professional-grade UASs needed for a producer or commercial consultant. Additionally, this study states that media often exaggerated the user-friendliness of the technology and that most operators will lack the expertise needed to interpret the massive amount of data in the form of high-resolution imagery (Freeman & Freeland, 2015). A review of new technologies used to advance PA reinforced these findings stating, "despite…early research successes and the fact that UASs can be cheaply purchased and that their use in agriculture is highly publicized, there are so far few examples of UASs creating actionable decisions by farmers" (Murray, 2017, para. 6).

Freeman and Freeland (2015) predict that hype can work in favor or against UASs in agriculture. Hype can benefit UASs in agriculture by bringing awareness to the new technology, which may result in funding opportunities and favorable government regulations. Contrariwise, consumers may become discouraged when high expectations from the media are not met, which would result in a slow adoption rate (Freeman & Freeland, 2015).

**Data acquisition and analysis.**

Hunt and Daughtry (2017) reviewed the different agricultural applications of UASs that are specific to farmers and categorized them into three different groups, highlighting the economic and technical benefits of each. The three applications were "(1) scouting for problems, (2) monitoring to prevent yield losses, and (3) planning crop management operations" (Hunt & Daughtry, 2017, p. 5356-5357).

Hunt and Daughtry (2017) found the first category, scouting for problems, was essentially low risk, low reward and currently the most common application among farmers and farm consultants. Using UASs to scout fields for "draught stress, pests and diseases [is] faster and more timelier [sic]" than the current method of "manually 'walking a field'" (Murray, 2017, para. 5). Scouting is the cheapest application as it often uses a common RGB (red, green, and blue) or visual camera to collect images or video footage that does not require complex analysis. Once the problem area is spotted, the farmer will go to that area in the field and investigate further. However, scouting may not always catch the problems, giving farmers a false sense of confidence (Hunt & Daughtry, 2017).

The second category, monitoring to prevent yield losses, provides the farmer with a means to examine changes in his or her field over the growing season. This application is more proactive and offers early detection of problems in the field, which can prevent yield losses. However, data acquisition and analysis is complex and costly. Therefore, better methods for the "automation of image processing [are] essential to reduce costs of using UAS technology" (Hunt & Daughtry, 2017, p. 5361).

This study indicated that the third category, planning crop management, provides the most environmental and economic benefits to the farmer. This application provides farmers with decision support models to make informed management decisions regarding inputs like field nutrients and pesticides. However, it has the "highest costs for data acquisition and analysis" (Hunt & Daughtry, 2017, p. 5359). Furthermore, it requires farmers to have additional PA resources such as variable rate technology (VRT). This is a limiting factor as a large portion of U.S. farmers still has not adopted VRT technology.

The second and third categories offer more benefits to the farmer but require sensors that collect high-resolution images that are calibrated and analyzed before providing useful information to the farmers. "Without interpretation or analysis, the images are fascinating pictures" (Hunt & Daughtry, 2017, p. 5349).

Though complex data collection and analysis methods are no stranger to PA, one study (Kitchen, Snyder, Franzen & Wiebold, 2002) pointed to a lack of education and training coupled with the complex nature of PA as potential barriers to adoption. "The new management complexities that [PA] technology adds to an operation require expanded skills and tools not previously taught or provided from an educational standpoint" (Kitchen, 2002, p. 343).

**Policy.**

The first powered UAS was developed during World War I (Braun et al., 2015; Efron, 2015) and has had a military connotation for most of its existence. However, the technology's recent translation to the commercial and hobbyist contexts of the civilian world has caused federal agencies to implement new laws and regulations to keep the public safe. The Federal Aviation Administration (FAA) has taken an "incremental approach to safe UAS integration as the agency acquires a better understanding of operational issues such as training requirements, operational specifications, and technology considerations" (United States Department of Transportation (USDOT), FAA, 2015, para 4).

In the last three years, the FAA has improved the registration and certificate process required for non-recreational small UAS operators to enter the NAS. In January of 2016, the FAA opened an online registration system that allowed users to register their UAS online for a nominal fee of $5. Shortly after the system went live, the FAA boasted in a press release that nearly 300,000 owners had registered their UAVs in the first 30 days (USDOT, FAA, 2016c). In addition to the online registration, the Small Unmanned Aircraft Rule (Part 107) came into effect on August 29, 2016, and eliminated significant barriers for commercial use of small UASs (weighing less than 55 pounds) (USDOT, FAA, 2016d).

Though Part 107 significantly streamlined the process, commercial pilots, such as farmers, must obtain a remote pilot certificate and follow several operating rules. A few requirements include but are not limited to, only flying: in class G airspace (unless previously approved from air traffic control), during daytime hours, below 400 feet, and under 100 miles per hour. Additionally, the pilot may not fly over people and must keep the UAS in visual line-of-sight (USDOT, FAA, 2016b).

Continued modernization of existing rules, such as Part 107, will only further aid the diffusion process of UASs in agriculture. Examples include the ability to fly beyond visual line-of-sight (Turner, 2014) and after dark. Both of these abilities may enhance the role UASs play in PA.

**Summary**

Media hype coupled with empty promises regarding the price and capabilities of the technology and strict federal policy may result in farmers' becoming disillusioned with UASs. Additionally, the slow adoption of PA technologies in developed countries (Schimmelpfennig, 2016; Tey & Brindal, 2012) solidify the importance in identifying and understanding the underlying factors influencing farmers' adoption to insure that new technologies, like UASs, are successfully diffused.

**Purpose and Research Questions**

The purpose of this study was to classify and describe the types of Texas crop (cotton, grain, fruits, nuts vegetables, sugar, biomass etc.) farmers based on their views of UASs in agriculture and to identify what factors influence their perspectives. The research questions (RQ) for this study are adapted from a previous master of science thesis, Speaking their language: Communicating to the different perspectives of agriculture (Homeyer, 2016).

RQ1: What are Texas crop farmers' perspectives on UASs in agriculture?

RQ2: What are the psychographic and sociodemographic characteristics that make up each perspective?

# CHAPTER II

# LITERATURE REVIEW

Adoption studies on PA and UASs indicate several factors that may explain a farmer's rate of adoption. Tey and Brindal's (2012) meta-analysis of 10 PA adoption studies produced 25 analyses using an economic approach and found 34 significant factors that influenced the decision-making process of farmers in developed countries. The 34 factors were distilled into seven categories: "(1) socio-economic factors, (2) agro-ecological factors, (3) institutional factors, (4) informational factors, (5) farmer perception, (6) behavioral factors, and (7) technological factors" (Tey & Brindal, 2012, p. 721). The seven categories are presented below in Table 1.

Table 1

*Significant Factors Influencing Adoption of PA Technology*

| Categories | Variables | |
|---|---|---|
| Socio-economic factors | Operators age | Formal education |
| | Years of farming experience | |
| Agro-ecological factors | Land tenure | Full-owner farmers |
| | Farm specialization | Farm income/profitability |
| | Farm size | Soil quality |
| | Farm scales | Percentage of main crop in total farmland |
| | Variable fertilizer rates | |
| | Livestock sales | Percentage of farmland as county land area |
| | Debt-to-asset ration | |
| | Production value | Percentage of cropped land to total farmland |
| | Owned land minus rented land | Percentage of farmland as large farms |
| | Yield | |
| | Part-owner farmers | Off-farm employment |
| Institutional factors | Distance from a fertilizer dealer | Use of forward contract |
| | | Development pressure |
| | Region | |
| Informational factors | Use consultant | Perceived usefulness of extension services in implementing precision farming practices |
| Farmer perception | Perceived profitability of using precision agriculture | |
| Behavioral factors | Willingness to adopt variable-rate technology | |
| Technological factors | Yield mapping | Farm has irrigation facility |
| | Use of computer | Generated own map-based input prescription |

*Note.* Adapted from "Factors influencing the adoption of precision agricultural technologies: A review for policy implications," by T. S. Tey, and M. Brindal, 2012, *Precision Agriculture, 13*(6), p. 721.

Although this study identifies the factors that are most positively associated with PA adoption, it also notes previous studies have ignored the "informational, behavioral, and social aspects of decision making," which may shed light on the low adoption rate of PA in developed countries (Tey & Brindal, 2012, p. 727).

A 2016 study conducted by the United States Department of Agriculture (USDA) used a treatment-effects model to estimate factors associated with the adoption rates of three PA technologies used in U.S. corn and soybean farms (Schimmelpfennig, 2016). Major findings indicated adoption rates varied across the following three technologies: 1) GPS soil/yield mapping, 2) guidance systems, and 3) VRT. The study also found that larger corn farmers were more likely to adopt PA technologies compared to smaller corn farmers. Additionally, Schimmelpfennig (2016) found a negative adoption association when the farmer already had a large stock of machinery, "possibly because of higher overhead costs, and less flexibility in taking on new capital outlays" (Schimmelpfennig, 2016, p. iv). Furthermore, the study found farmers that are producing maximum yields for their land are less likely to adopt PA technologies. Additionally, the study found all three PA technologies had a small positive economic impact on corn production "which may explain the slow but steady growth in adoption" (Schimmelpfennig, 2016, p.1). Though this study primarily focused on corn, the results are helpful to inform future adoption research and supports the findings of Tey and Brindal (2012) that agro-ecological factors such as farm size, debt-to-asset ratio, and yield play a large role in the adoption of PA technologies.

Daberkow and McBride (2003) analyzed existing data from the 1998 USDA Agricultural Resource Management Study. The study used a logit model to examine the correlation between awareness of new technologies and adoption of new technologies in agriculture. They found that raising the level of awareness of new technologies would not increase the probability of adoption because farmers who would profit from such a technology are already aware of it. Additionally, results showed that PA stakeholders including Extension agents should target promotional information to farmers for whom the PA technology would be profitable. Agro-ecological, institutional, and technological characteristics were found to be important determinants of PA awareness and adoption. They included "farm size, computer literacy, full-time farming, farm type, and farm location" (Daberkow & McBride, 2003, p. 175).

In addition to the adoption studies on PA, a case study used Rogers' Diffusion of Innovation Theory to guide 18 qualitative interviews of opinion leaders in forest health regarding the application of UAS technology for enhanced forest management (Zimmerman, 2015). This study targeted program managers and data collectors from the nine Forest Service regions in the U.S. (Zimmerman, 2015).

After distilling the qualitative data from interviews, Zimmerman (2015) was able to define 17 themes related to the acceptance of UASs in forest health. Zimmerman found that participants were overall accepting of the new technology, in favor of the decreased risk of personnel aboard aircraft and other benefits, had concerns related to: privacy, collision/FAA oversight, and developmental status of the technology as well as fear of being replaced. Additionally, participants were both knowledgeable and in need of more information regarding UASs, uncertain of costs, and overall believed this technology would improve data quality in forest management (Zimmerman, 2015).

## Conceptual Framework

"Getting a new idea adopted, even when it has obvious advantages, is difficult" (Rogers, 2003, p. 1). To better understand the perspectives of Texas crop farmers about use of UASs in agriculture, the Diffusion of Innovation Theory (Rogers, 2003) will be used as a conceptual framework.

The Diffusion of Innovation Theory has roots in social psychology, rural sociology, and agriculture. Rogers (2003) defines diffusion as the "process by which an innovation is communicated through certain channels, over time, among the members of a social system" (p. 5). To diffuse new agricultural technologies like UASs, Extension agents and UAS stakeholders need to have a deeper understanding of the types of individuals to whom they are marketing. Furthermore, research and development strategies may be enhanced by gaining a better understanding of the ideal perceived attributes and technical applications of an innovation (Rogers, 2003).

Before adopting or rejecting an innovation, every individual must go through the innovation-decision process in which an individual "passes from first knowledge of an innovation, to forming an attitude toward the innovation, to a decision to adopt or reject, to implementation of the new idea, and to confirmation of this decision" (Rogers, 2003, p. 170). Rogers found that if you plot adopters over time, the adoption process usually falls in a normal, bell-shaped curve. See Figure 1.

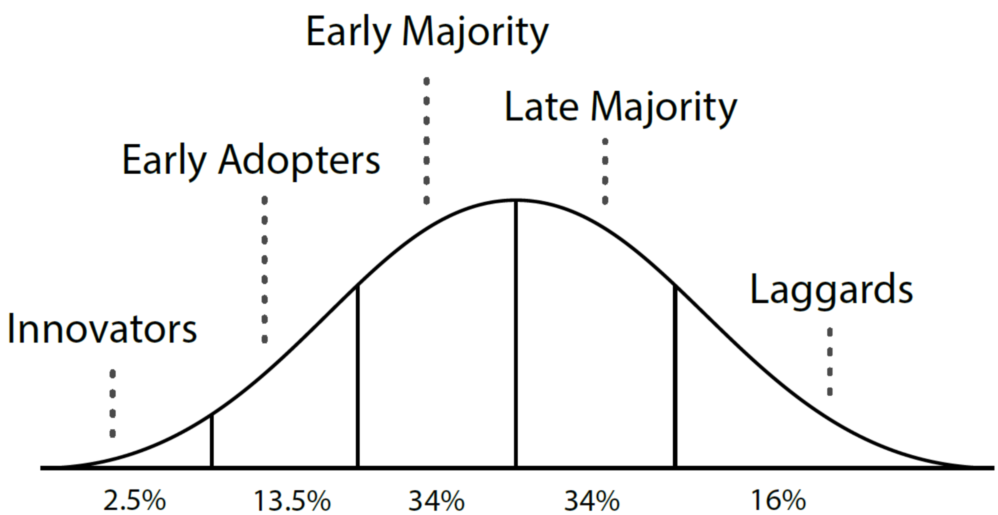


*Figure 1*. Adopter categorization on the basis of innovativeness. Adapted from *Diffusion of Innovations* (5th ed.). (p. 281), by E. M. Rogers, 2003, New York, NY: Free Press.

To make comparisons between groups possible, Rogers developed five adopter categories: innovators (2.5%), early adopters (13.5%), early majority (34%), late majority (34%), and laggards (16%). *Innovators* are venturesome risk takers who are eager to adopt new technology. *Early Adopters* are more selective about their adoptions and are looked at as opinion leaders in their social system. *Early Majority* takes their time before adopting and will only adopt if they understand how the new technology will benefit them. *Late Majority* are skeptical adopters and tend to adopt due to peer pressure and economic necessity. *Laggards* are resistant to new technologies and base their decision on the past (Rogers, 2003, p. 280-285).

Additionally, Rogers found the rate of adoption can be attributed to five variables; 1) perceived attributes of innovation, 2) type of innovation-decision, 3) communication channel, 4) nature of the social system, and 5) extent of change agent' promotion efforts. See Figure 2.

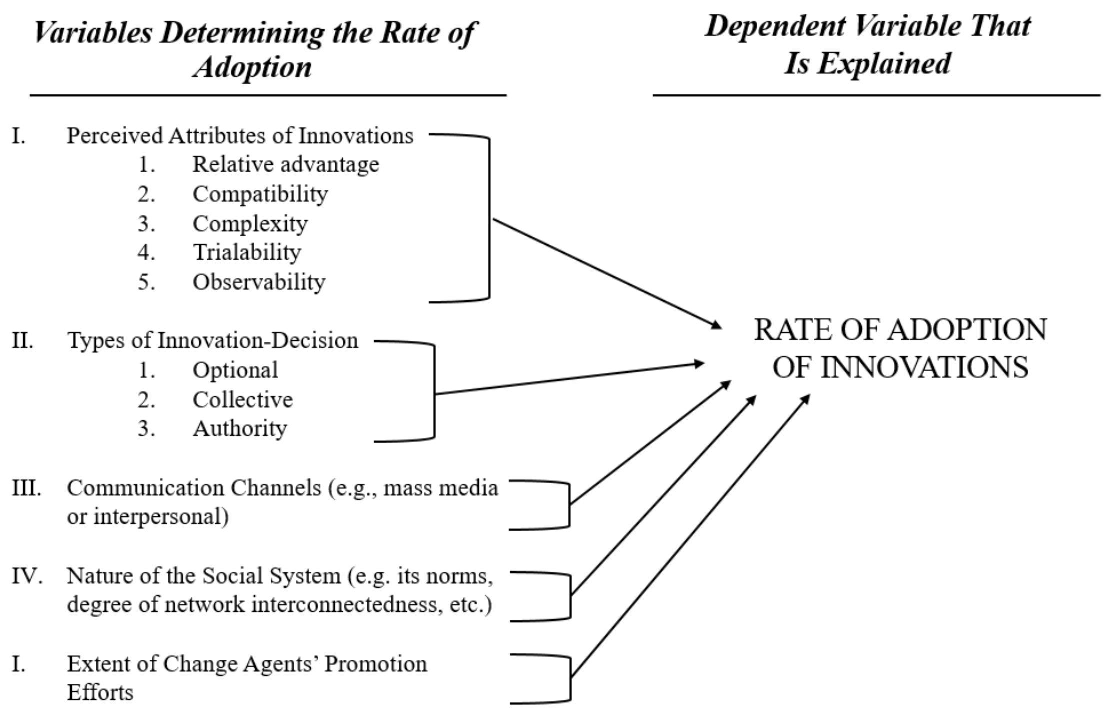


*Figure 2.* Variables determining the rate of adoption of innovations. Adapted from the *Diffusion of Innovations* (5th ed.). (p. 222) by E. M. Rogers, 2003, New York, NY: Free Press.

Of these five variables, past research indicates that an innovation's perceived attributes, specifically, relative advantage and compatibility, explain a majority of variance in the innovation's rate of adoption. "Innovations that are perceived by individuals as having a greater relative advantage, compatibility, trialability, and observability, and less complexity will be adopted more rapidly than other innovations"

(Rogers, 2003, p. 16). Additionally, Rogers posited that an investigation of the ideal perceived attributes of an innovation, known as acceptability research, can guide future research and development activities (2003).

**Q Methodology**

William Stephenson (1935) developed the Q method in 1935 for psychologists to study the human personality. This method is unique because it "provides a means for analyzing the phenomenological world of the individual (or of small numbers of individuals) without sacrificing the power of the statistical analysis" (Stephen, 1985, p. 193).

Q methodology is a promising technique for social scientists interested in the "elusiveness of subjectivity" and is relevant to diverse disciplines such as "psychology, social psychology, sociology, and political science" (McKeown & Thomas, 1988, p. 7). Furthermore, a recent philosophical study was conducted to "establish a contextual and philosophical understanding of Q methodology and articulate its uses in agricultural communications" (Leggette & Redwine, 2016, p. 59). This study noted, "the practice of agricultural communications rests largely on the subjectivity behind producers' and consumers' perceptions, behaviors, feeling and values" (p. 64). Therefore, the Q method "would provide researchers with another research method to further their understanding of agricultural stakeholders and constituents" (Leggette & Redwine, 2016, p. 65).

Q studies have their own unique terminology. For example, the participants are known as the P set (Watts & Stenner, 2012). The first step in conducting a Q study is to identify the concourse, or "flow of communicability surrounding any topic" (Brown, 1993, p. 96). Once identified, a Q set, or set of items that represent the concourse, is developed. The Q set is used in combination with a forced distribution form board to collect data from the P set in the form of a Q sort interview (Watts & Stenner, 2012). After the data is collected from the P set, factor analysis is used to identify the patterns of similarity present. The patterns represent distinct viewpoints and when combined with qualitative data aid in a holistic understanding of different types of people (Watts & Stenner, 2012).

**Summary**

The slow adoption of PA technologies has "attracted a number of domestic studies to identify the factors underlying adoption in varied forms" (Tey & Brindal, 2012, p. 726). Adoption studies of PA have indicated there are several factors that may explain a farmer's rate of adoption (Daberkow & McBride, 2003; Schimmelpfennig, 2016; Tey & Brindal, 2012). Tey and Brindal (2012) noted the social side of adoption has been "largely ignored" and suggested a different approach be taken to "understand these diverse considerations" which may or may not lead to adoption (p. 727). The Zimmerman (2015) study on the adoption potential of UASs aided in understanding the unique perspectives of opinion leaders in the U.S. forest management industry, finding that participants had a high level of interest in UAS technology but had concerns related to privacy and costs.

As UAS technology in agriculture is in its infancy, there is little research on behavioral and social aspects of its diffusion process. To understand potential UAS consumers and their preferences related to UASs, this study utilized Q methodology to holistically analyze Texas crop farmers. Additionally, this study relied on the information and factors gathered from the aforementioned PA and UAS adoption studies while focusing on the technical applications (Hunt & Daughtry, 2017), perceived attributes of UASs, and the adopter categories (Rogers, 2003) of Texas farmers. This conceptual framework facilitates a better and more holistic understanding of farmers' viewpoints and may enhance diffusion and guide future UAS research and development activities.

# CHAPTER III

# METHODS

UAS technology may aid farmers by increasing profits and reducing inputs, however, it is not clear if farmers are willing to adopt the new technology. Obtaining a deeper understanding of Texas crop farmers opinions related to UASs in agriculture through an inductive and Q methodological approach may enhance the diffusion process.

I chose an inductive approach because “it is more likely to identify the multiple realities to be found in … data” (Lincoln & Guba, 1985, p. 49). Q methodology pairs nicely with the inductive approach because it allows researchers to “reveal a series of shared viewpoints or perspectives pertaining to [a] topic of interest” (Watts & Stenner, 2012, p. 52). These viewpoints are often called factors (Brown, 1980; Stephenson, 1935). This section will discuss participant identification, instrument development, data collection, and data analysis.

**Participant Identification - P set**

Texas is a viable population for a UAS adoption study because agriculture plays such a large role in the state’s economy. According to the 2012 agriculture census data, Texas leads the nation in number of farms, with over 248,000 farms covering 130 million acres and sold over $25 billion in agricultural products. Over 104,000 of the farms (42.2% of total farms in Texas) harvested crops, (USDA, National Agricultural Statistics Service (NASS), 2014a).

Texas is a large state with a wide range in climate, soil types, precipitation, and geography. Tey and Brindal's (2012) study noted that several agro-ecological factors, "sometimes known as 'farm biophysical factors'" help explain the adoption of PA and "soil quality [type/variability] has been found to be the single significant factor" (p. 722). Additionally, this study noted that farm region, which "describes the general location of farms" can be used to "capture data on natural resources (e.g. soil fertility, climate, and rainfall)" (Tey and Brindal, 2012, p. 723). Because of the important role climate factors play in agricultural production practices, I included farmers from different regions of the state. To do this, I developed five target regions based on cropland density, irrigation, and major agricultural regions to insure the farmers were diverse in agro-ecological factors. Cropland irrigation, density, and agricultural region data were retrieved from USDA, NASS (2017b, 2018a) and Texas A&M AgriLife Research (n.d.) (Appendix A).

The five target regions of the study were labeled High Plains, Northeast, Southeast, Central, and South Texas. Figure 3 shows the geographic locations of the 25 participants and their respective regions. As aforementioned, a Q study requires only "enough subjects to establish the existence of a factor for purposes of comparing one factor with another" (Brown, 1980, p. 192). This differs from the traditional R methodology where "a large number of people [are] given a small number of tests…." Q methodology "give[s] a small number of people a large number of tests or test items" (Stephenson, 1935, p.18-19). Brown (1980) noted that this has been a "point of contention" in the past for those who are accustomed to R methodology and are concerned about generalizability (p.191). However, Q methodologists "look to a different kind of generalization, which focuses on concepts or categories, theoretical propositions and models of practice" (Watts & Stenner, 2012, p. 73). Additionally, Watts and Stenner (2012) recommend using "a number of participants that is less than the number of items in your Q set" (p. 73). This study meets those requirements.

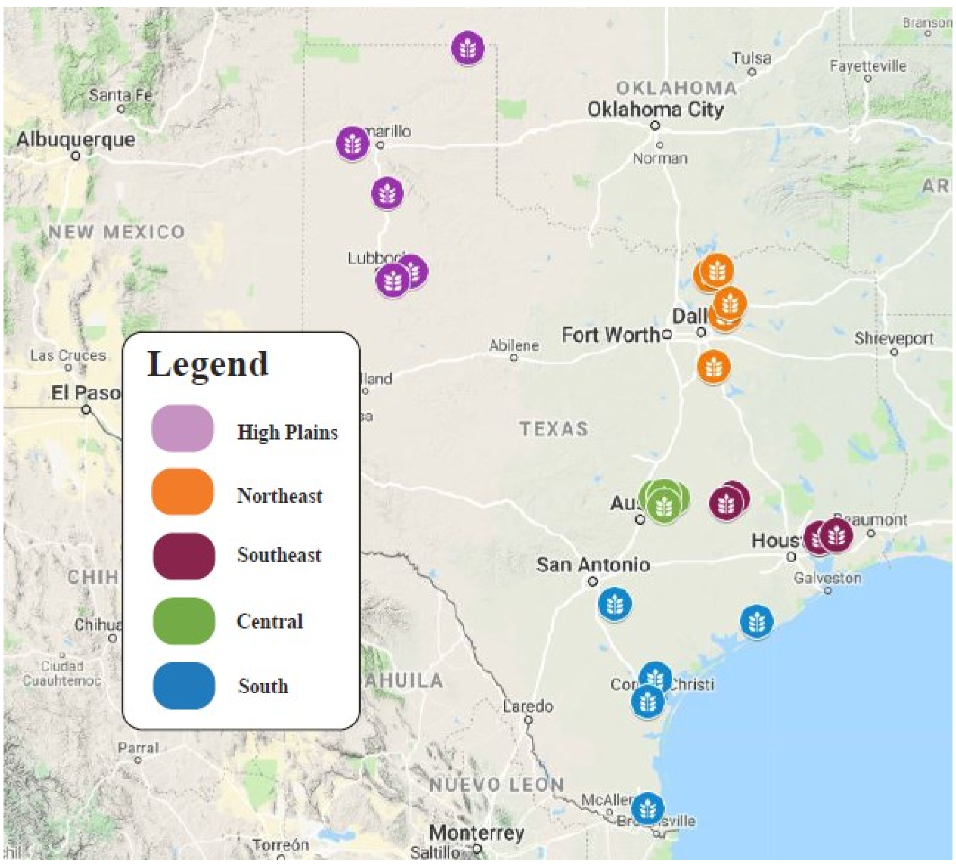

*Figure 3.* Map of Texas showing the geographic location of the 25 farmers. Google. (n.d.).

The Q method is used to "study intensively the self-referent perspective of particular individuals in order to understand the lawful nature of human behavior" (McKeown & Thomas, 1988, p. 36). To develop a P set with "a defined viewpoint to express… and to avoid an unduly homogenous participant group" (Watts & Stenner, 2012), I employed a purposive, snowball sampling technique. A purposive sampling technique is used to "maximize the investigator's ability to devise grounded theory that takes adequate account of local conditions, local mutual shapings, and local values (for possible transferability)" (Lincoln & Guba, 1985, p. 40). A snowball sampling technique is used to "identif[y], in whatever way one can, a few members of the phenomenal group one wishes to study" then "these members are used to identify others, and they in turn others" (Lincoln & Guba, 1985, p. 233). I started this phase by reaching out to AgriLife Research and Extension colleagues who had connections in each of the five target regions and asked them to pass my contact information along to Texas crop farmers. Identifying five crop farmers in each of the five agricultural regions satisfied the aim to obtain a varied P set with defined viewpoints (Watts & Stenner, 2012).

A majority of the agriculture census demographic data (gender, age, farming experience, GCFI) does not distinguish between crop and livestock farmers. However, 84% of principal farm operators (crop and livestock) in Texas are men and 15% are women, (USDA, NASS, 2014C). Additionally, 94% of Texas farmers are white (USDA, NASS, 2017a). Similar to the general Texas population of famers, this study consisted of a majority (n=24) male, (n=25) white farmers. Farmers' ages ranged from 27-77 years old (Table 2).

Table 2

*Demographics*

| Characteristic | n |
|---|---|
| Gender | |
| Male | 24 |
| Female | 1 |
| Race | |
| White | 25 |
| Age | |
| 27-40 | 10 |
| 41-64 | 6 |
| 65 and over | 9 |

### Instrument Development

To collect Q sort data, I identified a concourse, generated a Q set, created a Q sort form board, and developed a pre-sort survey.

#### Concourse.

A concourse is commonly developed from qualitative data such as interviews, commentaries, television, articles, etc. (Brown, 1993). To identify the concourse for the study, I consulted literature on adoption studies (Daberkow & McBride, 2013; Tey & Brindal, 2012; Turner, 2014; Zimmerman, 2015). Additionally, I conducted 10 semi-formal interviews of Texas crop farmers and cattle ranchers to understand their adoption process and their attitude toward UAS technology. Institutional Review Board (IRB) approval from Texas A&M University (IRB2013-0109D) was obtained for the concourse interviews.

The interview process was guided by naturalistic inquiry, “an approach to understanding the social world in which the researcher observes, describes, and interprets the experiences and actions of specific people and groups in societal and cultural context” (Armstrong, 2012, p. 2). This type of “contextual inquiry demands a human instrument” (Lincoln & Guba, 1985, p. 187); therefore, it is important to acknowledge the perspective from which I gathered these data. I am a Texas A&M AgriLife Research employee and I serve as project manager for the Texas A&M UAS Project for Precision Agriculture and High Throughput Phenotyping. This multidisciplinary project started in 2014 with approximately 20 faculty members and quickly grew to more than 60 faculty members and included seven AgriLife Research and Extension centers across the state. Research interests include, but are not limited to plant phenotyping, insect, weed, and disease detection, livestock and wildlife monitoring, rangeland management, and air quality. My background and interest in agriculture and UAS technology is essential because “it is unthinkable to study diffusion without some knowledge of the social structures in which potential adopters are located” (Rogers, 2003, p. 25).

Because conventional criteria for trustworthiness are inconsistent with the axioms and procedures of naturalistic inquiry” (Lincoln & Guba, 1985, p. 42), these terms are replaced with the following: “‘credibility” (in place of internal validity), “transferability” (in the place of external validity), “dependability” (in the place of reliability), and “confirmability” (in the place of objectivity)” (p. 219). These terms and the techniques used to operationalize them will be discussed throughout this Methods section.

The 10 concourse interviews took place between October 2017 and June 2018. Similar to the P set, I used purposive, snowball sampling by reaching out to participants at agricultural conferences/events in Texas and asking them to participate in the study.

After the farmer/rancher agreed to participate in the interview process, I followed the concourse interview protocol (Appendix B) and asked the participant if he or she was willing to participate in a face-to-face or phone interview. Before each interview, I went over the informed consent (Appendix C) document and asked for permission to record the interview for transcription purposes. Lincoln and Guba (1985) recommend audio or video recording, along with field notes, as recordings obtain the "greatest fidelity" (p. 240). If the participant did not feel comfortable signing the consent form, he or she was not included in the study.

Interview questions were derived from the aforementioned adoption studies (Turner, 2014; Zimmerman, 2015) and Rogers' Diffusion of Innovation Theory (2003) and can be seen in Appendix D. Open-ended questions were used to gather an "appropriate base of information" or "thick description" (Lincoln & Guba, 1985, p. 125). Thick description is important in a naturalistic study to provide enough context to make transferability possible (Lincoln & Guba, 1985). I also referred to UASs as the more common name, "drone," in all interviews to avoid any confusion. Interview questions were pilot tested at two agriculture conferences before the 10 concourse interviews.

The concourse interview phase was completed once I reached data saturation, meaning I was no longer recording new ideas from participants regarding the adoption process of UASs. (Lincoln & Guba, 1985). All consent forms, field notes, transcripts, and recordings were given a numerical code to preserve confidentiality. For example, the first participant was coded as R001 because he was a rancher (R). The only people who had access to these documents were my committee chair and I.

Though similar, the applications of UAS technology vary between farmers and ranchers. Following the naturalistic sampling recommendations in which a researcher continues to refine and focus the sample during the study (Lincoln & Guba, 1985), I chose to narrow my scope by eliminating ranchers. Narrowing the scope allowed me to focus on the technical applications and perceived attributes of UASs specific to crop farmers.

**Q set.**

The Q set is a set of items that can be thought of as a sample derived from the concourse (Watts & Stenner, 2012). Stephen (1985) notes that "virtually anything that can be lifted can be sorted (e.g. photographs, newspaper clippings, drawings, essays, objects, or inter-office memos). Using the naturalistic data processing technique, the transcripts from the concourse interviews were coded and unitized to develop the Q set statements. Lincoln and Guba (1985) recommend separating the transcripts into small but meaningful stand-alone ideas or units. After the transcripts were unitized, I imported each statement into an Excel® document and associated them with the code given to the participant as well as its own unique card number. For example, when I asked the first participant if he believed that UASs would be widely accepted in agriculture one day, he responded: “Oh yeah. I definitely think so. Plus you know, basically, we [farmers and ranchers] like toys anyway so that's just adding to the collection” (R001_17). This statement was coded as R001_17 because he was a rancher (R), the first participant (001), and this was the 17th unit in the concourse.

After the transcripts were unitized, I used the mail merge feature in Word® to import the statements and codes into a 5.5” x 4.25” index card template. The index cards were printed on a standard size sheet of perforated cardstock. Each sheet held four index cards that I later tore apart. Having each unit on a separate index card allowed for systematic categorization (Lincoln & Guba, 1985).  After the first five interviews, I sorted the cards into three themes with 12 subthemes. Lincoln and Guba (1985) add that during the constant categorization process, there will be a “shift from a more or less intuitive look-alike or feel-alikeness judgment to a judgment of whether a new incident exhibits the category properties that have been tentatively identified” (Lincoln & Guba, 1985, p. 343).  When this occurs, categories may be added or redefined. After the last five interviews were completed and transcribed, the categorization process led to the development of seven major themes with 23 subthemes.

In addition to these themes from the interviews, I considered the PA and UAS adoption studies literature when developing the general statements for the Q set. For example, statements were included to identify the adopter categories, perceived attributes of the innovation (Rogers, 2003), and preferred technical applications (Hunt & Daughtry, 2017). I was also careful to select layman terms to insure a wide variety of people with different educational backgrounds would understand the statements. This process generated 52 statements.

Stephen, (1985) stated that in Q methodology, “the goal should be to develop a well-rounded set of items which provides a fair representation of the larger, theoretical set of all possible items which relate to the dimension being studied” (p. 194). To insure I had the most diverse set of statements and to establish credibility, I “solicit[ed] agreement (including correction and expansion)” of the statements from the participants. This technique is known as a member check, the “most crucial technique for establishing credibility” (Lincoln & Guba, 1985, p. 236 & 314). Additionally, I secured feedback from a fertilizer company employee, an agriculture UAS manufacturer sales representative, and an organic farmer. Furthermore, the Q set was subject to peer debriefing, (Lincoln & Guba, 1985) another technique used to improve credibility, by submitting the statements to my research committee and several Texas A&M AgriLife Research staff and faculty members “for their critical appraisal” (Stephen, 1985, p. 195).

The number of items in a Q set largely depends on the subject matter but a sample of 40-80 has become the norm among Q methodologists (Watts & Stenner, 2012). Through this process, I condensed and revised the original 52 statements into 42 Q set statements (Table 3). An audit trail of field notes, recordings, transcriptions, unitization, category themes, and interpretations was used to establish dependability and confirmability (Lincoln & Guba, 1985).

Table 3

*Q Set Statements*

| # | Statement |
|---|---|
| 01 | My operation could be more efficient with drones. |
| 02 | I question whether drones could hold up to my work conditions. |
| 03 | I am not interested in drones because they have more capabilities (or functions) than I need. |
| 04 | A drone has to be affordable for me to buy one. |
| 05 | I need to know that drones will provide a good return on my investment before I buy one. |
| 06 | I need to see drones working properly before I will buy one. |
| 07 | Before I buy a drone, I must have assurance that technological upgrades will be handled routinely. |
| 08 | It should be clear that the drone will benefit me in my specific operation before I buy one. |
| 09 | I am more likely to buy a drone, if my peers have one. |
| 10 | I will not buy a drone only because many or all of my peers have a drone. |
| 11 | I must have assurance that drones will not become obsolete quickly due to technological advancement before I buy one. |
| 12 | I will buy a drone, only if it is easy for me to use. |
| 13 | I will buy a drone if it will keep me competitive in my operation. |
| 14 | I will buy a drone if it reduces my labor requirements. |
| 15 | I will buy a drone to have the latest and greatest "toy" on the market. |
| 16 | If I buy a drone, I will have to buy additional resources to support the drone. |
| 17 | I will buy a drone to be one of the first people to have one. |
| 18 | I will wait until drones have been on the market a little while before I consider buying one. |
| 19 | I will buy a drone if my peers are having success with theirs. |
| 20 | I can only see the younger generation using drones in agriculture. |
| 21 | I will buy a drone so I am not the only person who doesn't have one. |
| 22 | I won't buy a drone because I don't need one. |
| 23 | I am supportive of people who use drones in agriculture |
| 24 | I figure out how to use new technologies like drones, on my own. |
| 25 | The sales representative usually shows me how to use new technologies like drones. |
| 26 | I usually catch on to new technologies after being shown how to use them. |
| 27 | I can usually figure out how to use new technologies on my own after a little while. |
| 28 | I usually learn how to use new technologies by researching online. |

Table 3 Continued

| # | Statement |
|---|---|
| 29 | I will adopt a drone if it is a requirement of my job. |
| 30 | A drone service would be beneficial to me. |
| 31 | I would prefer to buy my own drone rather than use a drone service. |
| 32 | Receiving actionable data from the drone is important to me. |
| 33 | Using a drone in my operation is only beneficial to me if it will provide me with more than just a pretty picture. |
| 34 | I am interested in using drone imagery to detect invasive insects and weeds. |
| 35 | I am interested in using drones to spray pesticides in my fields. |
| 36 | I am interested in using drone imagery in conjunction with variable rate technology. |
| 37 | I am interested in using drone imagery to estimate yield. |
| 38 | I am interested in using drones to assess crop health. |
| 39 | I am interested in using drones to assess soil health. |
| 40 | Before subscribing to a drone service, I would need to know how quickly they will provide me with actionable data. |
| 41 | I would consider trying out a drone service before purchasing my own drone. |
| 42 | Privacy is a concern of mine as it relates to drone technology. |

**Q sort form board.**

The Q sort board forces the participant to rank all the Q set statements into a normalized bell curve. The forced or fixed distribution of the normalized bell curve requires that a specific number of statements be placed above "each point along the scoring continuum" (Brown, 1980, p. 288). Differing distributional schemes do exist; however, Brown (1980) concludes that "distribution effects are virtually nil" because the factors are affected by "the patterns of item placement" and "the same results occur whether or not intervals are assumed to exist" (p. 289). The forced and symmetrical distribution scheme "numbered from a positive value at one pole, through zero, to the equivalent negative value at the other pole" was chosen for the study, because it "represents the most convenient and pragmatic means of facilitating the item ranking process" (Watts & Stenner, 2012, p. 78).

Another factor that was considered when developing the Q sort form board was the range and slope of the distribution. Because 42 statements were generated for the Q set, Brown (1980) recommends an 11-point distribution (-5 to +5). In reference to the kurtosis, or flatness and steepness of the distribution, I chose a platykurtic, or flattened, distribution because I believe this topic is straightforward and though UASs are an emerging technology, it is an addition to the pre-existing PA technology suite. Furthermore, Watts and Stenner (2012) note that this distribution offers participants "to make fine-grained discriminations at the extremes of the distribution" allowing researchers to "maximize the advantages of our participants excellent topic knowledge" (p. 81).

I designed the 42-cell form board (Figure 4) in Adobe InDesign® with "most like me" printed on the furthest left side, "neutral" printed in the middle, and, "least like me" printed on the furthest right side. Then, I printed the form board on a large poster board and each Q set statement was printed on index cards with its corresponding random number on the back. The form board and cards were laminated to insure the instrument was durable to allow data collection to take place outside at the farm, barn, shop, etc.

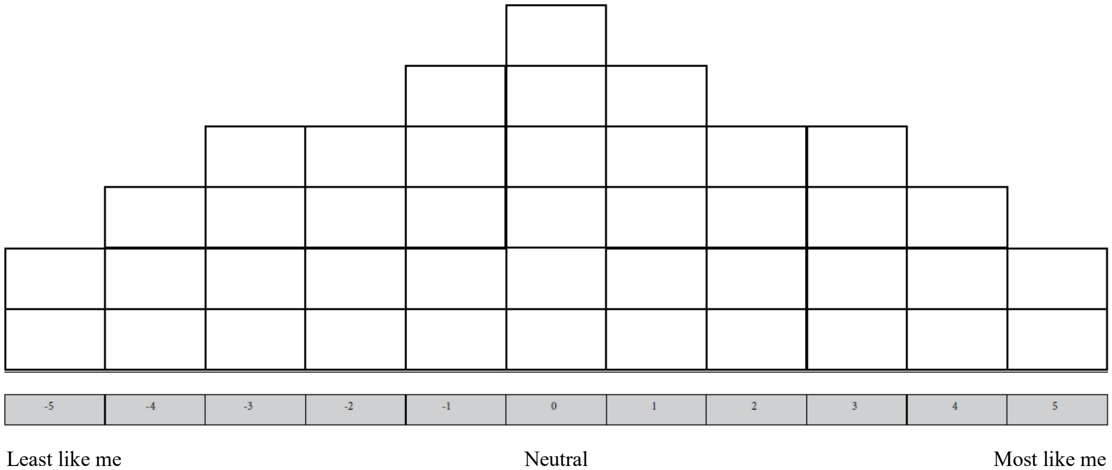


*Figure 4.* Q sort form board.

**Pre-sorting survey.**

To collect sociodemographic information about each participant that may influence his or her viewpoints, Watts and Stenner (2012) recommend asking a few open-ended questions before the Q sort. The open-ended questions allow for “more useful and information-rich [responses] than the mere tick of a box” (Watts & Stenner, 2012, p. 75). Based on the knowledge obtained from the previously discussed literature, I developed a short pre-sort survey (Appendix E) to collect the following: zip code, age, gender, race, education level, years in farming, number of acres in farming operation (crops only), irrigation techniques, PA technologies, crops, and gross cash farm income (GCFI). The study used ERS’s standard typology of farms by GCFI, defining small farms as those earning less than $350,000, medium farms as those earning between $350,000 and $999.999, and the large farms as those earning $1 million or more (Hoppe & MacDonald, 2013).

**Data Collection - Q sort**

I obtained IRB approval from Texas A&M University (IRB2018-1411M) for the Q sort interviews. The interviews took place in the winter months between December 2018 and February 2019, as to not interfere with the majority of the planting and harvesting schedules of Texas farmers (USDA, NASS, 2018b). The majority of the interviews took place at the farmer's homestead (house, barn, shop, etc.). It was important for the interviews to take place in a "'natural' setting because phenomena of study, whatever they may be—physical, chemical, biological, social, psychological—take their meaning as much from their contexts as they do from themselves" (Lincoln & Guba, 1985, p. 189).

After each participant was identified, I followed the Q sort interview protocol (Appendix F) and asked the participant if he or she was willing to participate in a 20-30 minute, face-to-face interview about the adoption of UASs in agriculture. Once the participant agreed, I began arranging a trip to the specific region of that farmer.

As UAS technology is still in the early stages of diffusion, I read the following brief introduction before each interview to insure all participants had a basic understanding of the technology.

> "In recent years, drones, have become a buzzword in the agricultural industry. Drones allow farmers and crop consultants to systematically monitor fields for drought stress, pests, and diseases. This new technology is said to be timelier, more affordable, and produces higher resolution imagery than other remote sensing platforms like manned aircraft, satellites, and ground vehicles."

During the interview process, I followed the same consent, audio recording, and confidentiality procedures as previously explained in the qualitative interview process used to create the concourse. A copy of the consent form can be seen in Appendix G. Before the Q sort process, I asked each respondent a few agro-ecological and sociodemographic questions from the pre-sort survey and recorded their answers.

After the survey was complete, I handed each participant the stack of Q set statement index cards and asked him or her to read them once before placing them in three different stacks: a) most like me, b) neutral, and c) least like me (Brown, 1993; Watts & Stenner, 2012). Next, I asked the participants to place each statement on the form board, starting with one side, until each cell was filled with a statement. While the participants were sorting the cards, I asked them to explain how and why they were sorting so I could take notes (Watts & Stenner, 2012). Once the participant completed the sort, I engaged him or her in a conversation about the two statements in the furthest left (least like me) and the furthest right (most like me) columns (Watts & Stenner, 2012). To insure data were recorded accurately, I wrote each number down on a blank Q sort form board sheet (Appendix H) and took a photo with my phone. All data were collected and recorded using a coding system to ensure confidentiality. The first letter in the code represented the participant's region. For example, respondent one was coded as C01 because he was from Central Texas. Upon completion of the 25 Q sort interviews, I mailed thank you letters to all participants.

**Data Analysis**

The R technique “is traditionally thought of when discussing factor analysis” (VandenBosch, 2001, p. 6) which puts an emphasis on the variables and not the individuals. This limitation was “Stephenson’s initial and primary motivation for developing Q methodology” (Watts & Stenner, 2012, p. 12). According to Brown (1980) and McKeown and Thomas (1989), several researchers are under the misconception that the Q technique is merely the transpose of the R matrix. Simply transposing data collected using R methodology would fail because R data matrices usually measure variables with different units (e.g. sex, age, race, etc.). Contrariwise, to employ Q methodological factor analysis, data must be collected under “the very special condition of universality of measuring unit i.e., when the same unit (e.g. the inch) is common to both rows and columns” (Brown, 1980, p. 13). The Q sort method allowed this to happen where traits become “single-centered around an average degree of ‘importance to me’ and correlation thereby becomes practicable (Brown, 1980, p. 15).

To factor analyze the Q sort data, I downloaded PQ Method, a free software package. PQ Method is a basic DOS package designed by Peter Schmolck and recommended by Watts and Stenner (2012). After the software was downloaded, I entered the 42 Q set statements and the data from the 25 Q sort interviews. I used three statistical procedures for data analysis: “correlation, factor analysis, and the computation of factor scores” (McKeown & Thomas, 1988, p. 46).

**Correlation and factor analysis.**

A correlation matrix was used as a measure of association between Q sorts and "represents a transitional phase between the raw data and factor analysis" (Brown, 1980, p. 207). "Factor analysis begins with the calculation of such correlation relative to all the variables in the data matrix" (Watts & Stenner, 2012, p. 8). After the correlation matrix is developed, you must choose between the principal component analysis or the centroid factor analysis model. Though both models provide similar results (Brown, 1993; Watts & Stenner, 2012), centroid is "highly regarded by Q methodologists precisely because of the permissiveness it allows in relation to data exploration" (Watts & Stenner, 2012, p. 100). Additionally, centroid is the oldest factor extraction technique and Stephenson's preference (Thomas & McKeown, 1988 p. 49). Therefore, I chose this model for factor analysis. Based on experience, Brown (1980) recommends extracting seven factors because "after rotation, insignificant residual factors are merely discarded" (p. 223). In other words, meaningless factors can always be eliminated after the initial extraction takes place.

The centroid factor analysis created an unrotated factor matrix for the seven factors to "identify distinct regularities or patterns of similarity in the Q sort configurations produced and hence in the viewpoints our participants have expressed" (Watts & Stenner, 2012, p. 99). Each of these patterns or viewpoints are considered factors (Brown, 1993). Several parameters can be used to analyze the unrotated data and determine how many factors to extract before rotation. A common parameter is the Kaiser-Guttman criterion in which I extracted the factors that have an eigenvalue of 1.00

or more. "An eigenvalue is the sum of squared loadings for a factor" (Brown, 1980, p. 222). Another method is Humphrey's rule which "states that a factor is significant if the cross-product of its two highest loadings (ignoring the sign) exceeds twice the standard error" (Brown, 1980, p. 223; Watts & Stenner, 2012, p. 107). A factor loading simply represents "the degree to which a Q sort correlated with a factor" (Brown, 1980, p. 222). Additionaly, Brown (1980) and Watts and Stenner (2012) note that Humphrey's rule may also be used to extract factors with a cross-product higher than the standard error. The formula to calculate the standard error is below:

Standard error = 1 / (√no. of items in the Q set)

= 1 / ( √42)

= 1 / (6.4807)

= **0.15**

Upon examination of the unrotated factor matrix, Factors 1, 2, and 3 meet Kaiser-Guttman's criteria of having an eigenvalue of 1.00 or more and there is a logical split between Factor 3 and 4. Additionally, all three factors meet Humprey's rule of having a cross product of its two highest loadings that is higher than the standard error of 0.15.

**Computation of factor scores.**

After identifying the three factors, I used the varimax option in PQ Method to rotate them analytically. "[F]actor rotation aims to position each factor so that its viewpoint closely approximates the viewpoint of a particular group of Q sorts, or perhaps just one or two Q sorts of importance" (Watts & Stenner, 2012, p. 127). After rotation, factor loadings, eigenvalues, and variances are adjusted but the "position of the Q sorts relative to one another are absolutely and permanently fixed by their unrotated factor loadings" (Watts & Stenner, 2012, p.129). These adjusted values are presented in a rotated factor solution matrix.

The varimax option automatically flags the significant Q sorts that "exemplify or define the viewpoint of a particular factor" (Watts & Stenner, 2012, p. 129). PQMethod's automatic flagging is based on two criteria: a significant factor loading at the 0.05 level and a squared factor loading higher than the sum of square loadings for all other factors. In other words, a flagged factor loading indicates that specific sort best defines that factor.

After rotation and Q sort flagging, PQ Method generates a weighted Q sort score for each statement based on significant factor loadings (Watts & Stenner, 2012). Unfortunately, these weighted scores do not allow for cross-factor comparison because each factor will have a different number of significant loadings. Therefore, "to facilitate cross-factor comparisons… the total scores must be converted into z (or standard scores)" (Watts & Stenner, 2012, p. 140). Z scores are then converted to factor array positions. For example, the two highest z scores will be given the factor array position or rank of +5 and the next three highest z score will be +4. These factor array positions may be used to create a factor array or "a single Q sort configured to represent the viewpoint of a particular factor" (Watts & Stenner, 2012, p. 140). PQ Method displays the statements that were ranked significantly different when compared to other factors with their respective factor array positions and z scores in a distinguishing statement table.

The qualitative data collected in the Q sort interview process were analyzed similarly to the concourse interviews. After each interview was transcribed and unitized, the units were categorized according to the three factors or viewpoints. The significant sorts were combined with the qualitative data to create thick descriptive viewpoints of farmers and their opinions on adopting UASs in agriculture. Similar to the development of the concourse and Q set, an audit trail was kept to establish dependability and confirmability (Lincoln & Guba, 1985).

**Factor reliability and validity.**

In Q methodology, factor reliability can be discerned in many ways, but Brown (1980) finds the test-retest reliability coefficient, which “measures the extent to which a person is consistent with himself” to be satisfactory. The PQ Method provided me with the test-retest reliability coefficient in the form of composite reliability score which is the reliability coefficient for all sorts for each factor. Brown (1980) recommends, through experience that the reliability coefficient be .80 or higher. All three factors in the study were considered reliable: Factor 1 (0.98), Factor 2 (0.97), and Factor 3 (0.88). Due to the nature of Q methodology, “the concept of validity has very little status since there is no outside criterion for a person’s own point of view” (Brown, 1980, p.174-175).

# CHAPTER IV

# RESULTS

To enhance agricultural production in the face of climate change, PA technologies like UASs need to be successfully diffused to farmers. This study employed a Q methodological approach to evaluate the opinions 25 Texas crop farmers have regarding UASs in agriculture.

**Research Question 1: What are Texas crop farmers' perspectives on UASs in agriculture?**

The three perspectives related to adoption of UASs in their operations were *high-tech harvesters* (Factor 1), *purposeful propagators* (Factor 2), and *conventional cultivators* (Factor 3).

The first viewpoint that emerged, *high-tech harvesters*, accounted for 30% of the total variance in the study. This viewpoint had the most knowledge of UAS technology and several of them owned their own UAS. The second viewpoint, *purposeful propagators*, accounted for 21% of the total variance. Though this group was interested and supportive of the technology, they needed more assurance that it would benefit their operation before adopting. The last viewpoint, *conventional cultivators*, accounted for 8% of the total variance. They were not against the technology but were more inclined to use a UAS service as opposed to purchasing their own.

After the 42 Q set statements and the data from the 25 Q sorts were entered into PQ Method, a correlation matrix (Appendix I) was generated to compare each individual participant's scores to the others. I then ran the centroid factor analysis model, which automatically generated an unrotated factor matrix (Table 4) showing seven extracted factors. The seven factors explained 67% of the variance in the study with a majority of the variance explained by Factor 1.

Table 4

*Unrotated Factor Matrix*

| | Q Sort | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|
| 1 | C01 | 0.48 | -0.18 | -0.18 | -0.34 | -0.22 | 0.18 | -0.06 |
| 2 | C02 | -0.06 | 0.18 | 0.37 | 0.02 | 0.15 | -0.08 | 0.19 |
| 3 | C03 | 0.56 | -0.53 | 0.21 | 0.25 | -0.18 | 0.18 | -0.14 |
| 4 | C04 | 0.76 | -0.23 | 0.14 | 0.22 | 0.20 | 0.03 | 0.17 |
| 5 | C05 | 0.54 | 0.48 | -0.06 | 0.09 | -0.08 | 0.11 | 0.06 |
| 6 | SE06 | 0.70 | 0.19 | 0.16 | -0.14 | 0.15 | 0.08 | -0.22 |
| 7 | SE07 | 0.74 | 0.35 | 0.08 | -0.21 | -0.12 | 0.15 | 0.01 |
| 8 | S08 | 0.85 | 0.20 | 0.17 | -0.14 | 0.07 | 0.08 | -0.07 |
| 9 | S09 | 0.54 | -0.22 | 0.11 | 0.12 | -0.19 | 0.05 | -0.27 |
| 10 | S10 | 0.65 | -0.02 | 0.28 | -0.14 | -0.12 | 0.11 | 0.33 |
| 11 | S11 | 0.65 | -0.20 | 0.16 | -0.13 | 0.31 | 0.10 | -0.06 |
| 12 | S12 | 0.80 | -0.09 | -0.25 | 0.07 | -0.21 | 0.03 | -0.12 |
| 13 | N13 | 0.11 | -0.60 | -0.52 | 0.07 | 0.01 | 0.27 | 0.17 |
| 14 | N14 | 0.75 | -0.07 | 0.45 | 0.22 | 0.01 | 0.12 | 0.06 |
| 15 | N15 | 0.70 | 0.37 | -0.03 | 0.15 | 0.09 | 0.05 | -0.14 |
| 16 | N17 | 0.92 | 0.15 | -0.10 | 0.06 | -0.07 | 0.01 | 0.05 |
| 17 | SE18 | 0.63 | 0.12 | 0.18 | 0.33 | -0.08 | 0.04 | 0.16 |
| 18 | SE19 | 0.70 | 0.07 | -0.41 | -0.16 | 0.21 | 0.10 | 0.12 |
| 19 | H20 | 0.86 | -0.14 | 0.22 | -0.10 | 0.25 | 0.08 | -0.02 |
| 20 | H21 | 0.65 | 0.30 | 0.15 | -0.08 | -0.24 | 0.13 | 0.07 |
| 21 | H22 | 0.47 | 0.09 | -0.07 | -0.05 | -0.08 | 0.02 | 0.09 |
| 22 | H23 | 0.50 | -0.45 | -0.13 | 0.03 | 0.13 | 0.08 | 0.05 |

Table 4 Continued

| | Q Sort | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|
| 23 | H24 | 0.91 | 0.20 | -0.03 | 0.14 | 0.18 | 0.01 | 0.14 |
| 24 | SE25 | 0.76 | -0.06 | -0.20 | 0.01 | 0.25 | 0.02 | -0.06 |
| 25 | N16 | 0.73 | 0.39 | -0.11 | 0.11 | 0.01 | 0.06 | -0.12 |
| | Eigenvalues | 11.25 | 1.97 | 1.31 | 0.64 | 0.68 | 0.28 | 0.50 |
| | % expl.Var. | 45 | 8 | 5 | 3 | 3 | 1 | 2 |

After examining the unrotated factor matrix, I followed the recommendations of Brown (1980) and Watts and Stenner (2012) and used the Kaiser-Gutmann criteria (eigenvalue of 1.00 or more) and Humphrey's rule (cross-product of the two highest factor loadings higher than the standard error) to extract Factors 1, 2, and 3. Because this study has a strong first factor, accounting for 45% of the variance that is closely associated with the second factor, it was appropriate to keep the third factor to increase the variance explained in the sample by 5%.

These three factors were then rotated analytically using the varimax option to better align each viewpoint with other sorts of close similarity. A factor matrix was generated (Table 5) showing these three factors with defining sorts distinguished with an "X." Twelve sorts defined Factor 1, eight sorts defined Factor 2, and two sorts defined Factor 3. Three sorts were eliminated as they did not statistically define any factors. The cumulative explained variance for these three factors is 59%.

Table 5

*Rotated Factor Solution*

| | Loadings | | |
|---|---|---|---|
| Q sort | Factor 1 | Factor 2 | Factor 3 |
| C01 | 0.27 | 0.31 | 0.35 |
| C02 | 0.01 | 0.05 | -0.41X |
| C03 | 0.03 | 0.77X | 0.22 |
| C04 | 0.38 | 0.68X | 0.17 |
| C05 | 0.72X | 0.04 | -0.06 |
| SE06 | 0.61X | 0.42 | -0.06 |
| SE07 | 0.76X | 0.31 | -0.07 |
| S08 | 0.73X | 0.50 | -0.05 |
| S09 | 0.23 | 0.53X | 0.14 |
| S10 | 0.41 | 0.57X | -0.08 |
| S11 | 0.33 | 0.61X | 0.12 |
| S12 | 0.57 | 0.43 | 0.44 |
| N13 | -0.22 | 0.15 | 0.76X |
| N14 | 0.43 | 0.75X | -0.18 |
| N15 | 0.76X | 0.21 | 0.01 |
| N16 | 0.81X | 0.18 | 0.07 |
| N17 | 0.80X | 0.44 | 0.22 |
| SE18 | 0.51X | 0.42 | -0.07 |
| SE19 | 0.63X | 0.19 | 0.47 |
| H20 | 0.50 | 0.73X | 0.08 |
| H21 | 0.65X | 0.31 | -0.12 |
| H22 | 0.42X | 0.21 | 0.13 |
| H23 | 0.09 | 0.50X | 0.44 |
| H24 | 0.81X | 0.45 | 0.14 |
| SE25 | 0.56 | 0.42 | 0.37 |
| % expl. Var. | 30 | 21 | 8 |

*Note.* “X” indicates a defining sort.

As previously discussed in the Methods section, Brown (1980) recommends that the test-retest reliability coefficient (composite reliability in PQ Method) be 0.80 or higher. All three factors are considered reliable; reliability coefficients of factors are displayed in Table 6.

Table 6

*Factor Reliability*

| | Factor 1 | 2 | 3 |
|---|---|---|---|
| Composite Reliability | 0.98 | 0.97 | 0.89 |

Factor intercorrelations were examined to evaluate how closely factors were correlated with one another. Factors 1 and 2 were highly correlated ($r = .70$). Systematic evaluation of the distinguishing statements and qualitative data revealed distinct differences emerged between these two groups. Because distinguishing perspectives are evident and differentiate these two factors, all three factors were kept. Factor correlations can be seen in Table 7.

Table 7

*Correlations Between Factor Scores*

| Factors | 1 | 2 | 3 |
|---|---|---|---|
| 1 | 1.00 | | |
| 2 | 0.70 | 1.00 | |
| 3 | -0.07 | 0.16 | 1.00 |

**Research Question 2: What are the psychographic and sociodemographic characteristics that make up each perspective?**

To identify and understand the psychographic and sociodemographic characteristics of the three perspectives, I holistically analyzed the pre-sort survey and distinguishing statements for each factor.

The entire P set consisted of farmers with small, medium, and large size farms, dryland irrigation (no irrigation) or irrigation, multiple PA technologies or very little PA technologies, and 18 different crops. Sociodemographic characteristics of the P set (n=22) can be seen in Table 8.

Table 8

*Sociodemographic Characteristics of P Set*

| Characteristic | n |
|---|---|
| Farming Experience (years) | |
| 2-20 | 9 |
| 21-40 | 4 |
| 41-60 | 9 |
| Education Level | |
| High School | 6 |
| Associate Degree | 1 |
| Bachelor's Degree | 13 |
| Graduate Degree | 2 |
| Gross Cash Farm Income (GCFI) | |
| Small- Less than $350,000 | 2 |
| Medium- $350,000-$999,000 | 5 |
| Large- $1 million or more | 15 |

Table 8 Continued

| Characteristic | n |
|---|---|
| Farm Acreage | |
| 999 and below | 0 |
| 1,000-1,999 | 4 |
| 2,000 and up | 18 |
| Irrigation | |
| Irrigated | 11 |
| Dryland (non-irrigated) | 11 |
| PA Technologies | |
| Very Little (0-1) | 4 |
| Multiple (2 or more) | 18 |
| Crops | Cotton, Corn, Soybeans, Wheat, Grain Sorghum, Sesame, Hay, Turfgrass, Rice, Citrus, Sugarcane, Watermelon, Onions, Fava beans, Sunflowers, Flaxseed, Barley, Rye |

*Note.* The three eliminated participants are not included in the table.

Each factor has a distinguishing statement table that "tell(s) you which items a factor has ranked in a significantly different fashion when compared to all the other study factors" (Watts & Stenner, 2012). The distinguishing statement tables provide the statement number (SN), array position (AP), and z score (Z) for each significant statement at the 0.05 level. An asterisk (*) indicates significance at the 0.01 level. Statements with higher z scores and array positions were ranked more "like me" by that perspective and statements with lower z scores and array positions were ranked less "like me" (Watts & Stenner, 2012).

I considered all distinguishing statements in the analysis process to insure I had a full understanding of each factor or viewpoint. Each factor is presented with a broad description of the distinguishing statements and sociodemographic characteristics for that specific viewpoint.

**Factor 1: High-tech harvesters.**

Twelve farmers are significantly associated with the first perspective, *high-tech harvesters.* The distribution of distinguishing statements for this perspective emphasized the importance of the technical applications offered by UAS technology. The *high-tech harvesters* were most interested in using UASs to detect invasive insects and weeds (SN=34, AP=5, Z =1.88) and to assess crop health (SN=38, AP =5, Z =1.77) for more efficiency in their operations (SN=34, AP=4, Z =1.40).

Furthermore, estimating yield, spraying pesticides, and use in conjunction with variable rate technologies were all of high importance to this group. The following quote exemplifies the perspective of the *high-tech harvesters*, "I can see myself using drones for…estimating yield, look[ing] at whether I need to spray pesticides, assessing crop health, assessing soil health—actionable data that I can use to provide a return on investment" (N16_10).

Additionally, this group does not wait to get feedback from their peers before adopting new technologies like UASs (SN=10, AP=-4, Z =-1.56). Defining quotes include, "I'm not worried about what people think" (H22_18) and "I really don't care who has one. I'm not the least bit concerned with being the first person with stuff so that doesn't really matter" (H24_10).

Factor 1 represented farmers from all five of the sampled regions of Texas, ranged from 27 to 77 years old, and had an average of 23 years of farming experience.

Five of the farmers obtained a high school education, five obtained a bachelor's degree and one obtained a master's degree. A majority (n=9) of the farmers in Factor 1 operated large farming operations based on GCFI, however, two of the farmers had small farms. The average acreage of their farms was 5,021. Ten of the 12 farmers indicated they had multiple forms of PA technology and seven of the 12 farmers had irrigation on their operations.

Factor 1's distinguishing statement table can be seen below in Table 9. For a complete factor array of Factor 1, see Appendix J.

Table 9

*Distinguishing Statements for Factor 1*

| No. | Statement | Array Position | Z Score |
|---|---|---|---|
| 34 | I am interested in using drone imagery to detect invasive insects and weeds. | 5 | 1.88* |
| 38 | I am interested in using drones to assess crop health. | 5 | 1.77* |
| 1 | My operation could be more efficient with drones. | 4 | 1.40* |
| 37 | I am interested in using drone imagery to estimate yield. | 3 | 1.31* |
| 35 | I am interested in using drones to spray pesticides in my fields. | 3 | 1.22* |
| 26 | I usually catch on to new technologies after being shown how to use them. | 3 | 1.21* |
| 36 | I am interested in using drone imagery in conjunction with variable rate technology. | 2 | 0.99* |
| 27 | I can usually figure out how to use new technologies on my own after a little while. | 2 | 0.91* |
| 13 | I will buy a drone, if it will keep me competitive in my operation. | 2 | 0.83 |
| 31 | I would prefer to buy my own drone rather than use a drone service. | 1 | 0.19 |
| 4 | A drone has to be affordable for me to buy one. | 0 | -0.14* |

Table 9 Continued

| No. | Statement | Array Position | Z Score |
|---|---|---|---|
| 16 | If I buy a drone I will have to buy additional resources to the drone. | 0 | -0.16 |
| 29 | I will adopt a drone if it is a requirement of my job. | -2 | -0.58* |
| 6 | I need to see drones working properly before I will buy one. | -2 | -0.80 |
| 10 | I will not buy a drone only because many or all of my peers have a drone. | -4 | -1.56* |

*Note*. ($p < 0.05$ ;  Asterisk (*) indicates significance at $p < 0.01$)

**Factor 2: Purposeful propagators.**

The second perspective, *purposeful propagators,* was defined by eight Q sorts. Distinguishing statements for this perspective indicate they are interested in the technology and willing to adopt but would be very deliberate about their purchase. This group was more selective about which technical applications interested them, focusing more on the overall benefit it may provide to their specific operation (SN=8, AP=5, Z =1.84). Additionally, they need assurances it would provide a good return on investment before adoption (SN=5, AP=4, Z =1.51). One farmer stated, “Got to prove it! You’ve got to be able to translate it to time, energy, and money. One of the three or all of them” (S10_32).

It is important to note that the technical applications of most interest to the *purposeful propagators* mirror the top applications of Factor 1: using the technology to detect invasive insects (SN=4, AP=4, Z =1.16) and to assess crop health (SN=38, AP=3, Z =1.11).

Adopting UASs as a job requirement ranked very low among this group as they do not find it to be applicable to their profession (SN=29, AP=-3, Z =-1.31). This was captured in the following quote: “Well, I don’t look at this as a job. This is my call and no one is going to download the pressure on me” (S10_49).

The *purposeful propagators* represented farmers from four out of the five sampled regions of Texas, ranged from 34 to 72 years old, and had an average of 34 years of farming experience. One of the farmers obtained a high school education, six obtained a bachelor’s degree, and one obtained a master’s degree. Five farmers operated large farming operations and three had medium-sized operations based on GCFI. The average acreage was 5,820. Seven of the eight farmers indicated they had multiple forms of PA technology, and four of the eight farmers had irrigation on their operation.

The distinguishing statements for Factor 2 can be seen below in Table 10. For a complete factor array of Factor 2, see Appendix K.

Table 10

*Distinguishing Statements for Factor 2*

| No. | Statement | Array Position | Z Score |
|---|---|---|---|
| 8 | It should be clear that the drone will benefit me in my specific operation before I buy one. | 5 | 1.84* |
| 5 | I need to know that drones will provide a good return on my investment before I buy one. | 4 | 1.51* |
| 34 | I am interested in using drone imagery to detect invasive insects and weeds. | 4 | 1.16* |
| 38 | I am interested in using drones to assess crop health. | 3 | 1.11* |
| 31 | I would prefer to buy my own drone rather than use a drone service | 2 | 0.63 |
| 42 | Privacy is a concern of mine as it relates to drone technology. | 2 | 0.58* |
| 36 | I am interested in using drone imagery in conjunction with variable rate technology. | 1 | 0.17* |
| 27 | I can usually figure out how to use new technologies on my own after a little while. | 0 | 0.05* |
| 23 | I am supportive of people who use drones in agriculture. | 0 | -0.01* |
| 35 | I am interested in using drones to spray pesticides in my fields. | -1 | -0.07 |
| 26 | I usually catch on to new technologies after being shown how to use them. | -1 | -0.08* |
| 10 | I will not buy a drone only because many or all of my peers have a drone. | -2 | -0.80* |
| 29 | I will adopt a drone if it is a requirement of my job. | -3 | -1.31* |

*Note.* ($p < 0.05$; Asterisk (*) indicates significance at $p < 0.01$)

**Factor 3: Conventional cultivators.**

Defined by two Q sorts, the third perspective is titled *conventional cultivators.* Though this group of farmers entertained the idea of purchasing a UAS if it would reduce their labor requirements (SN=14, AP=5, Z =1.61), they remained uncertain of the technology and felt like it would not hold up to their working conditions (SN=2, AP=4, Z =1.42). They also indicated they would adopt a UAS if it was a requirement of their job (SN=29, AP=3, Z =1.33). The *conventional cultivators* are more inclined to subscribe to a UAS service as opposed to purchasing their own UAS (SN=31, AP=-5, Z =-1.79). One farmer stated that a service would "put some of the technological requirements on the service and not on me." (N13_24).

The *conventional cultivators* represented farmers from two of the five sampled regions of Texas, were 69 and 77 years old, and had an average of 48.5 years of farming experience. Both farmers had bachelor's degrees, dryland (no irrigation), and multiple forms of PA technologies on their operations. One farmer operated a large farm while the other had a medium operation based on GCFI. The average acreage size was 4,450.

See Table 11 below for the distinguishing statement table for Factor 3. For a complete factor array of Factor 3, see Appendix L.

Table 11

*Distinguishing Statements for Factor 3*

| No. | Statement | Array Position | Z Score |
|---|---|---|---|
| 14 | I will buy a drone if it reduces my labor requirements. | 5 | 1.61 |
| 2 | I question whether drones could hold up to my work conditions. | 4 | 1.42* |
| 29 | I will adopt a drone if it is a requirement of my job. | 3 | 1.33* |
| 3 | I am not interested in drones because they have more capabilities (or functions) than I need. | 3 | 1.24* |
| 7 | Before I buy a drone I must have assurance that technologic upgrades will be handled routinely. | 3 | 1.20* |
| 12 | I will buy a drone only if it is easy for me to use. | 2 | 0.82* |

Table 11 Continued

| No. | Statement | Array Position | Z Score |
|---|---|---|---|
| 19 | I will buy a drone if my peers are having success with theirs. | 2 | 0.78* |
| 25 | The sales representative usually shows me how to use new technology like drones. | 2 | 0.55* |
| 10 | I will not buy a drone only because many or all of my peers have a drone. | 1 | 0.45* |
| 11 | I must have assurance that drones will not become obsolete quickly due to technological advancement before I buy one. | 1 | 0.36 |
| 9 | I am more likely to buy a drone if my peers have one. | 0 | 0.18* |
| 38 | I am interested in using drones to assess crop health. | 0 | 0.09* |
| 20 | I can only see the younger generation using drones in agriculture. | -1 | -0.32 |
| 22 | I won't buy a drone because I don't need one. | -1 | -0.32 |
| 28 | I usually learn how to use new technologies by researching online. | -2 | -0.68 |
| 34 | I am interested in using drone imagery to detect invasive insects and weeds. | -2 | -0.91* |
| 39 | I am interested in using drones to assess soil health. | -2 | -0.91* |
| 35 | I am interested in using drones to spray pesticides in my fields. | -3 | -0.92 |
| 36 | I am interested in using drone imagery in conjunction with variable rate technology. | -3 | -1.05* |
| 24 | I figure out how to use new technologies like drones, on my own. | -3 | -1.14* |
| 26 | I usually catch on to new technologies after being shown how to use them. | -3 | -1.33* |
| 27 | I can usually figure out how to use new technologies on my own after a little while. | -4 | -1.52* |
| 31 | I would prefer to buy my own drone rather than use a drone service | -5 | -1.79* |

*Note.* ($p < 0.05$ ; Asterisk (*) indicates significance at $p < 0.01$)

**General consensus.**

A table of consensus statements and their respective z scores (Table 12) was generated to identify statements that do not distinguish between any of the factors. In other words, they were similarly considered “most like me” or “least like me” for each perspective.

The z scores indicate all three perspectives feel receiving actionable data from UASs is important (SN=32). One farmer stated, “Receiving actionable data is important… so I don’t want to know just a story. I want to have data that I can use. Actionable means in a timely fashion, too” (S10_3).

Additionally, the three perspectives did not identify with the statement about adopting a UAS to insure he or she is not the only person who does not have one (SN=21). Another point of agreement was that owning the latest and greatest “toy” on the market was “not like the respondent” for all three perspectives (SN=15).

Table 12

*Consensus Statements*

| No. | Statement | Z Score Factor 1 | Factor 2 | Factor 3 |
|---|---|---|---|---|
| 15* | I will buy a drone to have the latest and greatest "toy" on the market. | -1.57 | -1.52 | -1.56 |
| 18* | I will wait until drones have been on the market a little while before I consider buying one. | -0.56 | -0.53 | 0.14 |
| 21* | I will buy a drone so I am not the only person who doesn't have one. | -1.67 | -1.74 | -1.42 |
| 28 | I usually learn how to use new technologies by researching online. | 0.21 | 0.17 | -0.68 |
| 30* | A drone service would be beneficial to me. | 0.05 | -0.34 | -0.64 |
| 32* | Receiving actionable data from the drone is important to me. | 1.39 | 1.81 | 1.56 |
| 40* | Before subscribing to a drone service I would need to know how quickly they will prove me with actionable data. | 0.15 | 0.55 | 0.32 |
| 41* | I would consider trying out a drone service before purchasing my own drone. | -0.20 | 0.07 | 0.41 |

*Note.* All listed statements are non-significant at $p > 0.01$ and those flagged with an * are also non-significant at $p > 0.05$

# CHAPTER V

# CONCLUSIONS

Agricultural researchers are working to find solutions to address the usual issues of spatial variability across a field as well as address newer pressures on farming that come from climate change. Though UAS technology is a promising tool that can aid farmers by increasing the return on investment by minimizing production inputs/costs, little research was found on the adoption and acceptance of this new technology. The study used an inductive and Q methodological approach to better understand the different perspectives Texas crop farmers have related to UASs and to identify the specific attributes and technical applications each perspective finds most important.

## Research Question 1: What are Texas crop farmers' perspectives on UASs in agriculture?

Three factors were identified regarding the farmers' perspectives of UASs in agriculture. The conceptual framework guiding the study used a "continuum of innovativeness [that] can be partitioned into five adopter categories (innovators, early adopters, early majority, late majority, and laggards)" (Rogers, 2003, p. 298). The three different perspectives identified in the study are most closely associated with innovators (*high-tech harvesters*), early adopters (*purposeful propagators*), and laggards (*conventional cultivators*). This study provides some support of Rogers' (2003) Diffusion of Innovation Theory as each of the three factors in this study is indicative of one of the five-adopter categories; however, two adopter categories were not identified.

In addition, the percentage of farmers in each of the three adopter categories described is substantially different than the percentage of each found by Rogers.

Factor intercorrelations were examined to evaluate how closely factors were correlated with one another. Factor 1 (innovators) and Factor 2 (early adopters) had a high correlation of .70. This, too, provides some support for Rogers as he wrote that innovators and early adopters share more characteristics with each other than they do with laggards. Systematic evaluation of the distinguishing statements and qualitative data revealed distinct differences between these two groups. Factor 1 and 2's close relationship corroborates Rogers' claim that "there are no sharp breaks or discontinuities between adjacent adopter categories (although there are important difference between them)" (Rogers, 2003, p. 282). Simply put, the higher correlation between these two factors can be attributed to the close relationship between innovators and early adopters on Rogers' (2003) adopter scale and their similar degrees of innovativeness. I believe this three-factor solution provides an accurate, valid, and reliable understanding of the perspectives in this P set as it relates to using UAS technology in agriculture.

This study also confirms the previously mentioned PA adoption studies (Daberkow & McBride, 2003; Schimmelpfennig, 2016; Tey & Brindal, 2012) that agro-ecological and technological characteristics are good indicators of farmers' likeliness to adopt new technology as a majority of this sample are innovators/early adopters and have large farms (GCFI), more than 1,999 acres, and multiple forms of PA. Results also showed that a majority of the participants were accepting of the technology—results similar to those found in Zimmerman's (2015) case study on the acceptance of UASs in the forest industry. Contrariwise, farmers in this study did not identify statements related to privacy and cost as “most like me” in their decision process.

**Research Question 2: What are the psychographic and sociodemographic characteristics that make up each perspective?**

Results from the study indicate that agro-ecological and technological characteristics play a large role in the adoption of UAS technology in agriculture. However, it is important to note that even with a homogenous sample, comprised of a majority of large-scale farmers with irrigated acres, psychographic characteristics play an important part in the distinction between these three perspectives.

**Factor 1: High-tech harvesters.**

The *high-tech harvesters* (n=12) are closely associated with the innovators on the Diffusion of Innovation adopter scale (Rogers, 2003). Innovators are the first to adopt new technologies, are not afraid of taking risks, and “understand and apply complex technical knowledge” (p. 282). The *high-tech harvesters* mirror these attributes, as the statements identified as “most like me” represented the technical applications offered by UASs— detecting insects/weeds and overall crop health.

Though four of the 12 farmers in this group already owned a UAS, several of them indicated they were not using the technology to its full capabilities. One farmer from Northeast Texas said, “I need to be using it, the only thing I use it for is just checking visually the crops. None of the real data collecting” (N_07). This could be the result of over adoption, a term Rogers (2003) used to describe the act of adopting an innovation even when they should not. This happens when an “innovation is perceived as so attractive to an individual that it overrules all other considerations" (p. 232). Furthermore, the hype surrounding the new technology (Freeman & Freeland, 2015) and the fact that data acquisition and analysis are more complex/costly than was originally perceived (Hunt & Daughtry, 2017) could have prompted the farmers to adopt before gaining complete knowledge about the innovation. One farmer who owned a UAS stated the following in regards to using the technology to estimate yield, "That's pretty interesting… I didn't know drones could do that yet" (N15_11).

Rogers (2003) says that innovators are more cosmopolite when compared to their peers because "their interest in new ideas leads them out of a local circle of peer networks" (p. 282). This perfectly describes the *high-tech harvesters,* as they did not base their adoption decisions off what their peers were doing. In fact, several of the farmers in this group mentioned they are not afraid to be the first person in their region to adopt a new technology. Rogers stated that innovators "travel widely and are involved in matters beyond the boundaries of their local system" (Rogers, 2003, p. 290). This phenomenon is captured in a quote from a Southeast Texas farmer: "I wouldn't say I try the newest things because the newest things happen in the Midwest," (SE18_84) but "I adopt the new technology in our area or our region probably way before everyone" (SE18_87).

Sociodemographic and agro-ecological characteristics for the *high-tech harvesters* varied greatly. However, a majority of this group had large operations, over 1,999 acres, a formal education, multiple PA technologies, and irrigation. These findings support the previously discussed PA adoption studies (Daberkow & McBride, 2003;

Schimmelpfennig, 2016; Tey & Brindal, 2012) and generalizations posited by Rogers (2003) when comparing earlier adopters to later adopters. Furthermore, Rogers (2003) found "inconsistent evidence about the relationship of age and innovativeness" (p 228). This is supported by the findings in this viewpoint as ages ranged from 27-77 years old.

**Factor 2: Purposeful propagators.**

The *purposeful propagators* (n=8) were comparable to the early adopters on Rogers' (2003) adopter scale. The early adopters are often considered opinion leaders in a social system who make "judicious innovation-decisions" (p. 283). Similar to the *high-tech harvesters*, this group was interested in the insect/weed detection and health application of UASs but were more closely aligned with statements that addressed the overall benefits and return on investment UASs could provide. This distinction of placing more value on the overall benefit of the UAS versus the technical applications indicates this group is more cautious than the venturesome *high-tech harvesters.*

A High Plains farmer reflected on a time when he was forced to adopt a new technology because of rapid growth in his operation. He was the first in his region to adopt a 36-row planter but maintained, "sometimes that's not the smart thing to do" (H20_11). Furthermore, he stated, "it's best, which is my philosophy on the drones that if you will wait, technology will improve and price competitiveness will fall" (H20_12).

Although none of the *purposeful propagators*, owned their own UAS, several of them knew of the current research at Texas A&M University, and one of the farmers had subscribed to a UAS service in the past. This indicates the farmers in this group, though hesitant to purchase a UAS, are still interested in the technology and are actively seeking information to reduce uncertainty. Gaining knowledge of an innovation is the first step in the innovation-decision process (Rogers, 2003, p. 174).

A similarity between the *purposeful propagators* and the *high-tech harvesters*, which comes as no surprise with the close positioning of innovators and early adopters on the adopter scale, was their similar ranking of statement regarding adopting new technologies like UASs because of their peers as "least like me". Neither a venturesome risk-taker (innovator) nor an opinion leader (early adopter) who "serve[s] as a role model for many other members of a social system" (Rogers, 2003, p.283) would put emphasis on their peers' perceptions and adoption practices. One farmer even explained that you cannot trust your peers when they claim success because "they are big on it and it takes a little while to see if it's a success." Noting, "By then, you can probably figure it out by looking at data or research" (N10_30).

Similar to the *high-tech harvesters*, sociodemographic and agro-ecological characteristics were overall homogeneous for the *purposeful propagators*. A majority had a large operation, over 1,999 acres, a formal education, and multiple PA technologies. The *purposeful propagators,* unlike the first perspective, were even in terms of technological factor as 50% (n=4) had irrigation and 50% (n=4) had dryland operations. One farmer was enthusiastic about the technology and said he would be pretty aggressive about integrating it if he had irrigation. He specified "but dryland… I have to wait and be a little more sure" (N10_35). This supports the literature that technological factors play a role in the adoption of new technologies in agriculture (Daberkow & McBride, 2003; Schimmelpfennig, 2016; Tey & Brindal, 2012). Simply put, "if a farmer has no way to manage a stress, they do not need to know about it and will not be willing to pay for this service" (Murray, 2017, para. 5). Additionally, age, ranging from 34-72 years-old, did not seem to play a factor in this viewpoint.

**Factor 3: Conventional cultivators.**

The *conventional cultivators* (n=2) were analogous to the laggards on Rogers' (2003) adopter scale. Rogers coined the laggards, the last group to adopt, as the traditionalists. Similar to laggards, the *conventional cultivators* are extremely reluctant to adopt UASs and seem to have a dogmatic or "relatively closed belief system" that hinders them from "welcome[ing] new ideas" (Rogers, 2003, p. 289).

This group identified the potential reduction in labor requirements as the most important attribute of UAS technology but were resistant to adopt because they did not feel it would benefit them in their operations. Because this group did not consider themselves to be technologically savvy, they were more apt to subscribe to a UAS service rather than purchase their own UAS. The *conventional cultivators* questioned whether UASs would hold up to their working conditions and thought the technology had more functions than they needed. This group was also the least knowledgeable of UAS technology. A Northeast Texas farmer stated, "You see some of these, I don't have good answers for because I don't understand drones well enough and what they will do" (N13_43).

Furthermore, the *conventional cultivators* were the only farmers who ranked the statement about adopting UAS technology if it were a requirement of their job as "like me." This thought process illustrates the conservative personality of this perspective and suggests they will most likely only adopt if they are forced to (Rogers, 2003).

The sociodemographic and agro-ecological characteristics of the *conventional cultivators* included farmers with a formal education, dryland farms, and multiple forms of PA technologies. One farmer had a medium operation with less than 1,999 acres and the other farmer had a large operation with over 1,999 acres. This is the only perspective in the study that does not support previous findings that farmers with a large operations and formal education are likely to adopt new technologies (Daberkow & McBride, 2003; Rogers, 2003; Schimmelpfennig, 2016; Tey & Brindal, 2012). Though ages were 69 and 77 years old, Rogers' notes that previous adoption studies have shown "inconsistent evidence about the relationship of age and innovativeness" (Rogers, 2003, p. 288). The large variation in ages of *high-tech harvesters* and *purposeful propagators* supports Rogers' conclusions that age is not a good indicator of adoption.

**Summary**

This study identifies unique viewpoints that can be used to build future research, training, and outreach as we continue to improve PA and UAS technologies for farmers.

It is important to note that the technical applications of most interest to a majority of farmers (n=20) is the ability to assess crop health and detect invasive insects and weeds. The *high-tech harvesters* who owned a UAS indicated they were using the technology to visually inspect their fields for crop health, which falls under Hunt and Daughtry's (2017) first category of using UASs to scout the fields for problems. This supports Hunt and Daughtry's (2017) observation that most farmers are currently using the technology to scout fields visually for major overall health problems and the next prevalent application of the technology will likely be the more proactive approach of monitoring the fields to prevent yield losses from pests like invasive insects and weeds. A South Texas farmer reflected on one of these applications, stating, “resistant weeds are a big issue, so knowing how many we have and knowing where they are can be huge” (S10_15).

Hunt and Daughtry (2017) noted the third category, planning crop management operation, though the most exciting and offering the highest environmental and economic benefits, would likely be the last application to be adopted. This is largely due to the “many steps between taking pictures and extracting usable information” (Murray, 2017, para. 6). Additionally, only about 20% of U.S. farmers have adopted VRT technology, which may slow the adoption of this third UAS application (Hunt & Daughtry, 2017). Technologies that allow farmers to manage stresses in the field are essential for farmers to implement the recommendations from UAS technology (Murray, 2017, para. 5). An interesting finding in the P set shows that although 45% of farmers (n=10) indicated using VRT on their operations, implementing crop management strategies such as estimating yield and using UASs in conjunction with VRT, though positively ranked, were not perceived as the most important technical application. This could indicate that farmers are not aware of the connection between VRT and UASs (Rogers, 2003). This lack of awareness may be due to the infancy of this application of UASs and the fact that researchers are still working to develop automatic processing tools for the high-quality data necessary to provide these recommendations.

## Limitations

Though the P set (n=22) represented farmers from five different agricultural regions, 18 different crops, and each side of the agro-ecological and technological spectrum, there was sampling bias and is considered a limitation of the study. For example, according to USDA, NASS, (2014a & 2014b), a majority of Texas farmers operate on less than 1,999 acres and have dryland farms. In contrast, the average farm size for farmers in the P set (n=22) was 5,260 acres with most (n=18) having over 1,999 acres and half (n=11) of the farmers using irrigation in their operations. The larger operations (Rogers, 2003), use of PA technologies, and irrigation facilities (Tey & Brindle, 2012) are all potential indications as to why a majority of this group were either innovators or early adopters on Rogers' adopter scale (2003).

This unintentional homogenous sample of farmers may be the result of the snowball sampling technique in which I asked AgriLife Research and Extension colleagues and farmers in the study to pass my contact information along to other farmers. This is underlined by Rogers' characterization of earlier adopters as more venturesome and integrated into their social system than others (2003) and, therefore, would be more likely to be recommended and to accept the offer to be interviewed.

## Recommendations and Implications

As this is a Q method study, I am not interested in generalizing to a population, but focused on establishing and understanding the different perspectives that surround using UASs in agriculture among Texas crop farmers. This study may serve as a basis for future research on the three emerging viewpoints or the consensus of the study as a whole.

I recommend this study be replicated in the form of a deductive study in which all five of Rogers' (2003) adopter types are included. A deeper understanding of each adopter type will allow UAS stakeholders to strategically market to consumers and speed up the diffusion process. To do this, I recommend employing a strategic sampling technique with a pre-survey that focuses on adopter types and not agricultural regions alone. Furthermore, it would also be beneficial to include more statements to measure the knowledge and awareness level of UAS technology for each farmer.

The three unique viewpoints identified in the study may assist and inform future UAS research and development. Specifically, it is recommended that researchers focus their attention on technical capabilities to enable farmers to monitor their fields proactively to prevent yield losses due to invasive insects/weeds and overall crop health. Researchers should consider focusing efforts on the monitoring to prevent yield losses (Category 2) application over the planning crop management application (Category 3) (Hunt & Daughtry, 2017) as a majority (n=20) of farmers found it most critical to their adoption of UASs. Research should continue to investigate new data acquisition and analysis methods that make this advanced application of UAS more user-friendly while keeping costs at an affordable price for farmers.

In addition to research and development, information about these three viewpoints can assist Extension agents and UAS stakeholders (industry and government) in the diffusion of UAS technology by shedding light on the types of farmers and their interests. Based on our findings and previous studies (Daberkow & McBride, 2003; Kitchen, et al., 2002; Tey & Brindal, 2012; Zimmerman, 2015), I recommend UAS stakeholders and Extension agents implement UAS training events across the state to educate farmers on use, data acquisition and analysis, and federal guidelines. Initial trainings should target *high-tech harvesters* and *purposeful propagators*. Targeting these types of farmers, specifically, the *purposeful propagators* is recommended as the early adopters are considered opinion leaders and will ultimately lead to the successful diffusion of UASs (Rogers, 2003).

The *high-tech harvesters*, who may already own a UAS would benefit from training sessions that teach them the '"how-to' knowledge" needed to effectively use the technology (Rogers, 2003, p. 173). This would prevent the farmers who have already adopted UASs from becoming disenfranchised with the technology, which would lead to a slower rate of adoption within the social system (Freeman & Freeland, 2015; Rogers, 2003). Additionally, *purposeful propagators* would be more inclined to purchase a UAS or service if they were given the opportunity to reduce their uncertainty about this complex but beneficial innovation (Rogers, 2003).

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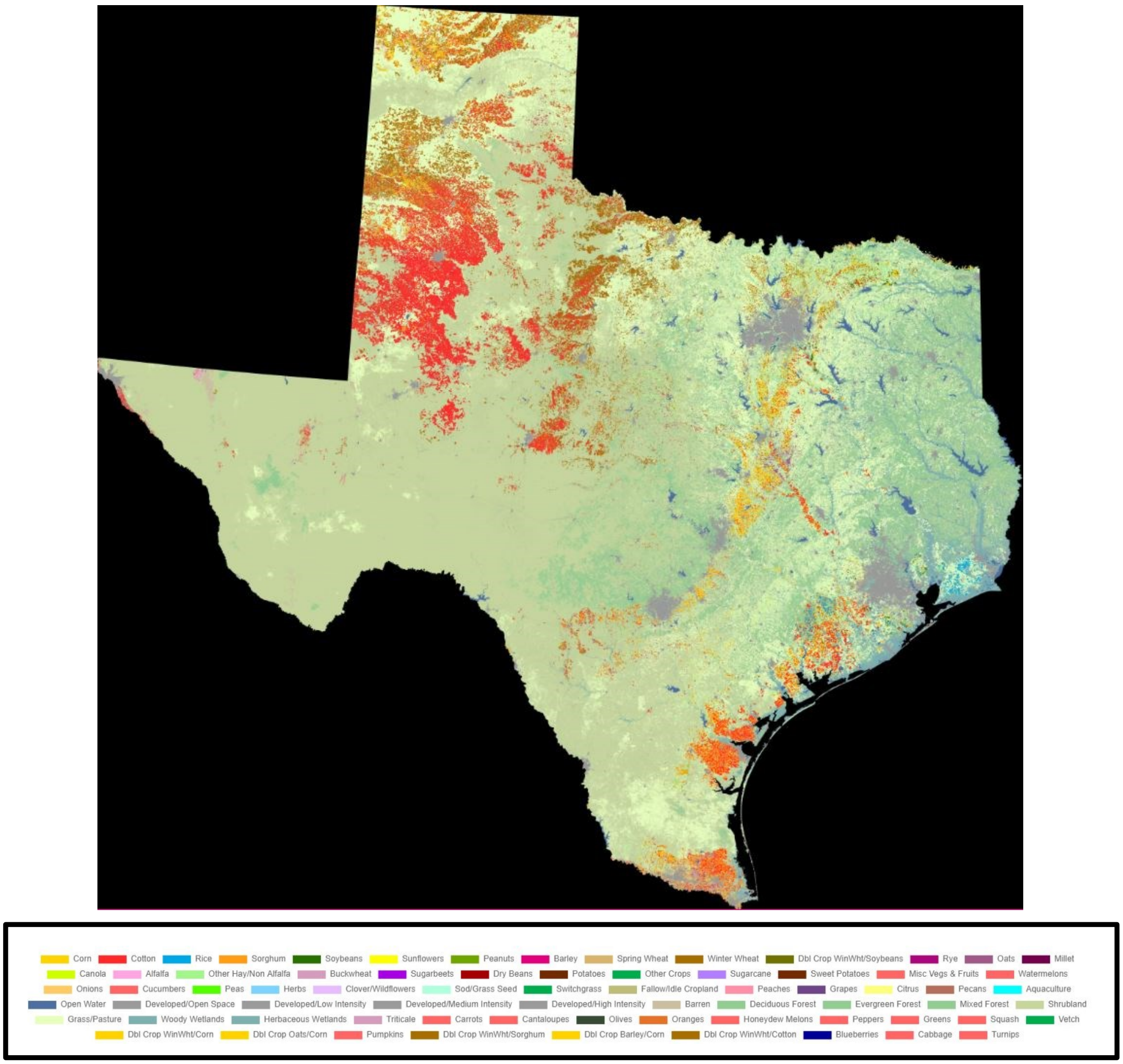
APPENDIX A

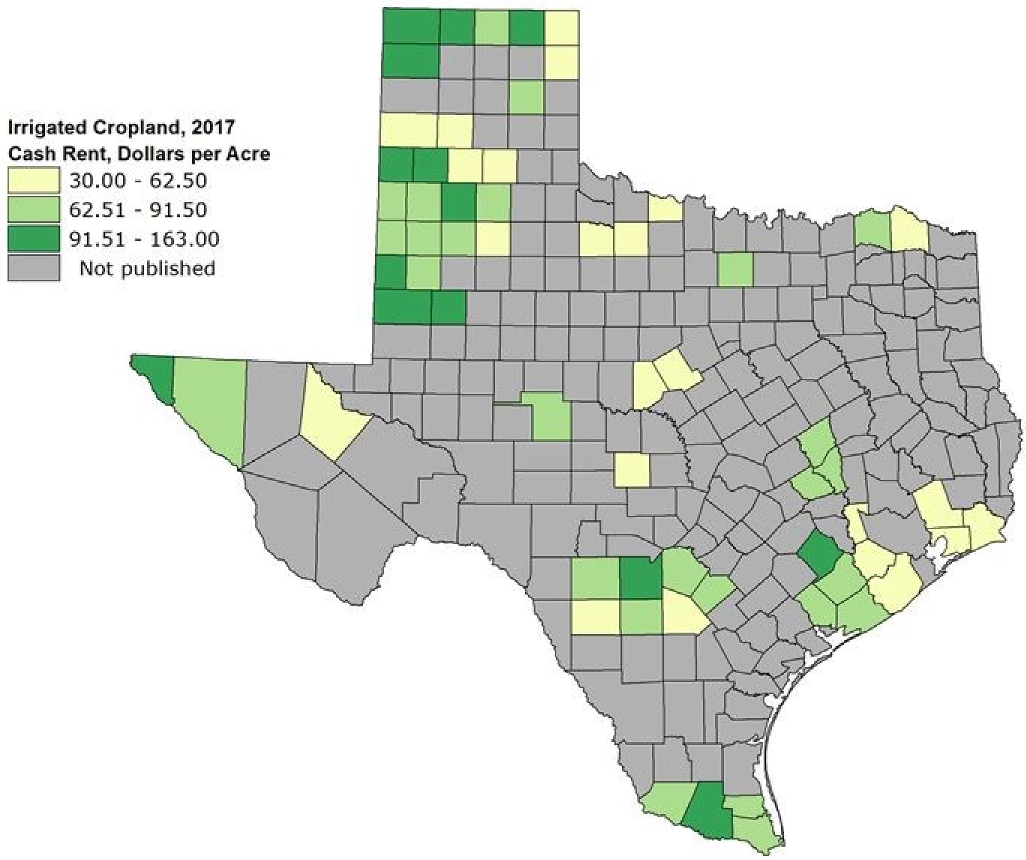
MAPS OF TEXAS




Map of Texas showing the location of various crops (2018). CropScape – Data Layer, United States Department of Agriculture, National Agricultural Statistics Service. Retrieved from https://nassgeodata.gmu.edu/CropScape/

APPENDIX A (CONTINUED)

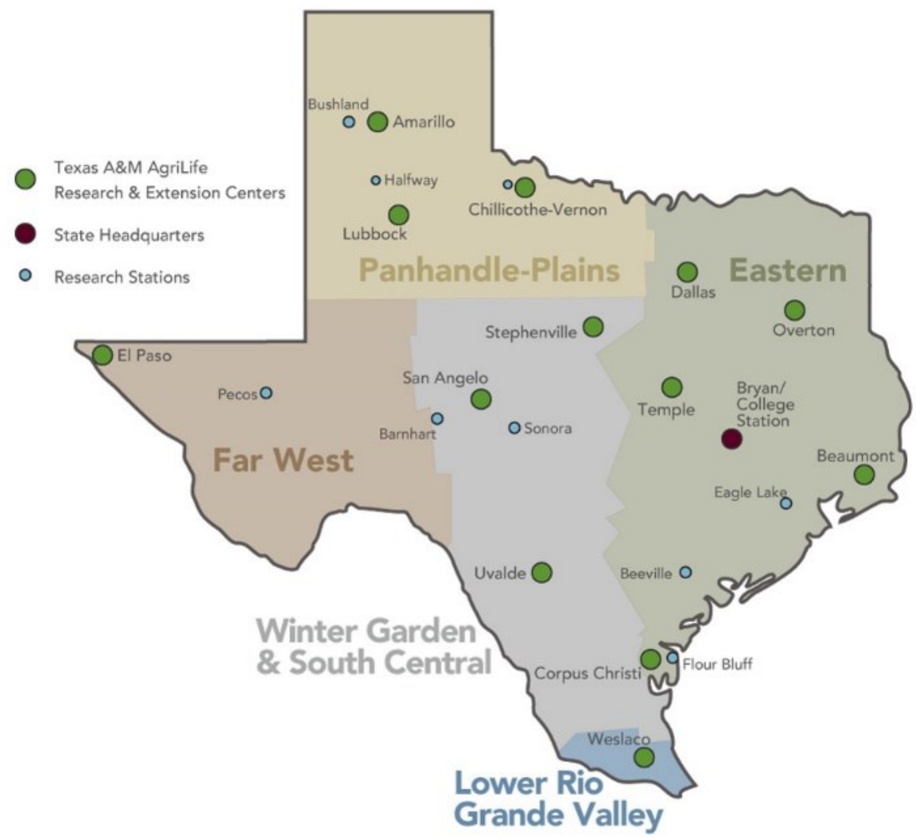
MAPS OF TEXAS




County estimate map, Rent irrigated cropland (2017b). United States Department of Agriculture, National Agricultural Statistics Service. Retrieved from https://www.nass.usda.gov/Statistics_by_State/Texas/Publications/County_Estimates/ce_maps/ce_rent_irr.php

APPENDIX A (CONTINUED)

MAPS OF TEXAS




Map of Texas divided into five agricultural regions (n.d.). Texas A&M AgriLife Research. Retrieved from https://agriliferesearch.tamu.edu/region/

APPENDIX B

INTERVIEW PROTOCOL - CONCOURSE

Howdy,

Thank you for agreeing to speak with me about new practices and technologies in agriculture.

My name is Misty Miles and I work at Texas A&M AgriLife Research. I got your information from ______(if applicable).

Would you be willing to speak with me for about 10-15 minutes regarding your views on drones in agriculture?

First off, are you a farmer or a rancher? Cattle? Row crops?

Are you willing to sign a consent form so that I can use your answers in my thesis research?

Are you ok with me recording this interview for transcription purposes?

*If yes, the researcher proceeded with the interview questions.*

APPENDIX C

CONSENT FORM - CONCOURSE INTERVIEWS

**Texas A&M University Human Subjects Protection Program**

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**CONSENT FORM**

**Project Title: Social Adoption of Unmanned Aerial Systems in Agriculture**

You are invited to take part in a research study being conducted by Misty Miles, a researcher from Texas A&M University and funded by the Texas A&M AgriLife Research. The information in this form is provided to help you decide whether or not to take part. If you decide to take part in the study, you will be asked to sign this consent form. If you decide you do not want to participate, there will be no penalty to you, and you will not lose any benefits you normally would have.

**Why Is This Study Being Done?**
The purpose of this study is to understand how unnamed aerial systems (UAS) in agriculture are adopted.

**Why Am I Being Asked To Be In This Study?**
You are being asked to be in this study because you are a resident of the State of Texas.
If you are not above the age of 18, please disregard and discard this packet.

**How Many People Will Be Asked To Be In This Study?**
100 people (participants) will be invited to participate in this study.

**What Are The Alternatives To Being In This Study?**
The alternative to being in the study is not to participate.

**What Will I Be Asked To Do In This Study?**
You will be asked to answer questions related to adoption of new technologies in agriculture. Your participation in this study will last up to [20 minutes].

**Are There Any Risks To Me?**
The things that you will be doing are no greater in risk than what you would come across in everyday life.

**Will I Be Paid To Be In This Study?**
You will not be paid for being in this study.

**Will Information From This Study Be Kept Private?**
The records of this study will be kept private. No identifiers linking you to this study will be included in any sort of report that might be published. Research records will be stored securely and only study personnel will have access to the records.

Information about you will be stored in a locked file cabinet; computer files will be stored on a password protected computer. This consent form will be filed securely in an official area.
People who have access to your information include the Principal Investigator and research study personnel. Representatives of regulatory agencies such as the Office of Human Research Protections (OHRP) and entities such as the Texas A&M University Human Subjects Protection Program may access your records to make sure the study is being run correctly and that information is collected properly. Information about you and related to this study will be kept confidential to the extent permitted or required by law.

**Who may I Contact for More Information?**
You may contact the Principal Investigator, Tracy Rutherford, Ph.D., to tell her about a concern or complaint about this research at 979-458-2744 or trutherford@tamu.edu. You may also contact the Graduate Student, Misty Miles at 979-229-6953 or misty.miles@ag.tamu.edu.

For questions about your rights as a research participant, or if you have questions, complaints, or concerns about the research, you may call the Texas A&M University Human Subjects Protection Program office at 979-458-1467 or irb@tamu.edu.

**What if I Change My Mind About Participating?**
This research is voluntary and you have the choice whether or not to be in this research study. You may decide to not begin or to stop participating at any time. If you choose not to be in this study or stop being in the study, there will be no effect on your student status, medical care, employment, evaluation, relationship with Texas A&M University.

**STATEMENT OF CONSENT**
**I agree to be in this study and know that I am not giving up any legal rights by signing this form. The procedures, risks, and benefits have been explained to me, and my questions have been answered. I know that new information about this research study will be provided to me as it becomes available and that the researcher will tell me if I must be removed from the study. I can ask more questions if I want. A copy of this entire consent form will be given to me.**

__________________________________ __________________________________
Participant's Signature Date

__________________________________ __________________________________
Printed Name Date

**INVESTIGATOR'S AFFIDAVIT**:
Either I have or my agent has carefully explained to the participant the nature of the above project. I hereby certify that to the best of my knowledge the person who signed this consent form was informed of the nature, demands, benefits, and risks involved in his/her participation.

__________________________________ __________________________________
Signature of Presenter Date

__________________________________ __________________________________
Printed Name Date

APPENDIX D

INTERVIEW QUESTIONS - CONCOURSE INTERVIEWS

1. When did you get your first smart phone and what type was it?
    a. What made you decide to get it?
2. What is the MOST important agricultural related technology that you have adopted in the past 5-10 years?
    a. Why do you consider that to be important?
3. If you were to compare yourself to other farmers/ranchers that you know, do you tend to adopt new technologies <u>before</u> or <u>after</u> them?
    a. If BEFORE- Do you like to be one of the very first people to have and use the new technology (Innovator) or do you wait until you are sure that the product works before getting it? (Early Adopter)
    b. If AFTER- Do you tend to wait until most of your peers have used the new technology so you can see if they are successful with it (Early Majority) do you end up adopting the new technology because you don't want to be left behind? (Late Majority) or do you usually not adopt new technologies? (Laggard)
4. Let's circle back around to that new ag-technology that you adopted.
    a. Where did you find out about it? Or who told you?
    b. Do you ever remember seeing an advertisement or a brochure on it?
    c. If you were on the edge of deciding to buy it… what was the deciding factor?
    d. How did you learn how to use the new technology?
    e. How long before you felt comfortable using the new technology?
5. So let's go back to the smart phone. Can you walk me through what you considered before purchasing your smart phone?
    a. So we are talking about adopting a smart phone and then a ______________.
        i. Do you consider the same things when you're buying something small or less expensive as you do when you're buying something large and more expensive?
6. Have you heard about people using drones in agriculture?
    a. If so, where did you hear about it?
7. How do you feel about using drones to monitor crops and livestock?
8. Do you know of any farmers or ranchers who are currently using drones in their operations?
9. Do you believe this technology will be widely accepted in agriculture one day?

10. What would your response be if a drone dealer or a drone service were to approach you about your operation?
11. As I mentioned, I am interested in learning about how farmers/ranchers accept or reject new technologies. Do you have anyone that you would recommend I speak with?
    a. Why would you recommend them?
    b. Do they tend to adopt new technologies first or last?
12. May I ask you what year you were born?
13. Highest level of education?
14. I am going to list three, very broad economic classes of farms and ranches here in Texas. Do you mind indicating which category your operation falls in for Gross Revenue?
    a. $1,000-$25,000
    b. $25,000-$100,000
    c. $100,000-$250,000
    d. $250,000- $1 mill
    e. $1 mill or more
15. Zip code?

# APPENDIX E

## PRE-SORT SURVEY

Zip code: ________

Age: ________

Gender: ________

Race: ________

Education Level: _____________

Number of years in farming: ________

Number of acres used in farming operation: ________

Please list any irrigation techniques that are used in your operation:

______________________________________________________________________

Please list any precision agricultural technologies you use in your operation:

______________________________________________________________________

Please list the crops you grow:

______________________________________________________________________

Participants were asked to self-report their farm revenue (crops only) before any deductions of expenses.

a. Less than $350,000
b. $350,000 - $999,000
c. $1 mill or more

APPENDIX F

INTERVIEW PROTOCOL - Q SORT

Howdy,

My name is Misty Miles. I’m a student at Texas A&M and I am currently study the adoption of drones in agriculture for my master’s research.

Would you be willing to speak with me for about 20-30 minutes regarding your views on drones in agriculture?

*If yes, I asked to set up a time in the near future for a face-to-face interview.*

**During the face-to-face interview:**

I asked if the participant was willing to sign the consent form and ok with me recording the interview for transcription purposes.

If the participant agreed, I started the interview process by verbally asking the questions from the presort survey.

Afterwards, I directed the participant to the Q sort form board.

During the Q sort process, I handed each participant the stack of randomly numbered Q set statement cards. I will asked the participant to read them once before placing them into three different stacks:

a) most like me,
b) neutral, and
c) least like me

Once the participant had three different stacks, I asked the participant to place each statement on the form board, in order of most like me to least like me, until each cell is filled with a statement. I asked them to explain how and why they are sorting the cards to aid in data analysis. When they were complete, I engaged them in a discussion about how and why they chose to sort the cards in that pattern. Next, I flipped each card over so I could see the number on the back and recorded the numbers on the blank Q sort distribution sheet. I aslo took a photo of the board with my phone.

APPENDIX G

CONSENT FORM - Q SORT INTERVIEWS

**Texas A&M University Human Research Protection Program**

## INFORMED CONSENT FORM

**Project Title: Adoption of Unmanned Aerial Systems by Farmers in Texas**

You are invited to take part in a research study being conducted by Misty Miles, a researcher from Texas A&M University. The information in this form is provided to help you decide whether or not to take part. If you decide to take part in the study, you will be asked to sign this consent form. If you decide you do not want to participate, it will not be held against you.

**Why Is This Study Being Done?**
The purpose of this study is to understand how drones in agriculture are adopted.

**Why Am I Being Asked To Be In This Study?**
You are being asked to be in this study because you are a Texas crop (cotton, grain, fruits, nuts vegetables, sugar, biomass etc.) farmer who is at least 18 years of age.

**How Many People Will Be Asked To Be In This Study?**
100 people (participants) will be invited to participate in this study.

**What Are The Alternatives To Being In This Study?**
The alternative to being in the study is not to participate.

**What Will I Be Asked To Do In This Study?**
Before the interview process, you will be asked to complete a short survey. Afterwards, you will be given a stack of cards that contain opinion statements about adopting drones in agriculture. You will be asked to read through them once before placing them in three different stacks: a) most like me, b) neutral, and c) least like me. Next, you'll be asked to place each statement on a poster board until each box is filled with a statement. While you are sorting the cards, the researcher will ask you to explain how and why you are sorting and take notes. Interviews will be recorded using audio recording devices. Recordings will assist with accurately documenting your responses. If you do not want to be audio recorded, you should not participate in this study. Your name and personal information will not be collected on the recording. The entire process will take up to one hour.

**Are There Any Risks To Me?**
No risks are expected to you from the participation in this study.

**Will I Be Paid To Be In This Study?**
You will not be paid for being in this study.

**Will Information From This Study Be Kept Private?**
Efforts will be made to limit the use and disclosure of your personal information, including research study and other records, to people who have a need to review this information. We cannot promise complete privacy. Organizations that may inspect and copy your information include the TAMU HRPP and other representatives of this institution.

**Who may I Contact for More Information?**
You may contact the Principal Investigator, Tracy Rutherford, Ph.D., to tell her about a concern or complaint about this research at 979-458-2744 or trutherford@tamu.edu. You may also contact the Graduate Student, Misty Miles at 979-229-6953 or misty.miles@ag.tamu.edu.

For questions about your rights as a research participant, or if you have questions, complaints, or concerns about the research, you may call the Texas A&M Human Research Protection Program office at 1-979-458-4067, toll free at 1-855-795-8636, or by email at irb@tamu.edu.

**What if I Change My Mind About Participating?**

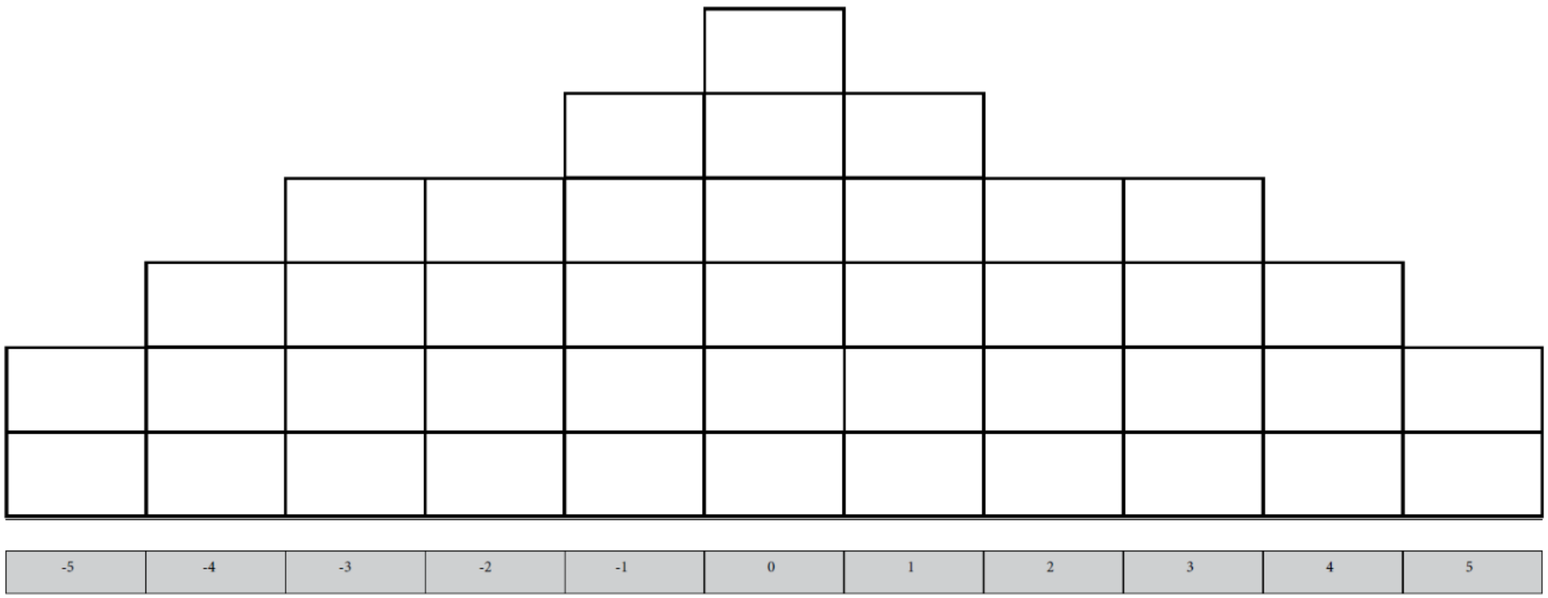
This research is voluntary and you have the choice whether or not to be in this research study. You may decide to not begin or to stop participating at any time.

Your signature documents your permission to take part in this research.

| Signature of subject | Date |
|---|---|
| Printed name of subject | |
| Signature of person obtaining consent | Date |
| Misty Miles<br>Printed name of person obtaining consent | |

APPENDIX H

BLANK Q SORT FORM BOARD SHEET




Least like me Neutral Most like me

# APPENDIX I

## CORRELATION MATRIX BETWEEN SORTS

| | Sorts | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | C01 | 100 | -25 | 30 | 19 | 25 | 33 | 40 | 33 | 31 | 37 | 34 | 44 | 24 | 22 | 27 | 37 | 17 | 43 | 39 | 27 | 24 | 38 | 33 | 41 | 18 |
| 2 | C02 | -25 | 100 | -14 | -3 | 7 | 5 | 3 | -2 | -13 | 0 | 6 | -18 | -36 | 17 | 2 | -7 | 15 | -15 | 12 | 1 | 0 | -9 | 1 | -10 | -11 |
| 3 | C03 | 30 | -14 | 100 | 65 | 8 | 33 | 24 | 37 | 54 | 42 | 46 | 52 | 29 | 53 | 30 | 45 | 46 | 13 | 54 | 25 | 17 | 51 | 40 | 37 | 18 |
| 4 | C04 | 19 | -3 | 65 | 100 | 27 | 49 | 41 | 65 | 38 | 55 | 53 | 53 | 26 | 71 | 47 | 61 | 59 | 43 | 74 | 37 | 36 | 52 | 73 | 62 | 41 |
| 5 | C05 | 25 | 7 | 8 | 27 | 100 | 43 | 59 | 57 | 18 | 34 | 25 | 39 | -21 | 37 | 58 | 61 | 46 | 38 | 31 | 50 | 30 | 15 | 59 | 40 | 55 |
| 6 | SE06 | 33 | 5 | 33 | 49 | 43 | 100 | 58 | 72 | 37 | 45 | 56 | 46 | -18 | 49 | 63 | 59 | 49 | 51 | 68 | 50 | 32 | 29 | 65 | 48 | 60 |
| 7 | SE07 | 40 | 3 | 24 | 41 | 59 | 58 | 100 | 72 | 31 | 56 | 42 | 53 | -21 | 65 | 65 | 76 | 45 | 57 | 65 | 66 | 39 | 9 | 68 | 49 | 66 |
| 8 | S08 | 33 | -2 | 37 | 65 | 57 | 72 | 72 | 100 | 42 | 58 | 63 | 56 | -12 | 63 | 69 | 75 | 55 | 55 | 75 | 62 | 45 | 25 | 81 | 63 | 64 |
| 9 | S09 | 31 | -13 | 54 | 38 | 18 | 37 | 31 | 42 | 100 | 38 | 36 | 53 | 6 | 60 | 30 | 48 | 38 | 22 | 45 | 27 | 17 | 25 | 42 | 34 | 41 |
| 10 | S10 | 37 | 0 | 42 | 55 | 34 | 45 | 56 | 58 | 38 | 100 | 39 | 41 | 8 | 66 | 33 | 55 | 47 | 49 | 59 | 55 | 25 | 24 | 55 | 38 | 34 |
| 11 | S11 | 34 | 6 | 46 | 53 | 25 | 56 | 42 | 63 | 36 | 39 | 100 | 39 | 10 | 55 | 32 | 56 | 28 | 37 | 77 | 42 | 27 | 58 | 55 | 56 | 38 |
| 12 | S12 | 44 | -18 | 52 | 53 | 39 | 46 | 53 | 56 | 53 | 41 | 39 | 100 | 28 | 52 | 55 | 75 | 45 | 55 | 67 | 50 | 51 | 42 | 64 | 64 | 63 |
| 13 | N13 | 24 | -36 | 29 | 26 | -21 | -18 | -21 | -12 | 6 | 8 | 10 | 28 | 100 | -4 | -9 | 5 | -2 | 23 | 7 | -24 | 13 | 43 | 4 | 21 | -8 |
| 14 | N14 | 22 | 17 | 53 | 71 | 37 | 49 | 65 | 63 | 60 | 66 | 55 | 52 | -4 | 100 | 50 | 70 | 53 | 38 | 76 | 54 | 21 | 29 | 69 | 56 | 51 |
| 15 | N15 | 27 | 2 | 30 | 47 | 58 | 63 | 65 | 69 | 30 | 33 | 32 | 55 | -9 | 50 | 100 | 69 | 50 | 58 | 52 | 53 | 26 | 18 | 71 | 57 | 66 |
| 16 | N17 | 37 | -7 | 45 | 61 | 61 | 59 | 76 | 75 | 48 | 55 | 56 | 75 | 5 | 70 | 69 | 100 | 52 | 67 | 71 | 67 | 48 | 40 | 85 | 69 | 78 |
| 17 | SE18 | 17 | 15 | 46 | 59 | 46 | 49 | 45 | 55 | 38 | 47 | 28 | 45 | -2 | 53 | 50 | 52 | 100 | 30 | 47 | 54 | 33 | 30 | 66 | 38 | 52 |
| 18 | SE19 | 43 | -15 | 13 | 43 | 38 | 51 | 57 | 55 | 22 | 49 | 37 | 55 | 23 | 38 | 58 | 67 | 30 | 100 | 53 | 37 | 35 | 37 | 71 | 65 | 62 |
| 19 | H20 | 39 | 12 | 54 | 74 | 31 | 68 | 65 | 75 | 45 | 59 | 77 | 67 | 7 | 76 | 52 | 71 | 47 | 53 | 100 | 50 | 43 | 50 | 75 | 66 | 57 |
| 20 | H21 | 27 | 1 | 25 | 37 | 50 | 50 | 66 | 62 | 27 | 55 | 42 | 50 | -24 | 54 | 53 | 67 | 54 | 37 | 50 | 100 | 39 | 16 | 62 | 42 | 58 |
| 21 | H22 | 24 | 0 | 17 | 36 | 30 | 32 | 39 | 45 | 17 | 25 | 27 | 51 | 13 | 21 | 26 | 48 | 33 | 35 | 43 | 39 | 100 | 19 | 44 | 31 | 35 |

APPENDIX I (CONTINUED)

CORRELATION MATRIX BETWEEN SORTS

| | Sorts | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 22 | H23 | 38 | -9 | 51 | 52 | 15 | 29 | 9 | 25 | 25 | 24 | 58 | 42 | 43 | 29 | 18 | 40 | 30 | 37 | 50 | 16 | 19 | 100 | 44 | 40 | 15 |
| 23 | H24 | 33 | 1 | 40 | 73 | 59 | 65 | 68 | 81 | 42 | 55 | 55 | 64 | 4 | 69 | 71 | 85 | 66 | 71 | 75 | 62 | 44 | 44 | 100 | 71 | 77 |
| 24 | SE25 | 41 | -10 | 37 | 62 | 40 | 48 | 49 | 63 | 34 | 38 | 56 | 64 | 21 | 56 | 57 | 69 | 38 | 65 | 66 | 42 | 31 | 40 | 71 | 100 | 57 |
| 25 | N16 | 18 | -11 | 18 | 41 | 55 | 60 | 66 | 64 | 41 | 34 | 38 | 63 | -8 | 51 | 66 | 78 | 52 | 62 | 57 | 58 | 35 | 15 | 77 | 57 | 100 |

APPENDIX J

FACTOR ARRAY FOR FACTOR 1

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | 40 | | | | | |
| | | | | 41 | 30 | 24 | | | | |
| | | 12 | 29 | 2 | 8 | 5 | 36 | 37 | | |
| | 3 | 17 | 11 | 19 | 4 | 33 | 27 | 35 | 1 | |
| 15 | 9 | 20 | 25 | 42 | 7 | 28 | 13 | 26 | 32 | 34 |
| 21 | 10 | 22 | 6 | 18 | 16 | 31 | 14 | 23 | 39 | 38 |
| **-5** | **-4** | **-3** | **-2** | **-1** | **0** | **1** | **2** | **3** | **4** | **5** |

Least like me | Neutral | Most like me

APPENDIX K

FACTOR ARRAY FOR FACTOR 2

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | 28 | | | | | |
| | | | | 2 | 7 | 40 | | | | |
| | | 25 | 18 | 35 | 1 | 16 | 14 | 38 | | |
| | 3 | 22 | 12 | 26 | 41 | 24 | 6 | 39 | 13 | |
| 21 | 15 | 29 | 19 | 30 | 27 | 37 | 31 | 4 | 5 | 8 |
| 17 | 9 | 20 | 10 | 11 | 23 | 36 | 42 | 33 | 34 | 32 |
| **-5** | **-4** | **-3** | **-2** | **-1** | **0** | **1** | **2** | **3** | **4** | **5** |

Least like me Neutral Most like me

APPENDIX L

FACTOR ARRAY FOR FACTOR 3

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | 9 | | | | | |
| | | | | 20 | 18 | 10 | | | | |
| | | 35 | 30 | 22 | 8 | 41 | 12 | 29 | | |
| | 21 | 36 | 28 | 37 | 38 | 11 | 4 | 3 | 32 | |
| 17 | 27 | 24 | 34 | 5 | 6 | 40 | 19 | 7 | 2 | 13 |
| 31 | 15 | 26 | 39 | 42 | 1 | 33 | 25 | 16 | 23 | 14 |
| **-5** | **-4** | **-3** | **-2** | **-1** | **0** | **1** | **2** | **3** | **4** | **5** |

Least like me      Neutral      Most like me