5-2019

A Behavioral Research Model for Small Unmanned Aircraft Systems for Data Gathering Operations

Paul Leonard Myers III

A BEHAVIORAL RESEARCH MODEL FOR SMALL UNMANNED AIRCRAFT SYSTEMS FOR DATA GATHERING OPERATIONS

By

Paul Leonard Myers III

A Dissertation Submitted to the College of Aviation
in Partial Fulfillment of the Requirements for the Degree of
Doctor of Philosophy in Aviation

Embry-Riddle Aeronautical University
Daytona Beach, Florida
May 2019

A BEHAVIORAL RESEARCH MODEL FOR SMALL UNMANNED AIRCRAFT SYSTEMS FOR DATA GATHERING OPERATIONS

By

Paul Leonard Myers III

This Dissertation was prepared under the direction of the candidate's Dissertation Committee Chair, Dr. Dothang Truong, and has been approved by the members of the dissertation committee. It was submitted to the College of Aviation and was accepted in partial fulfillment of the requirements for the
Degree of
Doctor of Philosophy in Aviation

Dothang Truong, Ph.D.
Committee Chair

John M. Robbins, Ph.D.
Committee Member

Mark A. Friend, Ed.D.
Interim Associate Dean, School of Graduate Studies, College of Aviation

Robert E. Joslin, Ph.D.
Committee Member

Alan J. Stolzer, Ph.D.
Dean, College of Aviation

Tony Kern, Ed.D.
Committee Member

Lon D. Moeller, J.D.
Senior Vice President for Academic Affairs and Provost

3/7/19
Date

ABSTRACT

Researcher: Paul Leonard Myers III

Title: A BEHAVIORAL RESEARCH MODEL FOR SMALL UNMANNED AIRCRAFT SYSTEMS FOR DATA GATHERING OPERATIONS

Institution: Embry-Riddle Aeronautical University

Degree: Doctor of Philosophy in Aviation

Year: 2019

According to Hitlin (2017) of the Pew Research Center, only 8% of U.S. citizens own an unmanned aircraft. Additionally, regarding feelings if U.S. citizens saw an unmanned aircraft flying close to where they live, 26% say they would be nervous, 12% feel angry, and 11% are scared. As of March 9, 2018, there were 1,050,328 U.S. small unmanned aircraft system (sUAS) registrations compared to 947,970 November 29, 2017. While sUAS use has increased in the U.S., it has lagged when compared to other items for personal use available to U.S. citizens as 92% own cell phones (Anderson, 2015). This slower acceptance rate identifies a potential need for more research as to why. No studies have specifically focused on individual factors for the behavioral intention of using sUAS for data gathering, encompassing the variables used in this study, nor a Structural Equation Model that shows relevant factors and associated relationships. Also, current ground theories fall short, lacking appropriate variables or modeling ability.

Thus, this dissertation study developed a new behavioral research model termed VMUTES to determine the factors that influenced individuals' intentions to operate small sUASs for data gathering and relationships between those factors. A sUAS system is comprised of integrated hardware, software, processes, or firmware. Data gathering is defined in this study as the transmission or recording of audio, pictures, videos, or

collection of other data for modeler, civil, or public use. The new VMUTES model integrates portions of the technology acceptance model (TAM) and theory of planned behavior (TPB) model integrated with new factors: perceived risk and knowledge of regulations. The study used random sampling of Amazon Mechanical Turk® (AMT) members using an AMT Human Intelligence Task (HIT) that included a link to an online cross-sectional large-scale survey to collect data. Data Analysis included descriptive statistics analysis and the SEM process. Besides developing and validating a model and determining influencing factors, attention was also on verifying the relationships between constructs. Study limitations and future research recommendations are also discussed.

Results indicated the VMUTES model had a strong predictive power of sUAS use for data gathering with seven of the ten original hypotheses supported while having a good model fit. Four new hypotheses were also identified with three supported. Additionally, all VMUTES model factors except for facilitating conditions were determined to have either a direct or indirect effect on behavioral intention and/or actual behavior with the TAM and TPB related factors having the strongest effects.

Practically, this study filled an aviation research knowledge gap for sUAS use for data gathering. It also provided a research model and identified influencing factors of individuals' behavioral intentions related to sUAS for data gathering. Thus, the newly developed model incorporating new variables can be used for further sUAS research and can provide an adaptable model for aviation and other technology areas to predict and facilitate new technology implementation where current models fall short. Finally, this study explored new and verified previously existing demographic variables for individuals who use sUASs for data gathering.

DEDICATION

I dedicate this dissertation to my family, especially to the love of my life; Terry, and my awesome son Thomas, as well as all the faculty members at Embry-Riddle Aeronautical University, whose tireless efforts and dedication made my education a reality.

ACKNOWLEDGEMENTS

The research model in this study; VMUTES (Viti, Myers/Mashburn, Uland, Truong, Embry-Riddle Aeronautical University) are those that I would like to thank, because those individuals have had a profound impact in shaping my life and education.

Concerning those at Embry-Riddle, I would like to express my unbounded gratitude to my dissertation committee members: Dr. John M. Robbins, Dr. Robert E. Joslin, and Dr. Tony Kern for their mentoring and help throughout this process. I would especially like to thank Dr. Dothang Truong, the chair of my dissertation committee, for countless questions answered, his patience, his caring and understanding, his guidance and mentoring, and his knowledge. I have never met a professor who was so involved and dedicated to the success of his students. I also would like to thank Cohort 7 for their support and encouragement during this program, especially to my good friend and project teammate; Bud Starr. I could not have made it through the program without all of you.

Most importantly, I would like to thank my family. For those in my family who are no longer on this earth but influenced me greatly include my grandparents; Paul and Mona Myers Sr., Lee and Gladys Sullenger, Sam and Gonda Viti, and Tom and Clota Mashburn. To my dearly departed parents Sam and Jean Viti who believed in me and sacrificed everything to allow me to pursue my dreams of going to college and becoming a pilot. Most importantly, thank you to my awesome wife Terry and son Thomas. Thank you both for believing in me, supporting me, and for sacrificing and allowing me the countless hours to work on school away from you.

TABLE OF CONTENTS

Page

Signature Page ... iii

Abstract ... iv

Dedication ... vi

Acknowledgements ... vii

List of Tables ... xv

List of Figures ... xvii

Chapter I Introduction ... 1

Background of the Study ... 1

Definition and Rapid Growth of sUAS ... 1

Specific Rules and Requirements for sUAS Operations ... 3

Current Usage of sUAS for Commercial and Public Purposes. ... 7

Major Trends in sUAS Research ... 8

Current Theories are Lacking ... 11

Statement of the Problem ... 13

Purpose Statement ... 15

Research Questions ... 15

Hypotheses ... 15

Significance of the Study ... 16

Delimitations ... 18

Limitations and Assumptions ... 20

Definitions of Terms 22

List of Acronyms 28

Chapter II Review of the Relevant Literature 33

sUAS Technology Overview 33

sUAS Data Gathering 34

Law and Border Enforcement 36

Wildlife Monitoring 37

Environmental 37

Agricultural 38

Transportation 39

Sports and Media Broadcasting 40

Humanitarian / Disaster Response 40

Energy 41

Education 41

Personal 42

Movie Filming 42

Detractors That Could Affect Individuals' sUAS Data Gathering Intentions 42

Physical Risk 43

Security Risk 44

Invasion of Privacy 45

Legal Risk 47

Financial Risk 48

FAA Regulations 48
Knowledge of Regulations.. 50
Airspace Deconfliction 51
Lack of Training 53
Personal Attitude Toward Use 55
Demographic Factors 55
Perceived Risk and sUAS Behavior 56
Perceived Risk Measurement.. 57
Ground Theories for the Study 58
Technology Acceptance Model (TAM)........................... 59
Theory of Planned Behavior (TPB) 71
TPB Model Effectiveness 82
Combined Models – TAM/TPB Model (C-TAM/TPB). . 83
Constructs Influencing Individuals' Intentions to Use sUASs for
Data Gathering 93
Perceived Usefulness 98
Perceived Ease of Use... 98
Subjective Norms... 99
Attitude Toward Use... 99
Facilitating Conditions.. 100
Perceived Risk 100
Knowledge of Regulations.. 101
Behavioral Intention.. 101

Actual Behavior/Use 102

Theoretical Framework and Hypotheses (VMUTES Model) 102

Chapter Summary 110

Chapter III Methodology 112

Research Approach 112

Research Design and Procedures 113

Apparatus and Materials 115

Research Procedure 116

Target Population 118

Sampling Frame 119

Qualifications of the Target Population 119

Sample Size 121

Sampling 124

Sources of the Data 125

Data Collection Device 125

Instrument Reliability 129

Instrument Validity 129

Ethical Issues and Considerations 131

Treatment of the Data 135

Demographic Data and Non-Response Bias 135

Descriptive Statistics 140

Missing Values 141

Outliers 141

Assumption Testing and Data Transformation (If Needed) 142
Examine Estimates 142
Confirmatory Factor Analysis 143
Post-Hoc Analysis 143
Reliability Testing 144
Construct Validity 145
Full Structural Model Testing 147
Examine Estimates 148
Full Structural Model Fit 148
Post-Hoc Analysis 148
Hypothesis Testing 149
Chapter IV Results 150
Pretest 150
Pilot Study 151
Survey Responses and Sample 156
Demographics 158
User Demographics 158
sUAS Users for Data Gathering Operation Characteristics 163
Descriptive Statistics 169
Non-Response Bias Testing 175
Additional Comments Summary 176

Confirmatory Factor Analysis 180
Normality 180
Missing Data 181
Outliers 182
Model Fit and Respecification 183
Reliability and Validity 186
Discriminant validity 197
Structural Model Assessment 199
Model Construction / Model Fit and Respecification as Required. 199
SEM Model Hypothesis Testing. 200
Four New Relationships Identified 203
Modified SEM model fit 207
Modified SEM Model Hypothesis Testing 208
Research Question One 211
Research Question Two 212
Rank-Ordered Standardized Indirect Effects of KR, PR, SN, PEOU, PU, and ATU on AB 214
Chapter Summary 214
Chapter V Discussion, Conclusions, and Recommendations 217
Discussion of Results 218
Individual and Operational sUAS Data Gathering User Characteristics 218

Additional Findings 224

Amazon Mechanical Turk (AMT) 224

VMUTES Model Modifications 226

VMUTES Model Results 228

Discriminant Validity 235

Research Question 1 237

Research Question 2 238

Conclusions 238

Theoretical Implications. 239

Practical Implications 241

Limitations of the Study 242

Recommendations for Future Research 244

References 248

Appendices 273

A Permission to Conduct Research 273

B Data Collection Device 282

C Tables 299

D Figures 307

LIST OF TABLES

Table Page

1 Selected TAM Studies and Constructs/Variables 61

2 Summary of TPB Selected Studies and Constructs/Variables 75

3 Summary of C-TAM/TPB and UTAUT Studies and Constructs/Variables 85

4 Souces Used for New Research Model Constructs 93

5 Operational Definitions of Research Model Constructs...................................... 97

6 Summary of Demographic Variables 126

7 Summary of Demographic Variable Comparison Values 136

8 Factor Loading, CR and Cronbach's Alpha - Pilot Study 151

9 Case Deletion Summary 158

10 Basic Demographic Characteristics - sUAS Users for Data Gathering 159

12 Descriptive Statistics Scores of Constructs 169

12 Descriptive Statistics Scores of Constructs 175

13 Chi-Square Comparison of Respondents and Non-Respondents 175

14 Summary of Additional Comment Responses 180

15 Comparison of Four Datasets 183

16 Model Fit Indices - Unspecified CFA Model and First Specified CFA Model 184

17 First Specified CFA Model Convergent Validty... 186

18 Discriminant Validity of First Specified CFA Model 188

19 Model Fit Indices for the CFA Models 195

20 Final Respecified CFA Model Construct Reliability and Covergent Validity. 196

21 Discriminant Validity Using Fornell-Larcker Critierion - Final CFA Model.. 197

22 HTMT Ratio Values for Final Specified CFA Model 198

23 Original Structural Model Hypothesis Testing 201

24 Model Fit Comparison Between SEM and Modified SEM Model 208

25 Modified Structural Model Hypothesis Testing 208

26 SEM Standardized Regression Weight Changes 211

27 Modified SEM Model Rank-Ordered Strength of Standardized Estimates 213

28 Factor Rank-Ordered Standardized Indirect Effects on BI 214

LIST OF FIGURES

Figure Page

1 Original Technology Acceptance Model 60

2 Components and Relationships of the Original Theory of Planned Behavior 74

3 Research Theoretical Framework and Hypotheses (VMUTES model). 103

4 SEM Process for the Study 115

5 Research Procedure 118

6 FAA Projected Hobbyist and Commercial UAS 139

7 U.S. Census Bureau Population Distribution and U.S. Regional Map 139

8 PU2, PU4, and ATU4 Histograms 175

9 First Specified CFA Model 185

10 Final Respecified CFA Model 194

11 SEM Model with Standardized Regression Weights Displayed 200

12 Modified SEM Model with Standardized Regression Weights Displayed 207

CHAPTER I

INTRODUCTION

Background of the Study

Definition and rapid growth of sUAS. Operations in U.S. airspace is comprised of manned and unmanned aircraft. An unmanned flying machine defines a *drone* (Federal Regulation, 2016). One of the Federal Aviation Administration (FAA) defined drone categories is a sUAS made up of the small unmanned aircraft and system. *A small unmanned aircraft* (sUA) is one that weighs less than 55 pounds (FAA, AC-107-2, 2016b). A *system* is defined as integrated elements that may comprise hardware, software, processes, or firmware and meet a set objective (Parnell, Driscoll, & Henderson, 2011). Thus, *a small unmanned aircraft system* (sUAS) is defined as a UA and its associated elements that meet U.S. Government requirements for safe and efficient operation in the National Airspace System (NAS) (Aeronautics and Space, 2017; FAA, AC-107-2, 2016b). Those sUAS elements consist of: (a) the sUAS vehicle, (b) a payload of a portable remote-sensing apparatus, (c) the human required for operation, (d) an interface and underlying structure used to transmit and translate information from the sUAS to the pilot on the ground, and (e) support equipment (Terwilliger, Ison, Robbins, & Vincenzi, 2017).

Small unmanned aircraft can be divided into three general categories: model, civil, and public aircraft (FAA, 2017c). *A model aircraft* is an unmanned aircraft flown for hobby or recreational purposes only (FAA, AC-91-57A, 2016a; FAA Modernization and Reform Act of 2012, 2012a). For the purposes of this study, a *modeler* is an individual flying a model aircraft under the Special Rule for Model Aircraft (FAA, 2017b). Modelers are also often referred to in the literature as hobbyists. The FAA further refines the modeler definition as not flying for work but for enjoyment (FAA, 2017b). *Civil use* includes non-government personal or commercial flights which do not fall in the model aircraft category (Blitz et al., 2015). Most commonly, U.S. citizens think of commercial use as for profit as evidenced by being charged to fly airline industry commercial aircraft. However, the FAA definition of *commercial use* is not just for profit, but furtherance of a business. For example, if a sUAS operator takes pictures for a realtor using a model aircraft and does not charge, it is considered furtherance of a business and therefore commercial use (FAA, 2017c). *Public use* includes non-commercial governmental functions such as biological or geological resource management, search-and-rescue, intelligence missions, firefighting, law enforcement, aeronautical research, or national defense (Department of Transportation, Federal Aviation Administration Final Rule, 2018; FAA Modernization and Reform Act of 2012, 2012b). However, this study excludes Department of Defense use since it is not voluntary. In the context of this research, the term sUAS includes model, civil, and public aircraft used for data gathering. *Data gathering*, in the context of this study, is defined as the transmission or recording of audio, pictures, videos, or collection of other data for modeler, civil, or public use. To be effective in the data gathering role in all three categories, sUASs can be easily modified by adding sensors and software automating data collection, transfer, and analysis.

The United States today has the busiest and most complex airspace in the world (Federal Regulation, 2016). Between 2016 and 2020, seven million UASs are expected to be flying in the U.S. alone (Klauser, & Pedrozo, 2017). As of March 9, 2018, there were 1,050,328 sUAS registrations with 896,728 modelers and 153,600 non-modelers (FAA, 2018). The current weekly registration rate is 5,000 to 7,000 with anticipated hikes during the holiday seasons for modelers and around 1,000 per week for non-modelers (FAA, 2017a). The modeler aircraft fleet is forecasted to triple over the next five years to over 3.5 million units by 2021, and the commercial fleet is forecasted to be as high as 742,000 by the end of 2019 (FAA, 2017a). Additionally, the FAA noted 82,113 remote pilot certificates have been issued. Finally, 1,457 FAA Part 107 waivers to the U.S. Code of Federal Regulations have been issued for operations at night, over people, for Beyond Visual Line of Sight (BVLOS), for lower altitudes, and from a moving vehicle (FAA, 2018). Commercial use waivers issued by the FAA were in the areas of aerial photography (34%), real estate (26%), construction or industrial use (26%), agriculture (21%), emergency management (8%), and insurance (5%) (FAA, 2017a). Supporting this rapid growth, Blitz, Grimsley, Henderson, and Thai (2015) describe a vast array of unmanned aircraft (UA) in development or on the market that are as small as an insect, are powered by the sun, have integrated cameras, autonomously track targets, and those that provide internet connectivity.

Specific rules and requirements for sUAS operations. Because of potential airspace conflicts and safety concerns, the U.S. Congress, FAA, and State and local governments have set initial sUAS operating procedures. For operations in the model aircraft category, Congress instituted Public Law 112-95, Section 336 which contains the Special Rule for Model Aircraft with FAA Part 101 Subpart E, Model Aircraft with Advisory Circular (AC) 91-57A providing guidance to that law (FAA, AC-91-57A, 2016a; FAA Modernization and Reform Act of 2012, 2012a). Title 14 of the Code of

Federal Regulations (14 CFR) Part 107 applies to sUASs used for commercial use and all others who do not meet the qualifications of being in the aircraft model category (Aeronautics and Space, 2017; FAA, 2016b). The 14 CFR Part 107 regulation consists of four parts including (a) general information, (b) operating rules, (c) remote pilot certification, and (d) waivers (Aeronautics and Space, 2017). While 14 CFR Part 107 provides the operating regulations to sUAS users, the FAA provides more detailed guidance in Small Unmanned Aircraft Systems (sUAS), AC-107-2, (2016) which is designed to aid sUAS users in compliance with 14 CFR Part 107 (Federal Regulation, 2016). Additionally, the FAA instituted a *know before you fly* education campaign for unmanned aircraft users (Federal Regulation, 2016). The education is meant as preventive and designed to make sure sUAS users are aware of FAA regulations and where they can fly (Werner, 2017).

For operations in the model aircraft category, the following criteria must be met including (a) the aircraft is flown for hobby or recreational use, (b) the aircraft is flown within the programming of a nationwide community-based organization and in accordance with community-based safety guidelines, (c) the aircraft weighs less than 55 pounds, (d) the aircraft is operated so as not to interfere with and gives way to manned aircraft, (e) notification is given to air traffic control (ATC) when flown within five miles of an airport, (f) the aircraft is capable of sustained flight, and (g) the aircraft is flown within visual line-of-sight (VLOS) of the person flying the aircraft (FAA, AC-91-57A, 2016a; FAA, AC-107-2, 2016b; FAA, 2017b; FAA Modernization and Reform Act of 2012, 2012a).

A model aircraft flown under the Special Rule for Model Aircraft (Public Law 112-95, Section 336) must be labeled with a registration number and the operator registered as a modeler. However, modelers are only required to have one registration number which can be used for multiple aircraft. To register, the owner must be 13 years of age or, if not, someone 13 years or older must register the sUAS (FAA, 2017b). The FAA also offers safety tips meant to be reviewed as part of the pre-flight checklist to help modelers fly safely. These include: (a) registering the sUAS, (b) keeping the sUAS in line-of-sight, (c) flying at or below 400 feet, (d) being aware of FAA airspace restrictions, (e) never flying near other aircraft especially near airports, (f) never flying over groups of people, stadiums, or society events, (h) never flying near emergencies, (i) never flying under the influence of alcohol or drugs, and (j) operating in accordance with a community-based set of safety guidelines and within the programming of a nationwide community-based organization (FAA, 2017b). Also, the owner must be a U.S. citizen or permanent resident (FAA, 2017b). While the modeler is loosely regulated by the FAA, if the modeler operates the sUAS in an unsafe or reckless manner, the FAA has the authority to pursue enforcement action against persons operating model aircraft who compromise the safety of the national airspace system (FAA, 2017c). Compared to the model aircraft category, the FAA has much more stringent requirements on sUASs and operators that are not categorized as modelers (Mariani, 2014).

Any sUAS personal operations not categorized for hobby or recreational purposes in the model aircraft category must comply with 14 CFR Part 107, unless operating under a Section 333 waiver (FAA, 2017b). Additionally, certain requirements must be met. FAA AC 107-2 details 14 CFR Part 107 requirements and defines registration, certification of sUAS, qualifications, and operating procedures for the sUAS. A sUAS must be registered using an online registration process prior to operating within the U.S. with each aircraft having its own registration number (FAA, AC-107-2, 2016). Operators must be mentally and physically fit enough to operate the sUAS, although no medical certificate is required; be at least 16 years of age; read, speak, and understand the English language; pass an initial FAA knowledge test to obtain a Remote Pilot Airman Certificate; and pass Transportation Security Administration (TSA) screening (FAA, AC-107-2, 2016). The knowledge test of operating procedures includes: (a) flight for hobby or recreational use, (b) deconfliction with and yielding to manned aircraft, (c) when operating within five miles of an airport, provide the air traffic control (ATC) tower and airport operator with prior notice, (d) the aircraft is flown in visual line-of-sight, (e) the aircraft is airworthy, (f) flight over people not under safe cover is prohibited, (g) flights must be conducted during the daytime, and (h) the sUAS cannot be operated in a reckless manner (FAA, AC-107-2, 2016). More specifically, the FAA expects sUAS CFR Part 107 operators to not fly a groundspeed faster than 87 knots, higher than 400 AGL, with less than a minimum visibility of three statute miles, and to remain 500 feet below a cloud and at least 2000 feet horizontally from the cloud. Some sUASs do not have instrumentation to measure airspeed or altitude. Therefore, the FAA expects sUAS users to estimate those parameters and offers non-precise methods to do so (FAA, AC 107-2, 2016). Waivers can be requested from the FAA to fly at night, directly over people, fly from a moving vehicle or aircraft, fly multiple aircraft with one pilot, fly beyond visual line-of-sight, fly above 400 feet, visual observer, operating limitations, and flying near airports / in controlled airspace. If a Section 333 waiver has been obtained, that takes precedence over 14 CFR Part 107 (FAA, 2017b).

For federal, state, and local government agencies, operations can be conducted using 14 CFR Part 107, but most likely those agencies will need to apply for a public Certificate of Waiver or Authorization (COA) for specific operations. After the COA is submitted, the FAA thoroughly reviews the operation and issues limitations or provisions to ensure safe operation with other airspace users. As with other users, government agencies are required to register their sUASs (FAA, 2017b).

In summary, the category of operation, model aircraft, civil, or public use, determines the specific rules to be followed. However, the application of the sUA can change the category of operation as noted in the previous example of using a model aircraft for taking pictures for a realtor, changing the category from model aircraft to commercial operation. Additionally, an individual can have more than one sUA that operates in different categories. For example, an individual can operate sUA that operates in the model aircraft category and another sUAS that operates in the commercial category. In this example, the individual would be responsible for complying with the rules of the applicable category being flown.

Current usage of sUAS for commercial and public purposes. Effectively, sUASs add a new dimension to data gathering, transfer, and analysis for data gathering (Klauser & Pedrozo, 2017). Thus, sUASs are a practical choice for commercial and public applications because of high-maneuverability and ability to hover, generally low acquisition and maintenance costs, and ease of deployment (Hayat, Yanmaz, & Muzaffar, 2016). Unmanned aircraft data gathering operations include those ranging from law enforcement to university research. Unmanned aircraft also have the potential to be used in other areas such as journalism, filmmaking, and transportation of medical supplies, food, and other goods. Additionally, the market for unmanned aircraft as a recreational device for personal use is also growing (Domestic Drones, 2016). Thus, sUASs are serving more and more needs in the aviation realm. Specifically, regarding data gathering, a sUAS extends the senses, has low visibility, and offers a comprehensive view using multiple measures offering data real-time using a video link. sUASs are also versatile enough to be applied to a multitude of tasks and applications (Bracken-Roche, 2016). sUAS technology has enabled these feats due to integrated circuit advances and advanced chip technology allowing sophisticated onboard processing of high-frame, high-resolution video (Villasenor, 2014). Terwilliger et al. (2017) agree with the uses but advocate more generalized categories to describe uses at the time of their writing that include: (a) aerial filming, (b) real estate, (c) environmental, (d) search and rescue, (e) construction, (f) utility inspection, (g) general aerial surveying, (h) agriculture, (i) emergency management, (j) other, and (k) insurance. Specific commercial and public uses are explored more in Chapter II.

Major trends in sUAS research. Although several studies have been conducted on technology behavioral intention models for UA, none focused on behavioral intention to use a sUAS for data gathering encompassing the variables in this study, nor a Structural Equation Model (SEM) showing relevant factors and associated relationships. Clothier, Greer, Greer, and Mehta (2015) focused on risk perception and society acceptance of drones. While the study provided valuable information on perceived risk (PR), it did not address individuals' behavioral intentions toward using a sUAS for data gathering. Another study focused on consumer acceptance of service delivery UA (Ramadan, Farah, & Mrad, 2017). However, the study was focused on studying consumer acceptance of service delivery UA by a retailer and not individuals' behavioral intentions. Additionally, the study was only a literature review and therefore offered no derived conclusions from a data analysis. Embry-Riddle Aeronautical University is a leader in the UAS field with several studies that focused on sUASs. Terwilliger et al. (2015) focused on determining influencing factors for use of UASs in support of aviation accidents and emergency response, providing valuable information on regulations governing sUASs operation, challenges of operating sUASs, and a literature review to determine relevant factors and conclusions. However, influencing factors were decided through a literature review only using simple descriptive statistics to determine factors. Also, the study was not focused in the area of sUASs used for data gathering. Other studies listed by Terwilliger et al. (2017), the Embry-Riddle Aeronautical University Hunt Library, and Google® Scholar focused on operations aspects of sUASs including integration into the National Airspace System, sUAS technology innovations, human factors, commercial applications, training, regulations, challenges, and career opportunities. Examples of these types of studies include Frew and Brown (2008) discussing airborne communication networks for sUASs; Paulson, Sóbester, and Scanlan (2017) focused on sUA design; Sabatini et al. (2015) researched an innovative navigation and guidance system; Wariach (2013) researched how to minimize human factor mishaps in unmanned systems; and Cutler et al. (2010) focused on energy harvesting and mission effectiveness of sUA. However, there were no studies found that specifically focused on factors relating to individuals' behavioral intentions toward using sUASs for data gathering.

How technologies are perceived by individuals can be a barrier to sUAS use and damage the relationship between unmanned aircraft users and those in society who are subject to their use (Bracken-Roche, 2016). Related, Bloss (2014) states the acceptance in the civilian world of sUASs was 67 percent for security, 88 percent for search and rescue, 63 percent for crime fighting, and 61 percent for commercial applications. However, the numbers only represent acceptance in society, not individual acceptance or behavioral intention. Additionally, the factors that determine individuals' behavioral intentions are not explained.

When comparing percentage of users between unmanned aircraft and other personal devices, 8% of U.S. citizens own an unmanned aircraft while 92% own a cell phone (Anderson, 2015; Hitlin, 2017). Concerning negative feelings and reluctance of use, when surveyed about feelings of unmanned aircraft flying close to their house, 26% said they would be nervous, 12% felt anger, and 11% were scared (Hitlin, 2017). Additionally, 54% felt unmanned aircraft should not be allowed to fly near homes, while 45% indicated that unmanned aircraft should not be allowed at public events like concerts or rallies (Hitlin, 2017). As previously stated, as of March 9, 2018, there were 1,050,328 U.S. small unmanned aircraft system (sUAS) registrations including 896,728 hobbyists and 153,600 non-hobbyists (FAA, 2018). Comparatively, there were 947,970 total registrations, 845,170 hobbyists, and 102,800 non-hobbyists as of November 29, 2017 (FAA, 2017e).

While sUAS use has increased in the U.S., as previously mentioned, it has lagged when compared to other items for personal use available to U.S. citizens as 92% own cell phones compared to 8% who own unmanned aircraft (Anderson, 2015). While the lagging acceptance rate is not catastrophic, there is a potential need for more research as to why. Additionally, when comparing unmanned aircraft and personal device use from the monetary standpoint, the U.S. non-military unmanned aircraft market represents $2.5 billion today and is expected to double by 2020. However, when compared to a $272 billion smartphone market and high percentage of use, the non-military unmanned aircraft market indicates there is much room for improvement to increase personal and civil use (Weissbach & Tebbe, 2016). However, an aviation technology behavioral intention model for sUAS data gathering does not exist to address this research need.

Therefore, an aviation gap in the sUAS literature can be filled by creating a research model focused on finding the factors influencing individuals' behavioral intentions toward using a sUAS for data gathering. Doing so provides organizations implementing aviation technology such as sUASs a research baseline to facilitate technology implementation. Additionally, the model, verified through future research studies, could possibly be adapted to determine the factors related to individuals' behavioral intentions toward using other technology. Also, incorporating perceived risk into the model allows other researchers to possibly evaluate the effect of perceived risk on behavioral intentions regarding any aviation or other technology in future studies.

Current theories are lacking. Andersen (2015) of the Pew Research Center, found in the information technology digital device realm that some technologies rate of acceptance is higher than others such as cellphones, and some technology rates have even declined such as e-reader devices. Because of historical trends such as this, technology acceptance and intention to use has been studied extensively the last two decades, attempting to determine the factors that positively or negatively influence technology acceptance and behavior intention (Teo, 2012). The most common ground theories for these areas include the Technology Acceptance Model (TAM), theory of planned behavior (TPB), the combined TAM/TPB model (C-TAM/TPB), and the Unified Theory of Acceptance and Use of Technology (UTAUT) model. However, few studies have been conducted in the aviation realm in the small unmanned aircraft system (sUAS) area and none specifically for data gathering operations.

TAM is intended to be used to study technology acceptance. Thus, while TAM can provide useful variables that can be used in the research model, it does not readily predict behavioral intention or actual use (Turner, Kitchenham, Brereton, Charters, & Budgen, 2010). TAM is also lacking in detail which may omit details to determine situation specific factors (Mathieson, 1991). Since TAM was primarily developed to study information technology (IT), the basic TAM model, until modified, is lacking variables needed for aviation and, more specifically, use of sUASs for data gathering.

The TPB model is designed to predict behavioral intention which is a very good predictor of actual use and the thrust of this study (Ajzen, 1991). In this study, the TPB model provided useful variables in the research model. However, the base TPB model lacked variables needed for aviation, more specifically sUAS for data gathering. Aviation-related variables are important to consider because the relative importance of human intentions and perceived behavioral control vary across situations and technology realms (Ajzen, 1991). Supporting this, environmental factors termed facilitating conditions that positively influence the decision to use sUASs for data gathering and enhance perceived behavioral control, need to be added to the TPB model variables.

The C-TAM/TPB model is designed to capitalize on strengths of and compensate for weaknesses using the TAM and TPB models alone (Mathieson, 1991). However, C-TAM/TPB models used to date have been lacking because they have not included all necessary variables, and none have been focused on determining the influencing factors to determine individuals' behavioral intentions toward using sUASs for data gathering.

The UTAUT (Venkatesh, Morris, Davis, & Davis, 2003) and UTAUT 2 (Venkatesh, Thong, & Xu, 2012) models were developed as consolidated models using eight technology acceptance models. Both models were designed and used for information technology with the UTAUT 2 model focused more on consumer context. Venkatesh et al. (2003) notes that the UTAUT model should be viewed as preliminary, and future research is needed to fully develop and validate the constructs of the model. Related to this study, the UTAUT model is not usable in its current form unless modified with variables for sUAS for data gathering. More importantly, the UTAUT and UTAUT 2 have not been vetted and validated to the extent of the TAM and TPB model, created approximately two decades earlier.

Statement of the Problem

Individuals who comprise society as stakeholders can induce undesired results when new technology is introduced such as slowing growth or rejecting it, wasting millions spent during the technology development process. Introduction of recent technology such as sUASs by a commercial company or government agency involves some level of defined risk to individuals in society along with other factors that are viewed as acceptable by the organization. However, individuals may perceive the organizational defined risk and benefit of the technology at a more negative level than the implementing organization, creating a disparity (Hunter, 2009). While perceived risk and other factors are recognized to some degree as influencing technology acceptance and intended use in society today, the problem is that technology implementation is often attempted concurrently with addressing society's concerns in a reactive versus proactive approach such as the case of the use of sUASs for data gathering. This reactive approach, coupled with not grasping the magnitude of the impact of perceived risk, and other influencing factors on technology acceptance and behavioral intention has resulted in undesired end-states (Choi, 2013).

When sUAS research was examined, a similar reactive approach was used as no studies to date were found focusing on identifying relevant factors of behavioral intentions of individuals toward using a sUAS for data gathering encompassing the variables in this study, nor a Structural Equation Model (SEM) showing relevant factors and associated relationships. Additionally, few studies were found that applied behavioral research models to aviation studies other than those focused on airline passengers. Thus, more knowledge is needed in this area, and a behavioral research model is needed by academia, industry, and government agencies that can be used to identify relevant factors to enhance individuals' behavioral intentions as well as correcting or minimizing factors that threaten safety and/or efficiency of operation.

Lastly, TAM and TPB ground theories used alone fell short in encompassing all the variables and predictive ability needed for this study. The C-TAM / TPB and UTAUT models noted in previous studies moved closer to meeting the needs of this study, but they do not include all the required variables specific to sUAS for data gathering. Thus, a research model was needed that included relevant variables and offered the ability to predict individuals' behavioral intentions for using sUASs for data gathering.

Purpose Statement

Since Laporte and Metlay's (1975a, 1975b), few scholarly studies have been conducted specifically dedicated to studying the major influencing factors on individuals' aviation technology acceptance and behavioral intentions. Many have been focused in the information technology realm. However, aviation technology implementation and aviation technology acceptance studies will most likely continue in the future. Thus, the purpose of this study was to develop and test a behavioral research model to identify the factors that influence small UAS (sUAS) individuals' behavioral intentions to use a sUAS for data gathering.

Research Questions

This study investigated the following research questions:

- To what extent does the VMUTES model explain individuals' intentions to use sUASs for data gathering?
- What factors at the .05 significance level influence individuals' intentions to use sUASs for data gathering?

Hypotheses

- H_1: Perceived ease of use positively influences perceived usefulness.
- H_2: Subjective norms positively influence perceived usefulness.
- H_3: Perceived usefulness positively influences attitude toward use.

- H_4: Perceived ease of use positively influences attitude toward use.
- H_5: Facilitating conditions positively influence perceived ease of use.
- H_6: Subjective norms positively influence attitude toward use.
- H_7: Facilitating conditions positively influence attitude toward use.
- H_8: Subjective norms positively influence behavioral intention.
- H_9: Attitude toward use positively influences behavioral intention.
- H_{10}: Facilitating conditions positively influence behavioral intention.
- H_{11}: Perceived risk negatively influences attitude toward use.
- H_{12}: Knowledge of regulations positively influences attitude toward use.
- H_{13}: Behavioral intention positively influences actual use of sUASs for data gathering.

Significance of the Study

The purpose of *intellectual merit*, gained knowledge such as the results of this research, is to advance the understanding of academia, industry, and government agencies (NSF, 2018). Thus, the overarching goal of this study is focused on developing and testing a new behavioral research model for sUAS use for data gathering. The newly developed model fills the gap in the technology acceptance literature including the lack of proper and validated combination of technology acceptance model (TAM) and theory of planned behavior (TPB) theories and the neglect of perceived risks' impact; these issues are not addressed in current studies. The model, so called VMUTES, uses a combined TAM / TPB model with added factors of perceived risk, knowledge of regulations, and facilitating conditions. The model was tested using large scale survey data obtained from sUAS users. The VMUTES model identifies influencing factors and examines the relationships among these factors on individuals' behavioral intentions and thus actual use of sUAS for data gathering. The findings will allow industry and government agencies implementing technology to use the model as a baseline. Knowing the influencing factors, as derived from the VMUTES model, provides the FAA, industry, and other stakeholders with essential information to understand and, if needed, to target factors that facilitate individuals' behavioral intentions toward using a sUAS for data gathering and to eliminate or minimize those factors that hinder intended use. Another intellectual merit benefit is the possibility that the developed model could be applied by academia, industry, and government agencies to other future aviation technology intention-to-use research studies and possibly to other technology areas such as railroad or automobile technology including self-driving cars. Lastly, the FAA has published little demographic data for sUAS users. Therefore, this study also increased the knowledge base of demographic information of sUAS users.

Broader impacts include the potential of the study to benefit society and contribute to achievement of specific, desired societal outcomes (NSF, 2018). Society and user benefits of this study could include possible renewed interest and growth of sUAS for data gathering as well as enhanced safety and improved security. First, if the research findings support, findings could aid the FAA in developing regulations that support growth of the use of sUASs for data gathering. These revised regulatory areas could better support sUAS users, facilitate more commercial use of sUASs, provide increased training for sUAS operators, and establish a protective legal environment that describes sUAS liabilities or requires insurance. Second, if research findings support, safety of stakeholders could possibly be enhanced by establishing regulations and/or procedures to reduce the physical risk posed to sUAS operators and/or residents, and establishing more regulatory guidance, or developing software to prevent a conflict with manned aircraft. Third, if research findings support, security enhancement might be achieved through software and/or procedures that prevent jamming and/or interference of sUAS operations for unlawful or terrorist operations and establishing regulatory standards to minimize invasion of privacy violations by sUAS users. Finally, sUAS use for data gathering is a cornerstone to future aviation advancement providing added security, disaster assistance, and geological applications. Identifying the factors that influence individuals' behavioral intentions toward using a sUAS could allow the FAA and industry to make informative decisions to facilitate the implementation and increase the growth of sUAS, which will lead to further aviation advancement and possibly aid in expanding commercial applications.

Delimitations

The first delimitation is that this study focused on sUASs only which include those UA under 55 pounds. However, doing so made this study more manageable given available resources while still encompassing model/hobbyist, civil, and public users who comprise a large sector of the sUAS population.

The second delimitation is that only modelers, civil (personal or commercial sUAS users), or public use (non-commercial government agency sUAS users) voluntary sUAS users were studied in this research. *Voluntary* in the context of this study means flying the sUAS for data gathering is not legally binding. The individual sUAS user has the option to not perform the required activity or quit their job if their personal values do not support performing the action. *Military users* are defined as those who fly sUASs for the United States Army, Air Force, Navy, Marines, or Coast Guard. Those users were excluded from this study since acceptance and intention to use is directed by military leadership and therefore is not optional. However, military members who also voluntarily use a sUAS for personal or commercial use could participate as respondents in the research process.

The third delimitation is that the study only included U.S. sUAS users. Cultural differences are influential factors and could skew the data (Alshare, Mesak, Grandon, & Badri, 2011; Choi, 2013; Clothier et al., 2015). Additionally, surveying the appropriate number of users to reflect a proper cross-section of sUAS users from different countries would be unrealistic and require time and resources beyond those available for this study.

The fourth delimitation relates to the currency of the sUAS operator. Research participants must have flown the sUAS within the last 24 months to participate in the study. This is consistent with FAA AC 107-2 which requires sUAS pilots to complete an aeronautical knowledge test every 24 months to continue to fly sUASs (FAA, AC 107-2, 2016).

The fifth delimitation is this research was focused on individuals' behavioral intentions of users of sUASs for data gathering. Therefore, conclusions can only made concerning the population of those who use sUASs for data gathering. Sampling all facets of sUAS use necessary to generalize about society would be unrealistic and require time and resources beyond those available for the study. However, because this study can be easily replicated, future research could be directed to other areas to expand conclusions.

Limitations and Assumptions

There are four limitations to this study. First, a self-administered online survey using non-stratified random sampling was used to strengthen generalization of results and external validity. However, the online self-administered survey can have a poor response rate (Babbie, 2016). Therefore, measures to increase response rate were taken which are discussed later. Also, non-response bias was computed to strengthen external validity.

Second, since the study only included U.S. modelers and voluntary commercial and government users, findings of this study were generalized to the U.S. market only, since sUAS users in other countries may not resemble the U.S. sUAS population due to cultural factors (Alshare et al., 2011; Broman Toft, Schuitema, & Thøgersen, 2014; Choi, 2013; Clothier et al., 2015). However, this study could be easily adapted to other countries by using the same research approach.

Third, the nature of this study is such that it examined a population during a selected period. Given rapidly changing sUAS technology and an evolving regulatory environment, the study results only represent a short time period and cannot provide information beyond that era (Babbie, 2016). However, since the study can be easily and accurately replicated, more research studies using the same methodology can be used to expand and validate the consistency of the results.

Fourth, since this study used self-reported data, the information was difficult to verify for every research participant (Vogt et al., 2012). The same author also states that respondents may find it difficult to answer accurately since the information is too hard to remember or is too sensitive. Thus, questions developed during the survey instrument construction process were clear, concise, and relevant to avoid these pitfalls (Babbie, 2016). Survey instrument instructions were also provided to increase clarity (Babbie, 2016). Additionally, each survey question was tied to a research question, and to the maximum extent possible, questions that had already demonstrated as effective in evaluating variables were used (Vogt et. al., 2012). Finally, rigorous statistical methods were used to test the reliability and validity of the instrument.

This study was built upon some assumptions. The first assumption is that it was assumed that sUAS model/hobbyist, civil, and public use voluntary operators would answer the survey questions honestly. Participation in this survey was voluntary, respondent anonymity was maintained to the maximum extent possible, and participants had the option to withdraw from the study at any time during the data collection process. Additionally, minimal personal information was collected since the only personal information revealed was by those who asked questions of the research team through email. However, the personal information provided could not be used to link the respondent to the survey responses. Thus, it was reasonable to assume participants would answer the questions based on their true thoughts.

Other assumptions are linked to the self-administered survey approach detractors that Vogt et al. (2012) describe. The second assumption in this study was that respondents taking the survey could read and meet the pre-screening requirements of the survey using a correct identity (Vogt et al., 2012). The third assumption was that the sample population and the broader population were alike allowing generalization of results (Vogt et al., 2012).

Definitions of Terms

Actual Use	The use of sUAS for data gathering that exists in fact of experience, real as opposed to just merely possible (Cayne, & Lechner, 1991).
Attitude Toward Use	The degree to which an individual has a favorable or unfavorable appraisal or evaluation of using sUASs for data gathering (Ajzen, 1991).
Behavioral Intention	An indication of how hard an individual is willing to try or how much effort they are planning to exert in order to use sUASs for data gathering (Ajzen, 1991).
Broader Impacts	The potential of the study to benefit society and contribute to achievement of specific, desired societal outcomes (NSF, 2018).
Civil Use	sUASs used for non-government personal or commercial flights which do not fall in the model aircraft category (Blitz et al., 2015).
Crowdsourcing	A job outsourced to an undefined group of individuals in the form of an open call (Mason & Suri, 2011).
Data Gathering	In the context of this study, transmission or recording of audio, pictures, videos, or collection of other data for modeler, civil, or public use.

Drone	An unmanned aircraft (FAA, AC 107-2, 2016).
Dull, Dirty, & Dangerous	Dull - stressful, long fatiguing, and non-desirable flights, dangerous - undue risk to the pilot, and dirty - contaminated chemical, biological, or radiation environment (Marshall et al., 2016).
Facilitating Conditions	Those environmental factors that are present that positively influence the decision to use sUASs for data gathering (Teo, Lee, & Chai, 2008).
Geofencing	A sUAS using Global Positioning System (GPS) position to determine and prevent the vehicle from entering controlled airspace (Rule, 2015).
Human Intelligence Tasks	Jobs offered on Amazon® Mechanical Turk® (Mason & Suri, 2011).
Intellectual Merit	Gained knowledge such as study results that advance the understanding of academia, industry, and government agencies (NSF, 2018).
Knowledge of Regulations	Small unmanned aircraft system operator comprehension of federal, state, and local laws and guidelines that apply to sUAS operations. More specifically, this includes Public Law 112-95, 14 CFR Part 107, FAA AC 91-57A, FAA AC 107-2, applicable state and local laws, and the FAA UAS website information (Aeronautics and Space, 14

	C.F.R pt. 1, 2017; FAA, AC 91-57A, 2016a; FAA, 2017b; FAA, AC 107-2, 2016b).
Military User	Those personnel who fly sUASs for the United States Army, Air Force, Navy, Marines, or Coast Guard.
Model Aircraft	An unmanned aircraft that is capable of sustained flight, flown within line-of-sight, and is flown for recreational or hobby purposes only (FAA Modernization and Reform Act of 2012, 2012a).
Modeler	An individual flying an unmanned aircraft under the Special Rule for Model Aircraft (FAA, 2017b).
Navigable Airspace	Airspace above the minimum flight altitudes described by 14 CFR or under 14 CFR, including airspace needed for safe takeoff and landing (Department of Transportation, Federal Aviation Administration Final Rule, 2018).
Non-response Bias	The effect of non-responses on survey estimates. If non-respondents had responded, those responses would have significantly changed the results (Creswell, 2014).
Perceived Behavioral Control (PBC)	Refers to the perceived ease or difficulty of performing the behavior of interest (Ajzen, 1991).

Perceived Ease of Use	The degree to which an individual believes that using sUASs for data gathering would be free of effort (Davis, 1989).
Perceived Risk	The perception individuals form and revise based on the possible danger of using sUASs for data gathering (Moussaïd, 2013).
Perceived Usefulness	The degree to which an individual believes that using sUASs for data gathering would enhance his or her job performance (Davis, 1989).
Performance Risk	System malfunction potential (Lee, 2009).
Privacy Risk	The potential loss of personal information (Featherman & Pavlou, 2003).
Psychological Risk	The choice or performance of the task will have a negative effect on the person's self-perception (Featherman & Pavlou, 2003).
Public Use	Those unmanned aircraft performing non-commercial governmental functions such as national defense, intelligence missions, firefighting, search-and-rescue, law enforcement, aeronautical research, or biological or geological resource management (Department of Transportation, Federal Aviation Administration Final Rule, 2018; FAA Modernization and Reform Act of 2012,

	2012b). For the purposes of this study, national defense use is excluded.
Physical Risk	Potential for harm of the sUAS user, other people, or damage to property (Lee, 2009).
Requesters	Employers or research teams using Amazon® Mechanical Turk® (Mason & Suri, 2011).
Risk	Expected losses mated with probability of those losses occurring (Stolzer & Goglia, 2015).
Sampling Bias	Respondents selected are not representative or typical of the larger population they have been chosen from (Babbie, 2016).
Security Risk	The potential threat to an individual's security (Lee, 2009).
Self-efficacy	A person's judgment as to the capability to use a device (Gong, Xu, & Yu, 2004).
Small Unmanned Aircraft (sUA)	An unmanned aircraft weighing less than 55 pounds including everything on board or attached to the vehicle and can be flown without the possibility of human intervention from within or on the aircraft (Aeronautics and Space, 2017).
Small Unmanned Aircraft System (sUAS)	A sUA and its associated elements (including communication links and the components that control the sUA) that are required for the safe,

	efficient operation in the National Airspace System (Aeronautics and Space, 2017).
Social Risk	The potential for media/society disapproval (Lee, 2009).
Society	In the context of this study, members of the general public including those individuals that use sUAS for data gathering for modeler, civil, or public uses.
Subjective Norms	Subjective norms refer to the perceived social pressure that significant others (parents, spouse, friends, etc.) desire the individual to use or not use sUAS for data gathering (Ajzen, 1991). Additionally, subjective norms include moral norms or the sUAS user's perception of correctness or incorrectness of using a sUAS for data gathering (Revis, Sheerman, & Armitage, 2009).
System	Integrated elements that may comprise hardware, software, processes, or firmware and meet a set objective (Parnell, Driscoll, & Henderson, 2011).
Time Risk	Inconvenience or time loss potential (Lee, 2009).
Turkers or Providers	The employees, workers, or independent contractors of Amazon® Mechanical Turk® (Mason & Suri, 2011).

Unmanned Aircraft System	A system composed of an unmanned aircraft, the operator, and the communication link to the vehicle (FAA, AC 107-2, 2016b).
U.S. Citizen	For this research, a U.S. citizen is a person who was born in the U.S., a naturalized citizen, or a lawful permanent resident (green card holder) (FAA, 2017b).
Voluntary	In the context of this study, flying the sUAS for data gathering is not legally binding. The individual sUAS user has the option to not perform the required activity or quit their job if their personal values do not support performing the action.

List of Acronyms

AAM	Automation Acceptance Model
AB	Actual Behavior
AC	Advisory Circular
AGFI	Adjusted Goodness of Fit Index
AGL	Above Ground Level
AMA	Academy of Model Aeronautics
AT&T	American Telephone & Telegraph
AMOS	Analysis Moment of Structures

ASSURE	Alliance for System Safety of UAS through Research Excellence
ATC	Air Traffic Control
ATU	Attitude Toward Use
AUVSI	Association for Unmanned Vehicle Systems International
AVE	Average Variance Extract
BI	Behavioral Intention
BVLOS	Beyond Visual Line of Sight
C-TAM/TPB	Combined TAM/TPB model
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CFR	Code of Federal Regulations
COA	Certificate of Authorization/Waiver
CR	Construct Reliability
df	Degrees of Freedom
EFA	Exploratory Factor Analysis
EM	Expectation Management
ERAU	Embry-Riddle Aeronautical University
FAA	Federal Aviation Administration
FC	Facilitating Conditions
GFI	Goodness of Fit Index
GPS	Global Positioning System

HACMS	High Assurance Cyber Military System
HIT	Human Intelligence Task
HTMT	Heterotrait-monotrait ratio of correlations
IOT	Internet of Things
IT	Information Technology
IRB	Institutional Review Board
KR	Knowledge of Regulations
LAANC	Low Altitude Authorization and Notification Capability
LCC	Low Cost Carrier
MI	Modification Index
MSV	Maximum Shared Variance
MTURK	Amazon® Mechanical Turk®
NAM	Norm Activation Model
NAS	National Airspace System
NFI	Normed Fit Index
NTSB	National Transportation Safety Board
PBC	Perceived Behavioral Control
PEOU	Perceived Ease of Use
PLS	Partial Least Squares
PR	Perceived Risk
PU	Perceived Usefulness
RMSEA	Root Mean Square Error or Approximation

RPC	Remote Pilot Certificate
SEM	Structural Equation Modeling
SAA	Sense and Avoid
SAC	Special Airworthiness Certificate
SME	Subject Matter Expert
SN	Subjective Norms
SNS	Social Networking Sites
SPSS	Statistical Package for the Social Sciences
SRW	Standardized Regression Weight
STEM	Science, Technology, Engineering, & Mathematics
sUA	Small Unmanned Aircraft
sUAS	Small Unmanned Aircraft System
TAM	Technology Acceptance Model
TRA	Theory of Reasoned Action
TPB	Theory of Planned Behavior
TSO	Technical Standard Orders
UA	Unmanned Aircraft
UAV	Unmanned Aerial Vehicle
UPS	United Parcel Service
UTAUT	Unified Theory of Acceptance and Use of Technology
VLOS	Visual line-of-sight

VMUTES Viti / Myers, Mashburn / Uland / Truong / ERAU /Sullenger

CHAPTER II

REVIEW OF THE RELEVANT LITERATURE

Chapter II contains six sections. First, an overview of sUAS technology and non-military data gathering applications are presented. Then, possible sUAS technology implementation barriers are reviewed. Subsequently, the concept, relevance, derivation, and measurement of perceived risk are reviewed. Additionally, perceived risk is justified as to why that factor should be included in the VMUTES model. Next, technology acceptance and/or behavioral intention ground theories are reviewed including the TAM, TPB, C-TAM/TPB, and UTAUT models. With each ground theory, an overview of the model is given, factors inherent to the model are explained, selected studies using the models are reviewed, and the efficiency of the TAM and TPB models is examined. Additionally, the VMUTES model is presented, and factors for the model are explained and justified. Finally, this chapter discusses hypothesis statements and theoretical frameworks used in this study.

sUAS Technology Overview

A sUA and its associated elements (including communication links and the components that control the sUA) define what is required for the safe, efficient operation in the National Airspace System (Aeronautics and Space, 2017). As previously noted, for the purposes of this study, the term sUAS includes model, civil, and public aircraft used for data gathering. Because of the smaller size, a sUAS is less expensive to operate than the larger UAS, and the smaller size facilitates easier transportation in a car or truck where they can be easily launched. As an example, video-capable quadcopters flown by a modeler only cost a few hundred dollars, weigh under a kilogram (2.24 lbs.), and are now widely available in the consumer market (Villasenor, 2014). Given the small size, sUASs are still large enough to carry a camera (McCormack, 2009). An example of typical weight and payload of a sUAS is described by Bloss (2014). In his article, the Microdrones GmbH md4-1,000 four prop aircraft is reviewed. The aircraft weighs only 3 kg (6.61 lbs.) but has a payload capability of 1.2 kg (2.64 lbs.). Even this small payload capability allows a wide range of sensors to be carried for data gathering including video or still cameras, gas and radiation sensors, and spectra or visual light sensing. Data gathering loiter times of the different models of sUASs described by Bloss (2014) are 15, 30, and 60 minutes respectively with size varying from 55 pounds to the size of a bird. An example bird-size application occurred in 2009, when the Texas Department of Public Safety deployed a bird-sized unmanned aircraft above a suspect's house to provide an aerial view of the property while waiting to execute a search warrant (Brice & Sifferd, 2017). Small unmanned aircraft systems can be operated using two modes: first and third person. First-person operation occurs when the sUAS provides a near real-time video stream representing a birds-eye view to enable operation beyond visual line-of-sight. Third-person operation occurs when the operator flies and controls the sUAS maintaining visual line-of-sight (Ayranci, 2017). Currently, the FAA requires all sUAS operations to be visual line-of-sight unless a waiver is obtained (FAA, 2017b; FAA, AC 107-2, 2016b).

sUAS Data Gathering

Unmanned aircraft have been around for decades, but recent advancements have created renewed interest in sUAS modeler, civil, and public use applications. Many cost less than two hundred dollars and can be controlled with a smartphone (Rule, 2015). Effective data gathering is dependent on the sUAS being at the right place, with appropriate sensors, at the right time, and having the right equipment to record or transmit data (Terwilliger et al., 2015).

The data gathering technology realms of small unmanned aircraft being explored and actively used are numerous (Floreano & Wood, 2015). This is in part because sUASs provide the means to gather multi-spectral imagery and can overcome limitations of satellites and manned aircraft with a shorter system setup and data return times (Hoffer, Coopmans, Jensen, & Chen, 2014; 2013). Additionally, sUASs possess the capability to conduct data gathering previously considered too dangerous, risky, or impracticable (Koerner, 2015; Terwilliger et al., 2017). Campolettano et al. (2017) and Marshall et al. (2016) use slightly different terms of dangerous, dirty, and dull to describe potential roles of sUASs replacing manned aircraft roles. Marshall et al. (2016) describes dull as stressful, long fatiguing, and non-desirable flights, dangerous as undue risk to the pilot, and dirty as a contaminated chemical, biological, or radiation environment. Thirdly, the ability of the sUAS in the data gathering role fills the gaps between expensive weather dependent images from satellites and images limited by the availability of accessible roads (Floreano & Wood, 2015). Most of these sUAS data gathering operations will occur at 400 feet above ground level (AGL) or below (Grose, 2016). Use of sUASs is estimated to expand more, and thus it is expected that development of sUASs will continue in the future as there are seemingly endless sUAS data gathering applications that are surfacing (Bracken-Roche, 2016), with Jensen (2016) alone providing 20 applications. As it is not practical to attempt to review all possible applications, some of the more common data gathering application areas derived from the literature review are examined. These various current and future roles of sUASs in the data gathering modeler, civil, and public realms include law and border enforcement, wildlife monitoring, environmental, agricultural, transportation, sports and media broadcasting, humanitarian/disaster response, energy, education, personal use, and movie filming, which are discussed next.

Law and border enforcement. Small unmanned aircraft systems offer the ability to enhance law and border enforcement operations because they can be fitted with an array of tools including facial recognition software, eavesdropping microphones, and infrared imaging (Lord, 2017). More importantly, sUASs are especially useful where it is too risky or difficult for humans (Terwilliger et al., 2017). The same authors note that in this role, sUAS create the volume and fidelity of information available to issue citations, investigate crime, request warrants, pursue criminals, and track illegal activities. Examples include bomb investigation, hostage negotiation, criminal pursuit, active shooting scenarios, crime scene analysis, and drug interdiction (Lord, 2017). Koerner (2015) describes an application of a sUAS that could be deployed to suspicious vessels in the data gathering role to sniff for chemical, biological weapons, illicit drugs, and explosives (Koerner, 2015). Loukinas (2017) studied another application of sUA: border security. Brice and Sifferd (2017) cite Washington Post statistics stating that between 2010 and 2012, UA were deployed some 700 times by the U.S. Customs and Border Protection on behalf of state and local agencies. Loukinas (2017) also states that using sUAS sophisticated technology for surveillance effectively extended the Greek border in different directions and expanded the Greek border zone itself, allowing more areas to be surveyed. However, with the use of sUAS for border security, questions of human rights and freedoms in a democratic society surface, raising questions that must be addressed (Loukinas, 2017).

Wildlife monitoring. Scobie and Hugenholtz (2016) advocate that sUAS use in wildlife research and management is increasing and offers several advantages. These benefits include lower cost, relative ease of use, real-time mapping and observation, and the ability to obtain a bird's-eye view (Scobie and Hugenholtz, 2016). However, the sUAS must fly high enough to avoid disturbing the wildlife while maintaining an altitude that provides sufficient image resolution. This may require the sUAS to fly higher than the FAA authorized height of 400 AGL which would require an altitude waiver (Scobie & Hugenholtz 2016). In another study, Wolinsky (2017) used a sUAS to obtain samples from blue whale blows to study the effects of contaminants on the animals. The sUAS successfully gathered the data and eliminated the need to use biopsy darts shot into the animal to obtain the data. However, Wolinsky (2017) also concluded that the sUAS must be flown at an altitude that does not disturb the wildlife being studied, higher than 400 AGL; the same conclusion as the Scobie and Hugenhotz research. Small unmanned aircraft systems also offer the opportunity to ensure wildlife laws are complied with. Examples include curbing illegal fishing and hunting operations (Lord, 2017).

Environmental. An environmental application was demonstrated using a sUAS to survey two coral reefs with 278 visual line-of-sight flights of approximately 20 minutes each. Fluid lensing imaging technology was used to image submerged objects in the presence of surface waves (Chirayath & Earle, 2016). The authors note that such surveys present unique environmental and weather challenges and require slower flight times, but their study demonstrated a sUAS could accomplish the task in a cost-effective manner. Pöllänen et al. (2009) studied another sUAS environmental application; radiation data gathering using a sUAS, determining equipment and methodology needed. In the aftermath of a nuclear accident or criminal actions, it would be necessary to assess the hazard. A sUAS in this role provides more loiter time than humans in an aircraft while also eliminating exposure hazards and reducing costs. In the case of ionizing radiation, humans would be prohibited from entering the area, but the sUAS could safely accomplish the task (Pöllänen et al., 2009). Additionally, since the sensor on the sUAS for the radiation study is also chemical and biological capable, similar equipment could possibly be used in those applications as well. Tauro, Porfiri, and Grimaldi (2016) conducted an experiment and determined that it was feasible to use sUASs to survey surface water flow movement. The authors also concluded that using a sUAS provided the capability for difficult-to-access water environments, especially during adverse hydro-meteorological events. Finally, Johnson (2017) successfully used a sUAS to monitor the Knepp Wildland Project in West Sussex, a southern England county. Traditional methods to monitor the project were difficult, time-consuming, and impractical over a large scale. Using a sUAS was practical, more cost-effective, and unlike traditional methods, was able to provide imagery detailed enough to pick out distinct shrubs and individual wildlife (Johnson, 2017).

Agricultural. Cruzan, Weinstein, Grasty, Kohrn, Hendrickson, Arredondo, and Thompson (2016) successfully surveyed a preserve using a sUAS to quantify the distribution and abundance of plants. The conclusion was that the low altitude surveys were highly efficient and relatively accurate, eliminating many hundreds of hours of work and major plant disturbance, while providing better mapping accuracy. In another study, the University of North Dakota used a CropCam sUAS to perform remote sensing of agricultural land. The CropCam sUAS was built on a commercially available remote-controlled model sailplane that has a two-meter wingspan with a payload capacity of one kilogram. The research was successful and allowed the farmer to analyze crop health, irrigation, damage caused by storms and wildlife, and drainage effectiveness. The sUAS saved the farmer time, fuel, and money (Straub, Vacek, & Nordlie, 2014). Supporting this, Terwilliger et al. (2017) advocate that sUAS provides farmers a better understanding of the state of the herds and crops because they can manage assets better, treat problems, implement protective measures, and plan for harvest.

Transportation. Small unmanned aircraft systems offer considerable promise in the transportation realm. Possible uses include operations and planning as well as maintenance functions. More specific examples include surveying, data collection and monitoring of roadway condition and congestion, crash scene photography, construction data collection, and security inspections (McCormack, 2009). In a test using an 11 Kg (24.24 lbs.) sUAS aircraft, successful collection of traffic counts, parking lot utilization, and intersection performance was demonstrated (McCormack, 2009). Williams (2017) also highlights the possibility of utilizing a sUAS to survey rail lines to replace people in trucks and eliminating the need to shut down the rail line during the inspection. Another example of sUAS use is sinkhole detection. In a sinkhole detection study using a sUAS and thermal camera, it was demonstrated the sUAS produced good detection results with the ability to monitor a large area at a lower cost. However, artificial sinkholes were used, and the sUAS also lost or falsely detected some sinkholes due to the movement of the sUAS and an unclear and similar pattern background (Lee, Shin, Ko, & Chang, 2016).

Sports and media broadcasting. Ayranci (2017) discusses the use of sUASs in sports broadcasting describing the risks and barriers to implementation. sUASs have video benefits traditional camera systems do not provide by allowing the journalist to get much closer to the subject providing a unique perspective at a lower cost. FAA regulation restrictions and civil liability are the two significant issues hampering implementation (Ayranci, 2017).

Humanitarian / disaster response. Small unmanned aircraft systems have several possible roles in disaster response. The Red Cross and other organizations list those possibilities which include: (a) reconnaissance and mapping, (b) assessment of structures, (c) high-rise building fire responses, (d) biological, chemical, or radiation event response, (e) insurance claims response and assessment of risk, and (f) search and rescue operations (Shaunnessey, 2015). In a Switzerland humanitarian example, emergency centers respond to approximately 1,000 calls per year for injured and lost hikers. Small unmanned aircraft system demonstrated technology provides for an autonomous sUAS that can recognize and follow forest trails to look for individuals, greatly reducing manpower and other costs (Drones May Search, 2016). Motlagh, Bagaa, and Taleb (2017) cite a real-world disaster application of sUAS with the Japan East great earthquake. The authors describe the uses during the disaster as providing real-time radiation levels for the power plant, coordinating disaster relief efforts, assessing the state of cleanup and reconstruction efforts, and capturing images of damaged reactors at the nuclear power plant. Terwilliger et al. (2017) describe sUAS advantages in this role as speed, endurance, range, rapid deployment, and an easily manipulated aerial perspective. Hayat et al. (2016) also explore the possibility of linking several sUAS vehicles together to share information for this purpose to increase capability. However, the authors note the capability is in the research stages and requires a dependable, secure, co-channel non-interference network between vehicles. Motlagh et al. (2017) agree but offer more of a specific solution using internet of things (IOT) networks. In this case, the sUAS downloads information through the internet to a ground-based laptop which collects the information and functions as the sUAS command and control. Doing so provides more real-time information and decision making (Motlagh et al., 2017).

Energy. Williams (2017) suggests the possibility of using sUASs for required inspections of pipelines as one of the many applications in the energy realm. Another developing application is inspection of power lines and power plant facilities. In this role, a sUAS reduces personal risks to employees and allows more regular inspections to reduce power shortages associated with normal wear and tear (Gregory, Tse, & Lewis, 2015).

Education. Small unmanned aircraft systems provide ample opportunities to enhance education and the integration of science, technology, engineering, and mathematics (STEM) concepts in the data gathering role. Gillani and Gillani (2015) describe one such data gathering project for six grade students where a sUAS was used to map a lake and determine drought levels. The students took apart a sUAS to learn how it worked, used mathematics to analyze the data, and learned about water conservation.

Additionally, universities such as Embry-Riddle Aeronautical University (ERAU) have added UAS training and degrees to their aviation education programs (Perritt &

Sprague, 2014). For example, ERAU operates the Gaetz Aerospace Institute which provides robust UAS courseware that includes sUASs flying in dozens of high schools throughout Florida (A. I. Cortés, personal communication, May 28, 2018).

Personal. Perhaps one of the areas that has a substantial chance of continued growth is personal use. Beeman (2017) provides a future picturesque view of several personal uses for a sUAS. These include applications within and outside the house. For example, within the house, a data gathering application might include sending and receiving information and outside the house, performing overhead security of the home (Beeman, 2017). A popular personal application is using a sUAS to take pictures or videos for personal use. Operating sUAS within these personal parameters specified does not require FAA authorization but does require registration (Federal Regulation, 2016). However, taking pictures for compensation or hire to another person does not qualify as personal use.

Movie filming. The movie industry has become interested and has obtained waivers for the use of sUASs for filming. Specifically, waivers were obtained to 14 CFR 107.39, operations over human beings (Aeronautics and Space, 2017). Using a sUAS provides a viewing angle that traditional cameras cannot attain. The premise for the waivers is that the sUAS is much safer than manned helicopters flying close to actors (Mariani, 2014).

Detractors That Could Affect Individuals' sUAS Data Gathering Intentions

While a sUAS offers many benefits and seemingly endless applications of use, there are also detractors associated with sUAS operation. Ultimately, benefits of sUAS must outweigh the perceived risks and other detrimental factors associated with their use for users to accept and intend to use sUAS for data gathering (Gallacher, 2016).

Physical risk. While the accident rate for UAS use is improving, as of 2003, the UAS accident rate was 100 times that of their manned counterpart (Gallacher, 2016). Related to accidents, Floreano and Wood (2015) use kinetic energy to define one aspect of physical risk of an unmanned aircraft which includes a sUAS. Kinetic energy is linearly proportional to the mass of the sUAS and quadratic in velocity. The authors use the example of a 500 g (just over a pound) sUAS flying at 5 Ms-1 (11.18 mph) is equal to 6.5 or the equivalent of a large apple dropped from about 2 meters (6.56 feet) (Floreano & Wood, 2015). More recently, Arterburn et al. (2017) further refined physical risk by establishing injury categories of concern related to sUAS applications with the focus on collision scenarios that lead to fatalities or permanent disability. The categories of concerns in order of severity included: (a) head and shoulders, (b) face and torso, (c) lacerations, (d) dropping of the payload on head and shoulders, (e) fire, and (f) chemical. Applying the concepts from their research, the most serious injuries to the head and shoulders would be caused by sUASs with cameras that fly directly over people. Such applications include real estate, surveying, construction site photography, emergency response, and agricultural inspections (Arterburn et al., 2017). Campolettano et al. (2017) in another study of physical risk, tested three commercial sUASs weighing approximately 3, 7, and 24 pounds colliding with a hybrid test dummy. The tests included falling impact and direct lateral collisions with the dummy's head. The major conclusions from the study included: (a) in general, falling impacts were of higher injury severity, (b) increasing sUAS mass was associated with higher injury severity impacts, and (c) injury risk was as high as 100% with the heaviest sUAS with a median of 70% injury risk for falling impacts (Campolettano et al., 2017). Related to physical risk, Gallacher (2016) found that the propellers of a sUAS in the 5-25 kg weight range are capable of inflicting serious injury while those sUASs weighing closer to 55 pounds could potentially kill an inattentive spectator or operator.

Historical examples of physical risk incidents include a UAS crashing in the stands of a Virginia speedway injuring several fans and a photographer's sUAS injuring a runner during a triathlon causing her to stop the race due to head injuries (Mariani, 2014). In a study of 3,000 participants in Switzerland, 89% of respondents thought that sUAS hobby unmanned aircraft should not be allowed to fly above high-risk sites, fearing accidents (Klauser & Pedrozo, 2017). To minimize physical risk, the FAA expects sUAS users to not intentionally fly over unprotected persons or moving vehicles and to remain at least 25 feet from vulnerable property and individuals (Federal Regulation, 2016). The reason for this rationale is the FAA assumes that at any point and time the sUAS could stop working and fall out of the sky, posing a physical risk to people and property (Williams, 2017). Additionally, the communication link between the sUAS and the operator is dependent on line-of-sight, with loss of line-of-sight resulting from excessive distance or obstructions. If this occurs, then loss of sUAS control can occur, causing possible damage to persons or property (FAA, AC-107-2, 2016).

Security risk. Rogue unmanned aircraft and hacking of software controlling the vehicles are real risks. To combat these risks, software needs to be developed such as the High Assurance Cyber Military System (HACMS) to prevent those possibilities (Grose, 2016). Gallacher (2016) further expands on security vulnerabilities stating that sUAS components are not typically encrypted. Thus, they are susceptible to jamming, spoofing, or hacking attacks. By using a global positioning system (GPS) spoofer, the possibility exists to change the location calculation of the sUAS without direct contact (Gallacher, 2017). Also, although unintentional, a crash of a hobbyist quadcopter on the White House lawn in January 2015 demonstrated the relative ease of using a sUAS to pose a society security threat (Klauser & Pedrozo, 2017).

Invasion of privacy. While sUASs have advantages discussed earlier, they also have disadvantages; one being invasion of privacy (Koerner, 2015; Takahashi, 2012). Small unmanned aircraft systems make it possible for anyone to inexpensively and easily obtain overhead imagery of spaces that many people would consider private such as a fenced-in backyard (Villasenor, 2014). Journalists seeking pictures of celebrities using a sUAS and other incidents in the civilian sector have also highlighted an invasion of privacy issue (Tate, 2015). Privacy in the U.S. falls into two categories: government and non-government operated. Related to privacy, Villasenor (2014) describes the Fourth Amendment of the Constitution which is the right of people against unreasonable searches and seizure. This amendment has surfaced as an issue with government-operated unmanned aircraft. There are two parts to the Fourth Amendment of the Constitution. Those two clauses include citizens are protected against unreasonable searches, and, secondly, warrants may only be used when they describe in particular, the place to be searched and the person or things to be seized (Brice & Sifferd, 2017; Koerner, 2015). However, the Supreme Court has ruled that information obtained by a craft flying in U.S. airspace is useable because it is from a generally accessible vantage point and not subject to Fourth Amendment protection (Brice & Sifferd, 2017).

Additionally, Villasenor (2014) notes that the First Amendment of the Constitution which concerns freedom of speech, conflicts with common law and statutory invasion of privacy protections. Obtaining pictures or video beyond fences, over society events, or through windows of a tall building is no longer a problem with a sUAS.

To compound the problem, most FAA regulations are geared toward safety and do not address privacy issues. However, Congress has addressed the issue through the Drone Aircraft Privacy and Transparency Act of 2017 (S. 631, 2017). The bill meticulously describes requirements to conduct operations that could invade individual privacy. Requirements in the bill include a data collection statement, operating within data collection prescribed guidelines, publication of persons or agencies conducting the operation as well as the type of operation, lawful use of collected information, and enforcement options for non-compliance (S. 681, 2017). Additionally, at the state level, some governments have implemented legislation to deal with privacy issues. For example, California passed legislation that makes flying a device over private property to capture sound or images an illegal invasion of privacy (Tate, 2015). Smith (2017) highlights in his article the varying state laws regarding unmanned aircraft and privacy. For example, in Florida, a warrant is required, there are data gathering limits of private property, and victims can sue. In Oregon, registration of unmanned aircraft is required, and unmanned aircraft cannot be used as weapons. The problem of enforcement is having adequate resources to enforce the law and non-standardization of laws. Challenges posed by modeler unmanned aircraft include peeping Tom issues and unmanned aircraft flying near airports (Bracken-Roche, 2016).

In a study by Klauser and Pedrozo (2017), overwhelmingly, 95% of the respondents asked for better privacy protection. Thus, more attention is needed to solve the invasion of privacy issue. More specifically, Bissonnette (2016) suggests that national laws need to be drafted to further detail sUAS certification, training and use, liability issues addressed including requiring liability insurance, privacy issues including distribution of images and video taken of a property or individual, and carriage of weapons on a sUAS. Mitigation techniques such as Geofencing, which is software that provides the sUAS automatic boundaries and required FAA registration, are helpful in reducing incidents (Terwilliger et al., 2017). However, a home-built sUAS or hacking could be used to defeat these protective measures (Bracken-Roche, 2016).

Legal risk. Small unmanned aircraft system users can be held accountable for damage to property or persons and negligent operation. This can also result in lawsuits or legal action (Mariani, 2014). Additionally, product manufacturers could face exposure and legal ramifications for software malfunctions, design or manufacturing defects, and negligently designed operating manuals (Mariani, 2014). Similar laws that affect privacy such as those banning a peeping Tom in a tree at the edge of your property and peering into a bathroom apply to sUAS users (Shultz, 2015). However, the Supreme Court has ruled that no one owns airways, and anyone can take pictures in society. Flying a sUAS in navigable airspace is legal. Navigable airspace is airspace at above the minimum flight altitudes described by 14 CFR or under 14 CFR, including airspace needed for safe takeoff and landing (Department of Transportation, Federal Aviation Administration Final Rule, 2018). Thus, a person could be convicted of growing illegal drugs based on sUAS images from their property; no different than aircraft (Shultz, 2015). Additionally, the FAA requires that any sUAS user report incidents involving serious injury to any person or loss of consciousness or damage to any property that exceeds $500 (FAA, AC-107-2, 2016).

Financial risk. McCormack (2009), in the transportation realm using commercial sUAS, estimated the cost of the system to be $50,000, $20,000 for 20 hours of training, and maintenance costs of $500 for every 200 hours of flight. A sUAS sold to a modeler can be relatively cheap to obtain. For example, a basic sUAS can be purchased for as little as $40 with a more sophisticated one with an extended flight time costing approximately $100, but that does not include repair costs (Tate, 2015). Terwilliger et al. (2017) describe diagnostic and measuring equipment and repair equipment and materials needed for preventive, routine, and unscheduled maintenance. The authors list nine diagnostic and measuring tools and 15 equipment repair tools/materials needed which are not included in the purchase cost of a sUAS. Additionally, negligence resulting in lawsuits could have a fiscal impact, especially if the operator does not have insurance, which is not currently required (Mariani, 2014). Concerning insurance, commercial operators are more likely to have insurance than hobbyists. Another cost that can be incurred includes technology improvements for airspace deconfliction if required by the FAA. Examples include ADS-B, fail-safe features to compensate for UAS failures, and sense and avoid (SAA) equipment (Perrit & Sprague, 2014).

FAA regulations. Development and implementation of FAA regulations is generally lagging sUAS development and use (Dalamagkidis, Valavanis, & Piegl, 2008; Tate, 2015). This sentiment is echoed by Marshall (2015) who points out that FAA oversight is comprised of a mixed bag of certifications, regulations, rulemaking processes, technical standard orders (TSO), advisory circulars, special authorizations, and directives. Current FAA regulations risk impairing innovation and may be infringing on basic Constitutional rights and freedoms (Straub et al., 2014). Additionally, at times, the regulations hinder or provide little guidance for sUAS use. Weissbach and Tebbe (2016) agree, advocating the ability of the FAA to adapt with needed regulations is one of the key elements for successful sUAS integration. In a study by McCormack (2009), the FAA regulations caused the study of transportation surveying to be terminated even though the sUAS was capable of the tasks because the regulation restrictions were too severe. Additionally, the FAA, in issuing regulations, has rightly focused primarily on safety as the first priority (Dalamagkidis et al., 2008). Unfortunately, less importance has been placed on privacy, human rights, or civil liberties raised by the introduction of sUAS (Bracken-Roche, 2016). However, if those tertiary considerations were considered with the issuance of initial guidance, it could be that basic safety regulations would not have been timely, creating a higher operating risk, due to the complicated nature of those tertiary issues (Bracken-Roche, 2016). Besides modeler rules, the FAA did prescribe rules for sUASs that are used for conducting non-modeler operations (Marais, Koelling, & Ballin, 2016). Further definition of those rules is described in FAA AC 107-2, discussed previously.

While FAA regulations can lag and at times be overly restrictive, the FAA is encouraging commercial entities to apply for waivers, and progress is being made. The intent is to produce new waiver procedures that are geared toward proposals that are limited, relatively low-risk operations (Werner, 2014a). Initially, it is expected that most waivers will be approved for rural operations and gradually become less conservative once the technology is improved (Williams, 2017). Concerning commercial use, Amazon® was granted a Special Airworthiness Certificate to develop unmanned aircraft delivery. Additionally, in 2015, the FAA considerably expanded the commercial operating freedom of sUASs including allowing journalists to capture images (Blitz et al., 2015). Some filmmakers and CNN have already taken advantage of that opportunity. Perritt and Plawinski (2016) expand on waivers noting that the FAA has granted more than 2,000 waivers to cover sUAS operations for precision agriculture, event photography, motion picture and television production, news-gathering, and infrastructure inspections. Additionally, at times, FAA regulations are being overruled. For example, a National Transportation Safety Board (NTSB) administrative law judge ruled against the FAA, dismissing their case in 2014 against Raphael Pirker, essentially allowing commercial sUASs, for a few months, to operate below 400 feet if out of controlled airspace (Werner, 2014b). Subsequently, the FAA settled with Pirker for a reduced fine and updated the rules for commercial sUAS use. The revamped rules provide the pathway for a multitude of applications in that flight regime.

Knowledge of regulations. One of the most important aspects of ensuring lawful and responsible conduct of an industry including sUAS operations is the ability to communicate and provide an outreach to operators regarding guidance, regulations, and best practices. Given the dynamic nature of the sUAS operating environment and rapid growth, the number of irresponsible and questionable actions conducted by sUAS operators has continued to rise (Terwilliger et al, 2017). Therefore, it is important for sUAS operators to have access to and fully understand not only FAA regulations, but also other federal, state, and local laws and guidelines that apply to sUAS data gathering operations. Other federal guidelines besides those previously mentioned in Chapter I include other parts of Title 14 CFR Part 107, FAA orders, and other Advisory Circulars dealing with supportive activities needed for sUAS flying.

Additionally, other FAA handbooks, manuals, and other publications such as aeronautical charts and the Pilot's Handbook of Aeronautical Knowledge offer useful knowledge as well (FAA, AC-107-2, 2016). State and local laws are important to review as well before operating sUASs as they may enact privacy restrictions (FAA, AC-107-2, 2016). Elias (2016) echoes that states and local municipalities have put flight restrictions on sUAS operations. For example, the state of New Jersey prohibits the use of UASs on state park lands except for pre-designated areas. Additionally, besides privacy laws, state and local laws can impose flight restrictions such as flight over certain areas (Elias, 2016). The Association for Unmanned Vehicle Systems International (AUVSI) state legislative map indicates 46 of the 50 states have regulations pertaining to 93 different areas (AUVSI, 2017). Additionally, private local entities such as ski resorts and Disney theme parks have instituted flight restrictions which sUAS operators need to be aware of (Elias, 2016). Finally, the FAA has created a website describing need-to-know information for sUAS operators (FAA, 2017b). This is especially important because of the rapidly-changing, dynamic nature of sUAS technology and regulations.

Airspace deconfliction. It is not feasible to hire enough air traffic controllers to manage hundreds of thousands of UAS flights each day (Grose, 2016). Additionally, it is difficult for manned aircraft to see sUA as they often are no larger than two feet square (Mariani, 2014). One of the biggest challenges is developing a deconfliction system to ensure a safe airspace environment in the national airspace system (NAS) to avoid collisions with other aircraft, obstacles such as buildings, and people (Grose, 2016). As technology improves, government and civilian applications using unmanned aircraft are expected to substantially increase resulting in the potential for more mishaps. Amazon® alone is expected to field some 130,000 unmanned aircraft flights per day for delivery purposes (Grose, 2016).

For deconfliction, the FAA expects sUAS users to comply with see and avoid procedures when operating below 400 feet to remain well clear of other aircraft, yield the right-of-way, and not create a collision hazard. This is compounded by the fact that aircraft used for firefighting, law enforcement, agricultural, wildlife survey operations, and other services also operate routinely at these altitudes (Federal Regulation, 2016). UAS FAA reported sightings by manned aircraft increased dramatically in 2015, with an average of more than 100 sightings per month (Gallacher, 2016). More recent data from 2017 indicates this trend is continuing and potentially increasing. For January through September, all months had reported sightings greater than 100 per month with three of the months greater than 150 and four of the months greater than 200 (FAA, 2017b). To combat this problem, some type of sense-and-avoid technology must be incorporated in the sUAS to comply with the FAA intent of see-and-avoid (Villasenor, 2014). This sense-and-avoid technology has been designed, demonstrated, and approved. However, the technology is crude and expensive. Thus, it is not currently practical for sUAS use (Williams, 2017). Dalamagkidis et al. (2008) echo the need for sense-and-avoid technology but also advocate that fault-tolerant control, reliable long-range communications, and fail-safe systems are also needed. Until technology matures, sUAS autonomous operation will not be allowed by the FAA where there is manned aircraft to avoid possible collision (Villasenor, 2014). Additional technology in the form of Geofencing software is available to help with airspace deconfliction. This allows sUASs to automatically detect permanent no-fly zones such as airports and temporary no-fly zones such as sporting events and take evasive action (Gallacher, 2016).

The Low Altitude Authorization and Notification Capability (LAANC) is another airspace deconfliction technology in the beta testing stages of development (Stansbury, 2018). The system takes advantage of the collaboration between industry and the FAA and supports UAS integration into the airspace (FAA, 2019). The LAANC system gives access to controlled airspace in the proximity of airports below approved altitudes using near real-time processing of airspace authorizations (FAA, 2019). UAS pilots can apply for an airspace authorization through FAA approved service suppliers using FAA automated applications. Applications are then checked against an array of airspace data sources such as temporary flight restrictions and UAS facility maps (FAA, 2019). After which, UAS pilots receive authorizations near real-time, dramatically reducing wait time compared to the older manual authorization process. Currently, there are 14 approved service suppliers which include companies such as Airbus, Aerodyne, and Skyward (FAA, 2019). At present, LAANC can provide access to almost 300 air traffic facilities covering approximately 500 airports (FAA, 2019; Stansbury, 2018).

Lack of training. For sUAS operations, the current Code of Federal Regulations requires operators to pass a sUAS operating rules knowledge test. However, the regulations do not require any formal operator flight training or proficiency standards (FAA, AC-107-2, 2016b). Groves and Zemel (2000) as cited by Choi and Chung (2012) provide examples of skills training, administrative support, and information or materials available that are key factors influencing instructional technologies. Wolinski (2017) stated that to use sUASs for collecting biology samples, research teams would need to obtain the unmanned aircraft and train themselves. Operation and increasing automation of sUASs necessitate operator intervention if a physical or software error occurs, requiring the pilot to utilize training, ingenuity, and human instincts to take appropriate corrective action to safely land the vehicle (Perritt & Plawinski, 2016). Cruzan et al. (2016), in reviewing sUAS use for plant sciences, advocate that quadcopters, hexacopters, and octocopters are easy to fly with the minimal amount of training and experience. Contrarily, Tauro et al. (2016), in an article concerning water surface flow measurements using unmanned aircraft, state that ease of implementation will only be achieved after some hours of training. Ayranci (2017) agrees with the need for training.

Concerning the use of sUASs for sports broadcasting, the author advocates the need for the FAA to establish minimum operating performance standards for pilots and pilot proficiency training and assessment programs before and after issuing a sUAS operating certificate. It is postulated that with properly trained sUAS operators, sUAS operation would likely be safer with fewer accidents (Ayranci, 2017). Dalamagkidis et al. (2008) state that the amount of training will most likely vary with the level of sUAS autonomy. Mariani (2014) advocates that more attention will be focused on the training requirements the FAA imposes as more accidents and incidents occur. Expanding on this point, many of the UAS accidents in Australia were attributed to human error resulting from inexperience. Subsequently, operator training became a major concern. Thus, the goal in Australia is to establish centers for operator training and proficiency certification (Dalamagkidis et al., 2008). Currently in the U.S., the FAA is sponsoring a study with the Alliance for System Safety of UAS through Research Excellence (ASSURE) UAS Research and Development Program on UAS Crew Training and Certification (Kansas State University, 2016). To temporarily fill the current void, Terwilliger et al., (2017) provides a list of nine online training tools available to fill the training void to build proficiency and experience with certain types of sUAS platforms.

Personal attitude toward use. Perritt and Sprague (2014), when describing the pilot work force, state that attitudes toward new technologies are generational. Thus, for example, the current generation of pilots where sUASs are introduced into society may feel threatened or uncomfortable with sUASs. However, those who have grown up with unmanned aircraft accept them as being part of aviation and aviation careers (Perritt & Sprague, 2014).

Demographic factors. While not specific to sUAS, age, education level, and cultural factors were identified to be factors in predicting use of technology (Czaja, Charness, Fisk, Hertzog, Nair, Rogers, & Sharit, 2006).

The sUAS literature review section first described the major capabilities of sUAS when used in the data gathering role. Subsequently, 11 possible application areas were reviewed. While these sUAS usages do not represent all sUAS possible applications, it is evident that sUASs offer many opportunities for saving resources, expanding data gathering capabilities, and at the personal level, increasing enjoyment. Then, possible detractors to use sUASs for data gathering were highlighted and discussed. All the detractors identified in the literature review needed to be accounted for in the research model and included: (a) physical risk, (b) security risk, (c) invasion of privacy, (d) legal risk, (e) financial risk, (f) FAA regulations, (g) knowledge of regulations, (h) airspace deconfliction, (i) lack of training, (j) personal attitude toward use, and (k) demographic factors.

Perceived Risk and sUAS Behavior

Perceived risk is inherent in aviation, including sUAS use for data gathering and other similar higher risk technologies compared to information technology, such as the automobile and railroad industry. However, many previous studies omitted the perceived risk factor because the risk associated with the technology was minimal. Not considering perceived risk when needed can cause organizations implementing sUAS data gathering technology to fail to grasp the magnitude of society's perceived risk due to lack of knowledge of perceived risk influencing factors and risk derivation processes (Lester, 2000; Myers, 2016; Sjöberg, 2000). As a result, the disparity between society's perceived risk and the organizational perceived risk derivation processes can result in technology acceptance and intended use being slowed or halted (Hunter, 2009; Myers, 2016). Therefore, it is necessary to include perceived risk as a factor in the model, to understand the processes of sUAS data gathering users risk assessment and the elements used to measure perceived risk. Doing so provides implementing organizations information to target relevant perceived risk factors to enhance sUAS for data gathering technology acceptance and intended use (Lester, 2000; Myers, 2016). Additionally, some sUAS user support predictability can be achieved.

Risk is defined as expected losses mated with probability of those losses occurring (Stolzer & Goglia, 2015). Parnell, Driscoll, and Henderson (2011) use a similar approach, defining risk as a probabilistic event that causes undesired changes in cost, schedule of events, or technical performance. *Perceived risk* is defined as the perception individuals form and revise based on the possible danger of hazardous technology or activity (Moussaïd, 2013). The two distinct levels of perceived risk are expert and layman (Dobbie & Brown, 2014). Organizational derived perceived risk is equated to expert perceived risk and is an all-encompassing risk management approach that is generally objective in nature. Society's derived perceived risk is considered layman and predominantly based on subjective norms including emotions (Dobbie & Brown, 2014). Concerning individual risk derivation, Young and Laughery (1994) found that people use a rather routine simple method to derive perceived risk that remains constant regardless of technology being considered. The authors also conclude that while the process is seemingly simple, a formal process is used in an individual's mind. Notably, it was also found that the process in an individual's mind does not change regardless of the technology being considered (Young & Laughery, 1994).

Members of society use a cognitive process to derive perceived risk that involves considering the risk elements and associated influencing factors (Choi, 2013; Myers, 2016). Therefore, if the implementing organization understands technology-specific risk elements and associated influencing factors, an educated gap analysis can be performed using organizational and society perceived risk. While the individual process to derive perceived risk is relatively simple, complications ensue when examining the basic elements and the numerous, often subjective, influencing individual factors in a person's decision process, which may seem irrational at times (Sjoberg, 2000).

Perceived risk measurement. Lee (2009) identified six elements that form the analysis framework of society's perceived risk and include: (a) physical, (b) performance, (c) time, (d) financial, (e) social, and (f) security risk. *Physical risk* is the potential for harm of the user, other people, or damage to property. *Performance risk* encompasses system malfunction potential (Lee, 2009). *Time risk* consists of inconvenience or time loss potential. *Financial risk* is defined as the likelihood of monetary loss. *Social risk* refers to potential media/society disapproval. The potential threat to an individual's security defines *Security risk*. Lee (2009) advocates that the six elements are applied as applicable to the technology being studied. Featherman and Pavlou (2003) agree with the elements identified by Lee (2009) but also add two more elements: privacy and psychological risk. *Privacy risk* is defined as the potential loss of personal information. *Psychological risk* means the choice or performance of the task will have a negative effect on the person's self-perception (Featherman & Pavlou, 2003). Boksberger, Bieger, and Laesser (2007), in their study of perceived risk in commercial air travel, agree with the elements Featherman and Pavlou (2003) describe minus privacy and security risk. These perceived risk elements, when considered for a lone individual, have little effect on technology acceptance and intended use, but individuals make up organizations in society, industry, and government. Thus, groups of individuals who share the same perceived risk levels can have a significant effect on technology acceptance and behavioral attention (Myers, 2016).

Ground Theories for the Study

The first chapter and previous sections in this chapter provided an overview of sUAS technology acceptance and some of the challenges facing individuals' behavioral intentions toward using sUASs for data gathering. This provides the knowledge base of sUASs, but more research is required to understand the decision process concerning individuals' behavioral intentions regarding using sUASs for data gathering. This study emphasizes the context under which an individual's behavior takes place. Thus, the selected ground theories for this study were required to provide previously validated models and variables applicable to effectively study an individuals' intentions to use sUASs for data gathering, as well as validating the methodology chosen for this study. To fulfill the research purpose, the TAM, TPB, C-TAM/TPB, and UTAUT technology acceptance and/or behavioral intention models and associated studies were explored for application to behavioral intention to use sUASs for data gathering. It was theorized that since the models were previously tested and validated, the models might contain factors applicable to individuals' behavioral intentions to use sUASs for data gathering. It was also theorized that even though these models have mostly been used in information technology studies, they might be adaptable to other technology realms including aviation and sUAS use for data gathering.

Technology acceptance model (TAM). Davis (1989) is the originator of the TAM information technology acceptance model shown in Figure 1. The model stemmed from the effort starting in the 1970s when a shift occurred to attempt to concentrate on finding factors that would facilitate technology acceptance. TAM has become the most popular technology acceptance model (Legris, Ingham, & Collerette, 2003). Davis (1989), in his research, recognized that performance gains are often restrained by users' unwillingness to accept and use systems. Additionally, Davis recognized that research had been constrained due to a lack of verified measures for determining user acceptance (Davis, 1989). Davis' founding TAM study focused on two important variables: perceived ease of use and perceived use. Thus, the model Davis developed can be successfully used for technology acceptance research. A major conclusion from Davis' study was that perceived usefulness had a strong correlation with user acceptance, and, therefore, it should not be ignored in a research study. TAM has become a dominant model since it was introduced more than a quarter century ago, in investigating the factors that affect user acceptance of technology (Marangunić & Granić, 2015).

Components of the TAM. TAM is one of the most widely used models in information technology, mainly because of simplicity and understandability (King & He, 2006). The original TAM model has four variables. The first variable is behavioral intention (BI). *Behavioral intention* is the level of a person's desire to use the technology. BI is influenced by attitude toward use (ATU) of the technology and to some degree perceived usefulness (PU) and perceived ease of use (PEOU) (Gong, Xu, & Yu, 2004). *Attitude toward use* constitutes the positive or negative feelings a person has about the technology. *Perceived usefulness* is the degree to which stakeholders believe the technology enhances their productivity. *Perceived ease of use* is defined as the perception of the user that the technology is free of effort (Davis, 1989). Both perceived usefulness and perceived ease of use directly influence attitude toward use and indirectly affect behavioral intention. Additionally, perceived ease of use has a direct effect on perceived usefulness (Davis, 1989; Teo, 2012).

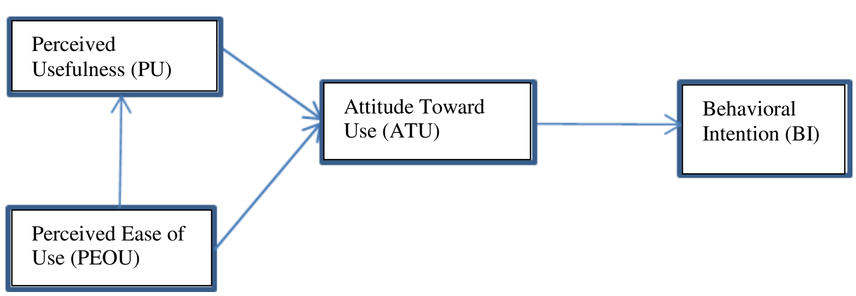


Figure 1. Original technology acceptance model. Adapted from Davis 1989.

Selected TAM studies. Numerous studies have verified the versatility and adaptability of TAM. Table 1 shows fourteen selected TAM studies from various technology realms and applications. The table is followed by a brief description of each study.

Table 1

Selected TAM Studies and Constructs/Variables

Technology Realm	Application	Constructs / Variables	Methodology	Reference
Information Technology	Social Networking Sites (SNSs)	Perceived Ease of Use, Perceived Usefulness, Attitude Toward Use, Intention to Use Subjective Norm, Perceived Social Capital (External Variable)	Survey, Descriptive, Exploratory correlation analyses	Choi & Chung (2012)
E-commerce	Shopping	Perceived Ease of Use, Perceived Usefulness, Attitude Toward Use, Intention to Use, Trust, Enjoyment, e-shopping quality	Pretest, CFA, Structural Equation Modeling	Ha & Stoel (2009)
Information Technology	Healthcare	Perceived Ease of Use, Perceived Usefulness, Intention to Use, Information Quality, Service Quality, System Quality	Pilot Test, Survey, Likert Scale, Descriptive Statistics, Correlation Analysis, CFA, SEM testing	Pai & Huang (2011)
Information Technology	Education	Perceived Ease of Use, Perceived Usefulness, Attitude Toward Use, Facilitating Conditions, Subjective Norm	Likert Scale Survey, Descriptive Statistics, SEM testing	Teo, Lee, & Chai (2008)
Information Technology	Education	Perceived Ease of Use, Perceived Usefulness, Attitude Toward Use, Intention to Use, Self-Efficacy	Likert Scale, Pilot Study, Partial Least Squares (PLS), Reliability and Validity Testing, SEM testing	Gong, Xu & Yu (2004)

Table 1 (*continued*)

Information Technology	Banking	Perceived Ease of Use, Perceived Usefulness, Attitude Toward Use, Intention to Use, Gender, Age, IT Competency	Pretest, Survey, CFA, Invariance Analysis	Lai, & Honglei (2005)
Information Technology	Energy	Perceived Ease of Use, Perceived Usefulness, Attitude Toward Use, Personal Norm, Acceptance	Survey, Descriptive Statistics, Multiple-Group CFA, SEM testing	Broman et al. (2014)
Information Technology	Internet Usage	Perceived Ease of Use, Perceived Usefulness, Attitude Toward Use, Intention to Use, External Variables, Actual System Use	Two-part Survey, CFA, SEM testing	Mallya & Lakshminarayanan (2017)
Information Technology	Banking	Perceived Ease of Use, Perceived Usefulness, Attitude Toward Use, Intention to Use, Perceived Risk	Survey, EFA, Mediating Effect Methodology, Multiple Regression	Kansal (2016)
Automobile Technology	Car Navigation Systems	Perceived Usefulness, Attitude Toward Use, Intention to Use, Perceived Locational Accuracy, Perceived Processing Speed, Service and Display Quality	Pretest, Survey, Descriptive Statistics, CFA, SEM testing	Park & Kim (2014)
Various Technologies	Automation	Perceived Ease of Use, Perceived Usefulness, Intention to Use, External Variables, Actual Use	Literature Review Only	Ghazizadeh, Lee, & Boyle (2012)
Information Technology	E-Commerce	Perceived Ease of Use, Perceived Usefulness, Intention to Use, Actual Use, Perceived Risk, Trust	Pretest, Chow's Test and Wilk's Lambda, Descriptive Statistics, EFA, CFA, Partial Least Squares (PLS)	Pavlou (2003)
Information Technology	Aviation	Consumer innovativeness, Perceived Personalization, Perceived Ease of Use, Perceived Usefulness, Attitude Toward Use, Intention to Use, Perceived Security, Perceived Privacy, Trust in Organizations	Survey, Descriptive Statistics, CFA, SEM testing	Morosan (2014)
Information Technology	Internet Banking	Perceived Usefulness, Perceived Ease of Use, Attitude Toward Use, Intention to Use, Perceived Web Security	Survey, Likert Scale, EFA, CFA, SEM model testing	Cheng, Lam, & Yeung (2006)

Choi and Chung (2012) used the TAM to study a population of 179 graduate students using social networking sites (SNSs). In their study, they added subjective norm and perceived social capital variables to the TAM model. Their results validated the TAM variables originally proposed by Davis and associated relationships. Notably, perceived usefulness and perceived ease of use had substantial effects on behavioral intention both directly and indirectly.

Another study conducted by Ha and Stoel (2009) focused on consumer e-shopping acceptance using TAM. The study included 298 respondents from a large Midwestern university. Ha and Stoel (2009) formed three main conclusions that included: (a) four dimensions of web quality, (b) the robustness of TAM to explain technology acceptance and the ability of TAM to be extended, and (c) perceived usefulness emerged as the most powerful predictor of attitude toward use relative to other factors. The perceived usefulness conclusion supports previous TAM research study findings.

Pai and Huang (2011) conducted a study applying an extended TAM model and some facets of the information system success model to the introduction of healthcare information systems. A total of 366 respondents from medical centers, regional hospitals, and district hospitals participated in the study. Major conclusions from the study included: (a) if the user's attitude toward information quality is more positive, perceived usefulness is higher, (b) when users feel more satisfied with service quality, their perceived usefulness and perceived ease of use will be higher, and (c) both perceived usefulness and perceived ease of use had a significant and positive impact on intention to use.

In another study, Teo, Lee, and Chai (2008) researched pre-service teachers' computer attitudes using an extended TAM model. Respondents included 239 pre-service teachers at the National Institute of Education in Singapore. The authors concluded that perceived usefulness and perceived ease of use were key determinants of attitude toward use as originally proposed by Davis (1989) in the original TAM. It was also found that subjective norm had an indirect and direct effect on attitude toward use. However, subjective norm had a stronger influence on perceived usefulness than attitude toward use. Facilitating conditions only indirectly influenced attitude toward use and did not influence attitude toward use directly. Finally, related to this study, this research again validated the original TAM and demonstrated the versatility of TAM by adding variables to extend the model.

Gong, Xu, and Yu (2004) conducted a study researching web-based learning using an expanded TAM. The population included 152 full-time teachers with an education certificate who were beginning the three-year bachelor's in education degree program. Conclusions from the study included: (a) perceived usefulness had both an indirect and significant direct effect on behavioral intention, (b) perceived ease of use simultaneously had a significant effect on teacher's attitude toward use and perceived usefulness, and (c) computer self-efficacy had a strong direct effect on both behavioral intention and perceived ease of use. Thus, the authors concluded that perceived ease of use, perceived usefulness, and computer self-efficacy needed to be increased for technology acceptance.

In another study, Lai and Honglei (2005) conducted a study on the technology acceptance of internet banking using TAM. Respondents included 247 business graduate students at a major university in Hong Kong. Conclusions included: (a) perceived ease of use, perceived usefulness, attitude toward use, and behavioral intention were significant and positive factors, consistent with prior TAM research, (b) TAM is a good model to use for evaluating intention to use and actual use of IT, and (c) specific to this study, the relationship of perceived usefulness to behavioral intention was not supported, which was surprising.

Broman Toft, Schuitema, and Thøgersen (2014) conducted a study to develop a model and apply it to consumer acceptance of energy smart grid technology to have it installed in their homes in Europe. Respondents included 324 citizens from Switzerland, 303 from Norway, and 323 from Denmark. The study combined the TAM with the Norm Activation Model (NAM). NAM was developed for decisions where the starting point is moral reasoning. NAM proposes people act in a certain way based on a personal feeling of obligation or norm. Conclusions included: (a) the importance of perceived usefulness and perceived ease of use was reinforced, (b) there were noted differences between the three countries and willingness to accept the technology highlighting the culture influence, (c) since the technology was at an early stage of implementation, respondents lacked knowledge and awareness indicating they had not yet formed strong opinions about the technology, and (d) a mixture of private and collective benefits stemming from perceived usefulness and perceived ease of use is necessary for smart grid technology acceptance.

Another study conducted by Mallya and Lakshminarayanan (2017) researched the factors influencing internet usage by 393 university students for academic purposes using the TAM. Conclusions from the study included: (a) the findings are consistent with the

TAM in predicting actual behavior/use, (b) attitude toward use of the internet was significantly predicted by perceived usefulness and perceived ease of use, (c) actual behavior/use was predicted the strongest by behavioral intention, and (d) attitude toward use and perceived usefulness significantly influenced behavioral intention.

Kansal (2016) studied self-service banking using the TAM integrated with perceived risk. The sample included 314 respondents from 26 cities in India. Conclusions included: (a) perceived ease of use and perceived usefulness mediated performance and social risk but did not have a mediating effect on financial risk, (b) intention to use was influenced by financial, performance, social, time, and security risk, and (c) consumers are willing to accept risk and use self-service banking if perceived usefulness and perceived ease of use are high.

Park and Kim (2014) researched driver acceptance of three aspects of car navigation systems. The sample included 1,181 respondents who had over one year of experience driving cars using navigation systems. Conclusions from the study included: (a) the research model thoroughly explained driver's perception and acceptance of car navigation systems, (b) perceived usefulness was found to guide drivers' behavioral intention and attitude toward use which is consistent with prior TAM studies, (c) perceived processing speed and perceived locational accuracy were key factors in determining attitude toward use of car navigation, and (d) satisfaction had a significant role in improving behavioral intention.

Ghazizadeh, Lee, and Boyle (2012), in their research, studied extending the TAM to assess automation creating the Automation Acceptance Model (AAM). Automation is designed to replace a function previously performed by humans. There were no respondents for this study as the purpose was to create but not test the model. Conclusions from the literature review by the authors were: (a) levels of high performance do not guarantee effective human-technology coexistence or acceptance, (b) perceived usefulness and perceived ease of use constitute primary and secondary determinants of attitude toward use; however, this could be affected by various automation applications, (c) an important feature of the theoretical AAM is the ability to capture the dynamic nature of automation adoption through the feedback mechanisms in the model, (d) actual behavior/use influences attitude toward use, and attitude toward use influences actual behavior/use, (e) understanding social norms dynamics and influence on perceptions of automation and user conformance with others' automation acceptance is a critical but an unexamined issue, and (f) in both the cognitive engineering and information systems communities, trust has been identified as an important influence on acceptance. Additionally, although the model was not explored using a statistics methodology, the authors did verify the TAM variables and the viability of the other variables through the literature review.

In another research study, Pavlou (2003) examined consumer acceptance of electronic commerce integrating risk and trust with TAM. Of the 2,000 respondents solicited, 154 respondents completed one of three surveys. Major conclusions included: (a) perceived usefulness was a significant predictor of behavioral intention, (b) perceived ease of use had a non-significant impact on actual behavior use, but like the original TAM, perceived ease of use may act indirectly on behavioral intention through perceived usefulness, (c) trust and perceived risk are direct influences on behavioral intention and must be for successful implementation of e-commerce, (d) trust had an indirect effect through perceived risk, perceived usefulness, and perceived ease of use, (e) perceived usefulness and perceived ease of use had a significant effect on transaction behavioral intention, and (f) behavioral intention did lead to actual behavior/use.

Morosan (2014), in an aviation-related study, developed an integrated model for examining technology acceptance of using mobile phones for purchasing ancillary services in air travel such as bag processing, preferred seating, pre-paid meals, check-in priority, etcetera. Respondents included 556 students from a small private university in a large metropolitan area of the southwestern U.S. Significant conclusions from the study included: (a) the developed model explained 84 percent of the behavioral intention to purchase ancillary air travel services, (b) perceived usefulness was the strongest predictor of attitude toward use, (c) perceived personalization was the strongest predictor of perceived usefulness, and (d) consumer beliefs that are fundamental to evaluation of technology can provide a solid foundation for a systematic and rigorous examination of technology adoption.

The last selected TAM study which focused on the adoption of internet banking was conducted by Cheng, Lam, and Yeung (2006). Respondents included 203 customers who used banking in Hong Kong. Major results consistent with previous TAM studies included: (a) intention to use is a major determinant of actual behavior (b) intention to use was significantly influenced by perceived usefulness and perceived ease of use, (c) perceived web security significantly influenced behavioral intention, and (d) perceived ease of use did not directly influence intention to use.

Summary of the TAM related studies to this research. Some overarching commonalities and findings related to this study emerge from the results of the selected

TAM studies. First, perceived usefulness and perceived ease of use variables were re-validated as being significant influences on attitude toward use as originally determined by Davis (1989) in the original TAM. Other TAM variables besides perceived usefulness and perceived ease of use were also validated as being important in the research process of the selected studies. Additionally, the TAM demonstrated through these studies that it is an adaptable model as many of the selected studies incorporated additional variables to successfully extend the model. Besides demonstrating the ability to incorporate more variables, the studies also demonstrated that the TAM is capable of being successfully combined with other models which might facilitate the C-TAM/TPB model in this study. Also, the studies demonstrated that the TAM could be applied to various technology realms including education, information technology, automobile technology, medicine, banking, energy, automation, aviation, and commerce. While TAM was applied to aviation, the study focused on airline passenger use of information technology, not sUAS use for data gathering. Additionally, no other TAM studies were found that focused on sUASs, further highlighting the literature gap identified in Chapter I. Also, Kansal's (2016) and Pavlou's (2003) studies demonstrated the ability of perceived risk to be integrated with TAM, further supporting the possibility of successfully integrating perceived risk into the research model. Finally, one or more TAM studies validated the methodology tools of a pretest, pilot study, a survey using a Likert scale, descriptive analysis, CFA, and SEM model testing in this study as valid methodologies for TAM. Thus, it is theorized that the TAM might be adaptable to this study.

TAM effectiveness. Turner, Kitchenham, Brereton, Charters, and Budgen (2010), in a review of 73 TAM studies to determine the effectiveness of TAM to predict actual use, found that many research studies used modified versions of TAM, and often results were influenced by the added variables. The same authors concluded that perceived usefulness and perceived ease of use are not as good predicting actual behavior/use as behavioral intention, and scholars using TAM may be measuring perceived use and not actual use (Turner et al., 2010). Yucel and Gulbahar (2013) noted TAM has been applied to a diverse set of technologies and users with various variables added. However, Yucel and Gulbahar (2013), in their review of fifty studies, found that the original TAM variables were the most effective. The same authors concluded that TAM when compared to other models is understandable and simple to use. Besides becoming a dominant model for technology acceptance and adaptable to many technologies, TAM has demonstrated good reliability in predicting user acceptance. King and He (2006) support this assertion, concluding that as of 2006, 140 different journals had published 178 TAM papers and numerous research articles. The model has good reliability predicting 51% of user acceptance with applications in numerous subject contexts with different types of technology (Teo, Ursavana, & Bahcekapili, 2011).

Davis' (1989) model has been shown to be readily adaptable to multiple study areas, as evidenced by the wide range of research study applications, but because of its generality, the detractor is that the research conclusions only allow general conclusions about the variables influencing behavior. Additionally, the model does not include social variables that may not be explained in other model variables which is another weakness. Another possible TAM detractor is the lack of detail in the perceived ease of use variable when examining perceived behavior control (PBC) which could result in failure to identify situation specific factors (Mathieson, 1991).

Theory of planned behavior (TPB). Ajzen (1991) is the originator of the TPB model which was derived from the Theory of Reasoned Action (TRA). The creation of the TPB model as an adjustment to the TRA model was necessary because of the TRA model limitations in dealing with behaviors over which people have incomplete volitional control. Thus, the primary difference between the TPB and TRA model is the addition of the perceived behavioral control variable (Ajzen, 1991). While the TAM model is geared toward acceptance, the TPB was founded on predicting intention to perform a given behavior or use. Ajzen theorized that intended behavior is the strongest predictor of actual behavior because it captures influencing individual motivational factors. Therefore, generally, the strength of the intention indicates the likelihood of the actual behavior occurring (Ajzen, 1991). Thus, the model is predicated on determining the factors influencing the intended behavior to use the technology. Additionally, it can be used practically to identify relevant factors to facilitate communication strategies to modify behavior and intention.

The TPB is a well-tested and pervasisve model of social psychology (Lee & Choi, 2009). The TPB model identifies significant beliefs that influence an individual's behavioral perceptions and ensuing actual behavior (Ajzen, 1991). The theory encapsulates social and behavioral principal concepts in the behavior and social sciences, and it explains these concepts to allow prediction and understanding of behaviors in specified contexts (Ajzen, 1991). According to the theory, perception of behavioral control, subjective norm, and attitude toward the behavior lead to the creation of a behavioral intention, which directly effects actual behavior (Lee & Choi, 2009). The TPB has become one of the most popular and influential ground theories for the study of human action (Ajzen, 2002). Ultimately, the model can provide a host of information that is extremely useful in understanding behavior or implementing interventions that are useful in changing behaviors (Ajzen, 1991).

Components of the TPB. The TPB model, when compared to TAM, has a unique element and some similar elements. *Attitude toward behavior* is the favorable or unfavorable appraisal of the behavior and has a significant effect on performing the behavior. Notably, in a review of 16 studies, attitude toward the behavior made significant contributions to prediction of intention to perform the behavior (Ajzen, 1991). *Perceived behavioral control* is like the perceived ease of use construct in the TAM model and refers to the individual's beliefs on how difficult or easy it would be to carry out a behavior (Ajzen, 1991). Perceived behavioral control is the distinguishing factor between the TPB and TRA models and is dependent on several factors. First, the individual must have the opportunity to perform the behavior and the necessary resources. The more resources and opportunities a person possesses, the greater the perceived behavioral control will be. Next, the amount of information a person has about the behavior, changing requirements, or when new and unfamiliar elements enter the situation, the individual's assessment can change. Notably, the individual's assessment of perceived behavioral control will vary across different behaviors and situations. Significantly, perceived behavioral control correlates well with behavioral performance (Ajzen, 1991). However, if available resources, opportunities change, or the individual has only limited information about behavior, then perceived behavioral control may not predict behavior (Ajzen, 1991). The *subjective norm* variable is unique to the TPB model and is defined as a person's perception of whether people important to the individual think that the behavior should be performed or, more simply, the effect of peer pressure (Ajzen, 1991; Teo, 2012).

Subjective norm forms one of the three major variables influencing intention and behavior (Ajzen, 1991). The factor influencing subjective norm is whether important individuals to the person approve or disapprove of the behavior. Interestingly, the strength of the person's desire to comply with those important individuals' beliefs did not add predictive power to predicting behavior. Instead, the desire to comply tended to suppress the correlation between subjective norm and behavior. However personal or moral norms contributing to subjective norm were found to increase explained variance by three to six percent, significantly contributing to predicting intention (Ajzen, 1991; Buchan, 2005). Revis, Sheerman, & Armitage (2009) support this conclusion and define *moral norms* as the correctness or incorrectness of using a sUAS for data gathering. Intention toward performing a given behavior is a central factor in the TPB model (Ajzen, 1991). The same author in the TPB model assumes intentions capture the motivational factors that influence a behavior since they are indications of how hard people are willing to try or the effort they are willing to exert to perform a behavior (Ajzen, 1991). Ajzen (1991) also theorizes that the stronger the intention to engage in a behavior, the more likely that behavior will be performed. *Behavior* constitutes the actions of an individual (Ajzen, 1991). The same author found that generally, when behaviors do not cause problems of control, behavior can be predicted from intentions with considerable accuracy. For example, in two different studies of people's voting intention in a presidential election and a mother's choice of feeding a baby, the prediction rate was .75 to .80 and .82 respectively (Ajzen, 1991). Behavioral intention is influenced by attitude toward the behavior, subjective norm, and perceived behavioral control, as shown in the model (Lee, Cerreto, & Lee, 2010). Teo (2012) and other studies found that external factors were found to have a significant influence on perceived ease of use. Thus, following Azjen's definition, *facilitating condition*s (FC) are the factors that influence a person's perception of ease or difficulty of performing a task (Teo, 2012). The components of the TPB model are shown in Figure 2.

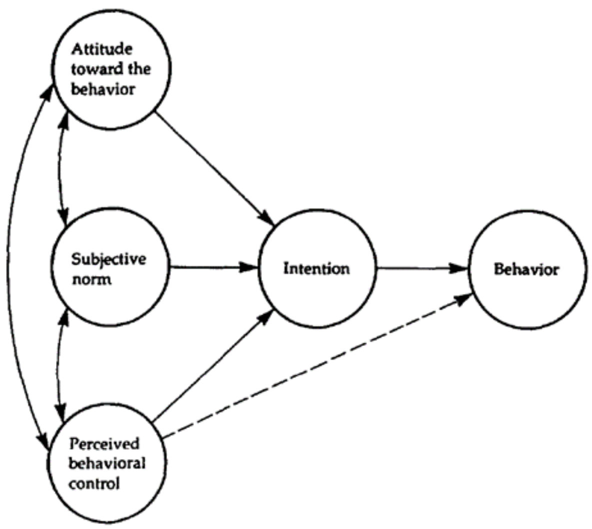


Figure 2. Components and relationships of the original Theory of Planned Behavior. Adapted from "The Theory of Planned Behavior" by Ajzen (1991).

TPB selected studies. The TPB has been used successfully to understand a wide array of human behaviors (Lee et al., 2010). Some of those behaviors include leisure, health care, and consumer purchasing (Morris et al., 2005). This section reviews 13 TPB studies. They are relevant to this study because they use the TPB model variables and apply those to information and other technology realms. A summary of the reviewed studies is shown in Table 2 with detailed descriptions of the studies following the table.

Table 2

Summary of TPB Selected Studies and Constructs/Variables

Technology Realm	Application	Constructs / Variables	Methodology	Reference
Education	Mental Health Profession	Attitude Toward Behavior, Subjective Norm, Perceived Behavioral Control, Behavioral Intention, Actual Behavior	Survey, Chi Square Analysis	Casper (2007)
Automobiles	Driving Violations	Attitude Toward Behavior, Subjective Norm, Behavioral Control, Behavioral Intention, Outcome Evaluations, Motivations to Comply, Sex, Age	Survey, Multivariate Analysis	Parker, Manstead, Stradling, Reason, & Baxter (1992)
Education	Science Fair Participation	Attitude Toward Behavior, Subjective Norm, Perceived Behavioral Control, Gender, Type of School, Level of Anxiety, Completion of Science Fair Project	Open Ended Survey, Multiple Regression, Discriminant Analysis	Czerniak & Lumpe (1996)
Transportation	Commuter Transport Mode	Attitude Toward Behavior, Subjective Norm, Perceived Behavioral Control, Behavioral Intention, and Actual Behavior, Moral Norm, Descriptive Norm, Environmental Concern, Habit	Survey, Descriptive Analysis, CFA, SEM testing	Donald, Cooper, & Conchie (2014)
Air Travel	Pro-Environment Consumer Behavior	Perception of Severity, Perceived Consumer Effectiveness, Self-Perception, Importance, Willingness to Compensate, Likelihood of Compensating	Snowball sampling, Survey with seven-point Likert Scale, Descriptive Analysis, SEM using PLS, Bootstrapping	Van Birgelen, Semeijn & Behrens (2011)
Aviation	Service-Delivery Drones	N/A	Literature Review Only	Ramadan, Farah & Mrad (2017; 2016)
Air Travel	Airline Co-Branded Credit Cards	Attitude Toward Behavior, Subjective Norm, Perceived Behavioral Control, Behavioral Intention, Perceived Benefits	Survey, Five-Point Likert Scale, Descriptive Analysis, EFA, SEM	Wang & Hsu (2016)
Environment/ Travel	Consumer Intention to Use Green Hotels	Attitude Toward Behavior, Subjective Norm, Perceived Behavioral Control, and Behavioral Intention, Environmental Concern, Perceived Moral Obligation	Survey, Seven-Point Likert Scale, CFA, SEM testing	Chen & Tung (2014)

Table 2 (*continued*)

Technology Realm	Application	Constructs / Variables	Methodology	
Human Factors	College Students Sleep	Attitude Toward Behavior, Perceived Behavioral Control, Behavioral Intention, Actual Behavior, Subjective Norms, Perceived Invulnerability, Parental Nurturance	Survey, Seven-Point Likert Scale, Pilot Study, Path Analyses using Maximum Likelihood Method	Lao, Tao, & Wu (2016)
Technology Realm	Application	Constructs / Variables	Methodology	Reference
Information Technology	Medical Records	Major Variables: Attitude, Subjective Norm, Perceived Behavioral Control, Institutional Trust, Perceived Risk, Usage Intention	Survey, Seven-Point Likert Scale, Pretest, Pilot Study, SEM using PLS	Hsieh (2015)
Human Factors	Nutrition & Body Satisfaction	Attitude Toward Behavior, Perceived Behavioral Control, Behavioral Intention, Actual Behavior, Subjective Norms	Survey, Ten-Point Likert Scale, Descriptive Statistics, Factor Analysis	Pickett et al. (2012)
Human Factors	Nutrition	Attitude Toward Behavior, Perceived Behavioral Control, Behavioral Intention, Subjective Norm, Self-efficacy, Perceived Barriers	Survey, EFA, CFA, SEM testing	Chan, Prendergast, & Ng (2016)
Transportation	Low Cost Carriers	Attitude Toward LCCs, Subjective Norms, Perceived Behavioral Control, Passenger Buying Intention, Passenger Buying Behavior	Survey, Five-Point Likert Scale, Pilot Study, CFA, SEM testing	Buaphiban, & Truong (2016)

Casper (2007), in his research study, applied the TPB model to continuing education of mental health professionals. Respondents included 94 mental health practitioners from Philadelphia and Pittsburgh randomly assigned to two different classes. Two major conclusions were derived from the study. First, the class using TPB model concepts had stronger intentions by participants to implement the assessment tool.

Second, the TPB model theory accurately predicted the effects of attitude toward the behavior, norms, and perceived behavioral control.

Parker, Manstead, Stradling, Reason, and Baxter (1992) conducted a study to determine intention to commit driving violations. Respondents included 800 drivers from various parts of England. Five major conclusions surfaced from the study including: (a) in the four scenarios, the TPB model explained from 23.4% to 47.2% of the variance in intentions, (b) the perceived expectations of others and the respondents ease with which they could avoid committing driving infractions were important factors in determining intentions, (c) the addition of perceived behavioral control significantly improved prediction of behavioral intentions, (d) the TPB model was found to almost completely be successful in mediating the impact of demographic differences and contextual variations, and (e) the TPB model and perceived behavioral control variable were validated in the study.

Another study conducted by Czerniak and Lumpe (1996) examined the predictors of science fair participation using the TPB model. Respondents included 303 junior high and middle school students. Conclusions from the study included: (a) subjective norm and participation in a gifted class were the strong predictors of attitude toward entering the competition, (b) predictors of social norm included the science fair grade counting in the class, the science fair being a requirement, and the parents' level of education, and (c) indirectly through attitude toward behavior and social norm and directly through perceived behavioral control, students have little control over their entry into a regional science fair competition.

Donald, Cooper, and Conchie (2014) conducted a study using an extended TPB model to examine the psychological factors affecting commuters' transport mode use. Respondents included 827 participants from urban and rural areas in England who had a high propensity to own a car. Major conclusions from the study included: (a) TPB variables are good predictors of commuters' model choice, but they are enhanced by added variables, (b) the added variables vary by transportation type, (c) the most important variable predicting intention to use was perceived behavioral control, consistent with previous research, (d) perceived behavioral control was also the strongest predictor of personal car and society transport habits, and (e) moral and descriptive norm failed to influence intention to drive, and only moral norm predicted society transport use.

Another study by Van Birgelen, Semeijn, and Behrens (2011) focused on explaining pro-environment consumer behavior in air travel. Respondents included 128 anonymous people including friends and family of the research team and others selected by the friends and family using a snowball sampling method. Major conclusions from the study included: (a) perception of air travel contribution to climate change had a significant positive effect on willingness-to-compensate, (b) there was no direct link between perceived effectiveness of individual actions and willingness-to-compensate, (c) a strong significant relationship existed between self-perception and willingness-to-compensate, and (d) there was a strong significant positive effect of willingness-to-compensate on likelihood of compensation.

Ramadan, Farah, and Mrad (2017; 2016), in their study used an adapted TPB approach for consumers' acceptance of service-delivery drones. While this study did not incorporate a data analysis, the literature review undertaken by the authors theoretically demonstrated the adaptability of the TPB model to an aviation technology, UAS, and the validation of incorporating perceived risk elements into an aviation-related model.

A study by Wang and Hsu (2016) focused on airline co-branded credit cards using an expanded TPB model. Respondents included 398 travelers from Taiwan Taoyuan International Airport. Major conclusions from the study included: (a) the relationships of the TPB variables to perceived benefits was confirmed, (b) consumers with positive perceptions of benefits of the co-branded credit cards are most likely to associate future use of the card with feelings of pleasure, (c) attitude, intentions, and perceived benefits will lead to better perceived behavioral control, (d) attitude toward using co-branded credit cards would be crucial in determining consumers' intention to use, and (e) subjective norm yields a positive influence on intention to use.

Chen and Tung (2014), in their study developed an extended TPB model to predict consumers' intention to visit green hotels. Respondents included 559 residents of Taiwan. Conclusions from the study included: (a) attitude toward use, subjective norm, and perceived behavioral control all had positive effects on intention to use, (b) the expanded TPB model results confirm it is a viable model to use for consumer's intention to visit green hotels, and (c) the added variables of environmental concern and perceived moral obligation had a positive effect on intention to use.

In another research study, Lao, Tao, and Wu (2016) used the TPB model to study healthy sleep of college students. Study respondents included 362 college students 18-25 years of age from a university in China enrolled in introductory courses. Major conclusions from the study included: (a) the expanded TPB model was satisfactory in understanding healthy sleep patterns and intentions of college students, (b) consistent with previous findings, perceived behavioral control and intention had a significant effect on behavior, (c) culture was noted as having a significant effect on the study, (d) parental nurturance had a positive effect on healthy sleep intentions, and (e) perceived invulnerability had a negative association with attitudes toward a specific health behavior.

Hsieh (2015) studied physicians' acceptance of an electronic medical records exchange using an extended TPB model integrated with institutional trust and perceived risk. Valid respondents included 191 physicians from Taiwan. Conclusions of the study included: (a) the model successfully explained physician electronic medical records behavior, (b) the TPB model was able to be extended with institutional trust and perceived risk, and (c) all major factors of attitude toward use, subjective norm, perceived behavioral control, institutional trust, and perceived trust had a significant effect on intention to use the medical records exchange.

Pickett, Ginsburg, Mendez, Lim, Blankenship, Foster, Lewis, Ramon, Saltis, & Sheffield (2012) conducted a TPB model study on eating disorders and body satisfaction. Respondents included 404 undergraduate students at a Texas State University. Findings were consistent with Ajzen's results and included: (a) behavioral intention was significantly predicted by perceived behavioral control, subjective norm, and attitudes, and (b) behavioral intention was found to significantly predict behavior.

Another selected TPB study was the first study to apply an expanded TPB model to predict healthy eating intentions (Chan, Prendergast, & Ng, 2016). The study consisted of 635 students from five schools in Shanghai and seven schools in Changchun.

Major results included: (a) perceived behavioral control was found to have a significant influence on behavioral intention which is consistent with previous TPB studies, (b) subjective norms were found to have a relatively lower level of influence on behavioral intention, although when frequency of past behavior increased, the influence strengthened, (c) male respondents were more likely to be affected by subjective norm than females, and (d) the TPB model was found to be useful in understanding the factors that influence behavior.

The final selected TPB study focused on determining factors that influence passenger buying behavior toward low cost carriers (LCCs) in the Southeast Asia region (Buaphiban & Truong, 2016). The final analysis included 781 respondents who were passengers using two different airports in Thailand. Major conclusions from the study included: (a) passenger attitudes toward LCCs and subjective norms have a positive impact on passenger buying intention, (b) passenger buying intention and perceived behavioral control have a positive impact on passenger buying behavior, and (c) the TPB model had a very high predictive power compared to the average predictive power of TPB literature studies.

Summary of selected TPB model studies related to this research. Related to this study, the TPB selected studies offer important conclusions. First, the studies validated the TPB model and associated variables. Next, it was demonstrated that the TPB model could be applied to other technology areas other than just information technology with three studies focused on aviation technologies. For example, Van Birgelen et al. (2010), Wang and Hsu (2016), and Buaphiban and Truong (2016) focused on airline passenger intention to support the environment, the use of airline branded credit cards, and passenger buying behavior toward LCCs, not sUASs used for data gathering. The article by Ramadan (2017; 2016) focused on consumer acceptance of small delivery of drones and demonstrated a theoretical possibility of applying the TPB model to drones and sUASs. However, the hypotheses were never tested as the study was a literature review only. Additionally, the study did not focus on individuals using sUAS for data gathering, further highlighting a literature gap. The studies also showed that the TPB model is readily adaptable to add variables to expand the model as Azjen (1991) advocated. Additionally, Hsieh (2015) demonstrated that perceived risk could be integrated into the TPB model. Finally, pretesting, using a pilot study, a survey instrument with seven-point Likert scale, descriptive analysis, SEM incorporating CFA and full structural model testing were readily demonstrated and validated for use with the TPB model, as was used in this study.

TPB model effectiveness. TPB, like TAM, is a well-tested and popular model having been used in an estimated 600 studies during the past 20 years in a wide range of subject areas (Casper, 2007). Additionally, like TAM, the TPB model has good predictability with a success rate of 41% to 50% for explaining intention effect on behavior and 28% to 34% for behavior (Morris et al., 2005). Armitage and Conner (2001), in a meta-analysis of 161 articles containing 185 empirical tests of the TPB, supported the efficacy of the model as a predictor of intentions and behavior.

However, the model does have several limitations identified in several studies and by Ajzen (1991). For accurate model predictions, the measure of perceived behavioral control and intention must be compatible with behavior the model is trying to predict. For example, if donating money to the American Cancer Society, the assessment should be done on donating money to the American Cancer Society, not just to donate money or help. Next, behavior control and intention are measured at a point in time, and the results are only good for that point in time. Lastly, prediction of behavior is expected to vary across behaviors and between situations. Generally, behaviors can be predicted with considerable accuracy if the behaviors pose no serious problems of control (Ajzen, 1991).

The TPB is founded on attitude toward behavior, perceived control over the behavior, and subjective norm with respect to the behavior which are usually found to predict behavioral intentions with a high degree of accuracy (Ajzen, 1991). While that has generally been demonstrated to be true, the TPB distinguishes between three types of beliefs: normative, behavioral, and control. Therefore, one detractor is the exact form of the relation between behavioral beliefs and attitudes toward the behavior, between control beliefs and perceptions of behavioral control, and between normative beliefs and subjective norm are uncertain (Ajzen, 1991). This is true because individual behavior is complex and varies greatly. However, after the primary variables have been considered, the TPB is open to the addition of other predictors provided it can be shown that those predictors capture a substantial proportion of the variance in behavior or intention (Ajzen, 1991; Pan & Truong, 2018).

Combined models – TAM/TPB model (C-TAM/TPB). Because of the limitations with both the TAM and TPB models, several research studies have used a combined TAM-TPB model which is simply a merger of various TAM and TPB model concepts. Previously, when scholars applied the TAM model alone, they missed the key positive influence of social norms which was only found because the TAM and TPB models were combined. Teo's and Lee's studies are two examples of successful use of the combined TAM/TPB model. Teo (2012) successfully used a combined TAM/TPB model to examine the intention to use technology among pre-service teachers. Additionally, Lee (2009), in his study of internet banking, not only integrated TAM and TPB models, but also successfully incorporated perceived risk and perceived benefits as possible factors influencing adoption of internet banking.

The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed from eight previous models including TAM and TPB with the intent to develop a unified model that determined acceptance and use of information technology (Venkatesh, Morris, Davis, & Davis, 2003). The UTAUT 2 was an extension of the UTAUT model designed to address use of the UTAUT model to a specific context of consumer behavior (Venkatesh, Thong, & Xu, 2012).

C-TAM/TPB and UTAUT model components. Several studies have successfully used the C-TAM/TPB in research. Fewer studies have employed the UTAUT models due to the relative newness of the models compared to the C-TAM/TPB model. This study examined six C-TAM/TPB and two UTAUT studies to review the nature of each study, technology realm explored, population and model variables used, methodology, and major results. The intent was to examine the viability of variables in the VMUTES model with previous research models and overall success of using the C-TAM/TPB and UTAUT models in previous research.

Studies that use the C-TAM/TPB model have at least some of the TAM and TPB model components incorporated in the research model. Table 3 consolidates the C-TAM/TPB studies examined and, among other things, lists variables used in each study. The variables of each C-TAM/TPB study can then be compared with the TAM and TPB models to see which of the model variables the scholar incorporated. For example, Lee (2009) in his study incorporated the TPB model variables of perceived behavioral control, subjective norm, attitude toward use, and intention. For the same study, the TAM variables included perceived usefulness, perceived ease of use, attitude toward use, and intention. Notably, attitude toward use and intention are common to both the TAM and TPB models.

The UTAUT and UTAUT 2 model components include similar variables from TAM, TPB, and other models. Specifically, four constructs that were theorized to be direct determinants of user acceptance and usage behavior were added (Venkatesh et al., 2003). The UTAUT 2 used the UTAUT as a base model and added those variables for consumer behavior, as can be seen in the selected studies in Table 3 (Venkatesh, 2012).

Table 3

Summary of C-TAM/TPB and UTAUT Studies and Constructs/Variables

Model/ Technology Realm	Application	Constructs / Variables	Methodology	Reference
C-TAM/TPB / Information Technology	Education	Perceived Ease of Use, Perceived Usefulness, Subjective Norm, Facilitating Conditions, Attitude Toward Use, Behavioral Intention	Survey, Five-Point Likert Scale, Descriptive Statistics, Validity Testing, SEM	Teo (2012)
C-TAM/TPB / Information Technology	Banking	Perceived Usefulness, Perceived Ease of Use, Perceived Risk, Perceived Benefit, Attitude Toward Use, Subjective Norm, Perceived Behavioral Control, Behavioral Intention	Survey, Descriptive Statistics, CFA, SEM testing	Lee (2009)

Table 3 (*continued*)

Model/ Technology Realm	Application	Constructs/Variables	Methodology	Reference
C-TAM/TPB / Information Technology	Online Tax Filing	Perceived Usefulness, Perceived Ease of Use, Tax Equity, Social Norms, Moral Norms, Perceived Behavioral Control, Attitude Toward Use, Subjective Norm, Behavioral Intention, Actual Behavior	Survey, Descriptive Statistics, CFA, SEM testing	Lu, Huang, & Lo (2010)
C-TAM/TPB / Information Technology	Mobil HealthCare	Perceived Usefulness, Perceived Ease of Use, Personal Innovativeness, Attitude Toward Use, Subjective Norm, Behavioral Intention, Perceived Behavioral Control, Perceived Service Availability	Survey, SEM using PLS, SEM testing	Wu, Li & Fu (2011)
C-TAM/TPB / Transportation	Bicycles	Perceived Usefulness, Perceived Behavioral Control, Perceived Green Value, Perceived Pleasure, Subjective Norms, Green Loyalty, Attitude Toward Protecting Environment	Survey, Five-point Likert Scale, Descriptive statistics, EFA, CFA, SEM testing	Chen (2016)
C-TAM/TPB / Information Technology	Library Self-Service	Perceived Usefulness, Perceived Ease of Use, Attitude Toward Use, Subjective Norm, Perceived Behavioral Control, Behavioral Intention	Survey, CFA, SEM testing	Chang & Chang (2009)
UTAUT / Information Technology	New Information Technology	Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Gender, Age, Experience, Voluntariness of Use, Behavioral Intention, Use Behavior	Longitudinal Study, Survey, Seven Point Likert Scale	Venkatesh, Morris, Davis, & Davis (2003)
UTAUT 2 / Information Technology	Tax Returns, Booking Society Facilities, Appointment Booking, Renewal of Driving Licences	Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit, Age, Gender, Experience, Behavioral Intention, Use Behavior	Online Survey, Demographic Variable Wave Analysis, Partial Least Squares, Structural Model Testing	Venkatesh, Thong, & Xu (2012)

Combined TAM/TPB and UTAUT model selected studies. Teo (2012), using a C-TAM/TPB, examined pre-service teachers' self-reported intention to use technology using 157 respondents in Singapore. Conclusions from the study included: (a) attitude toward use and subjective norm had significant effects on behavioral intention, (b) facilitating conditions had a small effect on behavioral intention, while perceived usefulness and perceived ease of use had a medium effect on behavioral intention, (c) integration of the TAM and TPB models were fairly efficient as a model with five variables contributed to 35% of the variance in behavioral intention, (d) if the respondents believed the technology improved work performance, had a positive attitude and believed the technology made them more efficient, they were likely to use the technology, (e) the facilitating conditions factor was a significant predictor of perceived ease of use which is consistent with the literature, (f) attitude toward use had a significant effect on behavioral intention, (g) subjective norm had a significant influence on behavioral intention and perceived usefulness but did not have a significant influence on attitude toward use, and (h) the C-TAM/TPB allowed the scholars to assess the synergy between and effects on the variables.

In another study using the C-TAM/TPB, Lee (2009) examined the factors influencing the adoption of internet banking in Taiwan. A final sample size of 368 respondents was obtained through the data collection process using an online survey with a seven-point Likert scale. Notably, perceived risk was included as a variable and broken into five sub-variables which included performance, social, time, financial, and security risk previously defined and discussed earlier in the chapter. Major conclusions from the study included: (a) all perceived risk sub-variables had a negative influence on intention to adopt online banking, (b) perceived benefit followed by attitude were the most important predictor variables for intention to use online banking, (c) perceived usefulness had a significant effect on intention to use, and (d) perceived usefulness was more influential than perceived ease of use in explaining online banking acceptance.

Lu et al. (2010) conducted a study of on-line tax filing using a C-TAM/TPB in Taiwan. There was a total of 422 valid survey respondents who were taxpayers and had filed taxes online. Major results from the study included: (a) perceived usefulness and perceived ease of use had a significant positive effect on perceived behavioral control, (b) social and moral norms were positively related to attitude, (c) attitude toward use was the key factor affecting intention to use, having a positive effect, and (d) integrating the TAM and TPB did explain and predict on-line tax filing.

Wu, Li, and Fu (2011) used the C-TAM/TPB to study the adoption of mobile healthcare by hospital professionals. A total of 140 respondents comprising health care professionals from 10 different Taiwan hospitals participated. Major findings included: (a) the model explanatory power was high with an R2 of 0.63, (b) perceived usefulness had a much greater influence on attitude than perceived ease of use which is consistent with earlier research studies, and (c) the components of TAM and TPB were important in the adoption of mobile healthcare.

Chen (2016), using a C-TAM/TPB model, conducted a study to analyze the effects of perceived green value on loyalty to a bike system for society. Respondents included 261 users of the bike system YouBike. Results included: (a) perceived behavioral control, subjective norms, and perceived pleasure had significant positive effects on users' green loyalty, and (b) notably, attitude of protecting the environment did not have an influential impression on users.

In another study, Chang and Chang (2009) examined library self-service to understand user intentions related to self-issue and return systems at a university in Northern Taiwan using a C-TAM/TPB. Respondents included 266 students enrolled in business courses at the university. Major results from the study included: (a) user attitude plays a robust role in determining user intention to use, (b) attitudes were determinants of behavioral intention, (c) attitudes were also affected by perceived ease of use and perceived usefulness, (d) subjective norm was found to be a significant factor influencing the user's intention, (e) perceived behavioral control should be taken into account since many of those elements are required in the execution of library self-service, and (f) study results were consistent with previous work, showing a direct effect of perceived usefulness on attitude and the intention to use (Chang & Chang, 2009).

Venkatesh et al. (2003) conducted a study to derive a unified model (UTAUT) that could be applied to information technology. Respondents were located at four organizations where new information technology was being introduced. Major results included: (a) the developed UTAUT model was successful in integrating key concepts from the eight models, (b) the UTAUT model is a definitive model that provides a foundation for future research in information technology, (c) the facilitating conditions factor was only significant when examined with moderating effects of age and experience, and (d) UTAUT measures should be considered preliminary. More research is needed to fully develop and validate appropriate construct scales.

To further refine the UTAUT for consumer behavior, Venkatesh et al. (2012) extended the UTAUT model and created the UTAUT 2 model. Respondents included 4,127 and 1,512 respondents respectively from a two-stage online survey. Major results included: (a) the UTAUT 2 is a powerful framework for consumer technology acceptance and use context, (b) when the UTAUT is extended with relevant constructs, it can contribute to an important understanding of specific technologies, (c) the fun or pleasure of using a technology was found to be a significant determinant of behavioral intention, and (d) facilitating conditions were influential on behavioral intention but more pronounced for older women.

Summary of the C-TAM/TPB and UTAUT model-related studies related to this study. Related to this research effort, the studies offer several important findings. The eight selected studies that used the C-TAM/TPB or UTAUT models have merit supporting the theoretical theory base for the VMUTES model. Next, most of the VMUTES model variables were tested in one or more studies, providing the foundation upon which to continue research in the field of aviation. The selected studies also verified the viability of the relationships between variables. Additionally, while five of the studies were in the IT realm, the studies demonstrated the viability of the C-TAM/TPB and UTAUT model to adapt to different applications within that technology realm. Concerning perceived risk, Lee (2009) theorized, integrated, and successfully tested perceived risk and effects in his model supporting the inclusion and testing of perceived risk in the research model. Chen (2016) also demonstrated through his transportation study that the C-TAM/TPB model could be adapted to another technology realm. Also, one or more of the C-TAM/TPB and UTAUT selected studies included and validated the methodologies used in this research effort including a survey instrument using a Likert scale, descriptive statistics analysis, and CFA and SEM model testing.

The C-TAM/TPB has three distinct advantages over the use of UTAUT model for this study. First, UTAUT was only used for information technology while TAM and TPB have been shown to be easily adaptable to other technologies. Second, the TAM and TPB models have been in use longer (1989 and 1991 respectively) versus UTAUT and UTAUT2 (2003 and 2012 respectively). The longer time period for the TAM and TPB models has allowed more studies and testing of TAM and TPB, strengthening model credibility. Finally, C-TAM/TPB effectiveness was comparable to TAM and TPB discussed earlier, lending credence to its ability to potentially model and identify factors influencing individuals' behavioral intentions toward using sUAS for data gathering.

Applying the C- TAM/TPB model to this study. Mathieson (1991) advocates the combined TAM/TPB model allows scholars to garner the benefits of both the TAM and TPB models in technology acceptance studies. For example, identifying the key positive influence of social norms can only be found when the TAM and TPB models are combined. Using the combined TAM/TPB was demonstrated by both Lee (2009) and Teo (2012) in their technology acceptance studies with success. Thus, a similar approach of using a derived combined TAM/TPB model was used in this study.

For the TAM and TPB models, the variables of behavior intention / intention are strong predictors of use of technology. Similarly, in the research model in this study, the behavioral intention variable was used to determine the intention to use sUASs for data gathering. Behavioral intention is influenced by attitude toward use. Applying TAM to the research model in this study, attitude toward use is the attitude toward use of sUAS for data gathering. As stated previously, both perceived usefulness and perceived ease of use directly influence attitude toward use and indirectly affect behavioral intention. Additionally, perceived ease of use has a direct effect on perceived usefulness (Davis, 1989; Teo, 2012). Applying TAM to the research model in this study, both variables were used. Perceived usefulness within the model represents the degree to which the users believe sUAS enhances their productivity. Additionally, *perceived ease of use* in this study is defined as the perception of the user that sUAS used for data gathering is free of effort (Davis, 1989).

TPB, when compared to TAM, includes a more detailed treatment of perceived behavior control which means it is more likely to capture situation-specific factors (Mathieson, 1991). Therefore, the TPB model has variables that were used and are important in the VMUTES model to cover the shortfalls of the TAM model. Subjective or social norm unique to the TPB is a necessary factor and is included in the research model. Subjective norm is defined as a person's perception of whether people important to the individual think that the behavior should be performed (Teo, 2012). Examples could include family, friends, and the the FAA since the FAA has mandated requirements established in CFR 14 part 107 and FAA AC 107-2. Specific to this study, subjective norms is the perceived need by individual sUAS operators to use the technology based on peer pressure of people of importance to the individual (Teo, 2012). Perceived behavioral control is like the perceived ease of use construct in the TAM model and therefore was not duplicated in the research model (Teo, 2012). Behavioral intention and intention represent how hard a person tries to perform a behavior and serve as a solid indication of whether subjects intend to actually use the technology. Therefore, to avoid duplication, only one of the two variables (behavioral intention) was used in the research model. Following Teo's approach, using Ajzen's definition of influencing external factors, facilitating conditions are used to represent perceived behavioral control facilitating influences (those factors that facilitate use) in the model (Teo, 2012). Actual behavior/used in this study represents the use of sUAS for data gathering.

Constructs Influencing Individuals' Intentions to Use sUASs for Data Gathering

The VMUTES model contains both original components of the TAM and TPB models with added external factors of perceived risk and knowledge of regulations. This section justifies the factors for the VMUTES model. The construct justification considers factors derived from Chapter II as related to an individual's use of a sUAS for data gathering. The VMUTES model derivation fills an identified aviation gap, more specifically the sUAS areas. The derived model will also possibly allow research applications in other technology realms as well. Table 4 shows the studies reviewed to derive the constructs and the major findings related to that factor.

Table 4

Sources Used for New Research Model Constructs

Factor	Findings Related to the Factor	Reference
Perceived Usefulness (PU)	PU had a substantial effect on BI	Choi & Chung, (2012); Pai & Huang (2011); Gong, Xu, & Yu (2004); Park & Kim (2014);

Table 4 (*continued*)

Factor	Findings Related to the Factor	Reference
Perceived Usefulness (PU)	PU was the most powerful predictor of attitude	Ha & Stoel (2009); Morosan (2014)
	PU was a key determinant of respondent attitudes	Teo, Lee & Chai (2008); Park & Kim (2014)
	PU had a medium effect on BI	Teo (2012)
	PU had a greater influence on ATU than PEOU	Wu, Li, & Fu (2011)
Perceived Ease of Use (PEOU)	PEOU had a substantial effect on BI	Choi & Chung, (2010); Pavlou (2003)
	PEOU was a key determinant of respondent attitudes	Teo, Lee, & Chai (2008); Gong, Xu, & Yu (2004); Park & Kim (2014)
	PEOU had a significant effect on PU	Gong, Xu, & Yu (2004)
	PEOU had a medium effect on BI	Teo (2012)
Subjective Norms (SN)	SN norm had an indirect and direct effect on attitude	Teo, Lee, & Chai (2008)
	SN had a stronger influence on PU then attitude	Teo, Lee, & Chai (2008)
	SN had a significant effect on BI	Teo (2012); Wang & HSU (2016)
	SN had a significant effect on PU	Teo (2012)
	SN are positively related to ATU	Lu, Huang & Lo (2010)
	SN are one of three major variables influencing intention and behavior	Ajzen (1991); Casper (2007);

Table 4 (*continued*)

Factor	Findings related to the factor	Reference
Subjective Norms (SN)	SN were the best predictors of ATU	Parker et al. (1992) Czerniak & Lumpe (1996)
Attitude Toward Use (ATU)	ATU had significant effects on BI	Teo (2012); Mallya & Lakshminarayanan (2017)
	SN did not have a significant effect on ATU	Teo (2012)
	ATU was one of the most important predictor variables for BIATU was the key factor affecting BI	Lee (2009)
Attitude Toward Use (ATU)	ATU plays a robust role in determining BI	Lu, Huang & Lo (2010)
	ATU was affected by PU	Chang & Chang (2009)
	ATU was significantly influenced by PU and PEOU	Mallya & Lakshminarayanan (2017)
Facilitating Conditions (FC)	FC indirectly influence ATU	Teo, Lee, & Chai (2008)
	FC had a small effect on BI	Teo (2012)
	FC was a significant predictor of PEOU	Teo (2012)
Perceived Risk (PR)	PR was a direct influence on BI	Pavlou (2003)
	PR sub variables had a negative influence on BI	Teo (2012)
	Respondents were willing to accept risk if PU and PEOU are high	Kansal (2016)
	Financial, social, time, and security risk influenced BI	Kansal (2016)

Table 4 (*continued*)

Factor	Findings related to the Factor	Reference
Knowledge of Regulations (KOR)	Very important to provide outreach to operators regarding guidance, regulations, and best practices	Terwilliger et al., (2017)
	State and local laws are important to review before operating sUASs as they may enact flight restrictions based on privacy	FAA, AC-107-2, (2016)
	States and local municipalities can impose flight restrictions over prohibited areas for security, noise, etc.	Elias (2016)
	CFR 14 Part 107 provides the federal regulation basis for FAA AC-107-2 that sUAS need to be familiar	Aeronautics and Space, 14 C.F.R. pt. 1 (2017)
	Given FAA regulations change often, the FAA UAS website provides a comprehensive overview of sUAS operator need-to-know information	FAA, (2017b)
Behavioral Intention (BI)	BI is influenced by ATU	Gong & Yu (2004)
	BI was the best predictor of AB	Mallya & Lakshimnarayanan (2017)
Actual Behavior/Use (AB)	AB was best predicted by BI	Mallya & Lakshimnarayanan (2017)
	AB was significantly affected by ATU	Ajzen (1991)

The VMUTES model contains nine constructs of perceived usefulness, perceived ease of use, subjective norms, attitude toward use, facilitating conditions, perceived risk, knowledge of regulations, behavioral intention, and actual behavior/use. For the survey questions related to each construct, respondents indicated their agreement with the statements using a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

The operational definitions of the research model constructs are shown in Table 5. While examples of questions for each variable are listed, the full listing of questions in the survey instrument related to each construct with supporting sources can be found in Table C1.

Table 5

Operational Definitions of Research Model Construct

Factor	Operational Definition	Variable Type
Perceived Usefulness	The degree to which an individual believes that using a sUAS for data gathering would enhance his or her job performance (Davis, 1989).	Endogenous
Perceived Ease of Use	The degree to which an individual believes that using a sUAS for data gathering would be free of effort (Davis, 1989).	Endogenous
Subjective Norms	Subjective norms refer to the perceived social pressure that significant others (parents, spouse, friends, etc.) desire the individual to use or not use a sUAS for data gathering (Ajzen, 1991).	Exogenous
Attitude Toward Use	The degree to which an individual has a favorable or unfavorable appraisal or evaluation of using a sUAS for data gathering (Ajzen, 1991).	Endogenous
Facilitating Conditions	Those environmental factors that are present that positively influence the decision to use a sUAS for data gathering (Teo, Lee, & Chai, 2008).	Exogenous
Perceived Risk	The perception individuals form and revise based on the possible danger of using a sUAS for data gathering (Moussaïd, 2013).	Exogenous

Table 5 (continued)

Factor	Operational Definition	Variable Type
Knowledge of Regulations	sUAS operator comprehension of Federal, state, and local laws and guidelines that apply to sUAS operations. More specifically, this includes Public Law 112-95, 14 CFR Part 107, FAA AC 91-57A, FAA AC 107-2, applicable state and local laws and the FAA UAS website information (Aeronautics and Space, 2017; FAA, AC-107-2016, FAA, AC-91-57A, 2016a; FAA, 2017b).	Exogenous
Behavioral Intention	An indication of how hard an individual is willing to try or how much effort they are planning to exert in order to use a sUAS for data gathering (Ajzen, 1991).	Endogenous
Actual Behavior/Use	The use of sUAS for data gathering that exists in reality or in fact, not false or just merely possible (Actual, n.d.).	Endogenous

Perceived usefulness. The first factor, perceived usefulness was assessed using previously validated questions from Lee (2009), Cheng et al. (2006), Teo (2012), Davis (1989), and Lu, Huang, and Lo (2010) modified for sUAS data gathering operations. The TAM and C-TAM/TPB sections in the literature review validated the need for this variable. Examples of these items include: "*I think that using a sUAS for data gathering would enable me to accomplish data gathering tasks more quickly*" and "*Using a sUAS for data gathering will enhance my productivity.*"

Perceived ease of use. The literature review for both the TAM, C-TAM/TPB, and perceived risk sections identified the need for the perceived ease of use construct. Perceived ease of use, the second factor, was assessed using previously validated questions from Lee (2009), Cheng et al. (2006), Teo (2012), Davis (1989), and Lu, Huang, and Lo (2010) modified for sUAS data gathering operations. Examples of these items include: "*I think that interaction with using a sUAS for data gathering does not* *require a lot of mental effort*" and "*I think it is easy to use a sUAS for data gathering to accomplish data gathering tasks.*" Additionally, one question was created to further explore this variable specific to using a sUAS for data gathering. This item includes: "*I have sufficient knowledge and experience to use a sUAS for data gathering.*"

Subjective norms. The subjective norms construct was identified as a needed factor from the literature review in the TAM, TPB, C-TAM/TPB, and perceived risk sections. The third factor, subjective norms, was assessed using previously validated questions from Lee (2009), Wu and Chen (2005) as cited by Lee (2009), Teo (2012), Ajzen (1991), and Davis et al. (1989) modified for sUAS data gathering operations. Examples of these items include: "*People who are important to me would think that I should use a sUAS for data gathering*" and "*People whose opinions I value will encourage me to use a sUAS for data gathering*." Additionally, a question was created to further explore this variable and includes: "*My individual values/beliefs morally support me using a sUAS for data gathering*."

Attitude toward use. The fourth factor, attitude toward use, was identified as a necessary construct from the literature review sections of the TAM, TPB, C-TAM/TPB, and detractors that could affect individuals' sUAS data gathering behavioral intentions. Attitude toward use was assessed using previously validated questions from Lu, Huang, and Lo (2010), Teo (2012), Compeau and Higgins (1995), Lee (2009), and Cheng et al. (2006) modified for sUAS data gathering operations. Examples of these items include: "*In my opinion, it is desirable to use a sUAS for data gathering*" and "*I like the idea of using a sUAS for my data gathering needs.*"

Facilitating conditions. The fifth factor in the VMUTES research model is facilitating conditions which was identified in the TAM, C-TAM/TPB, and sUAS detractors that could affect individuals' sUAS data gathering behavioral intentions literature review sections. Facilitating conditions was assessed using previously validated questions from Teo (2012), Thompson, Higgins and Howell (1991), and Venkatesh, Morris, Davis, and Davis (2003) modified for sUAS data gathering operations. More specifically, the developed questions covered the factors of supporting materials and information, regulations, avialable training, and the legal environment discussed previously. Examples of these items included: "*When I need help on how to use a sUAS for data gathering*, *guidance is available to me*" and "*When I need help on how to use a sUAS for data gathering, a specific person or company is available to provide assistance*." Additionally, new questions were developed from the literature review for this factor specific to using sUAS for data gathering. Examples include: "*The U.S. government facilitates my operation of sUAS for data gathering*" and "*If my sUAS breaks, it is easy to find help and/or replacement parts to fix it*."

Perceived risk. Perceived risk with associated elements was identified as a needed construct in the perceived risk, TAM, TPB, C-TAM/TPB, and detractors that could affect individuals' sUAS data gathering behavioral intentions literature review sections. More specifically, these previously defined risk elements include: (a) physical, (b) performance, (c) time, (d) financial, (e) social, (f) security, (g) privacy, and (h) psychological. The sixth factor of perceived risk was assessed using previously validated questions from Clothier et al. (2015), Lee (2009), and Fetherman and Pavlou (2003) modified for sUAS data gathering operations. Examples of these items include: "*Using a* *sUAS for data gathering is threatening to myself and/or others in society*" and "*Others in society using a sUAS for data gathering will lead to a loss of privacy for me*." Additionally, questions were created based on the literature review to further explore this variable in the context of using a sUAS for data gathering. Examples include: "*Using a sUAS for data gathering is physically threatening to other aircraft*" and "*The costs of procuring, operating, and maintaining a sUAS for data gathering is concerning.*"

Knowledge of Regulations. The seventh factor, knowledge of regulations was identified as a possible detractor in the literature review. The operator must have been exposed to and understand federal, state, and local laws and guidelines to conduct safe and responsible sUAS operations (Terwilliger et al., 2017). All knowledge of regulations questions were newly created based on the types of laws and guidelines that apply to sUAS operations. Examples include: "*I am familiar with state laws that apply to my sUAS operations or have determined that there are no state laws that apply*" and "*I am familiar with FAA Advisory Circular 91-57A as a model aircraft operator or FAA Advisory Circular 107-2 as a non-model sUAS operator.*"

Behavioral intention. The eighth factor was identified in the TAM, TPB, and C-TAM/TPB sections of the literature review. Behavioral intention was assessed using previously validated questions from Teo (2012), Davis et al. (1989), Lee (2009), Cheng et al. (2006), and Lu, Huang, and Lo (2010) modified for sUAS data gathering operations. Examples of these items include: "*When choosing data gathering task methods, use of a sUAS is my first choice*" and "*I would recommend using a sUAS for data gathering to my relatives and friends.*"

Actual behavior/use. The last factor, actual behavior/use, was assessed using previously validated questions from Lu, Huang, and Lo (2010), Davis et al. (1989), and Compeau and Higgins (1995) modified for sUAS data gathering operations. Examples of these items include: "*I have used a sUAS for data gathering purposes*" and "*I used a sUAS for data gathering purposes this year*." Also, questions were created to further explore the construct reflecting duration and/or frequency of use. Examples include: "*I have used a sUAS for data gathering more than once in the past two years*" and "*When I needed data gathering tasks completed, I used a sUAS*."

Theoretical Framework and Hypotheses (VMUTES Model)

Following the literature review, this study used the theoretical model shown in Figure 3 to determine individuals' intentions to use/actual use of sUASs for data gathering. The perceived risk and knowledge of regulations factors combined with applicable variables of the TAM and TPB form a solid theoretical basis for the VMUTES model used in the study. The exogenous variables in the model include subjective norms, perceived risk, knowledge of regulations, and facilitating conditions. The endogenous variables include perceived usefulness, perceived ease of use, attitude toward use, behavioral intention toward using sUASs for data gathering, and actual use. In Figure 3, factors and theorized relationships are presented. Perceived usefulness directly influences attitude toward use. Perceived ease of use directly influences perceived usefulness and attitude toward use. Subjective norms directly influence perceived usefulness, attitude toward use, and behavioral intention. Attitude toward use directly influences behavioral intention. Facilitating conditions directly influence perceived ease of use, attitude toward use, and behavioral intention. Perceived risk and knowledge of regulations directly influence attitude toward usefulness. Behavioral intention directly influences actual behavior/use. Since the VMUTES model is theoretical, it is important to note that after study completion, additional interrelationships between factors could exist in this model. Additionally, it was possible for factors not accounted for in the model to predict individuals' intentions to use sUASs for data gathering. Since this study was limited in scope, the factors and paths selected for the model were rationally restricted to include only those factors determined through the literature review to affect the relationships in the VMUTES model. The remaining portion of this section presents hypothesis statements derived from the model framework.

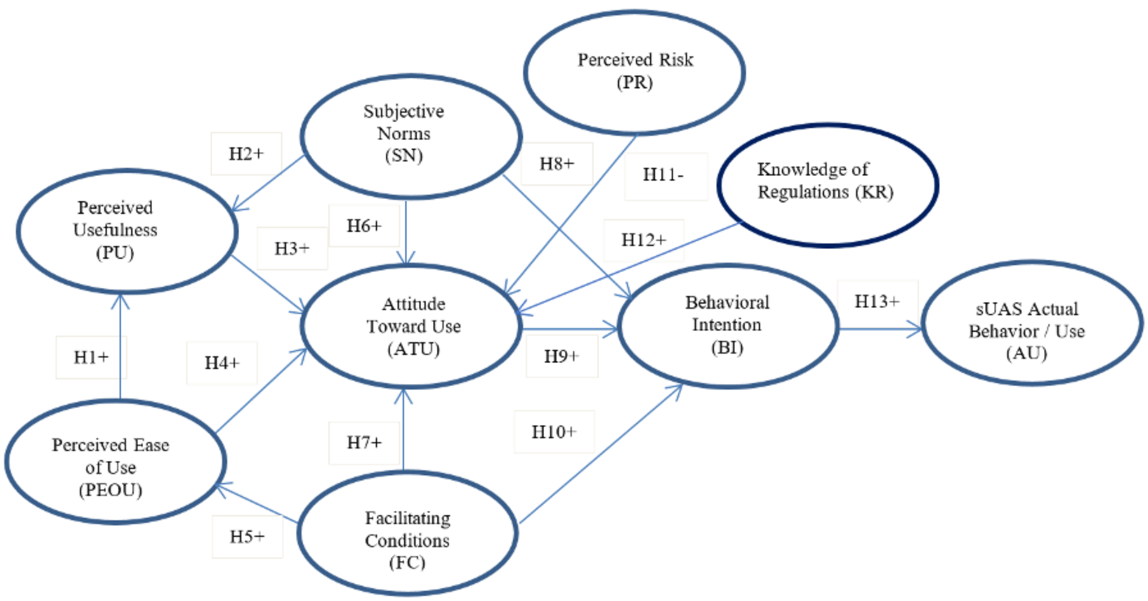


Figure 3. Research theoretical framework and hypotheses (VMUTES model).

The literature review portion of the study was used to aid to develop the conceptual framework for the VMUTES model including the hypotheses theorizing the relationships between variables. The hypotheses for the VMUTES model incorporated one new hypothesis, two hypotheses that were tested but not validated in previous studies, and ten existing hypotheses from other studies. The three unproven hypotheses were regarded as new hypotheses. Regarding the two existing hypotheses related to facilitating conditions from other studies, while they have been tested and unproven for other technologies, they had not been tested and validated for a sUAS used for data gathering. The third hypothesis regarding knowledge of regulations was a newly developed hypothesis not tested in previous sUAS studies. Therefore, the following hypothesis statements for the VMUTES research model were made:

H1: *Perceived ease of use positively influences perceived usefulness*.

Using the same hypothesis as in previous studies, it was hypothesized that perceived ease of use positively influences perceived usefulness of sUASs used for data gathering. This is because it is expected that increased perceived ease of use makes using sUASs for data gathering easier and therefore increases job performance. Supporting this, several selected studies in other technology realms found perceived ease of use to have a direct significant positive influence over perceived usefulness including Davis (1989) who founded this relationship in the TAM. Various other studies including Teo (2012), Wu, Li, and Fu (2011), Chang and Chang (2009) and others validated the same hypothesis.

H2: *Subjective norms positively influence perceived usefulness*.

Teo (2012), using a C-TAM/TPB model for information technology, found the subjective norm factor had a direct positive significant influence over perceived usefulness. Another study by Choi and Chung (2012) who used an extended TAM to study social networking sites, had similar results. Although, the previous studies were in the information technology realm, the same hypothesis was used since this same relationship was theorized to be evident in the VMUTES model. This is because it was expected that significant others who benefit from sUASs used for data gathering in areas such as home security, disaster and humanitarian missions, communication, photography, video recording, etcetera would support the sUAS user.

H3: *Perceived usefulness positively influences attitude toward use.*

Perceived usefulness was found to have a significant positive direct influence over attitude toward use in the five selected C-TAM/TPB studies reviewed (Chang & Chang, 2009; Lee. 2009; Lu, Huang, & Lo, 2010; Teo, 2012; Wu et al., 2011). Since sUASs used for data gathering offer several benefits to users that other tools, such as conventional cameras and video cameras do not provide, it was expected that the user would view sUASs used for data gathering as the preferred choice while at the same time being fun. As a result, attitude toward use was theorized to be positively affected. Thus, using the existing hypothesis, it was hypothesized that perceived usefulness positively influences attitude toward use. Other selected studies in the literature review using only TAM or an extended TAM also verified this relationship.

H4: *Perceived ease of use positively influences attitude toward use*.

Like other studies which used the same hypothesis, perceived ease of use was hypothesized to have a positive significant direct influence over attitude toward use. This is because it was expected that if using a sUAS for data gathering did not require a lot of effort and was easy to master, then the sUAS user would want to use sUASs for data gathering even more. Davis (1989), in his original TAM model, theorized and showed this positive relationship. The review of several selected previous studies also supports this hypothesis (Lee, 2009; Lu et al., 2010; Teo, 2012). However, at least one study, Wu et al. (2011), found a positive but non-significant relationship.

H5: *Facilitating conditions positively influence perceived ease of use.*

Choi and Chung (2012) provide specific facilitating conditions examples of skills training, administrative support, and information or materials available that are key factors influencing instructional technologies. Additionally, Lu´, Yu, Liu, and Yao (2003) describe other facilitating factors such as policies, regulations, and legal environment as conditions for technology acceptance. These same elements of facilitating conditions were postulated to be relevant and positive for sUASs used for data gathering. Thus, adapting a current hypothesis, it was hypothesized that facilitating conditions would positively influence perceived ease of use. Supporting this hypothesis, Teo (2012), using a C-TAM/TPB model, and Lu´, Yu, Liu, and Yao (2003), in a literature review only study, validated this hypothesis.

H6: *Subjective norms positively influence attitude toward use.*

It was expected that significant others who benefit from sUASs used for data gathering in areas such as home security, disaster and humanitarian missions, communication, photography, video recording, etc., would support the sUAS user. This, in turn, was expected to increase sUAS user attitude toward use. Thus, using an existing hypothesis, it was hypothesized that subjective norms would have a significant positive influence on attitude toward use. The literature review of previously selected studies showed mixed results with this relationship. Lao, Tao, and Wu (2016), using an extended TPB model, found that injunctive or social norms did have a significant positive effect on attitude toward use. Lu et al. (2010), using a C-TAM/TPB model, found the same result.

Teo, (2012) using a C-TAM/TPB model, hypothesized that subjective norm positively influenced attitude toward use. However, Teo (2012) found that subjective norm had a positive but non-significant influence over attitude toward use in his information technology study.

H7: *Facilitating conditions positively influence attitude toward use.*

While the sUAS literature shows both positive and negative support for the effect of facilitating conditions effect on UAS in general, it was expected that for sUASs, the previously described facilitating conditions would have a positive impact on the sUAS user. This is because sUASs are generally easier to operate and require less support than a larger UAS. Thus, it was theorized that facilitating conditions would have a significant positive influence on attitude toward use. Teo (2012) proposed this same hypothesis in his study, and while the results showed the relationship was positive, it was not significant. However, Teo's study was in the information technology realm while sUAS use for data gathering is in a different technology realm. Thus, it was theorized that the results could be different from Teo, and therefore the relationship should be tested as a new hypothesis since Teo's study failed to validate it.

H8: *Subjective norms positively influence behavioral intention.*

Using an existing hypothesis, it was hypothesized that subjective norms would have a significant positive influence over behavioral intention. This is because it was expected that significant others who support sUAS data gathering use would encourage sUAS users. Thus, sUAS users would want to use sUAS for data gathering more. This is supported from the literature review by studies conducted by Lee (2009), Teo (2012), Lu et al. (2010), and others.

H9: *Attitude Toward Use positively influences behavioral intention*.

Using an existing hypothesis, it was hypothesized, and the literature review supports, attitude toward use as having a significant positive direct influence over behavioral intention to use sUASs for data gathering. This was hypothesized and demonstrated in studies by Lee (2009), Teo (2012), Lu et al. (2010), and others.

H10: *Facilitating conditions positively influence behavioral intention*.

It was expected that previously described facilitating conditions would have a significant positive influence on behavioral intention of sUASs for data gathering users. This is because if these elements are positive from the sUAS user's perspective, then sUAS users would be willing to try harder to use the technology. Teo (2012) used this same hypothesis in his study. However, in Teo's (2012) study, while the relationship was positive, it was not significant. Small unmanned aircraft systems used for data gathering occurs in the aviation technology realm and not the information technology realm as in Teo's study. Thus, it was theorized that the results could be different from Teo, and therefore the relationship should be tested as a new hypothesis since Teo's study failed to validate it.

H11: *Perceived risk negatively influences attitude toward use.*

Perceived risk is an important factor because as identified in the literature review, if perceived risk is too high, technology acceptance and individuals' intentions to use a sUAS for data gathering can be slowed or halted. Thus, attitude toward use could also be negatively affected. The literature review identified potential perceived risks associated with sUASs to be: (a) financial (Lee; 2009; McCormack, 2009), (b) legal (Mariani, 2014), (c) invasion of privacy (Featherman & Pavlou, 2003; Tate, 2015; Villasenor, 2014), (d) security (Gallacher, 2016; Grose, 2016; Lee, 2009), (e) physical (Klauser and Pedrozo, 2017; Williams, 2017), (f) performance (Lee, 2009), (g) time (Lee, 2009), (h) social (Lee, 2009), and (i) psychological (Featherman & Pavlou, 2003). Additionally, Ramadan et al. (2017), deriving a proposed model from the literature for consumer acceptance of service-delivery drones, also hypothesized that perceived risks of privacy and safety risks had a negative effect on attitude toward use. Using a previous hypothesis derived by Lee (2009), it was hypothesized that perceived risk would have a direct and significant negative influence over attitude toward use.

H12: *Knowledge of regulations positively influences attitude toward use*.

Knowledge of regulations is an important factor in the VMUTES model because as identified in the literature review, if applicable federal, state, and local laws and guidelines are not effectively communicated to and understood by sUAS operators, safe and responsible operation can be difficult to achieve. However, if the sUAS operator knows where to find and has a sound knowledge of applicable laws and guidelines, then it was theorized that user knowledge would have a positive effect on attitude toward use and deter the sUAS operator from unsafe and irresponsible actions. Thus, this new hypothesis is included in the VMUTES model.

H13: *Behavioral intention positively influences actual behavior/use of sUASs for data gathering*.

Using an existing hypothesis, it was hypothesized that behavioral intention or a strong desire to use sUASs for data gathering would have a positive direct influence over actual behavior. Ajzen (1991) showed this in his TPB model, and other studies have validated this hypothesis.

Chapter Summary

Chapter II developed the literature foundation for the technology being studied, the ground-based theories used in the study, additional influences on the ground-based theories in this study, and provided the basis of the methodology used to complete the study. It also establishes the theoretical framework for the VMUTES model and justifies additional factor selection in constructing the predicting model.

More specifically, this chapter reviewed a wide range of selected studies with respect to TAM, TPB, C-TAM/TPB, and UTAUT models. Although studies examined various technologies and factors influencing outcomes, few focused-on aviation technology, and all failed to address sUAS technology that focused on behavioral intention. Thus, substantial gaps exist in understanding an individual’s behavioral intention toward using sUASs for data gathering, confirming the knowledge gaps outlined in Chapter I. The literature review also revealed the importance of the constructs and input variables in the VMUTES model.

Chapter II also provided an extensive review of sUAS technology, and possible detracting factors toward individuals’ intentions to use sUAS for data gathering. Subsequently, perceived risk and measurement of perceived risk were reviewed. The literature review indicated that knowledge of regulations and perceived risk and measurement elements of perceived risk should be incorporated into the VMUTES model. The chapter also reviewed TAM, TPB, C-TAM/TPB, and UTAUT studies. Conclusions indicate that a form of the C-TAM/TPB integrated with the perceived risk is a suitable ground theory for the VMUTES model. The VMUTES model includes five TAM and two TPB original components in the model with the selection of variables justified based on previous research and additional variables of perceived risk and knowledge of regulations. The next chapter discusses the research design and methodologies used for developing the VMUTES model and testing associated hypotheses.

CHAPTER III

METHODOLOGY

In the previous chapter, the academic foundation for the research methodology and design was examined, while this chapter focuses on describing the research methods and data analysis used. The overarching purpose is to detail and justify the steps used to answer the research questions and to address the research hypotheses. Doing so allows other scholars to replicate the study, increasing internal validity.

Research Approach

A non-experimental, large-scale survey approach with a quantitative data analysis was used in this study. The three components of a survey include a sample, questionnaire, and some type of quantitative coding to record the results (Babbie, 1990). A survey approach of the large population in this study best served research requirements for several reasons. A *survey* is defined as a systematic method for obtaining information from a sample for constructing quantitative descriptors of a larger population consisting of individual members (Groves et al., 2009). It is the best method available to scholars interested in collecting original data for describing a population that is too large to observe directly as in this study (Babbie, 2016). Surveys are considered the most commonly used research design in the behavioral and social sciences because they provide scholars with a great deal of evidence at a relatively small monetary cost (Vogt et al., 2012). Also, surveys are excellent tools to use to measure attitudes and orientations within a large population as in this study (Babbie, 2016; Vogt, 2012).

Additionally, Vogt et al. (2012) lists five factors when a survey should be used. First, as in this study, the data was best obtained directly from respondents. Second, the data is best obtained from short answers to brief questions such as described earlier. Third, respondents can be expected to give reliable information. As such, the quality of data serves as the basis for the data analysis and results. Since personal information is controlled and there is no pressure from external sources, it is assumed respondents will provide accurate information (Vogt et al., 2012). The survey itself only contained generic demographic data with no identifying personal data. Fourth, Vogt et al. (2012) states that the scholar must know how they are going to use the data. Chapter III of this dissertation describes in detail how that data was used. Fifth, an adequate response rate was expected (Vogt et al., 2012). Using Westland's (2010) formula to compute required sample size and employing the methods described earlier, the response rate was adequate to ensure the study was successful.

Research Design and Procedures

This study incorporated a survey research design and quantitative analysis to analyze the survey data. The survey used a cross-sectional approach to investigate a section of the population at a single point in time (Babbie, 2016). Survey questions were obtained from previous studies as much as possible and tailored for context, as this saved time and strengthened validity (Vogt, Vogt, Gardner, & Haeffele, 2014). However, questions were also created for areas identified in the literature review not covered by previous research study questions. The survey questions used for this study were short, clear, precise, non-biased, not negative, and properly ordered to allow for meaningful answers (Babbie, 2016). Ordering of questions is important. Thus, questions were grouped by constructs to aid in organizing data and allowing respondents to more easily follow the survey. Also, demographic data of sUAS users was collected. Finally, the survey questions were tied to the context of sUASs as each question related to a particular construct in the model to determine the influencing factors for individuals' intentions to use sUASs for data gathering (Vogt et al., 2014). Before using the questionnaire for the study, a pretest and small-scale pilot study was performed to test validity and reliability of the questionnaire (Babbie, 1990; Groves et al., 2009). When required in the pretest and pilot study, survey questions were modified as needed and the survey instrument distributed to obtain a minimum of 460 valid survey responses. The details of questions that were modified are discussed later.

Once the data collection was completed, descriptive statistics, SEM, consisting of CFA, and full structural model testing was employed for the data analysis. Descriptive statistics was appropriate to use to analyze the demographic variables and for checking normality (Babbie, 2016). SEM was useful in this study since (a) estimation of multiple and interrelated dependence relationships is needed, (b) an ability to represent unobserved concepts in the relationships and accounting of measurement error in the estimation process is needed, and (c) a model is needed to explain all the relationships (Hair, Black, Babin, & Anderson, 2010). Specifically, CFA and full structural modeling, which are part of the SEM process was appropriate in this study because the model was based on theory with the purpose of confirming the theoretical foundation (Hair et al., 2010). Hair et al. (2010) lists the six stages of SEM to include: (a) individual construct definition, (b) development of the overall measurement model, (c) designing a study to produce empirical results, (d) assessment of measurement model validity, (e) creating and specifying the structural model, and (e) assessment of structural model validity. The flow chart shown in Figure 4 depicts the steps used in the study to support the six stages.

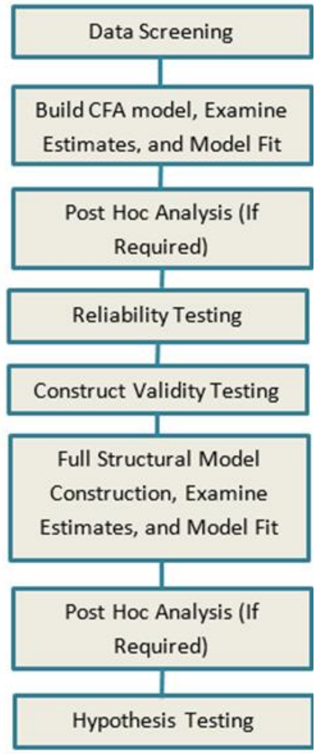


Figure 4. SEM process for the study.

Apparatus and Materials

The apparatus for this study was an online survey instrument facilitated through a link in the Amazon® Mechanical Turk® human intelligence task to Survey Monkey®. The survey instrument consisted of 78 questions. The introductory section contained the purpose of the study, survey procedures, and consent form. The first five questions were used to determine eligibility for the survey. The next 19 questions were used to collect demographic data. Fifty-three Likert scale questions measured the input variables for the individual constructs in the model. The final question offered the opportunity to provide additional comments on any topic the respondent thought was relevant.

Materials required for this study included standard office equipment and administrative materials. A computer with IBM SPSS 24® and AMOS 23® with compatible operating software was also needed for the data analysis portion of the study.

Research Procedure

The research procedure contains eight steps. Figure 5 depicts this procedure. The survey instrument was developed based on the findings of previous studies and other information derived from the literature review using the specific context under which the subjects are being investigated. The pre-test of the survey was conducted using five subject matter experts (SMEs) to test the survey instrument. Two SMEs were members of academia with knowledge of survey construction and had sUAS usage experience. The other three SMEs, one from each category (model, civil, and public use), were sUAS data gathering users. To be used in the pre-test as a sUAS user, participants had to meet the minimum criteria in the screening questions for the study. Conducting a pretest allowed assessment of the face validity of the instrument and allowed participants to provide an input on survey procedures (Babbie, 1990). Additionally, the pre-test allowed the SMEs to validate clarity of survey questions and potential overlap with other questions that belong to another factor. Subsequently, survey questions were revised as required based on the results of the pre-test information and reported in the research study (Bennett, Khaangura, Brehaut, Graham, Moher, Potter, & Grimshaw, 2010; 2011). Before starting the survey data collection process for the pilot study, the survey instrument was submitted to the institution review board (IRB) for review and approval (Embry-Riddle Aeronautical University, 2017).

Once the IRB approved the survey instrument, a pilot study was conducted.

Conducting a pilot study allows scholars to test the reliability of the instrument and identify any issues with the survey protocol and response rate (Foster, 2013). As study designs are not perfect, a pilot study will also point out errors in reasoning and/or design that can then be fixed (Babbie, 1990). The pilot study can also gauge respondent's reaction to data collection, the respondent's willingness to follow the study protocol, time to complete the survey, and unanticipated variance in the responses (Foster, 2013). To begin the pilot study, a representative sample was chosen in a similar way as the main study (Babbie, 1990). Additionally, similar to the main study, an AMT HIT was used with a link to an online survey in Survey Monkey to test the process.

Concerning pilot study sample size, several authors have proposed different strategies. Hill (1998) suggests ten to thirty participants. Hertzog (2008) suggests a sample size of 35 to 40 as preferable. Connelly (2008) and Simon and Goes (2018) suggest 10%. Simon and Goes' suggestion is based on the suggested level for dissertation and scholarly research. Using 10% yields a pilot study sample size of 46 given a required study sample size of 460 which satisfies Hill's (1998), Hertzog's (2008), and Simon and Goes' (2018) advocated numbers including the suggested level for dissertation and scholarly research. Thus, the pilot study used 10% of the calculated sample size as a minimum to validate the survey and research procedure including reliability and validity. Once the pilot study was completed and the survey revised as required, data collection began. After data collection, descriptive statistics, CFA, and full structural model testing was used for data analysis and to answer the research questions. The statistical significance level of $p < .05$ was used for the models since this is a common p-value used to test hypotheses (Vogt et al., 2014). Since AMOS sets the default p-value of 0.001, the hypotheses supported with a p-value of ≤ 0.05 were reported with a separate annotation.

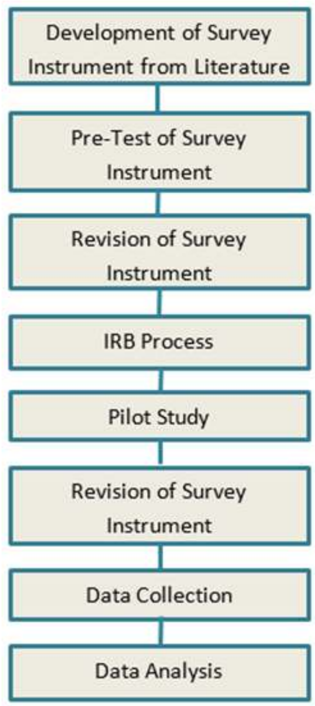


Figure 5. Research procedure.

Target Population

It was necessary and important to define the target population and sampling frame for this study (Bennett et al, 2010; 2011). Groves et al. (2009) describes a *target population* as a finite set of individuals with a defined group of elements where the survey investigator uses sample statistics to make inferences. For this study, the target population consisted of U.S. citizens who use model, civil, or public small unmanned aircraft for data gathering.

Sampling Frame

Babbie (2016) defines a *sampling frame* as the list or quasi list of elements from which a probability sample is selected. For example, if survey respondents were selected from a roster, the roster would be the sampling frame (Babbie, 2016). Groves et al. (2009) further simplifies the definition stating it is the delimited population from which a sample is taken. The sampling frame associated with the first sampling mechanism consisted of workers who are members of MTurk. It is important that the sample frame be representative of the general population to be able to generalize results as much as possible. Buhrmester, Kwang, and Gosling (2011) found that Amazon® Mechanical Turk® participants are more representative than and at least as diverse as traditional samples. Additionally, the same authors found that MTurk met or exceeded psychometric standards associated with published research. Each qualified member of the population using Amazon® Mechanical Turk® has an equal probability of completing the survey with the ability to ensure only one response from each participant (Mason & Suri, 2011). Given these factors, the sample was considered to be representative of the population (Babbie, 2016; Vogt et al., 2012). Although respondents were limited to those who use that website, Babbie (2016) cites Wilson (1999) who points out that some respondent populations are ideally suited to this technique; specifically, those who visit a particular website.

Qualifications of the Target Population

In the context of this research, a *U.S. citizen* was defined as a person who was born in the U.S., a naturalized citizen, or a lawful permanent resident (green card holder). Respondents were limited to U.S. citizens as cultural differences could have skewed the data and created inaccurate results (Choi, 2013; Clothier et al., 2015). Additionally, the resources available for the study did not permit an expanded approach beyond the U.S. Also, this approach was generally consistent with FAA registration requirements (FAA, 2017b). However, non-U.S. citizens can fly sUASs for commercial purposes by obtaining a U.S. Remote Pilot Certificate (RPC) and completing necessary screening and administrative paperwork (FAA, 2017b). The sample unit which is the element considered in the sampling is the individual sUAS user (Babbie, 2016). Those sUAS users who are mandated in the commercial, government agency, or military sector to use sUAS in their occupation were excluded from the study, since that data could skew the study results. However, those military members who own a sUAS for personal use or those individuals who voluntarily use commercial or government agency sUASs could participate in the study. There is no minimum age for modelers since someone else of age can register the sUAS. However, for the person who accomplishes the modeler registration, the minimum age is 13 years (FAA, 2017b). To operate a sUAS for commercial operations or other civil operations that do not fall in the model aircraft category, the operator must be 16 years of age (FAA, AC 107-2, 2016).

Respondents were required to be a minimum of eighteen years of age to participate in the study since it represents a higher level of maturity that includes more established personal values. This is consistent with Amazon Mechanical Turk® that was used in the study which requires workers to be at least 18 years of age (Mason & Suri, 2001). Additionally, it is also consistent with many commercial companies including American Telephone and Telegraph (AT&T), United Parcel Service (UPS), and public agencies such as police and fire departments that might or are currently using a sUAS

(Discoverpolicing.org, 2018; FireRecruite.com, 2018; Job-applications.com, 2018a, Job-applications.com, 2018b). Therefore, most individuals who are under 18 years of age fall in the model aircraft category of operation under Public Law 112-95, Section 336 and represent a smaller portion of the population. Thus, it was postulated that not including minors would have only at best, a small effect on the generalization of study results. Also, including minors in the study could have introduced confounding variables such as parental influence, education level, lack of work experience, and attention level in the SEM model process. Confounding variables could have contributed to measurement error meaning that one or more of the SEM model latent constructs of interest are not adequately described (Hair et al., 2010). Besides being at least 18 years of age, study participants must have operated a sUAS for data gathering within the past two years. The two-year requirement is consistent with the FAA requirement of reviewing FAA regulations for operation of sUAS every two years (FAA, AC 107-2, 2016).

Sample Size

Vogt et al. (2014) lists adequate sample size as one of the two requirements to be able to make inferences or generalizations about a population. Sample size determines the precision and stability with which the model is estimated, power of statistical tests, and it influences the various model fits measures (Blunch, 2008). Kline (2016) agrees, advocating SEM generally requires large sample sizes because smaller sample sizes typically result in a poor model fit. Westland (2010) echoes that sentiment stating that having too small of a sample size results in poor conclusions, and too big of a sample size results in unnecessary research study costs. Additionally, SEM is more sensitive to sample size than other multivariate approaches, and thus it is an important consideration in the analysis process (Hair et al, 2010).

There are different opinions concerning the minimal sample size for SEM studies. Hair et al. (2010) list rules of thumb for sample size to be used and three factors that require an increased sample size. The VMUTES model has nine constructs. Given that, 500 is the suggested sample size for a large model (Hair, et al, 2010). Additionally, the same authors advocate that sample size should be increased for: (a) data that deviates from multivariate normality, (b) sample-intensive estimation techniques, or (c) missing data exceeds 10 percent (Hair et al., 2010). This study did not use sample-intensive techniques, and normality and missing data was unknown until the data collection process was completed. Fan, Thompson, and Wang (1999) found that a sample size of 50 is too small, and goodness of fit index (GFI) and adjusted goodness of fit index (AGFI) were the model indexes most affected by a sample size that was too small. Kline (2016) suggests that most published SEM studies are most likely based on sample sizes that are too small. While a specific number is not given, a sample size less than 100 may be untenable. Additionally, a median sample size may be about 200 based on the number of parameters requiring estimates (Kline, 2016). Iacobacci (2010) suggests using a sample size of at least 50 with each construct ideally measured by at least three indicator variables, but having a few constructs with a single indicator variable is okay.

Westland (2010) in his study advocates that many existing methods used to calculate the minimum sample size for SEM were misleading. His comprehensive study resulted in a new formula for determining the sample size lower limit for the SEM analysis. Westland (2010) in his study compared the sample sizes used in 74 research studies to draw conclusions using the new equation to calculate the lower limits. Study Results indicated that in the 74 research studies, typically the sample size was only 50% of that required necessary to draw relevant conclusions advocated by the studies (Westland, 2010). Westland's minimum sample size formula for SEM studies is shown in Equation 1:

$$n = 1/2H\,(A\,(\pi/6 - B + D) + H$$

$$n = 1/2H\,(A\,(\pi/6 - B + D) + H$$

$$+\sqrt{(A\,(\pi/6 - B + D) + H)^2 + 4AH\,(\pi/6 + \sqrt{A} + 2B - C - 2D))} \tag{1}$$

where :

$A = 1 - \rho^2$.

$B = \rho$ arcsin $(\rho/2)$.

$C = \rho\ arcsin\ (\rho)$.

$D =$ A / $\sqrt{3} - A$.

$H = \left(\frac{\delta}{z_{1-\alpha/2} - z_{1-\beta}}\right)^2$.

Given the comprehensive nature of Westland's study, his equation was used for determining the minimum sample size for the VMUTES model. Because of the calculation complexity, Soper's online SEM sample size calculator that uses Westland's formula to check the equation results was also used (Soper, 2017). With the effect size set at 0.2, the statistical power level at 0.8, and using 9 latent variables, 53 observable variables, and a probability level of 0.05 for the model, the formula and calculator yield a recommended minimal sample size of 460 for the VMUTES model.

Sampling

Non-stratified, probability sampling using a random sampling technique was utilized for the online survey using Amazon® Mechanical Turk® (MTurk) (Babbie, 2016; Creswell, 2014). Snowball sampling was considered, but not used, since an adequate response was obtained and using snowball sampling would have increased the risk of sampling bias (Babbie, 2014; Vogt et al., 2012; Woodley & Lockard, 2016). A small monetary compensation was offered for the human intelligence task (HIT) or survey shown in Appendix E, which is required by Amazon® Mechanical Turk®. A lower compensation rate was offered and then reviewed for an increase if the rate of completed work appeared to be too low to increase response rate (Mason & Suri, 2012). The same authors advocate that offering an amount that is abnormally high will often evoke a negative response from workers due to possible deception and fraud. A review of other comparable HITs and pilot study results indicated an increase of the pilot study rate was not required for the main study.

Providing an incentive can increase response rates (Babbie, 2016). Groves, Cialdini, and Courier (1992) support this theorizing that increased happiness facilitates higher survey response rates. Besides offering a small incentive, additional measures were taken to increase response rates. One cause of poor response rates is the number of contacts members are subjected to with surveys (Bickart & Schmittlein, 1999). Therefore, minimal effort was required from respondents to take and submit the survey, respondents were notified they had been specially selected for the survey, and a deadline for completing the survey of one month was also used (Babbie, 2016). Finally, respondents were reassured that their survey responses would be anonymous (Vogt et al., 2012).

Sources of the Data

The source of the data for this research was the survey data. Demographic baseline data used for comparison with respondent demographics was obtained from the FAA and the U.S. Census Bureau. Other data required for the research analysis was generated by SPSS, AMOS, and Excel.

Data Collection Device

The survey instrument used in this research contained 78 questions. The first part of the survey provided the purpose of the study and a consent form followed by screening questions. Section 1 contained five screening questions – "*Are you a U.S. citizen*"(U.S. Citizen, naturalized citizen, or green card holder), "*Are you eighteen years of age or older*", "*Have you flown a sUAS for the purposes of transmitting or recording pictures, audio, video, or have collected other data in the last two years*", "*Use of sUAS for the purposes of transmitting or recording pictures, audio, video or collecting other data has been voluntary*", and "*Are you currently using a sUAS for military use only?*" The questions in section one were used as screening questions to confirm the eligibility of respondents. Yes-no questions were used to obtain information in section one. To participate in the survey, participants had to meet the criteria of all five questions.

The purpose of section two was to collect sUAS user demographic information. Section two demographic information was collected using 19 questions. Table 6 shows a summary of the demographic variables for the study derived from the literature review. Cultural factors was not included as a demographic variable since the study is limited to the U.S. only. Additionally, variables that expand sUAS demographic data and could also be confounding variables are indicated by an underlined variable name. A discussion of available U.S. census and FAA data used as a comparison with the study-derived demographic data is discussed in the demographic and non-response bias section in this chapter.

Table 6

Summary of Demographic Variables

Question No.	Variable Name	Rationale for Use	Variable Type	How Measured
1	Gender	Lit review identified as possible demographic factor detractor (Hertzog et al., 2006)	Nominal Categorical Variable	Male or Female
2	Age	Lit review identified as possible demographic factor detractor (Hertzog et al., 2006). Also, directly contributes to personal attitude toward use generational detractor (Perritt & Sprague, 2014)	Ordinal Categorical Variable	Years
3	Highest Education Level	Lit review identified as possible demographic factor detractor (Hertzog et al., 2006).	Ordinal Categorical Variable	Degree Level
4	<u>Annual Income</u>	Author identified as a possible confounding factor. Adds to FAA demographic database.	Ordinal Categorical Variable	Dollars
5	<u>Occupation</u>	Author identified as a possible confounding factor. Adds to FAA demographic database.	Nominal Categorical Variable	Occupation Category type.
6	<u>Use Category</u>	Author identified as a possible confounding factor. Adds to FAA demographic database.	Nominal Categorical Variable	CFR, FAA, Defined Categories
7	<u>sUAS Experience Level</u>	Author identified as a possible confounding factor. Adds to FAA demographic database.	Ordinal Categorical Variable	Years

Table 6 (*continued*)

Question No.	Variable Name	Rationale for Use	Variable Type	How Measured
8	Region of Operation	FAA identified sUAS demographic data (FAA, 2017a)	Nominal Categorical Variable	U.S. Census Bureau Geographic Regions
9	Urban metro, Urban micro or Rural Area	FAA identified sUAS demographic data (FAA, 2017a).	Nominal Categorical Variable	U.S. Census Bureau defined Population size
10	Remote Pilot Certificate	Author identified as a possible confounding factor. Adds to FAA demographic database.	Nominal Categorical Variable	Yes/No format
11	Type of Operation	Author identified as a possible confounding factor. Adds to FAA demographic database.	Nominal Categorical Variable	sUAS FAA / Lit review defined operation types
12	Formal Training	Lit Review identified as a possible detractor (Tauro et al.,2016; Ayranci, 2017), and Author identified as a possible confounding factor. Adds to FAA demographic database.	Nominal Categorical Variable	Yes/No format
13	Possession of Manned Aircraft Operating Certificate	Author identified as a possible confounding factor. Adds to FAA demographic database.	Nominal Categorical Variable	Yes/No format
14	Manned Aircraft Experience Level	Author identified as a possible confounding factor. Adds to FAA demographic database.	Nominal Categorical Variable	Years
15	Type of sUAS vehicle used	Author identified as a possible confounding factor. Adds to FAA demographic database.	Nominal Categorical Variable	Fixed wing or Rotorcraft categories
16	Type of Waiver Requested if Applicable	Author identified as a possible confounding factor. Adds to FAA demographic database.	Nominal Categorical Variable	FAA waiver category lists
17	Confirmation of Registration	Author identified as a possible confounding factor. Adds to FAA demographic database.	Nominal Categorical Variable	Yes/No format
18	Cost of sUAS	Author identified as possible confounding factor. Adds to the FAA demographic database.	Ordinal Categorical Variable	Dollars

Table 6 (*continued*)

Question No.	Variable Name	Rationale for Use	Variable Type	How Measured
19	Type(s) of Sensor	Adds to FAA demographic database.	Nominal Categorical Variable	Defined types

Section three assessed the factors (constructs) that may have influenced individuals' intentions to use sUASs for data gathering and consisted of 53 questions. At least three question items were used to assess each construct (Hair et. al, 2010). Thirty-one measurement instruments (questions) were obtained from previous studies, with modifications made to better reflect the context of this study; sUAS for data gathering. Twenty-two questions were created from the literature as noted in Table C1, which shows the measurement instruments and related sources. More specifically, five questions were created for the facilitating conditions construct, one question for the perceived ease of use construct, one question for the subjective norms construct, seven questions for the perceived risk construct, five questions for knowledge of regulations, and three questions for the actual behavior construct. Survey participants were asked to rate the construct-related questions using the seven-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree). The Likert answer format is one of the most frequently used tools in contemporary questionnaire design because it allows respondents to provide unambiguous responses that are better suited for data analysis (Babbie, 2016). The final question was an open-ended additional comments question where respondents could comment on any subject desired.

Instrument Reliability

Creswell (2014) defines *reliability* as whether scores on items in an instrument are internally consistent with item responses consistent across constructs, stable over time, and the administration and scoring was consistent. In other words, if a technique is applied repeatedly, the same result is yielded each time (Babbie, 2016). This study used multiple constructs that were measured by several items, each applied to a new subject area. Additionally, since individuals were being surveyed in this study, there was no guard against the impact of that respondent's subjectivity (Babbie, 2016).

The possibilities for misunderstanding survey questions are endless. Thus, to increase reliability, survey questions were constructed and were properly ordered, simple, clear, and concise (Babbie, 2016). Pretesting of the survey during the study served as a quality control device for those survey question qualities discussed by Babbie (2016). Additionally, for reliability, respondents should have been competent to answer the questions (Babbie, 2016). To ensure respondents were competent, screening questions were used in the beginning of the survey to ensure respondents met minimum qualifications.

Instrument Validity

Babbie (2016) discusses two types of validity testing that were applicable to this study: face and construct validity. Besides testing validity with face and construct validity, the study incorporated questions from previous studies that were validated as part of those studies and applicable to using a sUAS for data gathering. Using questions from other valid studies also improved the validity of this study because they served as a pilot test and allowed comparison of results with previous studies (Vogt et al., 2014).

The same authors advocate that using questions from previous studies also saves the research team a significant amount of time.

While reliability tests that the survey consistently measures the same thing, it does not ensure the survey components measure what they are supposed to measure (Babbie, 2016). Therefore, validity also needs to be examined. Creswell (2014) defines *validity* as whether one can draw useful and meaningful conclusions from scores on particular instruments. More simply, *validity* is how well the survey measure accurately reflects the intended constructs (Groves et al., 2009).

Face validity is not concerned with determining whether a measure is adequate or not, but rather determining if a scale appears to measure what it is intended to measure (Babbie, 2016). To test face validity, five external experts were used to pre-test the survey instrument after receiving an explanation of the study. Two of the preferred experts were academia with a Master's or Doctoral degree that met the screening criteria of the survey. The other three experts represented each of the three sUAS categories (modeler, civil use, and public use) and are a sUAS data gathering user who met the survey screening criteria. The charter of the experts was to evaluate the question wording, question structure, question order, response alternatives, and questionnaire navigational rules (Groves et al., 2009). After the feedback was attained from the experts, the questions were reworked or discarded as necessary (Ison, 2011; Olson, 2010).

During the pretest, SMEs identified seven questions that needed adjustment requiring either rewording for clarity or allowing multiple responses to a question which previously allowed only a single response. Additionally, participants identified the word surveillance as connotating spying. During the pilot study, five questions with low factor loadings were examined and were determined to have possible overlap with other survey questions. Therefore, those questions were reworded before data collection in the main study. The five questions included FC4, PEOU1, PR3, PR7, and PR8. More detail concerning reworking of the pretest and pilot study questions is provided in Chapter IV.

Establishing face validity was needed before using any CFA theoretical testing in this study. Without an understanding of every item's meaning or content, it is impossible to express and correctly specify a measurement theory (Hair et al., 2010).

Construct validity is based on the logical relationships among the model variables in this study (Babbie, 2016). The same author defines *construct validity* as the degree to which a measure relates to other variables as expected in the VMUTES model theoretical relationships. Hair et al. (2010) defines construct validity as the extent to which a set of measured variables represent the constructs those variables are designed to measure. Construct validity is important in the CFA process since one of the primary objectives of the methodology is to provide a confirmatory test of the measurement theory. How measured variables logically and systematically represent constructs defines *measurement theory* (Hair et al., 2010). Construct validity testing was used for both the pilot study and large-scale survey. The methodology that assessed construct validity is described later in Chapter III.

Ethical Issues and Considerations

Compared with observational or experimental research which requires considerably more direct contact and interaction with people, ethical concerns in survey research is considered relatively minor (Vogt et al., 2012). Additionally, by design, survey research includes many ethical choices built into the design, as is the case in this study (Vogt et al., 2012). However, survey research involves a request that people provide information about themselves that is not readily available requiring several ethical considerations to be considered (Babbie, 2016). As such, ethical issues were important in this study (American Psychological Association, 2010). Therefore, ethical considerations are addressed from the following five aspects, each containing measures to protect participants and the integrity of the study.

Voluntary consent

1. A written explanation was provided at the beginning of the questionnaire disclosing the research nature and purpose. Additionally, there were no conflict of interests that needed to be explained (Vogt et al., 2012).
2. Research participants were free to decide if they wanted to participate in the survey and/or skip questions (Vogt et al., 2012). The survey included a paragraph stating the same in the introductory section. After survey completion, respondents were free to ask questions of the survey administrator using contact information in the survey.
3. The informed consent form was integrated electronically into the survey introduction for potential respondents to acknowledge by checking a box after reading a short introductory paragraph before participating in the survey (Vogt et al., 2012).

Protection from harm

1. This research focused on sUAS individuals' behavioral intentions, and asked survey questions about respondents' beliefs, values, and attitudes.

Thus, sensitivity in the question design was imperative for the research team.

2. Respondents can be distressed about questions that can make them uncomfortable. Therefore, as previously discussed, participants were free to decide to skip any question they did not want to answer. Also, there was no insistence by the survey administrator to provide an answer when a participant was uncomfortable giving one (Pan &Truong, 2018; Vogt et al., 2012).
3. There was no physical, psychological, financial, or reputational harm anticipated in this study (Vogt et al., 2012). Harm was unlikely in this survey study. However, awareness of harm factors was maintained when administering the survey (Vogt et al., 2012).
4. The survey was expected to be finished in a reasonable timeframe. Potential respondents were informed in the introductory portion of the survey of the time needed (approximately 40 minutes) and deadline (one month) for completing the questionnaires, to enable their decision to participate in the survey.

Privacy

1. For the Survey Monkey self-administered online survey, no personal identifiers and only generic demographic information which cannot be tied to an individual were required during the process of data collection. The survey was constructed to ensure that participant identities could not be identified through the demographic characteristics (Vogt et al., 2012).

2. For those respondents who asked questions of the research team, personal information was obtained. As such, the information was kept confidential and/or destroyed. If research information is shared in the future, the personal identifying information will be masked or deleted (Vogt et al., 2012).
3. Confidential research data obtained by the survey administrator was treated as confidential information in password-protected computer systems, and perturbation was used for the personal identifying information (Vogt et al., 2012).

IRB

1. The IRB must review and approve all research involving human subjects prior to starting to advertise, recruit, or conduct research (Embry-Riddle Aeronautical University, 2017). The IRB process is designed to protect the welfare and rights of human research participants and safeguard that the ethical principles of the Belmont report are followed during the research process (Embry-Riddle Aeronautical University, 2017). For this study, an application and supporting documentation shown in Appendix A including the survey and consent documents was submitted to the Embry Riddle Aeronautical University IRB (Embry-Riddle Aeronautical University, 2017).
2. As a student of Embry-Riddle Aeronautical University, IRB training was completed as required by the university policy, before obtaining IRB

review of the research project using human participants (Embry-Riddle Aeronautical University, 2017).

Integrity of the Study

1. Respondent responses were reported fairly and accurately (Vogt et al., 2012).
2. When analyzing data, the research team did not side with participants, presented both positive and negative results, and privacy and anonymity of participants was respected (Creswell, 2014).
3. During reporting, sharing, and storing data, the following actions were taken including: (a) avoiding falsifying authorship, data, findings, evidence, and conclusions, (b) avoiding plagiarism, (c) avoiding disclosing data that could harm research participants, (d) keeping records of raw data and other materials, (e) avoiding piecemeal or duplication of publications, and (f) providing complete compliance proof for research ethical compliance (Creswell, 2014).

Treatment of the Data

The collected survey data was examined for missing values, coding errors, and aberrant values by transferring the survey data into Excel™ and then importing the data into SPSS® (Hair et al., 2010). To increase internal validity, if possible, a second person was planned to be used to spot check the data analysis process for accuracy but was not available.

Demographic data and non-response bias. Limited demographic data for U.S. sUAS users was available from the FAA, no demographic data was found in previous

U.S. sUAS studies, and only limited data was found in a study conducted in Switzerland. The FAA demographic data includes: modeler versus non-modeler, rural versus metro, type of operation, and type of waiver. FAA data for modeler versus non-modeler, rural versus metro, and U.S. 2016 census data for gender, age, education level, and monthly income was used to determine if the sample is representative. Those six demographic variables that are underlined that were compared are shown in Table 7. As previously described, other demographic variables are presented to further define the sUAS population specific to the study and eliminate confounding variables.

Table 7

Summary of Demographic Variable Comparison Values

Question No.	Variable Name	Source of Comparison Data	Comparison Values
1	Gender	U.S. Census data (U.S. Census Bureau, 2016). New sUAS demographic data produced.	Females 50.8% Males 49.2%
2	Age	U.S. Census data (U.S. Census Bureau, 2016). New sUAS demographic data produced.	22.8% < 18 years Approximately 62% between 18 & 64 years 15.2% >=65
3	Highest Education Level	U.S. Census data (U.S. Census Bureau, 2016). New sUAS demographic data produced.	87% of population have high school diploma or higher. 30.3% have a bachelor's degree or higher
4	Anuual Income	U.S. Census data (U.S. Census Bureau, 2016). New sUAS demographic data produced.	Median income $55,322 Per capita income $29,829
5	Occupation	No U.S. comparison data available. Possible confounding variable. New sUAS demographic data produced.	No comparison data available.
6	Use Category	FAA data (FAA, 2018)	1,050,328 total registrations 896,728 hobbyists (modelers) (85.4%) 153,600 non-hobbyists (14.6%)

Table 7 (continued)

Question No.	Variable Name	Source of Comparison Data	Comparison Values
7	sUAS Experience Level	No U.S. comparison data available. Possible confounding variable. New sUAS demographic data produced.	No U.S. comparison data available.
8	Region of Operation	FAA UAS forecasted data (FAA, 2017a) & U.S. Census Data (U.S. Census Bureau, 2016)	See figure 8.
9	Urban metro, Urban micro or Rural Area	FAA UAS forecasted data (FAA, 2017a) & U.S. Census data (Ratcliffe, Burd, Holder, & Fields, 2016)	Urban metro & urban micro population = approximately 94%. Approximately 6% rural (Ratcliffe, Burd, Holder, & Fields, 2016).
10	Remote Pilot Certificate	FAA data (FAA, 2018)	1,050,328 total registrations 82,113 remote pilot certificates issued (approximately 8%)
11	Type of Operation	FAA data (FAA, 2017a). Also new data possibly produced for types of operation identified in Lit review, but not identified by the FAA.	FAA type of operation ranking: 1. Aerial Photography (34%) 2. Real Estate (26%) 3. Construction, Industrial, & Utility Inspection (26%) 4. Agriculture (21%) 5. Emergency Management (8%) 6. Insurance (5%) Lit Review: Wildlife Monitoring, Movie filming, Education, Environmental, Law or Border Enforcement, & Sports or Media Broadcasting.
12	Formal Training	No comparison data available. Possible confounding variable. New sUAS demographic data produced.	No comparison data available.
13	Possession of Manned Aircraft Operating Certificate by sUAS users	No comparison data available. Possible confounding variable. New sUAS demographic data produced.	No comparison data available.
14	sUAS user Manned Aircraft Experience Level	No comparison data available. Possible confounding variable. New sUAS demographic data produced.	No comparison data available.
15	Type of sUAS vehicle used	No comparison data available. Possible confounding variable. New sUAS demographic data produced.	No Comparison data available.

Table 7 (*continued*)

Question No.	Variable Name	Source of Comparison Data	Comparison Values
16	Type of waiver requested if applicable	FAA data (FAA, 2018)	Top five waivers Night operations (71%) Operations over people (28%) BVLOS (17%) Altitude (9%) Ops from moving vehicle (7%)
17	Confirmation of Registration	No Comparison data available. Possible confounding variable. New sUAS demographic data produced.	No comparison data available.
18	How much participants paid for model aircraft or sUAS.	No comparison data available. New sUAS demographic data produced.	No comparison data available.
19	Type of sensor used.	No comparison data available. New sUAS demographic data produced.	No comparison data available.

To summarize the 19 demographic variables, four are compared generally to U.S. Census Bureau data, four are generally compared to FAA data, one is generally compared to FAA and Census data, and 11 offer no comparison data and produce new sUAS demographic data. For those demographic variables compared generally to U.S. Census Bureau, the Census data may not represent the UAS data since the Census data is generalized to the whole population instead of a sUAS application. For demographic variables 9 and 10; region of operation and type of population area, the geographic distribution of modeler UAS ownership and commercial ownership shown in Figure 7 was pictorially compared with the similar U.S. Census population geographic distribution shown in Figure 8. Thus, the terms urban metro, urban micro, and rural areas were derived from the U.S. Census geographic distribution to correspond with the UAS geographic distribution (Ratcliffe et al., 2016). Additionally, a generic U.S. geographic region shown in Figure 8 was used to divide the country. The four underlined U.S. Census Bureau data variables and to a lesser degree, the two underlined FAA data variables shown in Table 7 were used to evaluate the sampling bias. If the sample seemed biased, more data would have been collected to reduce the bias.

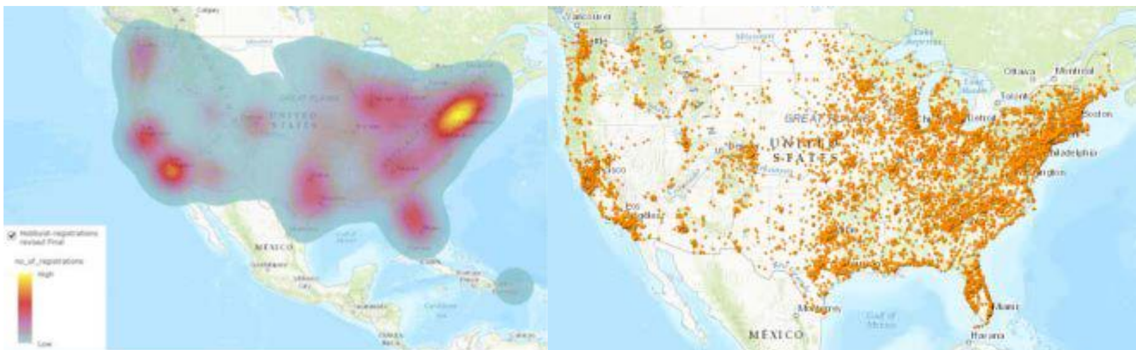


Figure 6. FAA projected hobbyist (left) and commercial UAS (right) (FAA, 2017a).

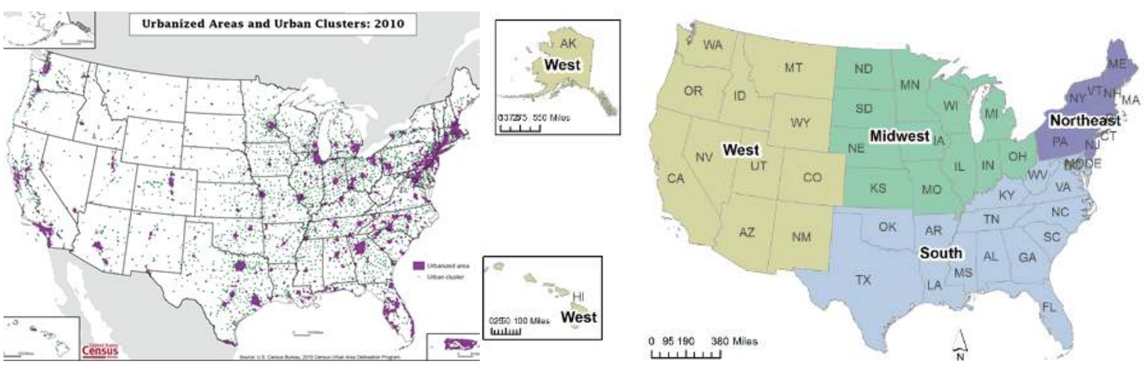


Figure 7. U.S. Census Bureau population distribution (left) (Ratcliffe, Burd, Holder, & Fields, 2016) and U.S. regional map (right) (U.S. Census Bureau, 2018).

Non-response bias is defined as the effect of non-responses on survey estimates and can significantly affect the results. More specifically, if non-respondents would have responded, those responses would have significantly changed the results (Creswell, 2014). Non-respondents in this study were those who answered less than 50% of the Likert scale questions or gave straight line responses to the Likert scale questions. Additional comments were optional, so they were not required to regard the survey as complete. A Chi-square test was used to compare available demographic data between the respondent and non-respondent groups to test for non-response bias. If a significant bias would have been noted, more data would have been collected to reduce the bias.

Descriptive statistics. The next step in the data analysis process was descriptive statistics. Babbie (1990) describes descriptive statistics as a method for presenting quantitative descriptions in a manageable form. Descriptive statistics allows scholars to summarize data in a clear, understandable way enabling general trends and patterns to be discerned (Simon & Goes, 2018). For a quantitative study such as this research, graphing the data distribution is routinely an indispensable tool to explore data (Vogt et al., 2014). Descriptive analysis measures for this research included mean, standard deviation, kurtosis, and skewness using the statistical package for the social sciences (SPSS) (Babbie, 2013; Creswell, 2014; Field, 2013). The descriptive statistics results are displayed and summarized using graphs and tables as appropriate (Field, 2013). More specifically, histograms were used to aid in checking normality before the CFA process began. Additionally, the demographic variables are presented in a table format from histogram data generated in SPSS. Each demographic variable is shown with sub-items shown and associated percentages (Creswell, 2014). This gives the reader an at-a-glance profile of survey respondents. Additionally, the table provides the data to allow a comparison of the study respondent demographics against census demographics to determine if the sample is representative.

Missing values. Prior to running CFA, it was necessary to check the pattern and extent of missing data to prevent the model from being unspecified (Hair et al., 2010). The collected survey data was examined for missing data by importing the Excel™ data into SPSS®. If more than 10 percent of the data items are missing or the if the missing data are in a non-random pattern, then the missing data must be addressed (Hair et al., 2010). Byrne (2010), Field (2013), and Hair et al. (2010) list several approaches for handling missing data including pairwise deletion, listwise deletion, imputation techniques, and model-based approaches. Two common methods include deletion and imputation. Pairwise deletion is suggested when sample sizes exceed 250, as in this study, and the total amount of missing data involved among the measured variables is below 10 percent. However, if the missing data occurs randomly, missing data comprises less than 10 percent of the observations, and factor loadings are relatively high (>=0.7), then any of the approaches are appropriate (Hair et al., 2010).

Outliers. Another facet of normality to examine is the existence of outliers. Outliers represent cases with scores substantially different than all others in a set of data (Byrne, 2010). Mahalanobis D-square values are outliers detected by AMOS and are produced as part of the AMOS output. Mahalanobis D-square case values greater than 100 are cause for concern. The decision was made whether to keep or delete these cases. Kline (2015) suggests two options to handle outliers including transformation and converting extreme scores to a value that equals the next most extreme score. Additionally, two models can be run, one without the outliers and one with the outliers to compare the results. SPSS was also used to identify outliers through a descriptive analysis.

Assumption testing and data transformation (if needed). It is also important to check for normality because normality is a critically important assumption in the conduct of SEM analysis and in the use of AMOS (Byrne, 2010: Hair et al., 2010). Normality was checked two ways; using AMOS and SPSS. Using AMOS, the output shows both skewness and kurtosis values. The SEM model can be affected more by kurtosis values. Specifically, kurtosis severely affects tests of covariances and variances (Byrne, 2010). A kurtosis value of zero in AMOS indicates perfect normality. However, typically kurtosis values less than three are considered acceptable. Byrne (2010) also states that kurtosis values of less than five are still acceptable. If the values are too high, then options for the study included transforming the variables using SPSS or running two models with transformation and no transformation and comparing the results. Besides AMOS, SPSS provides the other method to test for normality. Thus, normality was also tested in SPSS using the descriptive analysis (Field, 2013). Specifically, the histograms of the variables were examined. Additionally, the Kolmogorov-Smirnov and Shapiro-Wilk test results were examined (Field, 2013).

Examine estimates. Following the examination of outliers, the next step was to examine the estimates. Estimates are called factor loadings and represent the regression weights in the model. Examining estimates is accomplished by selecting estimates and viewing the unstandardized and standardized regression weights. Ideally, the factor loadings should be >0.7, but at least >0.5 (Hair et al., 2010). However, conclusions regarding factor loadings could not be made until the model fit was acceptable. Low or negative factor loadings should be of concern. Low factor loadings are usually associated with low critical ratio (CR) values and possibly non-significant p-values. Byrne (2010) states that non-significant p-values can indicate the need for deletion of that item. However, this was done methodically only after carefully evaluating the model fit and in concert with what the literature supported.

Confirmatory factor analysis. The next step of the data analysis was CFA. Hair et al. (2010) defines *CFA* as a multivariate technique used to confirm or test a pre-specified relationship. CFA focuses solely on how and extent to which observed variables are linked to the respective underlying latent factors (Byrne, 2010). More specifically, it is concerned with the factor loadings or strength of the regression paths from factors to observed variables and thus is known as a measurement model in the framework of SEM. CFA is used when there is literature-based knowledge of the underlying latent variable structure (Byrne, 2010). Furr (2011) expands on this, advocating that CFA allows scholars to evaluate the degree to which the measurement hypotheses are consistent with actual respondent produced data using the scale. Through the model fit process of examining parameter estimates, fit indices, and potentially modification indices, measurement hypotheses can be formally tested and modified to be more consistent with the actual structure of participants' responses to the scale (Furr, 2011).

Post-hoc analysis. When the post-hoc analysis was required, modification indices were examined for large values representing relationships between two error terms or suggested regressions between an item and a factor representing cross loading. Other relationships are not meaningful. Only one model change was made each time since model fit and modification indices changed. The model fit was re-examined, and the process repeated if necessary. If an item needed to be deleted such as cross-loading, ground theories and literature were reviewed to see if it made sense to do so (Byrne, 2010; Hair, 2010).

Reliability testing. After the model fit was deemed a good fit using the CFA process, construct reliability (CR) and convergent and discriminate validity were computed. First, construct reliability was examined which measures the extent to which a set of measured variables represents the construct those variables are designed to measure (Hair et. al., 2010). The CR index equation with Excel™ and SPSS® is used to compute CR. Equation 2 shows the CR formula. First, the CR was computed attempting to use the formula, then Excel™ was used to verify the results. For the Excel™ process, first, the sum of the factor loadings for each construct were squared. Then that squared value was divided by the squared value plus the sum of the error variances. A value ≥ 0.7 indicated good construct reliability. SPSS® was then used to compute Cronbach's Alpha (Cronbach, 1951; Field, 2013). If the Excel™ value was <0.7 but the Cronbach's value was 0.7 or greater, then it was argued that the construct had good construct reliability. If both the Excel™ and SPSS® value were below 0.7, then the CR for that construct would have been considered bad (Hair et. al., 2010). At that point, items were reviewed as necessary, and deletion of one item at a time would have been accomplished as required to improve the CR. However, before deletion, the literature would have been consulted to make sure deletion of the item was supported.

$$CR = \frac{(\sum_{i=1}^{n} \lambda_i)^2}{(\sum_{i=1}^{n} \lambda_i)^2 + (\sum_{i=1}^{n} \delta_i)} \tag{2}$$

where:

λi refers to standardized factor loading,

i refers to the number of items,

n refers to n items,

δ_i refers to error variance terms for a construct

Construct validity. Construct validity, which includes convergent and discriminant validity, was examined next in the methodology process. Hair et al. (2010) defines *convergent validity* as the extent to which indicators converge or share a high proportion of variance in common for a specific construct. The same authors define *discriminant validity* as the extent to which a construct is truly distinct from other constructs regarding two facets. These facets include how much the construct correlates with other constructs and how distinctly measured variables represent only the single construct. Average Variance Extract (AVE) is a common methodology for evaluating convergent validity, with an AVE ≥ 0.5 indicating adequate convergence (Hair et al., 2010). If the AVE values are not satisfactory, then consideration should be given to remove one item at a time consistent with the literature support to improve convergent reliability (Byrne, 2010). Factor loadings were examined and reported with AVE values. Factor loadings of 0.7 or higher indicate good convergent validity while factor loadings of 0.5 or higher were considered acceptable. If the AVE values were unsatisfactory, some changes had to be made such as removing the item with the lowest factor loading and running the CFA model again. Equation 3 is the formula for AVE. Excel™ was also used to calculate AVE to crosscheck equation computation results and to increase validity. For discriminant validity, when the AVE for each factor was compared with the maximum shared variance (MSV), it was expected that all MSV values of one factor with other factors must be less than the AVE for that factor (Hair et al., 2010). Once again, Excel™ was used to calculate discriminant validity to check equation results and increase validity.

$$\text{AVE} = \frac{\sum_{i=1}^{n} L_i^2}{n}, \tag{3}$$

where:

L_i refers to standardized factor loading,

i refers to the number of items,

n refers to n items

A second methodology to test discriminant validity was used in this study. This was necessary since in some cases the Fornell-Larcker did not provide enough evidence to confirm discriminant validity and the heterotrait-monotrait ratio of correlations (HTMT) was required (Henseler, Ringle, & Sarstedt, 2015). Failure of the Fornell-Larcker approach to provide enough evidence for discriminant validity can occur especially when factor loadings of observed variables differ only slightly such as between 0.60 and 0.80 (Hair, Hult, Ringle, & Sarstedt, 2017). Many of the factor loadings, 30 of 41 or 73%, in this study, were in that range.

The HTMT ratio represents an estimate of the true correlation between two constructs if they were perfectly measured. There are different opinions on what is desired and what is acceptable. A conservative value of 0.85 and a less conservative value of 0.90 generally are suggested as desired. A lack of discriminant validity is indicated if the correlation between two constructs is close to 1. What constitutes “close to 1” is debatable so a value something less than 1 is generally deemed acceptable (Hair, Hult, Ringle, and Sarstedt, 2017). The formula used to calculate HTMT is shown below and is facilitated by using PLS-SEM or SPSS to compute the correlations table and Excel® to perform the calculations. The computation method used in this study included SPSS and Excel®. If either the Fornell-Larcker or HTMT methodology indicated acceptable values, then discriminant validity was rated as acceptable.

$$\mathrm{HTMT}(Y1,Y2) = \frac{\text{Average correlations between all indicator variables of Y1 and Y2}}{\text{SQRT(Mean of correlations of Y1 indicator variables – Mean of correlations of Y2 indicator variables)}}$$

Full structural model testing. Once the CFA process was completed and construct reliability and validity testing parameters were met, the next step was to test the full structural model constituting the last step of the SEM data analysis process. The full structural model shows the relationships between constructs based on the ground theory. The model diagram can only be built after an acceptable model fit is achieved and construct reliability and convergent and discriminant validity are met (Byrne, 2010; Hair et al., 2010). The SEM model process began by using the CFA path diagram, removing covariances, adding residual items to the endogenous variables, and adding hypothesis arrows to the model. Covariance between constructs was removed and hypothesis arrows drawn between applicable constructs. Arrows pointing to a latent variable indicated that they are endogenous. Additionally, to ensure model identification, it was important to add a residual item of 1 for all endogenous variables (Byrne, 2010). Thus, these values were not estimated and 1 was used for residual values. Subsequently, the full structural model testing followed a similar model examination process methodology used for the CFA model (Hair et al., 2010).

Examine estimates. After running the model and selecting the model with outputs, the full structural model diagram with standardized regression weights was examined. Positive and negative relationships were determined as well as the relative strengths of relationships (Hair et al., 2010). Additionally, using the variable summary, the list of observed and unobserved variables were checked and verified.

Full structural model fit. It was expected that the full structural model fit would be satisfactory and similar to that of the CFA model, if the CFA model fit and the reliability and validity checks were satisfactory. The same model fit indices as the CFA were used and included CFI, GFI, AGFI, NFI, CMIN/df, and RMSEA. The acceptable value criteria was the same as previously described for the CFA model. If all values met the minimum criterion, then it was concluded that the model had a generally good fit, and no further adjustments were made. If the model fit indices did not meet the minimum values, then a post-hoc / model specification process was performed.

Post-hoc analysis. For the post-hoc analysis when required, the MI values under Modification Indices were reviewed. As with CFA, the focus was on high MI values for the regression weight between an item and a factor, and the covariance between error terms, possibly indicating a cross-loading situation. Also, MI values between factors were examined to determine if there is a potential new relationship in the model. Before adding a new relationship, careful consideration was needed to ensure the literature supported it. Other MI values for relationships such as between a residual and a factor required no action (Byrne, 2010; Hair et al., 2010).

Hypothesis testing. Standardized regression weights (SRW), t-values (CR), and significance level from the AMOS output were reported to test the hypotheses. The t-value (CR) criteria required was >1.96, and p-value criteria used was <0.05 for the hypothesis to be supported. AMOS defaults to a significance level of .001, but 0.05 was used instead (Hair et al., 2010). The standardized regression weights were compared between constructs to determine the strongest to weakest relationships in the model. Once the full structural model was successfully tested, relationships between factors that influence individuals' intentions to use sUAS for data gathering were examined, and factors that affect individuals' intentions toward using sUAS for data gathering identified.

Utilizing the SEM process provided the best data analysis methodology to answer the two research questions in this study. The model fit results showed how well the observed data fit the restricted structure of the model, answering research question one. The full structural model testing identified the significant factors, the positive or negative relationship of each, as well as the strength of each relationship, answering the second research question.

CHAPTER IV

RESULTS

This study investigated the extent to which the VMUTES model explained individuals' intentions to use sUASs for data gathering, the factors that influence individuals' intentions to operate sUASs for data gathering, and relationships among those factors. This chapter presents significant findings in nine sections along with a chapter summary: pretest, pilot study, survey responses and sample, demographics, descriptive statistics, additional comments summary, confirmatory factor analysis (CFA), structural model assessment (SEM), and chapter summary.

Pretest

As planned, five subjects participated in the pretest including a sUAS modeler, civil, and public user. The other two participants were from the academic environment: one being a PhD and the other in an aviation PhD program. Both respondents from the academic environment are familiar with survey construction and are active sUAS flyers. Four of the five respondents completed the survey in less than 20 minutes, and one respondent needed 35 minutes. Survey instrument changes as a result of the pretest included: (a) changing two questions to allow multiple responses, (b) rewording five questions to clarify meaning to respondents, and (c) adding definitions to clarify terms in the survey. Besides changing the survey instrument, the minimum age to participate in the survey was validated as 18 because of adult respondents being more mature in responding, the likely small effect of this population segment on the study results, and the difficulty of ensuring proper consent in the online environment. Additionally, three of the five respondents were confused by term surveillance, equating it to spying. To alleviate the confusion, the word surveillance was changed to data gathering in the survey instrument and throughout the dissertation document.

Pilot Study

The two-phase pilot study was conducted using Amazon Mechanical Turk®. The first pilot study phase yielded 11 valid responses. This was due in part to the author's unfamiliarity with available logic in Amazon Mechanical Turk® to filter respondents. A second sampling was taken using a different logic approach resulting in 101 valid responses for a total of 112 valid responses for the two-phase pilot study. It was discovered during the data preparation process that there was a duplicate and missing question in the survey that occurred when the survey was transferred online. The data was prepared, the CFA model was constructed and ran, and reliability analysis completed.

Table 8 shows the analysis results. Five questions including FC4, PEOU1, PR3, PR7, and PR8 showed load factor loadings < 0.5 indicating the need to examine them for deletion (Hair et al., 2010). Reliability was assessed as acceptable.

Table 8

Factor Loading, CR and Cronbach's Alpha & Convergent Validity (AVE) – Pilot Study

Construct	Item Question	Factor Loading	CR (≥.7)	Cronbach's Alpha (≥.7)	AVE (≥.5)
Facilitating Conditions	FC1	.675	.685	.807	.424
	FC2	.733			
	FC3	.745			
	FC4	**.367**			
	FC5	.508			
	FC6	.743			
	FC7	.690			

Table 8 (continued)

Construct	Item Question	Factor Loading	CR (≥.7)	Cronbach's Alpha (≥.7)	AVE (≥.5)
Perceived Ease of Use	PEOU1	**.358**	.714	.819	.449
	PEOU2	.660			
	PEOU3	.771			
	PEOU4	.710			
	PEOU5	.621			
	PEOU6	.804			
Perceived Usefulness	PU1	.775	.824	.874	.579
	PU2	.778			
	PU3	.663			
	PU4	.770			
	PU5	.813			
Social Norms	SN1	.722	.757	.847	.526
	SN2	.738			
	SN3	.707			
	SN4	.729			
	SN5	.733			
Behavioral Intention	BI1	.809	.716	.822	.477
	BI2	.722			
	BI3	.668			
	BI4	.616			
	BI5	.620			
Attitude Towards Use	ATU1	.860	.803	.908	.663
	ATU2	.836			
	ATU3	.762			
	ATU4	.797			
	ATU5	.813			
Perceived Risk	PR1	.900	.705	.849	.362
	PR2	.863			
	PR3	**.426**			
	PR4	.512			
	PR5	.587			
	PR6	.549			
	PR7	**.157**			
	PR8	**.427**			
	PR9	.515			
	PR10	.716			
Knowledge of Regulations	KR1	.612	.727	.874	.582
	KR2	.637			
	KR3	.878			
	KR4	.827			
	KR5	.823			
Actual Behavior	AB1	.859	.804	.891	.680
	AB2	.887			
	AB3	.753			
	AB4	.795			

FC4 (“The U.S. government facilitates my operation of a sUAS for data gathering.”) The construct reliability was the lowest of any factor at .685. Convergent validity was also low with a value of .424. Factor loading was low with a value of .358 ranking second lowest. Additionally, from SPSS computations, deleting FC4 resulted in the highest increase in Cronbach’s Alpha of .028, although Cronbach’s Alpha was good with a value of .807. From the literature, Dalamagkidis, Valavanis, and Piegl (2008), Tate (2015), and Marshall (2015) advocate that FAA regulations are generally lagging a sUAS development and, at times, hinder use. Because Cronbach’s Alpha was satisfactory, and the literature supported it, the question was kept but reworded to make it clearer and focused more on regulations than the government in general: “Current U.S. government regulations facilitate my use of a sUAS for data gathering.”

PEOU1 (“I think that interaction with using sUAS for data gathering does not require a lot of mental effort.”) The construct reliability was the third lowest of the nine factors at .714. Convergent validity was also low with a value of .449. Factor loading was low with a value of .367 ranking third lowest. Additionally, from SPSS, deleting FC4 resulted in the second highest increase in Cronbach’s Alpha of .020, although Cronbach’s Alpha was good with a value of .819. From the literature (Lee, 2009), although for a different technology, Lee used a very similar question for internet banking producing a good factor loading, CR, AVE, and Cronbach’s Alpha. Because Cronbach’s Alpha was satisfactory, deleting the item had no effect on other factor loadings, and the literature supported it, the question was kept but reworded to make it clearer and more concise: “Using a sUAS for data gathering does not require a lot of mental effort.”

PR3 (“A sUAS may not perform well by failing to transmit or record video, audio, photography, or other data correctly.”) This indicator variable had the second highest factor loading of the five and would decrease Cronbach’s Alpha for the PR factor if deleted. Lee (2009) supported using this question, but emphasized relevance is dependent on the technology being studied. Therefore, the question was kept and reworded to make it clearer and more concise: “My sUAS may not perform data gathering well.”

PR7 (“Being held legally liable for damage to property or injuries to persons is a concern.”) There was minimal impact on raising Cronbach’s Alpha for the PR factor, but this indicator variable had the standout lowest factor loading of .157. Also, this indicator variable demonstrated the highest difference (.201) between the next factor loading of .358 in the five questions. The literature is neutral regarding legal risk. Lee (2009) concluded that perceived risk factors are dependent on the technology being studied. Since Cronbach’s Alpha was satisfactory for the PR factor, and it is necessary to make sure the wording is not causing the low values, PR7 was kept but reworded to make it clearer: “Legal liability is a concern when using my sUAS for data gathering.”

PR8 (“The media and/or family and friends have a strong influence on my perceived risk level.”) This indicator variable had the highest factor loading of the five items and would decrease Cronbach’s Alpha for the PR factor if deleted. The literature supported keeping the question, but relevance was dependent on technology being studied. Therefore, the question was reworded to make it clearer and more concise: “The media and/or society influence my perceived risk level of using a sUAS for data gathering.”

Construct reliability was good for all constructs except for facilitating conditions, but Cronbach's Alpha was good for all constructs, therefore it was concluded that the survey instrument exhibited good reliability. Given the Cronbach's Alpha values, the five questions with a low factor loading were not deleted but instead reworded to make them more concise and clearer.

Besides identifying questions possibly needing deletion, other lessons learned from the pilot study that were applied to the main study included:

- To alleviate missed and duplicate survey questions, the main study survey was taken by the author and a second person to verify the online survey was correct and complete before allowing respondents to take it.
- The survey logic was changed to force respondents to exit if consent was not given or one or more filter questions were answered incorrectly, disqualifying them from the survey.
- A filter was applied to the Amazon Mechanical Turk® HIT to accept only U.S. participants.
- Demographic question 2.8 was deleted since a unique survey web link could be assigned if another form of sampling such as snowball sampling was required.
- Using guidelines from the Amazon Mechanical Turk Requester Best Practices, the HIT format was bulletized, and qualifications and payment requirements were added to make the HIT clearer to respondents.
- To avoid confusion, the word current was added to demographic question 2.5 regarding occupation.

- Question 2.17 was changed to make it more concise and clearer to respondents.
- Another form of sampling to obtain an adequate number of responses was not required since an adequate number of valid responses was obtained for the pilot study. The same approach was used in the main study as enough valid responses were obtained.
- The wording of the omitted pilot study survey question was compared to other questions to make sure there was no duplication, and the question was kept.
- The author received email feedback from four AMT workers who complained about the small pay for the HIT. Other similar HITs were reviewed, and the average completion time reviewed. Therefore, the pay was not increased. An additional comment was added to the HIT to emphasize that while the published allotted time was 40 minutes, the average completion time for the pilot study was less than 20 minutes to further justify the pay amount to respondents.

Survey Responses and Sample

Main study data collection was initiated using Amazon Mechanical Turk®. The Human Intelligence Task in Appendix E was posted which directed workers to the Survey Monkey online survey. To achieve the minimum of 460 valid responses, 750 responses were solicited using AMT. To receive payment, AMT workers were required to copy a provided code at the end of the Survey Monkey online survey and enter it in the AMT website. Those respondents who did not answer or answered one or more of the survey qualification filter questions incorrectly were automatically exited from the survey without receiving the survey code to get paid.

The 1,798 Survey Monkey survey case results, collected in a span of approximately 72 hours, were exported to Excel® and then to SPSS to screen and clean the data. Upon completion, 662 valid cases remained which exceeded the minimum of 460 required for data analysis for a response rate of 88.3%. Because an adequate number of valid responses was received using AMT, another form of sampling was not required. By not having to use another form of sampling such as snowball sampling, the risk of sampling bias was reduced since a probability sample is more likely to be representative of the population drawn from than non-probability sampling (Babbie, 2016). Table 9 shows the number and rationale for case deletions during the data screening and cleaning process. The demographic data of the 53 respondents who did not answer 50% or more of the Likert Scale questions and the 3 respondents who provided straight-line responses to the Likert Scale questions that are shown in the table were considered non-respondents for the non-response bias test.

Table 9

Case Deletion Summary

Rationale	Number of Cases
Total responses received	1798
Respondents failed to answer one or more filter questions	616
Respondents answered the consent question and nothing else including the filter questions	361
Respondents answered no to the consent question	9
Respondents answered the filter questions only and nothing else	94
Respondents answered the consent question, filter questions and at least some demographic questions, but did not answer any (52) or less than 50% (1) of the Likert Scale questions	53
Respondents answered the Likert Scale questions using a straight-line response	3
Valid responses after deletion of non-usable cases	662

Demographics

The demographics of this study comprise two major areas which include basic user demographic characteristics and sUAS users for data gathering operation characteristics. User demographic characteristics include gender, age, highest education level, annual income, current occupation, sUAS data gathering category, sUAS data gathering experience level, and U.S. region of operation. All other demographics sampled in the study concerning sUAS users for data gathering operation characteristics was done to provide more detailed demographic information regarding actual operation of sUASs for data gathering.

User demographics. User demographic information shown in Table 10 was collected during the survey. Specific demographic results are discussed in the next section.

Table 10

Basic Demographic Characteristics – sUAS Users for Data Gathering

Characteristics	Subgroup Categories	Frequency (N=662)	Percentage
Gender	Male	427	64.5%
	Female	231	34.9%
		4*	.6%
Age	18-20 years	23	3.5%
	21-30 years	298	45%
	31-40 years	240	36.3%
	41-50 years	66	10%
	51-60 years	25	3.8%
	Older than 60 years	8	1.2%
		2*	.3%
Highest Education Level	Attending high school	2	.3%
	High School Diploma	116	17.5%
	Bachelor's Degree	362	54.7%
	Master's Degree	153	23.1%
	Higher than Master's Degree	27	4.1%
		2*	.3%
Annual Income	< $30,000	86	13%
	$30,000 to $50,000	199	30.1%
	$51,000 to $100,000	301	45.5%
	$101,000 to $150,000	45	6.8%
	$151,000 to $200,000	21	3.2%
	More than $200,000	9	1.4%
		1*	.2%
Current Occupation**	Student	71	10.7%
	Commercial Company Employee	344	52%
	Self-Employed	175	26.4%
	Government Employee	64	9.7%
	Unemployed	19	2.9%
	Business owner	41	6.2%
	Other	45	6.8%
sUAS Data Gathering User Category	Modeler user only	334	50.5%
	Civil user only	100	15.1%
	Public user only	87	13.1%
	Modeler and civil user	45	6.8%
	Modeler and public user	58	8.8%
	Modeler and military user	22	3.3%
	Civil and military user	13	2.0%
		3	.5%
sUAS Data Gathering Experience Level	< Six months	135	20.4%
	Six months to < 1 year	189	28.5%
	1 to < 2 years	134	20.2%
	2 to < 3 years	100	15.1%
	3 to < 4 years	44	6.6%
	4 to < 5 years	35	5.3%
	5 years to < 10 years	17	2.6%
	10 years or greater	8	1.2%

Table 10 (*continued*)

Characteristics	Subgroup Categories	Frequency (N=662)	Percentage
U.S. Region of Operation	Northeast	150	22.7%
	West	149	22.5%
	Midwest	121	18.3%
	South	241	36.4%
		1*	.2%

Note. * Number of respondents who chose not to answer. ** Respondents allowed to select more than one response so percentage may exceed 100%.

Results indicate that among all the respondents who use sUASs for data gathering, 64.5% were male and 34.9% were female. The gender ratio for sUAS for data gathering users was different than the U.S. population which indicated that 50.8% were female and 49.2% were male (U.S. Census Bureau, 2016). However, study results were generally comparable to the gender-ratio FAA U.S. civil airmen statistics which showed most remote pilot certificates were held by males compared to females (FAA, 2017d).

Most respondents fell in two age groups encompassing 21-30 years (45%) and 31-40 years (36.3%) of age. Other age groups followed with 41-50 years (10%), 51-60 years (3.8%), 18-20 years (3.5%), and older than 60 years (1.2%). The U.S. census bureau indicated that approximately 62% of the population were in the range of 18 and 64 years, but the census bureau statistics included those under that age of 18 (22.8%) which were not considered in this study (U.S. Census Bureau, 2016). Generally, comparing the two groups, most of the population was in the range of 18 to 64. Additionally, compared to the FAA U.S. civil airmen statistics for those who have remote pilot certificates, the relative distribution was similar (21-30 years-27%, 40-50 years-21.6%, 51-60 years-17.4%, 18-20 years-7.4%, and older than 60 years-10.3%), but the percentages for the study were higher (FAA, 2017d). The difference in percentages could possibly be explained by the FAA civil airmen data only considers those who registered while this study considered those who were not registered as well.

Concerning highest education level, most respondents (54.7%) had a bachelor's degree followed by a master's degree (23.1%) and a high school diploma (17.5%). The census data indicated that 87% of the population had a high school diploma or higher and 30.3% had a bachelor's degree or higher (U.S. Census, 2016). Comparing the two groups, while those with a high school diploma were generally similar (87% and 95%), it is evident that sUAS for data gathering users have an overall higher post-graduate education level than the U.S. population.

Regarding annual income, most respondents were included in three groups which included \$51,000 to \$100,000 (45.5%) followed by \$30,000 to \$50,000 (30.1%) and then less than \$30,000 (13%). The census data indicated the median income of the population was \$55,000, which is comparable to the weighted means of the population of this study (\$51,500) (U.S. Census Bureau, 2016).

For current occupation, most respondents were commercial company employees (52%), followed by self-employed (26.4%), student (10.7%), and government employee (9.7%). Since there was no U.S. census or FAA data to compare this data to, this information is considered new demographic information.

With respect to sUAS data gathering user category, most respondents were model aircraft users (50.5%), followed by civil users (15.1%), public users (13.1%), and model aircraft and public user (8.8%). Model aircraft users being the highest number of UAS users is consistent with the FAA data, although the FAA percentage of 85.3% was somewhat higher than the results of this study (FAA, 2017a).

Concerning sUAS data gathering experience level, most respondents had an experience level between less than six months and three years. More specifically, experience levels six months to less than one year (28.5%), less than six months (20.4%), one to two years (20.2%), and two to less than three years (15.1%). Since there is no FAA data to compare these results to, this is considered new demographic data.

For region of operation, the south (36.4%) contained the highest number of sUAS data gathering users followed by the northeast (22.7%), West (22.5%), and Midwest (18.3%). Comparing the results with the FAA projected hobbyist and commercial UAS distribution map in Figure 7 (FAA, 2017a) and the U.S. Census Bureau regional map in Figure 8 (U.S. Census Bureau, 2016), generally, the results of this study are consistent with FAA projections versus regions of the country.

In summary, the demographic information of sUAS use for data gathering respondents generally reflected either U.S. census data or FAA statistics, with minor differences. Although the gender ratio did not follow U.S. census data, it did generally follow FAA aviation data. Concerning age groups, the study results generally agreed with the U.S. census data but had higher percentages than FAA overall aviation data indicating that the respondents who use sUASs for data gathering is slightly different than the FAA overall aviation data. Additionally, the study results indicated that the education level of respondents who use sUASs for data gathering had a slightly higher education level than the U.S. population sampled by census. Notably, new demographic information for respondents who use sUASs for data gathering generated by the study included current occupation and sUAS data gathering experience level.

sUAS users for data gathering operation characteristics. Table 11 shows the operational characteristics of respondents who use sUASs for data gathering. The specifics of each category are discussed next.

Table 11

sUAS Users for Data Gathering Operation Characteristics

sUAS Operations	Category	Frequency (N=662)	Percentage
Population Area	Urban metro area (≥ 50,000)	264	39.9%
	Urban micro area (≥10,000 to < 50,000)	223	33.7%
	Rural area (<10,000)	174	26.3%
		1*	.2%
Remote Pilot Certificate	Yes	326	49.2%
	No	333	50.3%
		3*	.5%
Type of Operation	Insurance purposes	32	4.8%
	Agriculture	44	6.6%
	Aerial photography	265	40%
	Movie filming	59	8.9%
	Real estate	29	4.4%
	Wildlife monitoring	29	4.4%
	Education purposes	43	6.5%
	Environmental	51	7.7%
	Emergency Management	26	3.9%
	Infrastructure Inspections	18	2.7%
	Law or border enforcement	6	.9%
	Sports or media broadcasting	22	3.3%
	Other	37	5.6%
		1*	.2%
sUAS Formal Training	Yes	375	56.6%
	No	286	43.2%
		1*	.2%
14 CFR Part 61 FAA Manned Operating Certificate	Yes	265	40%
	No	395	59.7%
		2*	.3%
Manned Aircraft Operating Experience	None	184	27.8%
	< Six months	101	15.3%
	Six months to < 1 year	140	21.1%
	1 year to < 2 years	84	12.7%
	2 to < 3 years	62	9.4%
	3 to < 4 years	28	4.2%
	4 to < 5 years	30	4.5%
	5 to < 10 years	18	2.7%
	10 years to < 20 years	8	1.2%
	20 years or greater	5	.8%
		2*	.3%

Table 11 (*continued*)

sUAS Operations	Category	Frequency N = 662	Percentage
Type of sUAS used	Fixed wing	218	32.9%
	Vertical takeoff and landing	402	60.7%
	Other	40	6.0%
		2*	.3%
Type of FAA Waiver Most Frequently Used	107.25- Ops from moving vehicle	27	4.1%
	107.29- Daylight operation	101	15.3%
	107.31- Visual line of sight	62	9.4%
	107.33- Visual observer	38	5.7%
	107.35- Ops of multiple sUASs	25	3.8%
	107.37- Yielding right of way	5	.8%
	107.39- Operation over people	13	2%
	107.41- Operation in certain airspace	29	4.4%
	107.51- Operating limitations for sUASs	14	2.1%
	Other	17	2.6%
	None	331	50%
sUAS Registered	Yes	417	63%
	No	245	37%
Amount Paid for sUAS	0 to < $200	53	8.0%
	$200 and < $500	148	22.4%
	$500 to < $1,000	163	24.6%
	1,000 to < $2,000	107	16.2%
	2,000 to < $5,000	83	12.5%
	5,000 to < $10,000	49	7.4%
	> $10,000	18	2.7%
	Unknown, the company or agency paid for the UAS	41	6.2%
Type of Sensor Used on sUAS**	Camera	528	79.8%
	Infared	143	21.6%
	Video	455	68.7%
	RGB camera	155	23.4%
	Synthetic Aperture Radar	72	10.9%
	LiDAR	95	14.4%
	Multispectral	82	12.4%
	Thermal	112	16.9%
	Other	17	2.6%

Note. * Number of respondents who chose not to answer. ** Respondents allowed to select more than one response so percentage may exceed 100%.

sUAS use for data gathering operations was split among three population areas. Most respondents operated their sUASs for data gathering in an urban metro area (39.9%) or an urban micro area (33.7%). Those respondents who operated in a rural area was less (26.3%). Generally, this was consistent with U.S. census information as most of the population resides in urban metro or urban micro areas (approximately 94%) versus rural areas (6%) (U.S. Census Bureau, 2016). However, the percentages of urban versus rural areas for sUAS for data gathering were more evenly split between urban and rural areas than the census results. This indicates there were four times as many respondents who were rural residents who operated sUASs for data gathering compared to census data.

Regarding having a remote pilot certificate in this study, it was generally evenly split between those who do have a remote pilot certificate (49.2%) and those who do not have one (50.3%). The FAA data lists 1,050,328 total registrations with 82,113 or approximately 8% having a remote pilot certificate which is considerably lower than the study results (FAA, 2017a). However, FAA data includes all UAS aircraft whereas this study focused only on sUAS for data gathering which could possibly explain the difference.

The top five types of sUAS used for data gathering operations identified by the study included aerial photography (40%), movie filming (8.9%), environmental (7.7%), agriculture (6.6%), and education purposes (6.5%). The lowest of the thirteen types of operations was law or border enforcement (.9%). Most respondents were modelers only (50.5%) or 333 respondents as indicated in the previous discussion. Using the raw data and comparing modeler user only with type of operation, the percentage of those flying sUASs without any associated purpose was low as indicated by the other category (5.6%). Similarly, upon examination of the raw data for example, of those who fly as modelers for recreational purposes, 172 respondents or 51.6% did so using aerial photography. Surprisingly, other respondents while responding as modelers only, also indicated other options such as environmental, real estate, agriculture, and insurance purposes which are generally associated with business type operations. This could possibly indicate use of the sUAS for operations outside of authorized limits, use in those areas without compensation, or confusion on what the survey question was asking. Comparing the study results to FAA data, both listed aerial photography as the most popular type of operation. However, after that, the study results differed from the FAA results. After aerial photography, the FAA listed real estate (26%), construction, industrial and utility inspections (26%), agriculture (21%), and emergency management as the next most popular types of operations (FAA, 2017a). Comparably, real estate (4.4%), construction, industrial and utility inspections (2.7%), agriculture (6.6%), and emergency management (3.9%) were rated much lower for respondents who use sUASs for data gathering.

Most respondents did have sUAS formal training (56.6%), while (43.2%) did not have any formal training. Formal training includes some type of supervised sUAS pilot proficiency. Training source examples include the manufacturer, local sUAS membership organization, or another more experienced sUAS operator. Since there was no FAA data to compare this information to, this information is considered new demographic information for individuals operating sUASs for data gathering.

Also, the majority of respondents (59.7%) did not have a 14 CFR Part 62 FAA manned aircraft operating certificate, while 40% did have one. Since there was no FAA data to compare this information to, this information is considered new demographic information for individuals operating sUASs for data gathering.

Concerning manned aircraft operating experience, the majority of respondents were in the range of no experience to less than two years of experience (76.9%). After that, the percentage of respondents decreased from 9.4% to .8% as the level of experience increased. Since there was no FAA data to compare this information to, this information is considered new demographic information for those individuals operating sUASs for data gathering.

For type of sUAS used, most respondents indicated that vertical takeoff and landing (60.7%) followed by fixed wing (32.9%) and other (6.0%) were used. Since there was no FAA data to compare this information to, this information is considered new demographic information for those individuals operating sUASs for data gathering.

Concerning type of FAA waiver requested, 50% of the respondents indicated they had not requested a waiver. The FAA data does not track those who have not requested a waiver, therefore this aspect is new demographic information for those individuals operating sUASs for data gathering. For those that had requested a waiver, the top five waivers were for daylight operation (15.3%), visual line of sight (9.4%), visual observer (5.7%), operation in certain airspace (4.4%), and operations from a moving vehicle (4.1%). The study results and FAA agreed regarding three of five of the top five waivers including night operations, visual line of sight, and operations from a moving vehicle. The FAA and study results differed in the top five regarding altitude and operations over people (FAA, 2017a). The study results listed visual observer and operation in certain airspace higher with operation over people and altitude (other) at 2.0% and 2.6% respectively.

For sUAS registration, 63% of respondents indicated their sUAS used for data gathering was registered, while 37% indicated it was not. The FAA data does not track those who do not register their sUAS used for data gathering, therefore this is new demographic information for those individuals operating sUASs for data gathering.

Regarding amount paid for the sUAS, most respondents (75.7%) paid between $200 and $5,000 for their sUAS with 24.6% of respondents in the category of $500 to $1,000. As the cost increased beyond $5,000, the percentage of respondents decreased. Since there was no FAA data to compare this information to, this information is considered new demographic information for those individuals operating sUASs for data gathering.

Nine sUAS sensors were sampled in the survey. Of the top five sensors, most respondents used a camera (79.8%), followed by video (68.7%), RGB camera (23.4%), infared (21.6%), and thermal (16.9%). Since there was no FAA data to compare this information to, this information is considered new demographic information for those individuals operating sUASs for data gathering.

In summary, like the demographic characteristics, operational characteristics generally followed U.S. census data and/or FAA aviation data with a few differences. The study results indicated a higher percentage of respondents who used sUASs for data gathering lived in rural areas compared to the U.S. population sampled by the census. Compared to FAA results, the respondents in the study who possessed a remote pilot certificate was considerably higher. While the most popular type of sUAS operation gathering operations agreed with FAA data, the last four differed and offered most likely the most disagreement of any operational characteristic. Notably, new operation characteristics of those respondents who use sUASs for data gathering were generated by the study. This new characteristic information included sUAS formal training, possession of a 14 CFR Part 62 FAA manned operating certificate, manned operating experience, type of sUAS used, respondents who did not register their sUAS, amount paid for the sUAS used for data gathering, and type of sensors used on the sUAS for data gathering.

Descriptive Statistics

Table 12 shows the mean, standard deviation, kurtosis, and skewness descriptive statistics of the item questions for the various constructs. sUAS for data gathering respondents used a seven-point Likert scale to answer the survey questions that ranged from Strongly Disagree (1) to Strongly Agree (7).

Table 12

Descriptive Statistics Scores of Constructs

Construct	Item Question	Mean (N=662)	SD	Skewness	Kurtosis
FC	FC1	5.10	1.295	-.933	.943
	FC2	4.86	1.429	-.609	-.114
	FC3	5.25	1.189	-.824	.720
	FC4	4.61	1.532	-.561	-.212
	FC5	4.94	1.411	-.530	-.389
	FC6	5.20	1.276	-.971	1.060
	FC7	4.88	1.356	-.586	-.062
PEOU	PEOU1	4.41	1.645	-.244	-.935
	PEOU2	5.08	1.264	-.697	.275
	PEOU3	5.38	1.084	-.860	1.275
	PEOU4	5.28	1.141	-.892	1.010
	PEOU5	5.05	1.330	-.571	-.077
	PEOU6	5.34	1.175	-.799	.850
PU	PU1	5.50	1.161	-.919	1.016
	PU2	5.48	1.170	-1.035	1.750
	PU3	5.43	1.204	-.949	.984
	PU4	5.61	1.165	-1.144	1.835
	PU5	5.68	1.135	-1.094	1.638
SN	SN1	5.01	1.260	-.514	.092
	SN2	4.99	1.268	-.481	.113
	SN3	5.04	1.267	-.611	.408
	SN4	5.21	1.213	-.815	.747
	SN5	5.42	1.185	-.806	.534

Table 12 (*continued)*

Construct	Item Question	Mean (N=662)	SD	Skewness	Kurtosis
BI	BI1	5.55	1.166	-1.140	1.747
	BI2	5.57	1.198	-.995	1.095
	BI3	5.19	1.366	-.680	.053
	BI4	5.10	1.255	-.602	.101
	BI5	5.27	1.221	-.766	.590
ATU	ATU1	5.58	1.113	-.938	1.346
	ATU2	5.51	1.142	-.906	1.154
	ATU3	5.58	1.301	-.996	.800
	ATU4	5.53	1.257	-1.008	1.030
	ATU5	5.61	1.147	-1.127	1.754
PR	PR1	3.42	1.869	.273	-1.209
	PR2	3.62	1.832	.197	-1.106
	PR3	3.56	1.667	.235	-.959
	PR4	4.16	1.628	-.255	-.850
	PR5	3.93	1.720	-.007	-.993
	PR6	4.17	1.638	-.249	-.824
	PR7	4.65	1.530	-.606	-.196
	PR8	4.15	1.627	-.323	-.781
	PR9	4.03	1.613	-.076	-.921
	PR10	3.42	1.758	.329	-1.106
KR	KR1	4.95	1.383	-.716	.045
	KR2	4.93	1.432	-.663	-.069
	KR3	4.61	1.539	-.552	-.371
	KR4	4.66	1.554	-.523	-.431
	KR5	4.91	1.440	-.757	.069
AB	AB1	5.50	1.269	-.983	.825
	AB2	5.42	1.351	-1.106	1.089
	AB3	5.00	1.415	-.642	-.030
	AB4	5.47	1.385	-1.115	1.077
	AB5	5.25	1.234	.819	.765

Note. FC = Facilitating Conditions; PEOU = Perceived Ease of Use; PU = Perceived Use; SN = Subjective Norms; BI = Behavioral Intention; ATU = Attitude Toward Use; PR = Perceived Risk; KR = Knowledge of Regulations; AB = Actual Behavior.

Computing the average mean and standard deviation of each factor allowed a general assessment of the effect of each factor on use of sUASs for data gathering. For many respondents, eight of the nine factors were neutral or higher and one was only slightly negative related to the Likert scale. The factors displayed in Table 12 above are discussed in rank order from highest to lowest mean average.

Attitude Toward Use (ATU) had the highest mean item average (5.56) of all the factors with an average standard deviation of 1.192, meaning many respondents had a favorable appraisal of using a sUAS for data gathering that was somewhere between "somewhat agree" to "agree". Additionally, all five items of the construct indicated similar results.

Perceived Usefulness (PU) had a mean item score of (5.54) similar to ATU. The average standard deviation was 1.167. Average response range was between "somewhat agree" to "agree" indicating that many respondents supported the idea that using a sUAS for data gathering would enhance his or her job performance. This was consistent with all item scores of the PU factor.

Behavioral Intention (BI), or how hard a person is willing to try to use sUASs for data gathering had a mean average item score of 5.34 and an average standard deviation of 1.241. This indicates that many respondents were positive with a range between "somewhat agree" and "agree" on the willingness to try to use sUASs for data gathering. Three of the five items (planning to use sUASs every 90 days, recommending sUASs for data gathering to friends and family, and when choosing data gathering task methods, a sUAS is my first choice) favored more toward somewhat agree. Two items (I would use a sUAS for my data gathering needs, and I will use a sUAS for data gathering in the future) were mid-range between "somewhat agree" and "agree".

Actual Behavior (AB), meaning how much respondents are actually using sUASs for data gathering, had a mean item score of 5.33 which was in the range of "somewhat agree" to "agree". The average standard deviation was 1.330. Three items scored mid-range between "somewhat agree" and "agree" meaning respondents when given the choice, were positive overall on using sUAS for data gathering. However, two items (I have frequently used a sUAS for data gathering, and When I needed data gathering tasks completed, I used a sUAS) were less positive, scoring closer to “somewhat agree” than “agree”.

Subjective Norms (SN), meaning those elements that positively influence the decision to use sUASs for data gathering, had a mean item score of 5.13 close to “somewhat agree” and an average standard deviation of 1.238. Four items were consistent with this score, while one item (My individual values/beliefs morally support me using a sUAS for data gathering) was more positive with a mid-range score between “somewhat agree” and “agree”.

Perceived Ease of Use (PEOU) indicates how strong the individual believes that using sUASs for data gathering is free of effort. The overall mean item score 5.09 was positive and closest to “somewhat agree” indicating that many respondents at least to some degree, supported that using sUASs for data gathering is free of effort. This was indicated by four of the five items. However, one item (using a sUAS for data gathering does not require a lot of mental effort) scored closer to “neutral”. The average standard deviation was 1.273.

Facilitating Conditions (FC) are those elements that positively influence the decision to use sUASs for data gathering. The average standard deviation was 1.355. The average mean item score was 4.98 indicating many respondents “somewhat agreed” that facilitating conditions included in the survey influenced the decision to use sUASs for data gathering. More specifically, four items scored near or slightly above “somewhat agree” while three items scored below “somewhat agree”. Those three items included (when I need help, a specific person or company is available to provide assistance and current U.S. government regulations facilitate my operation of a sUAS for data gathering and the legal environment facilitates me using a sUAS for data gathering.)

Knowledge of Regulations (KR) pertains to Federal, state, and local laws and guidelines that apply to sUAS operations. The average standard deviation was 1.469, and the average mean item score was 4.81 which is in the range between “neutral” and “somewhat agree”. Three items were closest to “somewhat agree” while two items were closest to “neutral”. Those two items included familiarity with FAA advisory circular 91-57a and familiarity with Public Law 112-95 as a model aircraft operator or 14 CFR Part 107 as a non-model sUAS operator.

Perceived Risk (PR) which is the perception people form and revised based on the possible danger of using sUASs for data gathering, had the lowest mean item score of 3.91 and an average standard deviation of 1.688. This meant that the overall opinion of many respondents was between “somewhat disagree” and “neutral” but favoring more toward “neutral” regarding the perceived risk of using a sUAS for data gathering. This was consistent with physical, performance, time, and psychological risks. However, for financial, security, legal, social, and privacy risks, the means indicated that respondents were between neutral and somewhat agree regarding the perceived risk.

It is noteworthy that all the external factors (FC, KR, and PR) had the lowest mean item scores while the components of the TAM and TPB had the highest mean item scores. Additionally, for the three external factors, individual items scores varied more than the scores for the TAM and TPB components which were more consistent among items.

Normality was checked using the Kolmogorov-Smirnov and Shapiro-Wilk tests, Table 12 data, histograms, and CFA and SEM normality outputs. Both the Kolmogorov-Smirnov and Shapiro-Wilk tests were significant for all items meaning non-normality. However, both tests are sensitive to large sample sizes as is the case in this study (Field, 2013). That is, these tests tend to be significant as sample size increases. Therefore, other measures were also examined to assess normality. From the Table 12 data, all items except for four PR items and one AB item exhibited a negative skewed distribution with the highest being PU4 (-1.444) with most of items below 1.0. Concerning kurtosis, the items displayed a mixture of both leptokurtic (positive kurtosis) as shown by PU2 (1.750) and platykurtic values (negative kurtosis) as shown by PU4 (-1.444). The histograms showed these same pictorial results. While it was not practical to display all histograms, the two variables with the highest kurtosis values (PU2 and PU4) and one histogram in the middle range between the high and low kurtosis values (ATU4) are shown in Figure 9. While zero is ideal normality, generally, both skewness and kurtosis values between values of -1 to +1 are considered acceptable (Hair, et. al, 2017). For skewness, 45 values were under 1.0 while 8 were slightly above 1.0 with the highest value PU4 (-1.44). For kurtosis, 35 values were under 1.0 with 18 above 1.0. Of those, 10 were below 1.2 (close to 1.0) and 8 were above 1.2 with the PU items exhibiting the highest values. Those items with skewness and kurtosis values greater than 1.0 were examined using the boxplots and most items had multiple outliers which most likely caused the aberrant values. Outliers are discussed later, but data computation results with and without outliers indicated little difference so outliers were kept. Additionally, both CFA and SEM normality kurtosis outputs indicated acceptable values of less than two where three is acceptable and up to five is allowable (Byrne, 2010). Thus, it was judged that the data met normality.

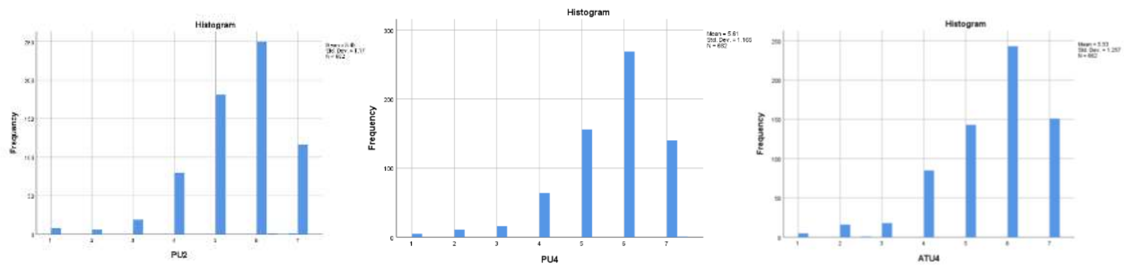


Figure 8. PU2, PU4, and ATU4 Histograms.

Non-response bias testing. Non-response bias testing compared demographic variables between two samples: respondents and non-respondents. Non-respondents in this study were those 53 respondents who answered 50% or less of the Likert Scale questions and the 3 respondents who provided straight-line responses to the Likert Scale questions. None of the nine demographic variables examined in Table 13 exhibited significant differences between respondents and non-respondents, indicating the sample was free of non-response bias and the sample was representative of the sUAS use for data gathering population.

Table 13

Chi-Square Comparison of Respondents and Non-Respondents

Demographic	Chi-Square (*X*2)	Probability (*p*)	Significant
Gender	1.314	.971	No
Age	44.480	.157	No

Table 13 *(continued)*

Demographic	Chi-Squre (X2)	Probability (*p*)	Significant
Highest Education Level	14.672	.795	No
Annual Income	30.218	.455	No
Current Occupation			
Student	.241	.623	No
Commercial	1.114	.291	No
Self-Employed	.034	.855	No
Government Employee	.022	.883	No
Unemployed	.119	.730	No
Business Owner	.199	.656	No
Other	.294	.588	No
sUAS Data Gathering User Category	40.423	.061	No
sUAS Data Gathering Experience Level	50.882	.399	No
U.S. Region of Operation	9.565	.888	No

Note. p is significant at $p < .05$.

Additional Comments Summary

An additional comments question at the end of the survey allowed respondents to insert a comment about anything they deemed pertinent. Table 14 shows an overview of the type and number of responses. While definite conclusions cannot be reached because of the low percentage of responses in a category, the comments do give a glimpse into areas where more research may be needed. Most of the respondents (73.5%) of the sampled population chose not to answer at all (54%) or indicated they had no additional comments (19.5%). A positive comment about the survey or study included such comments as “great study” and “I like the survey”. Negative comments about the survey or study included comments such as “this was unnecessarily long” and “some of the questions are cut and dry yes or no, however the scale of strongly disagree/agree is still used and can be confusing”. Thus, most negative comments indicated dissatisfaction with the survey length, followed by survey question composition. Within the group of those who chose to respond with additional comments, the number of positive comments exceeded the number of negative comments indicating overall satisfaction with the survey and study.

The most interesting responses were in the other category in basic categories of operations, education, and regulations. Significant operations comments are discussed next. Generally, the comments indicated respondents' positive perception of the usefulness of sUASs used for data gathering, lack of registration, types of data gathering operations, sUAS data gathering used for business operations, the negative perception of other users and the word drone, adherence to laws, and formal training.

- "In my opinion, using this type of device to record is very efficient and fun, I really enjoy it:D"
- "I don't own any licenses. I live in Indianapolis Indiana and I fly daily for years and never had a legal problem"
- "My use of and training with a UAV is for the purpose of counter-surveillance. To evaluate current threats in the environment and to insure a safe path through unfamiliar terrain"
- "I used a small video and camera enable drone purchased at Brookstone to record photos/videos of my surrounding area for personal recreational purposes"
- "I don't do much "work" with mine, but I do a little under the table stuff. It's not really a business."

- “I’ve only flown one a few times, semi recreationally, and in helping a friend with his business.”
- “I think one of the best sUAS for beginners is the Parrot Bebop 2. It is the one I used to learn.”
- “While there is indeed some risk to others when irresponsible people operate any kind of vehicle, remotely operated or otherwise, you cannot legislate against stupidity. I have flown (responsibly) since the age of 4 all types of “model” aircraft. I started with control line and free flight models (fixed wing). I now fly fixed wing, collective pitch helicopters and quadcopters (so called “drones”) and have never injured anyone. The mass media promoting the use of the word “drone” I believe is the cause of much of the problem now, along with undisciplined “children” (of all ages) who take pictures of people without permission, fly in crowded areas and such do present risk. It is already against the law to behave in such a way. Prosecute those who do it wrong and leave those of us who do it right the hell alone”
- “I am serious while capturing data and following laws supplied for it”
- “I use mine in geomatics, it’s incredible using it for surveying but it does have limitations when we use it in an urban environment”
- “It is not safe to use sUAS without enough training and guidance”
- “I am using filming as the idea of data gathering since the film is captured as data on the device. I mainly use my aircraft to film wakeboarding”
- “I use a DJI Phantom 4 Pro Quadcopter”

- "I am very interested in developments concerning UAS platforms and laws as it could change the way myself and company does work. We follow developments closely and are often testing platforms."
- "Some of these questions seem ambiguous so I want to make it clear…I do NOT use a drone for any military purposes nor do I use it for my job. I use it for recreation and for aerial video and photography only. I don't have it registered or anything nor have any formal training other than former r/c aircraft experience. I pretty much ignore regulation regarding my use of it but I do keep it at a safe ceiling height in general. Thanks!"

The education comment was "nice study I have learned extra points about small unmanned aircraft systems for data gathering operations". This indicated that at least for one participant, one of the benefits of taking the survey was learning more about sUASs used for data gathering.

Significant comments regarding regulations are listed next. While few comments pertained to regulations, responses indicated the study highlighted the lack of knowledge some had regarding regulations, the negative attitude toward current regulations, and the perception that more regulations were forth coming.

- "This survey made me aware that I may need to do some research into if I'm operating legally. I didn't think there was legislation already out"
- "I travel a lot and have primarily use my "SUAV" overseas, in large part because of the legal/regulatory headache and risk in the US"
- "As an operator I will continue to educate myself on the laws related to UAS operations"

- "I expect to see more regulations regarding sUASs in the near future do to more users"

Table 14

Summary of Additional Comment Responses

Type of Response	Number of Responses	Percentage of Total Responses
Left additional comments box blank	358	54%
Verbiage indicating no additional comments	129	19.5%
A positive comment about the survey or study	140	21.1%
A negative comment about the survey or study	8	1.2%
Other category:		
sUAS Operations for data gathering	19	2.9%
Education	1	.2%
Regulations	4	.6%
Comment not understandable	3	.5%
Total	662	100%

Confirmatory Factor Analysis

The confirmatory factor analysis process included examination of results for normality, missing data, outliers, model fit and respecification if required, and reliability and validity (Hair et al., 2010). Besides using CFA results, normality, missing data, and outlier attributes were also examined during the dataset screening and cleaning process.

Normality. Normality is a critical assumption for CFA (Hair et al., 2010). Normality was checked two ways using SPSS descriptive statistics and AMOS. SPSS was used to generate a descriptive analysis previously discussed. For the CFA results, Byrne (2010) indicates that Kurtosis values less than 3 are acceptable while values less than 5.0 show data normality that is allowable. All values from the sUAS use for Data

Gather Imputation 4 dataset with outliers were in the acceptable range (less than 2.0) for both the original and final CFA models meaning the normality assumption was met.

Missing Data. Upon examination of the dataset during the data cleaning process, missing data was noted. Additionally, the CFA model failed to run because of missing data. The researcher's challenge is to address the missing data issues relative to the generalization of the study results (Hair et al., 2010). Therefore, a missing data analysis using SPSS was accomplished using the 662-case dataset. There were 113 missing values noted from a total of 35,086 Likert-Scale responses representing less than one percent after the case deletions previously discussed. Additionally, all variables had less than one percent missing data. There was one case with 17, 9, and 6 missing values, respectively. Three cases had five, two cases had four, and two cases had three missing values. All other cases had two or less missing values. When variable deletion results were examined, the best case was a gain of four cases. Therefore, the decision was made to keep all variables as well as all remaining cases in the data analysis process. Hair et al. (2010) states that if the missing data comprises less than 10% and the missing data is at random, then any method is appropriate to eliminate missing data. However, the Missing Completely at Random (MCAR) test was significant at .000 indicating the missing data pattern was not at random (Hair et al., 2010). In this instance, Hair et al. (2010) recommends using a specifically designed modeling approach such as the Expectation Management (EM) approach. EM is an iterative approach where the E stage of EM replaces the missing data with the best possible estimates and the M stage estimates standard deviation, mean, and correlations (Hair et al., 2010). Thus, using the EM process, a dataset for each of the nine factors was generated and then the EM datasets were combined to form one EM dataset. Additionally, multiple imputation was used to generate five datasets to be used as a comparison to the EM dataset. Essentially, all multiple imputation datasets produced similar results with the Imputation dataset four producing slightly higher numbers for model fit. Thus, Multiple Imputation dataset number four was the Multiple Imputation dataset of choice.

Outliers. Outliers were examined using the Mahalanobis D-square values in the CFA output. Mahalanobis D-square values greater than 100 are concerning since they represent extreme outliers. Fifty-three extreme outliers were noted in the CFA output. Subsequently, a what-if exercise was performed by deleting one outlier at a time, starting with the highest value, and then running CFA to note any changes in the number of outliers. Doing so did not solve the outlier problem. Hair et al. (2010) offers a solution of running the analysis with and without outliers to determine the effects. Therefore, four datasets were created: EM with and without outliers and Multiple Imputation Dataset 4 with and without outliers. To choose the best dataset and to evaluate the effects of deleting outliers, the CFA process was accomplished without a post-hoc analysis to assess model fit, reliability, convergent, and discriminant validity. Results are shown in Table 15. Ultimately, the datasets produced similar results with all datasets passing construct validity and failing convergent and discriminant validity. Additionally, Hair et al. (2010) notes that while deleting outliers may improve the analysis, generalizability is limited. Thus, the decision was made to keep the outliers. Therefore, comparing the model fits of the EM dataset and Imputation 4 dataset with outliers, the Imputation dataset 4 with outliers had slightly better GFI model fit results. Therefore, Imputation dataset 4 was chosen as the dataset used for the analysis.

Table 15

Comparison of Four Datasets

Dataset	Model Fit	Reliability	Convergent Validity	Discriminant Validity
EM with outliers	CMIN/df 1.348 GFI .919 AGFI .901 NFI .929 CFI .981 RMSEA .023	Satisfactory	Unsatisfactory – 3 factors below 0.5	Unsatisfactory – 16 bad, 20 good
EM without outliers	CMIN/df – 1.236 GFI .920 AGFI .901 NFI .936, CFI .987 RMSEA .020	Satisfactory	Unsatisfactory – 4 factors below 0.5	Unsatisfactory – 17 bad, 19 good
Imputation 4 with outliers	CMIN/df 1.340 GFI .920, AGFI .901, NFI .930, CFI.981 RMSEA .023	Satisfactory	Unsatisfactory - 3 factors below 0.5	Unsatisfactory – 18 bad, 18 good
Imputation 4 without outliers	CMIN/df 1.218 GFI .920, AGFI .901, NFI .937, CFI.988 RMSEA .019	Satisfactory	Unsatisfactory - 4 factors below 0.5	Unsatisfactory – 17 bad, 19 good

Model fit and respecification. Maximum Likelihood Estimation (MLE) with the acceptance values shown in Table 16, was chosen for the model fit parameters because MLE provides valid and stable results and the normality assumption was met (Hair et al., 2010). However, because the sample size in this study sample (662) exceeds 400, goodness of fit including GFI and AGFI measures become more sensitive and may suggest a poor fit (Hair et al., 2010). Therefore, the other fit parameters were used as the primary indicators with GFI and AGFI as secondary measures approximating .90.

After running the unspecified CFA model, the model fit was poor as indicated by CMIN/df, NFI, CFI, and RMSEA values. Thus, respecification was required to improve the model fit. The first specified CFA model fit parameters are shown in Table 16.

Table 16

Model Fit Indices - Unspecified CFA Model and First Specified CFA Model.

Model Fit Indices	Acceptance Value	Unspecified CFA Model	First Specified CFA Model
X^2	-	3929.247***	2185.067***
df	-	1289	1232
CMIN/df	<= 3	3.048	1.774
GFI	> .90**	.790	.888
AGFI	> .90**	.767	.870
NFI	> .90	.823	.901
CFI	> .93	.873	.954
RMSEA	< .06	.056	.034

Note. ** Approximations due to large sample size. ***p is significant at $p < .001$.

While the fit parameters for the first specified CFA model appear to indicate a good fit, there were crossloadings and covariances between items of different factors as shown in Figure 9 which are not desirable. Therefore, the next step of examining model reliability and validity was needed to determine the next course of action.

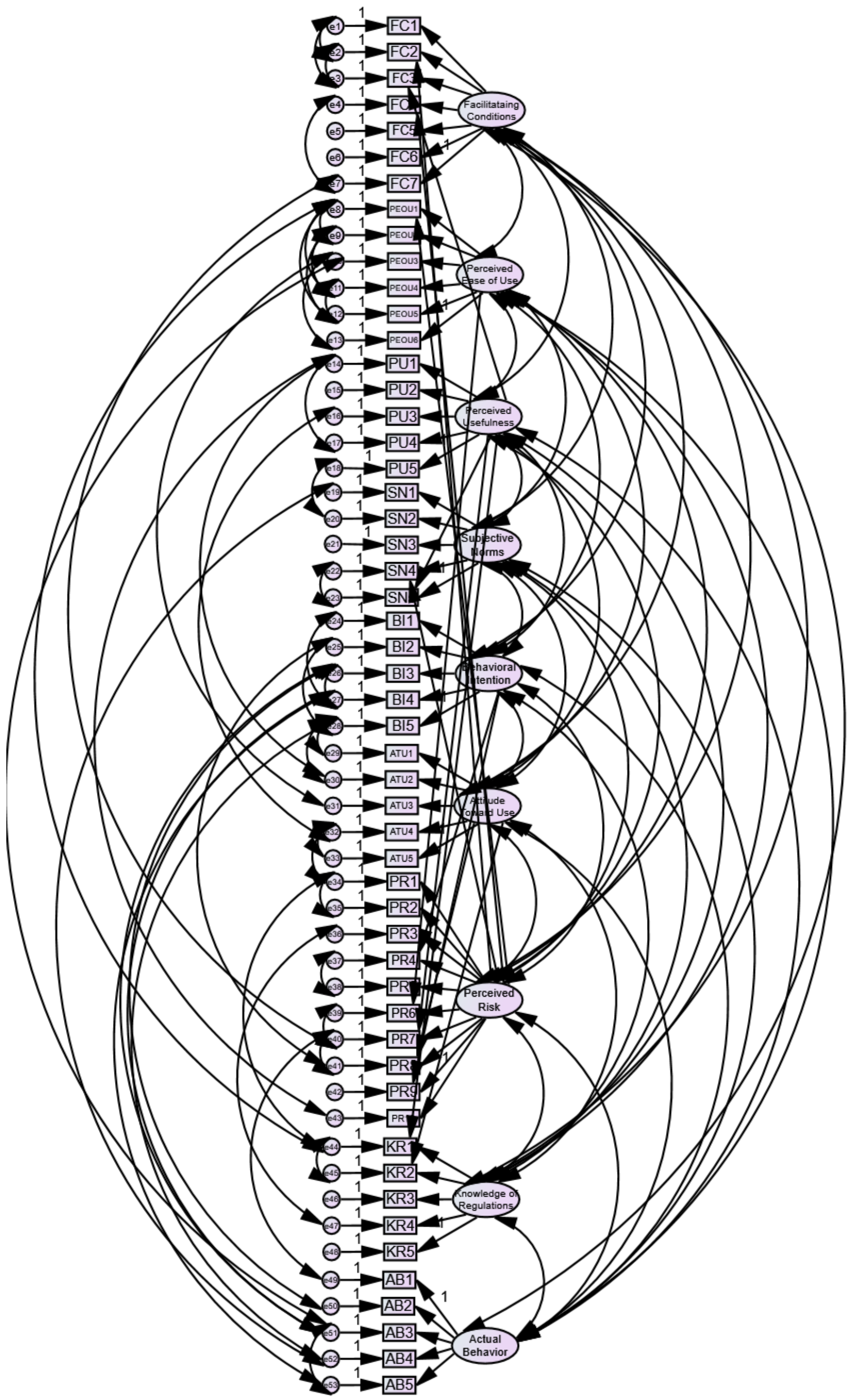


Figure 9. First specified CFA model. PEOU = Perceived Ease of Use; PU = Perceived Usefulness; SN = Subjective Norms; BI = Behavioral Intention; ATU = Attitude Toward Use; PR = Perceived Risk; KR = Knowledge of Regulations; AB = Actual Behavior.

Reliability and validity. The first specified CFA model was tested for convergent validity by evaluating factor loadings, construct reliability / Cronbach's Alpha and average variance extract (AVE). The criteria used to evaluate factor loading was 0.7 with a minimum acceptable level of 0.5 (Hair et al., 2010). For construct reliability, the minimum acceptable value used was ≥ 0.5 and for Cronbach's Alpha ≥ 0.7, and AVE criteria used was ≥ 0.5 (Hair et al., 2010).

As can be seen from Table 17, some items had low factors loadings below 0.5, all factors had good construct reliability and acceptable Cronbach's Alpha, and three factors had an AVE value less than 0.5. Items with low factor loadings included FC3 (.424), FC4 (.342), PEOU1 (.273), SN5 (.290), and BI5 (.435). Factors with a low AVE included FC (.279), PEOU (.397), and BI (.434).

Table 17

First Specified CFA Model Convergent Validity

Construct	Item	Factor Loading (Desired ≥ 0.7, Min ≥ 0.5)	Construct Reliability (≥.7)	Cronbach's Alpha (≥.7)	AVE (≥ .5)
Facilitating Conditions	FC1	.568	.966	.810	**.279**
	FC2	.551			
	FC3	**.424**			
	FC4	**.342**			
	FC5	.536			
	FC6	.654			
	FC7	.561			
Perceived Ease of Use	PEOU1	**.273**	.971	.800	**.397**
	PEOU2	.550			
	PEOU3	.795			
	PEOU4	.694			
	PEOU5	.519			
	PEOU6	.792			
Perceived Usefulness	PU1	.764	.989	.885	.619
	PU2	.825			
	PU3	.697			
	PU4	.841			
	PU5	.799			

Table 17 (*continued*)

Construct	Item	Factor Loading (Desired ≥ 0.7, Min ≥ 0.5)	Construct Reliability (≥.7)	Cronbach's Alpha (≥.7)	AVE (≥ .5)
Subjective Norms	SN1	.792	.984	.869	.539
	SN2	.795			
	SN3	.833			
	SN4	.812			
	SN5	**.290**			
Behavioral Intention	BI1	.810	.981	.818	**.434**
	BI2	.827			
	BI3	.600			
	BI4	.530			
	BI5	**.435**			
Attitude Toward Use	ATU1	.826	.987	.876	.577
	ATU2	.774			
	ATU3	.732			
	ATU4	.707.			
	ATU5	.755			
Perceived Risk	PR1	.785	.984	.913	.528
	PR2	.785			
	PR3	.792			
	PR4	.680			
	PR5	.729			
	PR6	.690			
	PR7	.503			
	PR8	.674			
	PR9	.711			
	PR10	.860			
Knowledge of Regulations	KR1	.554	.978	.878	.546
	KR2	.549			
	KR3	.862			
	KR4	.859			
	KR5	.800			
Actual Behavior	AB1	.816	.986	.872	.597
	AB2	.761			
	AB3	.717			
	AB4	.825			
	AB5	.739			

The Fornell and Larcker method of comparing AVE values with the correlation estimates of any two constructs was first used to test discriminant validity (Hair et al., 2010). As can be seen in Table 18, several values denoted by an asterisk failed the discriminant validity test for the first specified CFA model.

Table 18

Discriminant Validity of First Specified CFA Model.

	FC	PEOU	PU	SN	BI	ATU	PR	KR	AB
FC	**.279**								
PEOU	.775*	**.397**							
PU	.645*	.833*	**.619**						
SN	.678*	.593*	.601*	**.539**					
BI	.619*	.764*	.870*	.579*	**.434**				
ATU	.651*	.733*	.870*	.623*	.918*	**.577**			
PR	.061	-.159	-.260	.122	-.251	-.268	**.528**		
KR	.569*	.409*	.334	.477	.246	.297	.270	**.546**	
AB	.583*	.718*	.775*	.555*	.825*	.780*	-.144	.471*	**.597**

Note. FC = Facilitating Conditions; PEOU = Perceived Ease of Use; PU = Perceived Usefulness; SN = Subjective Norms; BI = Behavioral Intention; ATU = Attitude Toward Use; PR = Perceived Risk; KR = Knowledge of Regulations; AB = Actual Behavior. * = insufficient evidence to determine discriminant validity.

Because the first specified CFA model had low factor loadings, cross-loadings, covariances between factors, factors with unacceptable AVE values indicating poor convergent validity, and several discriminant validity problems, it was necessary to evaluate the model and consider deleting one or more factors and/or items to improve the model in those areas. This was done only if the literature supported it in some way. Hair et al. (2010) echoes this sentiment. Deletion was accomplished using a step-by-step approach. Thus, when a factor or item was deleted, the AMOS respecification process was used and the CFA model run again to evaluate model fit, reliability, and validity. The final specified CFA model is shown in Figure 11. In sum, to obtain the final specified CFA model solution, the FC factor with seven associated items and five other items (PEOU1, PEOU5, BI4, BI5, and PR7) were deleted from the first specified CFA model. The rationale for doing so is discussed next.

When the validity was checked for the first specified CFA model, as noted previously, the AVE for the FC construct was 0.279, well below the minimum of 0.5. Contributing to this, FC4 (.342) and FC3 (.424) had factor loadings below the minimum acceptable level of 0.5. Additionally, all the FC items squared loadings were low with two below .2, one below .3, three below .33, and one below 4.3, contributing to the low overall AVE value. To improve the FC factor AVE, one FC item at a time was deleted starting with FC4 which had the lowest factor loading until four of the FC items had been deleted, leaving three FC items, the minimum suggested (Hair et al., 2010). With four items deleted, the best AVE obtained was approximately .394, well below the minimum acceptable level of 0.5. An AVE less than .05 indicates on average that the variance explained by the latent factor structure imposed on the measure is less than the error that remains in the items (Hair et al., 2010).

The literature also supported deleting the FC factor. Techau (2018), in his study of electronic flight bag acceptance and adoption in general aviation, experienced similar problems with the FC factor and deleted it. Teo (2012) using a combined TAM/TPB model to study an information technology application, found two FC hypotheses not supported. Additionally, Davis (1989), in the TAM model, found that FC only had an indirect versus direct influence on ATU. Therefore, the FC factor was deleted from the CFA model.

PEOU1 ("Using a sUAS for data gathering does not require a lot of mental effort.") was identified in the pilot study as having a poor factor loading and an attempt was made to improve the wording of the question, as previously noted. When the next respecified CFA model ran without the FC factor, PEOU1 had the lowest factor loading of any item (.273), well below the minimum threshold of 0.5 with an associated square loading that was very low (.0745). Deleting PEOU1 would therefore improve AVE (.3971) for the PEOU factor. Additionally, deleting PEOU1 resulted in the PEOU factor still having four items remaining, one above the minimum of three recommended (Hair et al., 2010). Supporting the statistical rationale, PEOU was compared to other items in their designated scales to check for redundancy of content overlap. It was noted in the respecified CFA model that a covariance existed between PEOU1 and PEOU2, supporting possible redundancy. For example, when examined, PEOU1 ("Using a sUAS for data gathering does not require a lot of mental effort.") was similar to ("I think it is easy to use a sUAS for data gathering to accomplish my data gathering tasks."). It might have been difficult for respondents to decipher between easy to use and not requiring a lot of effort. Therefore, PEOU1 was deleted.

PEOU5 ("It is easy to become skillful at using a sUAS for data gathering operations.") After the next respecified CFA model ran with the FC factor and PEOU1 deleted, PEOU5 had the lowest factor loading (.503) and the lowest squared loading of the remaining five PEOU items. Additionally, the AVE for the PEOU factor (.457) was still below 0.5 which was unacceptable. Comparing the PEOU5 ("It is easy to become skillful at using a sUAS for data gathering.") to the PEOU2 question ("I think it is easy to use a sUAS for data gathering to accomplish my data gathering needs.") revealed possible redundancy between questions which supported the need to delete the item. Possible redundancy was also indicated by a covariance in the respecified CFA model between PEOU5 and PEOU2. Therefore, PEOU5 was deleted from the CFA model attempting to improve AVE and because of question overlap. Subsequently when the next respecified CFA model ran without the FC factor, PEOU1, and PEOU5, the PEOU factor AVE improved to .509 which was acceptable.

BI4 ("When choosing data gathering methods, use of a sUAS is my first choice.") Upon completion of the respecified CFA model run without the FC factor, PEOU1, and PEOU5, BI4 had the lowest factor loading (.586) of the BI items and the lowest squared loading value (.343). Given that the AVE for the BI factor (.460) was unacceptable, BI4 was considered for deletion. Additionally, possible redundancy was indicated in the respecified CFA model by a covariance from BI4 to BI1, and from BI5 to BI4. Comparing BI4 ("When choosing data gathering methods, use of a sUAS is my first choice.") and BI1 ("I would use a sUAS for my data gathering needs"), both questions could be construed as overlapping. Thus, BI4 was deleted from the model. After the respecified CFA model ran without the FC factor, PEOU1, PEOU5, and BI4, the AVE for the BI factor improved to .489 which was an improvement, but still deemed unacceptable.

PR7 (Legal liability is a concern when using my sUAS for data gathering.") As previously discussed, PR7 had a low factor loading in the pilot study, and an attempt was made to reword the question rather than delete the item. After the respecified CFA model ran with the FC factor and items PEOU1, PEOU5, and BI4 deleted, problems were indicated with PR7 and the BI factor AVE. The factor loading for PR7 (.444) was below the minimum acceptable with an associated low squared loading of .197 contributing to a low, but acceptable AVE of .499. Additionally, possible cross loading to PR7 was indicated from the PU factor by the modification indices, and covariances existed between PR7 and three other items (PR9 - Loss of privacy, PR8 -media and/or society influence my perceived risk level, and PR4 – cost is concerning) in the respecified CFA model. Lee (2009) advocates that the elements of risk are applied as applicable to technology, meaning that risk elements may vary among technologies and therefore may or may not be applicable. These attributes indicated PR7 should be considered for deletion. However, besides the PR7 attributes, the BI factor AVE was .489, below the minimum acceptable. BI5 had the lowest squared loading of all BI items (.379), contributing to the low AVE.

Therefore, two avenues were explored with the respecified CFA model since both were supported by the literature; deleting PR7 first and deleting BI5 first. Deleting BI5 first solved the BI factor AVE (.590) and increased the PR AVE (.511) and PR7 factor loading (.519) to an acceptable level. However, the AVE for the PEOU factor dropped to an unacceptable level of .473, and cross loading was still indicated from PU to PR7 in the respecified CFA model. Subsequently, deleting PEOU2 improved the AVE to .495, below the minimum but deemed acceptable. However, cross loading was still indicated from PU to PR7 in the respecified CFA model. Deleting PR7 first and then BI4 proved to be the better choice as PEOU AVE (.509) was satisfactory, cross loading to PR7 was eliminated, and BI AVE improved to .544 which showed satisfactory convergent validity.

BI5 ("I would recommend using a sUAS for data gathering to my relatives and friends.") After running the respecified CFA model with the FC factor, PEOU1, PEOU5, BI4, and PR7 deleted, BI5 had the lowest factor loading (.612) of the remaining four BI items and the lowest squared loading of .375. Given that the AVE for the BI factor was .481, which was still unacceptable, BI5 was considered for deletion. Subsequently, when the respecified CFA model ran with the FC factor and PEOU1, PEOU5, BI4, PR7, and BI5 deleted, the AVE for the BI factor improved to .544 which was acceptable while still maintaining a minimum of three items for the factor. The final CFA model with the FC factor and PEOU1, PEOU5, BI4, PR7, and BI5 items deleted is shown in Figure 10.

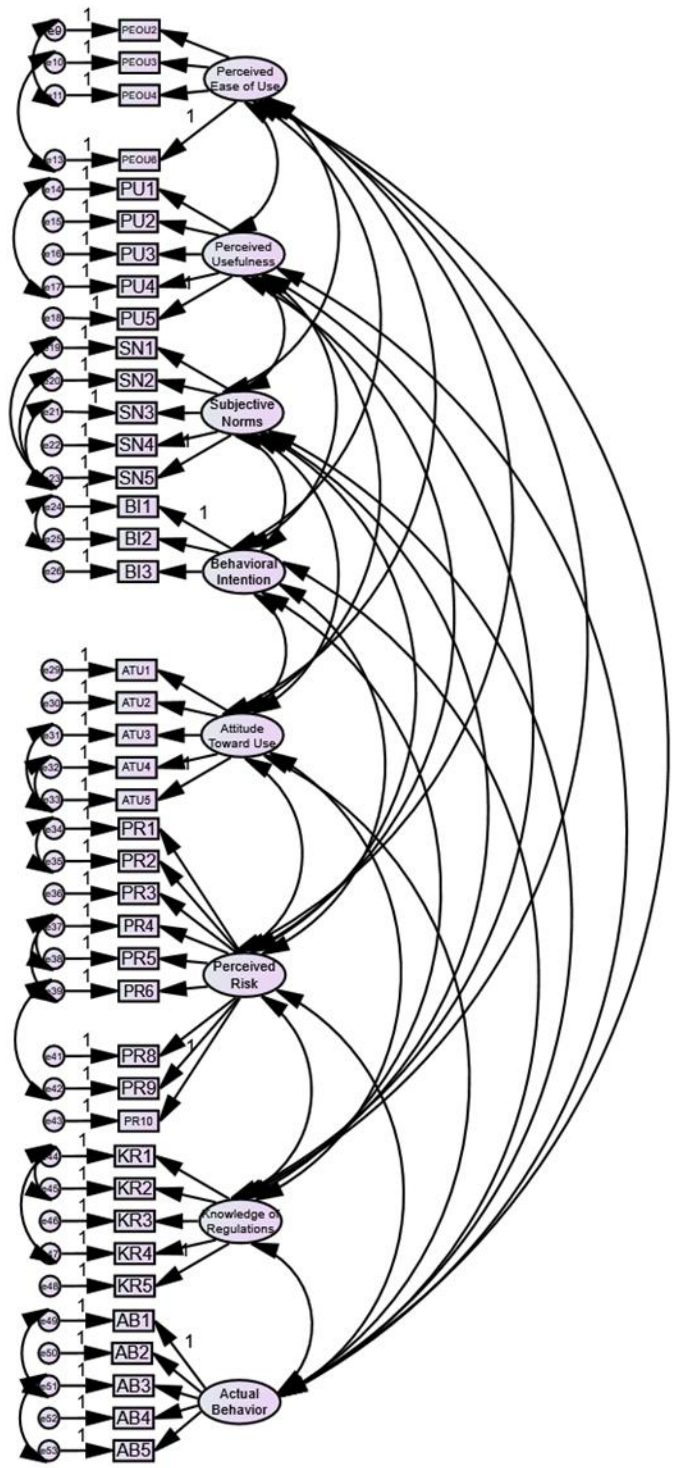


Figure 10. Final respecified CFA model with items deleted. PEOU = Perceived Ease of Use; PU = Perceived Usefulness; SN = Subjective Norms; BI = Behavioral Intention; ATU = Attitude Toward Use; PR = Perceived Risk; KR = Knowledge of Regulations; AB = Actual Behavior.

As can be seen from Table 19, after deleting the FC factor and PEOU1, PEOU5, BI4, PR7, and BI5 items, the final respecified model shows a good model fit. Since the model was deemed acceptable, the next step in the process was to examine reliability and validity.

Table 19

Model Fit Indices for the CFA Models

Model Fit Indices	Acceptance Value	Unspecified CFA	First Respecified CFA Model	Final Respecified CFA Model
X^2	-	3929.247***	2185.067***	1632.142***
df	-	1289	1232	734
CMIN/df	≤ 3	3.048	1.774	2.224
GFI	> .90**	.790	.888	.888
AGFI	> .90**	.767	.870	.869
NFI	> .90	.823	.901	.908
CFI	> .93	.873	.954	.947
RMSEA	< .06	.056	.034	.043

Note. *** p <.001

The construct reliability and convergent validity for the final respecified CFA model was computed the same way as in the original CFA model. All factor loadings, construct reliability, Cronbach's Alpha, and AVE values were satisfactory as shown in Table 20. Thus, construct reliability and convergent validity were met.

Table 20

Final Respecified CFA Model Construct Reliability and Convergent Validity

Construct	Item	Factor Loading (Desired ≥ 0.7, Min ≥ 0.5)	Construct Reliability (≥ 0.7)	Cronbach's Alpha (≥ 0.7)	AVE (≥ 0.5)
Perceived Ease of Use	PEOU2	.539	.976	.797	.509
	PEOU3	.784			
	PEOU4	.681			
	PEOU6	.817			
Perceived Usefulness	PU1	.769	.989	.885	.619
	PU2	.792			
	PU3	.731			
	PU4	.851			
	PU5	.786			
Subjective Norms	SN1	.774	.987	.869	.625
	SN2	.804			
	SN3	.844			
	SN4	.745			
	SN5	.780			
Behavioral Intention	BI1	.772	.970	.791	.544
	BI2	.783			
	BI3	.651			
Attitude Toward Use	ATU1	.823	.987	.876	.582
	ATU2	.775			
	ATU3	.739			
	ATU4	.708			
	ATU5	.763			
Perceived Risk	PR1	.794	.983	.983	.533
	PR2	.807			
	PR3	.769			
	PR4	.627			
	PR5	.738			
	PR6	.632			
	PR8	.651			
	PR9	.698			
	PR10	.823			
Knowledge of Regulations	KR1	.654	.979	.979	.577
	KR2	.617			
	KR3	.850			
	KR4	.861			
	KR5	.782			
Actual Behavior	AB1	.837	.983	.872	.575
	AB2	.772			
	AB3	.703			
	AB4	.750			
	AB5	.721			

Discriminant validity. Discriminant validity ensures that each construct is distinct from the other constructs and captures phenomena not found in other constructs (Hair et al., 2010). The method of computing discriminant validity using the Fornell and Larcker method of comparing AVE values with the correlation estimates of any two constructs was used for all models in the CFA respecification process (Hair et al., 2010). Throughout the CFA model respecification process in this study, each model including the final model demonstrated that there was insufficient evidence to determine discriminant validity for one or more correlations using this method. Table 21 shows the discriminant validity for the final respecified CFA model comparing the AVE values denoted in bold with the squared correlation estimates. The squared correlation estimates denoted with an asterisk indicate there was insufficient evidence to determine discriminant validity in the final respecified CFA model.

Table 21

Discriminant Validity Using Fornell-Larcker Criterion – Final CFA Model

	PEOU	PU	SN	BI	ATU	PR	KR	AB
PEOU	**.509**							
PU	.707*	**.619**						
SN	.373	.454	**.625**					
BI	.650*	.805*	.472	**.544**				
ATU	.548*	.740*	.449	.891*	**.582**			
PR	.015	.033	.006	.035	.046	**.533**		
KR	.189	.154	.215	.124	.108	.063	**.577**	
AB	.513*	.610*	.338	.814*	.638*	.023	.202	**.575**

Note. PEOU = Perceived Ease of Use; PU = Perceived Usefulness; SN = Subjective Norms; BI = Behavioral Intention; ATU = Attitude Toward Use; PR = Perceived Risk; KR = Knowledge of Regulations; AB = Actual Behavior. * = insufficient evidence to determine discriminant validity.

Since there was not enough evidence for acceptable discriminant validity, the Fornell-Larcker approach may have failed to accurately measure discriminant validity in this study. Therefore, an alternative method of measuring discriminant validity using the heterotrait-monotrait ratio of correlations (HTMT) methodology described in Chapter III was used. (Henseler, Ringle, & Larcker, 2015). Values of 0.90 were used as desired, and less than 1 was used as acceptable (Hair, Hult, Ringle, & Sarstedt, 2017). Table 22 shows the HTMT values calculated using SPSS and Excel® for the final model. Given the results, discriminant validity was deemed acceptable since all values were less than 1, and all but one (BI↔ ATU = .912), were below 0.90.

Table 22

HTMT Ratio Values for Final Specified CFA Model

Correlation	HTMT Ratio	Correlation	HTMT Ratio
PEOU ↔ PU	.847	SN ↔ ATU	.701
PEOU ↔ SN	.658	SN ↔ PR	.103
PEOU ↔ BI	.800	SN ↔ KR	.522
PEOU ↔ ATU	.023	SN ↔ AB	.616
PEOU ↔ PR	-.002	BI ↔ ATU	.912
PEOU ↔ KR	.479	BI ↔ PR	-.136
PEOU ↔ AB	.706	BI ↔ KR	.393
PU ↔ SN	.719	BI ↔ AB	.885
PU ↔ BI	.882	ATU ↔ PR	-.174
PU ↔ ATU	.868	ATU ↔ KR	.379
PU ↔ PR	-.004	ATU ↔ AB	.779
PU ↔ KR	.444	PR ↔ KR	.241
PU ↔ AB	.782	PR ↔ AB	-.003
SN ↔ BI	.697	KR ↔ AB	.488

Structural Model Assessment

The structural model assessment process included model construction, model fit and respecification as required, and reliability and validity testing (Hair et al., 2010).

Model construction / model fit and respecification as required. The final respecified CFA model previously discussed was converted to the original SEM model shown in Figure 11 by using AMOS to delete covariances between factors, adding one-way arrows to represent the hypotheses, adding residuals to the endogenous factors, and adding covariances between exogenous variables. The model fit of the SEM model showed similar results compared to the final specified CFA model indicating an acceptable model fit and thus requiring no model respecification.

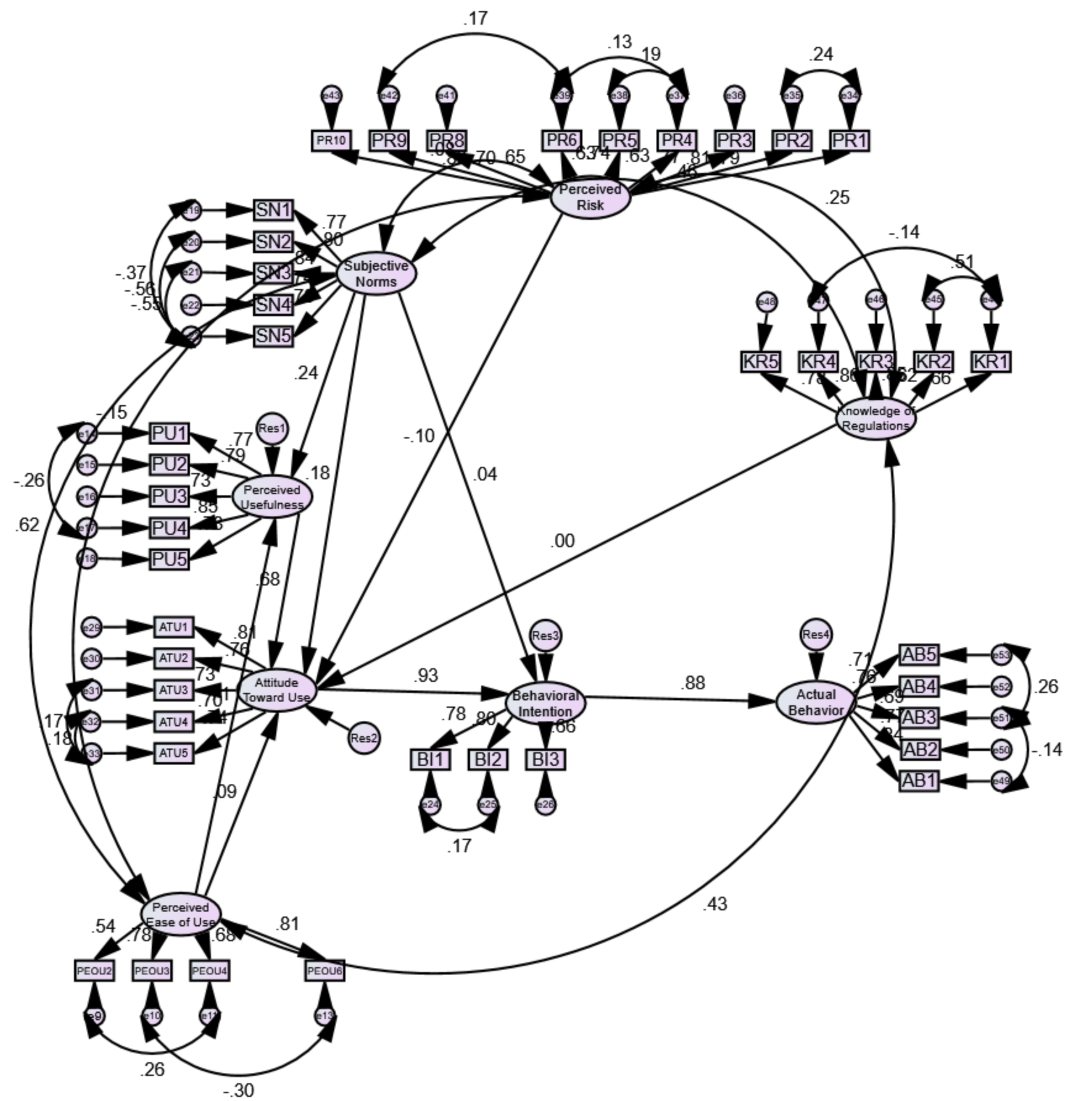


Figure 11. SEM model with standardized regression weights displayed.

SEM model hypothesis testing. Deleting the FC construct negated the ability to test the FC related hypotheses (H5, H7, and H10). The test results of the other ten hypotheses are shown in Table 23 and discussed in the next section.

Table 23

Structural Model Hypothesis Testing

Hypothesis / New Relationship	Standardized Regression Weight	Critical Ratio (t-value)	*p*-value	Result
H1 PEOU positively influences PU	.708	12.650	***	Supported
H2 SN positively influences PU	.237	6.594	***	Supported
H3 PU positively influences ATU	.681	9.411	***	Supported
H4 PEOU positively influences ATU	.095	.123	.902	Not Supported
H5 FC positively influences PEOU	-	-	-	CD
H6 SN positively influences ATU	.176	4.881	***	Supported
H7 FC positively influences ATU	-	-	-	CD
H8 SN positively influences BI	.036	.011	.991	Not Supported
H9 ATU positively influences BI	.931	12.333	***	Supported
H10 FC positively influences BI	-	-	-	CD
H11 PR negatively influences ATU	-.105	-3.231	.018**	Supported
H12 KR positively influences ATU	-.003	-.374	.406	Not Supported
H13 BI positively influences AB	.877	18.860	***	Supported

Note. CD = Could not determine.

Hypothesis 1 (H1) is supported indicating that perceived ease of use (PEOU) has a positive influence on perceived usefulness (PU). This conclusion was reinforced by the significance value of the relationship ($p < .001$), and t-value > 1.96. This means that if PEOU increases one point, PU will increase 0.708.

Hypothesis 2 (H2) is supported indicating that subjective norms (SN) has a positive influence on perceived usefulness (PU) which means if SN is increased one point, then PU will increase by 0.237. The results also indicated the same relationship was significant ($p < .001$), and the t-value was > 1.96 reinforcing the importance of the relationship.

Hypothesis 3 (H3) is supported indicating perceived usefulness has a positive influence on attitude toward use. Reinforcing this, the relationship is significant ($p < .001$), and the t-value is greater than 1.96. Thus, if PU is increased one point, ATU will increase 0.681.

Hypothesis 4 (H4) is not supported indicating perceived ease of use does not positively influence attitude toward use. This conclusion was verified as the relationship was not significant (p = .902), and the t-value was less than 1.96.

Hypothesis 6 (H6) is supported indicating subjective norms has a positive influence on attitude toward use. This was reinforced because the relationship was significant ($p < .001$), and the t-value was greater than 1.96. This means that if SN increases one point, then ATU will increase 0.176.

Hypothesis 8 (H8) is not supported indicating subjective norms do not have a positive influence on behavioral intention. Reinforcing this conclusion, the relationship was not significant (p = .991), and the t-value was less than 1.96.

Hypothesis 9 (H9) is supported indicating attitude toward use has a positive influence on behavioral intention. Aiding this conclusion, the relationship was significant ($p < .001$) and the t-value was greater than 1.96. Thus, if ATU increases by one point, BI will increase 0.931.

Hypothesis 11 (H11) is supported indicating perceived risk has a negative influence on attitude toward use. The relationship was significant (p = .018) at the p

< .05 level, and the t-value was greater than 1.96, supporting this conclusion. This means that if PR increases one point, then ATU will decrease 0.105.

Hypothesis 12 (H12) is not supported indicating that knowledge of regulations does not positively influence attitude toward use. The relationship not being significant (p=.405) and a t-value less than 1.96 supported this conclusion.

Hypothesis 13 (H13) is supported indicating behavioral intention has a positive influence on actual behavior. The relationship was significant ($p < .001$), and the t-value was greater than 1.96, supporting this assertion. This means that if BI increases one point, then AB will increase 0.877.

Four new relationships identified. Since the SEM model fit, reliability, and validity were acceptable, a post-hoc analysis was not required. However, the modification indices were reviewed to determine if any new relationships were identified. Four possible new relationships were identified that needed to be reviewed for possible inclusion in the SEM model. These relationships rank-ordered by strength included KR→AB (26.906), PR→PU (16.054), KR→BI (7.014), and PEOU→BI (5.395). When new relationships are indicated, before adding any new relationship, the literature must support inclusion of the relationship since CFA and SEM are theory driven (Hair et. al, 2010). The rationale for including the new relationships is discussed next.

The potential KR to AB relationship is directly and indirectly supported in the literature. For the KR factor, the associated questions were created by the author for this study as few TAM, TPB, or combined TAM/TPB studies could be found with a KR or similar variable. However, KR like FC and PR are considered external variables since they represent an extension of the TAM, TPB, and TAM/TPB models. There have been many TAM, TPB, and TAM/TPB studies that incorporated external variables outside the basic TAM and TPB model structure. Therefore, a search of TAM, TPB, TAM/TPB, or UTAUT studies was performed incorporating the direct relationship of a similar KR or an external variable to actual behavior. The direct or closest variable to KR was self-reported knowledge about computer usage in a study of the moderating role of national culture on an extended TAM (Alshare et al., 2011). The hypothesized relationship was tested and proven significant. Donald, Cooper, and Conchie (2014) conducted a study using an extended TPB model on the psychological factors affecting commuters' transport mode use. The hypothesized relationship of Habit, an external variable related to behavior, was tested and supported. Lastly, while the UTAUT model was not used in this study, it does incorporate the TAM and TPB variables in the model. Two initial UTAUT studies: Venkatesh, et al. (2003) and Venkatesh et al. (2012) theorized that facilitating conditions are directly related to use behavior. Lastly, Yucel and Gulbahar (2013), in their study of the prior predictors of TAM which included the UTAUT variables, reviewed prior studies examining the relationship of facilitating conditions, an external variable to usage behavior. They found that the FC relationship was not among the most effective relationships in the model. Since there were studies that tested and found that self-reported knowledge and other external variables supported the relationship to actual behavior, the KR to AB relationship was added to the modified SEM model and the hypothesis tested.

The potential PR to PU relationship is supported in the literature. Featherman and Pavlou (2003) tested and supported this hypothesis in their study of an information technology application, predicting e-services adoption. Lee (2009) provides another example of this relationship using performance risk, creating a hypothesis, and testing it in a combined TAM/TPB study integrating perceived risk. The hypothesis yielded a negative relationship and was significant. Therefore, since there was some support found for this relationship, it was included in the modified SEM model and the hypothesis tested.

The potential KR to BI relationship is indirectly supported in the literature. The KR factor and associated questions were created for this study by the author as few TAM, TPB, or combined TAM/TPB studies could be found with a KR or similar variable. However, KR like PR and FC, are considered external variables since they are essentially extensions of the TAM, TPB, and TAM/TPB model. There have been many TAM, TPB, and TAM/TPB studies that incorporated external variables outside the basic TAM and TPB model structure. For example, Cheng, Lam, and Yeung (2006) hypothesized and tested that perceived web security had a direct effect on intention to use which was supported in the results. Lee (2009) in his study of the adoption of internet banking, hypothesized and tested that perceived benefit and elements of perceived risk, both external variables, directly affected intention. Both hypotheses were supported in his study. Similarly, Hsieh (2015) in his study of physician's acceptance of an electronic medical records exchange using an extended TPB model, hypothesized and tested that perceived risk directly influenced intention. Once again, the hypothesis was supported. Because this external variable relationship was supported, the KR to BI relationship was added to the modified SEM model and the hypothesis tested.

Concerning the potential PEOU to BI relationship, perceived ease of use as defined previously in this study, is the degree to which an individual believes that using a sUAS for data gathering would be free of effort (Davis, 1989). *Perceived Behavioral Control* is defined as the perceived ease or difficulty of performing the behavior of interest (Ajzen, 1991). The two variables are alike and were combined for the purposes of this research model. The PBC/PEOU to BI relationship is supported by many authors in the literature including Azjen in his TPB model, Buaphiban and Truong (2017) in their study of passenger buying behaviors toward low cost carriers in southeast Asia, and Donald, Cooper, and Conchie (2014) using an extended TPB model to study the psychological factors affecting commuters' transport mode use. Thus, this relationship was added and tested. The adjusted SEM model with the added new relationships is shown in Figure 12. New hypotheses included in the modified SEM model and tested were as follows:

H14: Knowledge of regulations positively influences actual behavior.

H15: Perceived risk negatively influences perceived usefulness.

H16: Knowledge of regulations positively influences behavioral intention.

H17: Perceived ease of use positively influences behavioral intention.

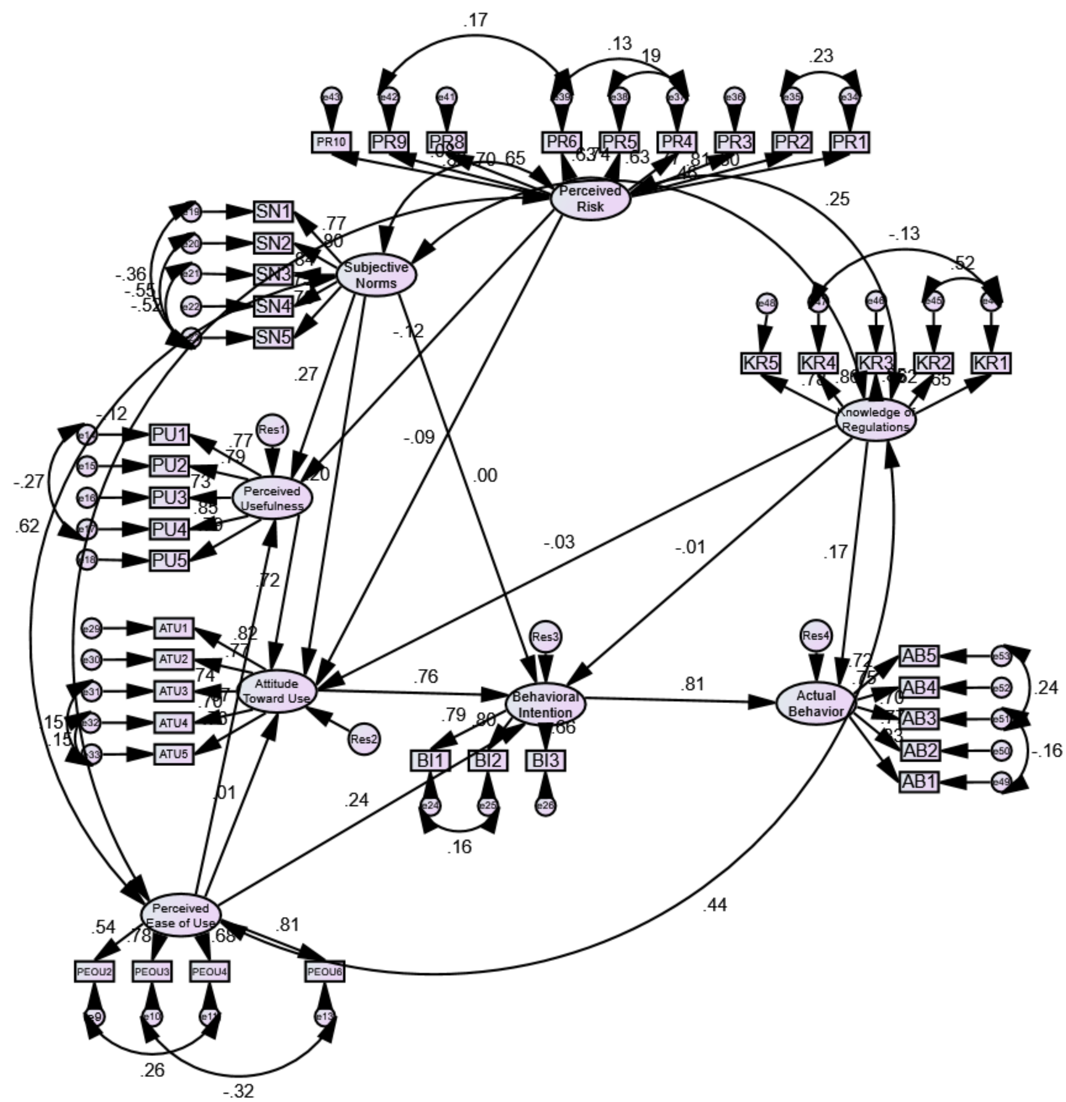


Figure 12. Modified SEM model with standardized regression weights displayed (PR→PU, KR→BI, PEOU→BI, and KR→AB).

Modified SEM model fit. It is apparent from Table 24 that adding the four new relationships to the modified SEM model improved the model fit compared to the first SEM model. Once again, new relationships that were added to the SEM model included PR to PU, KR to BI, PEOU to BI, and KR to AB.

Table 24

Model Fit Comparison Between SEM and Modified SEM Model.

Model Fit Index	SEM Model	Modified SEM Model
X2 (Chi-square)	1724.262	1647.774
Degrees of freedom	746	742
Probability	***	***
CMIN/df	2.311	2.221
GFI	.881	.887
AGFI	.863	.869
NFI	.903	.907
CFI	.942	.946
RMSEA	.045	.043

Note. *** ($p < .001$). Modified SEM model includes four new relationships: PR→PU, KR→BI, PEOU→BI, and KR→AB.

Modified SEM model hypothesis testing. The 14 hypotheses, including the four new hypotheses, were tested using the same methodology as in the original SEM model testing process. A summary of the hypothesis testing results is shown in Table 25, and testing results are discussed in the next section.

Table 25

Modified Structural Model Hypothesis Testing

Hypothesis / New Relationship	Standardized Regression Weight	Critical Ratio (t-value)	*p*-value	Result
H1 PEOU positively influences PU	.666	12.650	***	Supported
H2 SN positively influences PU	.273	6.594	***	Supported
H3 PU positively influences ATU	.723	9.411	***	Supported
H4 PEOU positively influences ATU	.008	.123	.902	Not Supported
H5 FC positively influences PEOU	-	-	-	CD
H6 SN positively influences ATU	.203	4.881	***	Supported

Table 25 (*continued*)

Hypothesis / New Relationship	Standardized Regression Weight	Critical Ratio (t-value)	*p*-value	Result
H7 FC positively influences ATU	-	-	-	CD
H8 SN positively influences BI	.000	.011	.991	Not Supported
H9 ATU positively influences BI	.760	12.333	***	Supported
H10 FC positively influences BI	-	-	-	CD
H11 PR negatively influences ATU	-.095	-3.231	.018**	Supported
H12 KR positively influences ATU	-.028	-.374	.406	Not Supported
H13 BI positively influences AB	.814	18.860	***	Supported
H14 KR positively influences AB*	.169	5.094	***	Supported
H15 PR negatively influences PU*	-.120	-4.337	***	Supported
H16 KR positively influences BI*	-.013	-.374	.708	Not Supported
H17 PEOU positively influences BI*	.238	4.655	***	Supported

Note. *** significant at $p < .001$. ** significant at $p < .05$. CD = Construct Dropped. * new relationship/hypothesis.

As previously discussed, four new potential relationships were identified in the full structural model process. The literature supported including the new relationships and associated hypotheses and testing them. The four new hypotheses (H14 – H17) discussed next, like the other hypotheses, were deemed as supported if they were statistically significant at the $p < .05$ level and had a t-value > 1.96.

Hypothesis 14 (H14) is supported indicating knowledge of regulations has a positive influence on actual behavior. The relationship was significant ($p < .001$), and the t-value was greater than 1.96 reinforcing this conclusion. Thus, if KR increases one point, then AB will increase 0.169.

Hypothesis 15 (H15) is supported indicating that perceived risk has a negative influence on perceived usefulness. The conclusion is supported as the relationship was significant ($p < .001$) and the t-value is greater than 1.96. Therefore, if PR increases one point, then PU will decrease 0.120.

Hypothesis 16 (H16) is not supported indicating knowledge of regulations does not have a positive influence on behavioral intention. The relationship was not significant ($p = .708$), and the t-value was less than 1.96 supporting this assertion.

Hypothesis 17 (H17) is supported indicating perceived ease of use has a positive influence on behavioral intention. This conclusion is supported as the relationship was significant ($p < .001$), and the t-value was greater than 1.96. Therefore, if PEOU increases one point, BI will increase 0.238.

The addition of the new relationships in the Modified SEM model improved the model fit as previously discussed. Additionally, adding the new relationships did not change whether the 10 testable of the original 13 hypotheses were supported as determined in the original SEM model hypothesis testing. However, the additional relationships did influence the existing factors standardized regression weight strength as shown in Table 26. Six decreased while four increased.

Table 26

Standardized Regression Weight Change Between SEM and Modified SEM Model

Hypothesis	SEM Model Regression Weight	Modified SEM Model Regression Weight	Change
H1 PEOU positively influences PU	.708	.666	.042↓
H2 SN positively influences PU	.237	.273	.036↑
H3 PU positively influences ATU	.681	.723	.042↑
H4 PEOU positively influences ATU	.095	.008	.087↓
H5 FC positively influences PEOU	-	-	-
H6 SN positively influences ATU	.176	.203	.027↑
H7 FC positively influences ATU	-	-	-
H8 SN positively influences BI	.036	.000	.036↓
H9 ATU positively influences BI	.931	.760	.171↓
H10 FC positively influences BI	-	-	-
H11 PR negatively influences ATU	-.105	-.095	.010↓
H12 KR positively influences ATU	-.003	-.028	.025↑
H13 BI positively influences AB	.877	.814	.063↓

Note. ↑ = increase. ↓ = decrease.

Research question one. The first research question was "to what extent does the VMUTES model explain individuals' intentions to use sUASs for data gathering?" The VMUTES adjusted full structural model fit was good considering GFI and AGFI are sensitive to sample size. Model fit parameters are shown in Table 24 above. Model fit was the primary confirmation of how well the model explained individuals' intentions to use sUASs for data gathering. Deleting the FC factor negated the ability to test three hypotheses. After the FC factor was deleted, 70% of the hypotheses were supported and

30% were not which was another confirming factor model confidence. However, there were three new supported relationships/hypotheses discovered that were not part of the original model which indicates the original model, while having a good fit, was lacking somewhat in capturing all relevant relationships.

The predictive power of the model was strong overall. The sample squared multiple correlation coefficient measures total variance proportion on dependent variables that is accounted for by predictors in the model (Kwan & Chan, 2014). The predictive power of the model for behavioral intention is .896 and for actual behavior is .785.

Research question two. The second research question was "what factors at the .05 significance level influence individuals' intentions to use sUASs for data gathering? The factors that remained in the model after the CFA and SEM process answer question two that either directly or indirectly influence sUAS operator's use (AB) of sUASs for data gathering. Those factors include knowledge of regulations (KR), attitude toward use (ATU), perceived risk (PR), behavioral intention (BI), perceived ease of use (PEOU), subjective norms (SN), and perceived usefulness (PU). The positive and negative rank-ordered strength of those factors on other factors including the new relationships/hypotheses is shown in Table 27. The BI factor had the strongest and KR had the weakest positive effect. Additionally, it was noteworthy that the factors that are part of the TAM or TPB had stronger effects than the external variables that remained (PR and KR).

The two strongest factors indicating whether individuals will use sUASs for data gathering include behavioral intention and actual behavior. As can be seen from Table

25, ATU and PEOU directly affect BI while BI and KR directly affect AB. However other factors affect BI and AB indirectly. Those indirect effects are discussed next.

Table 27

Modified SEM Model Rank-Ordered Strength of Standardized Estimates

Supported Factor Relationship	Positive Rank-Ordered Strength	Negative Rank-Ordered Strength
BI → AB	.814	--------------------------------------
ATU → BI	.760	--------------------------------------
PU → ATU	.723	--------------------------------------
PEOU → PU	.666	--------------------------------------
SN → PU	.273	--------------------------------------
PEOU → BI**	.238	--------------------------------------
SN → ATU	.203	--------------------------------------
KR → AB**	.169	--------------------------------------
PR → PU**	-------------------------------------	-.120
PR → ATU	-------------------------------------	-.095

** New Relationship/Hypothesis

Besides direct effects as listed in Table 27, there are also indirect factor effects. Thus, Table 28 shows the indirect effects on BI from the KR, PR, SN, PEOU, and PU factors in the modified SEM model. As can be seen from the table, PU has the highest positive indirect effect on BI while PR has the highest negative indirect effect on BI.

Table 28

Factor Rank-Ordered Standardized Indirect Effects on BI

Factor	Indirect Effect on BI
PU	.549
PEOU	.372
SN	.304
KR	-.021
PR	-.138

Table 29 shows the rank-ordered indirect effects of KR, PR, SN, PEOU, PU, and ATU on AB in the modified SEM model. As can been seen, ATU has the highest positive indirect effect on AB, and PR has the highest negative indirect effect on AB.

Table 29

Rank-Ordered Standardized Indirect Effects of KR, PR, SN, PEOU, PU, and ATU on AB

Factor	Indirect Effect on AB
ATU	.618
PEOU	.497
PU	.447
SN	.248
KR	-.027
PR	-.112

Chapter Summary

This chapter focused on presenting the analytical results of the use of sUAS for data gathering. A pretest and pilot study were conducted and the questionnaire revised by rewording questions in both instances. Additionally, Amazon Mechanical Turk lessons learned from the pilot study were incorporated to better the data collection process for the main study. Since an adequate number of responses was attained using Amazon Mechanical Turk for both the pilot and main study data collection, another form of sampling such as snowball sampling was not required which reduced the possibility of sampling bias. After cleaning the data, the sample size for the final analysis was 662, well above the minimum of 460 required.

Descriptive statistics summarized individual demographics and sUAS for data gathering operational characteristics. Generally, the study results followed the U.S. Census Bureau and FAA information with a few exceptions. Notably, some new demographic information was attained that the FAA did not have previously.

The measurement model assessment of sUAS use for data gathering was accomplished using the CFA process. The initial model contained several cross loadings, low factor loadings, unsatifactory convergent validity values, and unsatisfactory discriminant validity values. The model was improved by eventually deleting the FC factor with seven associated items as well as five other items. Additionally, for discriminant validity it was necessary to use HTMT ratios as the alternate method to test discriminant validity, which proved successful. The final respecified CFA model produced a good fit without cross loadings and covariances between factors.

The full structural model process was performed next. The SEM model fit was comparable to the final respecified CFA model fit. Even though model respecification was not required due to an adequate model fit, four new potential relationships were identified and literature supported including those new relationships and testing them in the full structural model. The modified SEM model fit with the four new relationships incorporated had the best model fit compared to the final respecified CFA and SEM model. The modified SEM model was deemed a good fit because of acceptable model fit indices and the predictive power of the model on BI and AB, which answered research question one. For hypothesis testing, H5, H7, and H10 could not be tested since the FC construct was dropped from the model. Of the remaining hypotheses, seven of the remaining ten hypotheses were supported (H1, H2, H3, H6, H9, H11, and H13). Three hypotheses were not supported which included (H4, H8, and H12). Of the four potential new relationships/hypotheses, three were supported (KR to AB, PR to PU, and PEOU to BI) and one was not (KR to BI). All factors (PEOU, SN, PU, ATU, PR, BI, KR, AB) but FC were relevant in the model when the three new relationships were incorporated. Additionally, several factors had direct and indirect effects on BI and/or AB. The next chapter discusses sUAS for data gathering results using the literature in both research and theoretical areas, draws study conclusions, and provides recommendations for future research.

CHAPTER V

DISCUSSION, CONCLUSIONS, AND RECOMMENDATIONS

This research effort assessed how well the new VMUTES model explained an individual's intent to use sUASs for data gathering and the relevant factors of influence in the VMUTES model. As part of the research, personal and operational demographic information was obtained with many demographic attributes providing new information for researchers, the FAA, and other entities.

The VMUTES model was developed based on the literature review, the sUAS use for data gathering environment, and the ground theory of the TAM, TPB, and C-TAM/TPB models. External variables were dictated by sUAS use for data gathering and included perceived risk, facilitating conditions, and knowledge of regulations. The author collected survey data from sUAS for data gathering users using a random sampling approach through Amazon Mechanical Turk® facilitating an online survey using Survey Monkey. Data analysis was accomplished using descriptive analysis and the CFA and SEM processes. Results indicated that after deletion of the FC factor causing three hypotheses to be non-testable, 7 of the remaining 10 hypotheses were supported (H1, H2, H3, H6, H9, H11, H13) relating to the VMUTES model. Additionally, during the SEM respecification process, four new potential relationships were discovered; three of which were validated in the final SEM model (KR to AB, PR to PU, and PEOU to BI). Chapter 5 is the final chapter and includes three major sections that discuss the model results, offers conclusions, and provides recommendations for future research.

Discussion of Results

Chapter IV results are critically examined with respect to ground theories and effects on or relationships with other study findings. Additionally, new findings are highlighted providing more insight to the sUAS operation for data gathering.

Characteristics of individual and operational sUAS data gathering use. Both individual and operational sUAS data gathering user demographic data was obtained in this study. Characteristics of individual data gathering use is reviewed first followed by new individual characteristic data, then charcteristics of operational data gathering use and finally new operational characteristics.

Characteristics of individual data gathering use. Characteristics of individual data gathering use which can be compared to FAA and/or U.S. census data include gender, age, education level, annual income, and region of operation. Results indicated that more males (64.5%) responded to the survey than females (34.9%). This gender ratio was not consistent with the U.S. population, but it did generally coincide with the FAA remote pilot certificate data which also favored more males than females (FAA,2017d).

Regarding age of survey respondents, most respondents comprised two age groups: 21-30 years (45%) and 31-40 years of age (36.3%) with other age ranges decreasing in percentage as age increased. Considering the census bureau includes those under the age of 18, which were not included in this study, generally, both indicated the majority of the population was between the ages of 18 and 64 (U.S. Census Bureau, 2016). Additionally, the relative age distribution of respondents was similar to the FAA U.S. civil airmen statistics for those people who have a remote pilot certificate. However, the percentages of the specific age groups were higher for the study than the FAA data. This possibly could be explained by the study considering those people who have not registered a sUAS used for data gathering whereas the FAA data did not include that data.

Concerning education, most respondents had a bachelor's degree (54.7%) or master's degree (23.1%). While the census data generally indicated similar results regarding those with a high school diploma, sUAS for data gathering users were more educated than the general U.S. population (U.S. Census Bureau, 2016). A large percentage of respondents were commercial company employees (52%) which could possibly explain the higher education level depending on occupation. Additionally, according to the U.S. Bureau of Labor Statistics (2018), commercial pilots usually have a high school diploma while airline pilots usually have a bachelor's degree. Certainly, it cannot be concluded that commercial and airline pilot education requirements equate to sUAS use for data gathering, but the data could suggest overall that aviation enthusiasts may have a higher education level than the general population due to the higher technical cognitive skills required.

The median annual income of study participants was approximately $51,000 with most respondents comprising three income levels of $51,000 to $100,000 (45.5%), $30,000 to $50,000 (30.1%), and less than $30,000 (13%). The median income of respondents was comparable to the U.S. population who had a comparable median income of $55,000.

Most study participants were model aircraft users (50.5%), civil users (15.1%), public users (13.1%), and model aircraft and public users (8.8%). While the FAA data indicated that the majority of UAS users were model aircraft users similar to the study results, the FAA percentage was much higher (85.3%). However, the FAA data considers all UAS operation, whereas this study was more focused on a specific application of sUASs. Therefore, the demographic of respondents who use sUASs for data gathering may be different than that of the whole FAA UAS population. More samples need to be taken in future studies to support this possibility as it could also be a function of the sampled population.

Regarding region of operation of sUASs for data gathering, most respondents resided in the south (36.4%), followed by the Northeast (22.7%), West (22.5%), and Midwest (18.3%). When compared to the FAA projected hobbyist and commercial UAS distribution map and the census regional map, results were comparable (Census Bureau, 2016; FAA, 2017a).

New characteristics of individual data gathering use. New individual data gathering use characteristics were obtained which included current occupation and sUAS data gathering operator experience level. For current occupation, most respondents were commercial company employees (52%), followed by self-employed (26.4%), then student (10.7%), and government employee (9.7%). Concerning experience level, most respondents were in the range of less than six months to less than three years. More specifically, 28.5% had an experience level less than six months to one year, 20.4% had an experience level less than six months, 20.2% had an experience level of one to two years, and 15.1% had an experience level of two to less than three years.

Generally, the respondent data and FAA and/or U.S. census data largely agreed with minor differences indicating the sample was reflective of the FAA and/or U.S. population. While gender ratio did not follow U.S. census data, it did parallel FAA data. Concerning age, respondent data generally agreed with U.S. census data, but indicated higher percentages compared to FAA data showing that individuals who use sUASs for data gathering are slightly different than the overall FAA aviation data. Additionally, respondent data indicated that individuals who use sUASs for data gathering have a slightly higher education level compared to the U.S. general population.

Characteristics of operational data gathering use. Characteristics of operational data gathering use that can be compared with existing FAA and/or U.S. census data include area of operation, possession of a remote pilot certificate, types of sUAS data gathering operations, and type of FAA waiver. The majority of respondents indicated they operated their sUAS for data gathering in an urban metro area (39.9%), followed by an urban micro area (33.7%), and a rural area (26.3%). Generally, this compared with U.S. census information where most of the population was in the urban areas (94%) versus rural areas (6%) (U.S. Census Bureau, 2016). However, the percentage of respondents in this study operating in rural areas was four times more than the U.S. general population.

Concerning having a remote pilot certificate, 49.2% of respondents indicated they had a remote pilot certificate while 50.3% indicated they did not. The FAA data indicated that approximately 8% had a remote pilot certificate, which is considerably lower than the study results (FAA, 2017a). This could possibly be explained because the

FAA data includes all UAS aircraft versus just those in the sUAS used for data gathering category.

For types of data gathering operations, most respondents indicated that they used aerial photography (40%), followed by movie filming (8.9%), environmental (7.7%), agriculture (6.6%), and education purposes (6.5%). Interestingly, most respondents who indicated they were modelers only flying for recreational enjoyment did so with a purpose, the most popular being aerial photography. Few (5.6%) flew the sUAS just for fun with no purpose. The FAA data compared favorably regarding aerial photography but differed somewhat after that. Next, the FAA listed real estate (26%), construction, industrial and utility inspections (26%), agriculture (21%), and emergency management (FAA, 2017a). Besides aerial photography, respondents rated the other FAA types of operations much lower: real estate (4.4%), construction, industrial and utility inspections (2.7%), agriculture (6.6%), and emergency management (3.9%). Perhaps this difference can be explained because the FAA includes all UASs while this study focused on sUASs used for data gathering only. However, more research is needed to verify this theory.

Concerning type of FAA waiver, 50% of respondents indicated they had not requested a waiver. Of the waivers requested, the top five included daylight operation (15.3%), visual line of sight (9.4%), visual observer (5.7%), operation in certain airspace (4.4%), and operations from a moving vehicle (4.1%). The percentage of respondents who had not requested a waiver is a new data point since the FAA does not track that statistic. Comparing the FAA data, three of the top waivers respondents indicated as the most requested agreed with FAA data. However, the FAA data ranked altitude and operations over people above the study findings of visual observer and operation in certain airspace.

New characteristics of operational data gathering use. New operational data gathering use characteristics obtained by this present research include formal sUAS training, possession of a 14 CFR Part 62 manned operating certificate, manned operating experience, type of sUAS used, non-registered sUAS users, amount paid for the sUAS, and type of sensor(s) used. Most respondents (56.6%) indicated they have had some type of formal training while (43.2%) did not. Concerning possession of a manned aircraft operating certificate, most respondents (59.7%) indicated they did not have one while (40%) did have one. For manned operating experience, most respondents were in the range of no experience to less than two years of experience (76.9%). Relative to the increase in experience level, the percentage of respondents decreased from 9.4% to 0.8%. Concerning type of sUAS aircraft used, most respondents indicated they are operating vertical takeoff and landing sUASs (60.7%), followed by fixed wing (32.9%), and other types (6.0%). Regarding registration of sUASs used for data gathering, 63% of respondents indicated their data gathering, 75.7% of respondents paid between $200 and $5,000 for their sUAS with 24.6% paying $500 to $1,000. As the amount increased above $5,000, the percentage of respondents decreased. Lastly, for type of sensor(s) used, most respondents used a camera (79.8%), then video (68.7%), RGB camera (23.4%), infared (21.6%), and thermal (16.9%).

Like characteristics of individual gathering use, characteristics of operational data gathering use generally parallels the FAA and/or U.S. census data with some noted differences. There were more respondents in rural areas than U.S. census data, there were considerably more respondents who possessed a remote pilot certificate than the FAA UAS population, there were two differences in the top five types of operations when comparing respondent and FAA data, and there were some differences in the types of waivers most frequently requested (FAA, 2017a; U.S. Census Bureau, 2016).

Additional findings. Most respondents chose not to answer or provided a response indicating that they chose not to enter additional comments and therefore definitive conclusions cannot be reached based on such a limited sample. However, while the respondents who did provide a response was comparatively small, some responses worth noting surfaced that could warrant further research. Of those that responded, the majority viewed the study and/or survey in a more positive than negative way. Additionally, respondents indicated general satisfaction with using sUASs for data gathering, described different types of data gathering operations, some showed a negative view of others operating sUASs for data gathering, or indicated the importance of adhering to laws and having formal training. Importantly, some respondents commented that the study highlighted their unawareness of the various regulations pertaining to operation of sUASs for data gathering. While not a conclusion, this indication regarding lack of knowledge of regulations governing sUAS use for data gathering, further reinforces the need to include a knowledge of regulations factor in the research model.

Amazon Mechanical Turk (AMT). Buhrmester, Kwang, and Gosling (2011), as previously discussed, found that Amazon Mechanical Turk participants are at least as diverse as and more representative than traditional samples. This present research generally supported that assertion with noted exceptions as evidenced by the previously discussed demographic data. For sampling, each MTurk participant had an equal chance of participating in the survey if they were qualified. Thus, study participants represented a random sampled population.

There were 750 responses solicited using AMT with 1,798 Survey Monkey questionnaire responses received within a relatively short time span of 72 hours. There were 662 cases of the 1,798 responses judged as usable after deletion of non-usable cases. Constructing the Human Intelligence Task (HIT) on the Amazon Mechanical Turk website was relatively straight forward. While AMT has the capability for the researcher to construct a survey, using an external link such as Survey Monkey for the questionnaire offers more survey construction and logic options than the AMT website. However, doing so causes all responses to be listed on Survey Monkey while AMT only lists those that had completed the survey and obtained a survey completion code to receive payment. As a result, many non-usable responses from the Survey Monkey questionnaire were collected and had to be deleted in the data cleaning process. However, subsequently adding filter logic to the survey screening questions aided in eliminating those who attempted but were not qualified to take the survey and avoided paying some individual's worker fees unnecessarily.

Amazon Mechanical Turk requires those participating in HITs to be paid. The amount of payment for this study was $1.50 which was derived by comparing similar HITs and the time required to complete similar HITs to determine a fair payment. Many past studies have offered participants a small gift to participate in a survey on par with the payment provided in this study. Babbie (2016) discusses this topic and cites authors Singer, Groves, and Corning (1999) who reviewed several studies that offered incentives and found that response rates increased and also found no negative effects on the quality of responses collected.

VMUTES model modifications. Modifications to the initial CFA model were required to improve AVE of three constructs and to improve the model by addressing indicated cross loading and co-variances of items between different factors. To achieve these goals, one factor was deleted and three factors were modified. More specifically, the FC factor and five items including PEOU1, PEOU5, BI4, BI5, and PR7 were deleted from the model. This was done systematically in concert with literature support by deleting one factor or item at a time and then re-running the CFA model to determine the effects on the model, model fit, reliability, and validity.

Facilitating conditions (FC). The facilitating conditions construct was deleted. An attempt was made to delete one item of the construct at a time with the lowest squared loading resulting in the deletion of four items with the AVE value still less than 0.5. Therefore, the construct was deleted. This is supported in the literature by Techau (2018), Teo (2012), and Davis (1989) who also found either the need to delete the FC factor, found FC related hypotheses not supported, or found the FC factor weak in relationships between factors. Since both Techau (2018) and this study focused on aviation and deleted the FC factor, further research would be prudent to see if other aviation studies using the UTAUT2 or VMUTES model result in having to delete the FC factor.

Perceived Ease of Use (PEOU). The PEOU1 item displayed the lowest factor loading and associated lowest squared loading value. Additionally, PEOU1 displayed some overlap with the PEOU2 question indicating possible redundancy. Therefore, PEOU1 was deleted. Additionally, similar to PEOU1, PEOU5 displayed a low factor loading with associated low squared loading value and some possible question overlap with PEOU2. Therefore, PEOU5 was deleted. After deletion of both items, the PEOU factor AVE improved to .509 which indicated satisfactory convergent validity.

Behavioral Intention (BI). BI4 had the lowest factor loading of any BI item and the lowest squared loading value. Additionally, BI4 when compared to BI1 displayed possible question redundancy. Therefore, BI4 was deleted. Similar to BI4, BI5 after BI4 was deleted had the lowest factor loading and associated squared loading of any BI items. Therefore, BI5 was also deleted. Subsequently, the BI AVE value improved to an acceptable .544 value.

Perceived risk (PR). After an attempt to reword PR7 in the pilot study, PR7 again presented a low factor loading an associated low squared loading. Additionally, cross loading was indicated from PU to PR7 in the model, and covariances or possible question redundancy was indicated between PR7 and three other items. Therefore, PR7 was deleted in concert with Lee (2009) in the literature who advocates that the risk elements are dependent on the technology being used.

Specific order of deletion of items. When accomplishing the model modifications discussed previously, it was discovered through exploration that deleting BI5 or PR7 made a difference in the results which was an unexpected result. As previously discussed in Chapter IV, deleting PR7 first and then BI5 showed the best results considering AVE values for PR, BI, and PEOU factors. Hair et al. (2010) supports this approach as CFA is an iterative approach, and only after careful consideration should an item be deleted. Considerations for deleting an item should include low factor loadings contributing to low convergent validity, poor model fit, poor construct validity, and literature support.

VMUTES model results. The VMUTES model included seven predictor variables comprising behavioral intention, attitude toward use, perceived usefulness, subjective norms, perceived ease of use, knowledge of regulations, and perceived risk. The relevant influencing factors are discussed in rank order of strength of influence.

Behavioral intention (BI). Behavioral intention in the VMUTES model had a very strong positive influence on actual use of sUASs for data gathering meaning individuals were willing to try very hard to use sUASs for data gathering. This relationship is explained in the TPB model proposed by Ajzen (1991). The effect of BI on AB is supported by many studies in the literature, some of which include Mallya and Lakshminarayanan (2017), Parker et al. (1992), and Lao, Tao, and Wu (2016).

Practically, behavioral intention or the will to use sUASs for data gathering is the strongest predictor of actual use. Most likely, if the will to use sUASs for data gathering is strong, then actual use will occur. In the context of using sUASs for data gathering, attitude toward using sUASs for data gathering and subjective norms have a direct positive influence on the will to use sUASs for data gathering. Therefore, if stakeholders desire to improve behavioral intention, efforts should focus on those two influencing factors of behavioral intention. The influencing factors of attitude toward use and social norms are discussed in the next sections.

Attitude toward use (ATU). In this study, attitude toward use had a strong positive influence on behavioral intention. The more favorable the attitude, the higher the intention to use sUASs for data gathering. The attitude toward use effect on behavioral intention relationship is a basic component of the TAM model, and therefore it was expected (Davis, 1989). Examples of other studies that have verified this same TAM relationship include: Choi and Chung (2012), Lai and Honglei (2005), and Mallya and Lakshminarayanan (2017). ATU also had an indirect positive effect ($\beta = .618$) on AB which is supported by the TPB model (Ajzen, 1991).

From a practical standpoint, attitude toward using sUASs for data gathering is a positive influence on the will to use sUASs for data gathering. Thus, individuals have positive feelings about using sUASs for data gathering. This finding is important from a psychological perspective because it establishes the positive relationship of attitudes to an individual's choice of using sUASs for data gathering. In the context of sUASs used for data gathering, if stakeholders desire to improve attitude toward use, then the focus should be on those factors that directly influence attitude toward use including subjective norms, perceived usefulness and perceived ease of use.

Perceived usefulness (PU). Perceived usefulness or the degree to which an individual believes that using sUASs for data gathering would enhance his or her job performance had a strong positive influence on attitude toward use. The more favorable the perceived use, the more favorable attitude toward using sUASs for data gathering is. Literature also supports this relationship. This relationship is supported as one of the basic tenets of the TAM model and supported in other studies, so it was expected (Davis, 1989; Teo, 2012). Examples of other studies where this relationship was verified include Choi and Chung (2012), Ha and Stoel (2009), and Mallya and Lakshminarayanan (2017). PU was also found to have an indirect positive influence on BI which is a basic premise of the TAM model (Davis, 1989) and an indirect positive influence on AB as depicted in Lee's (2009) TAM/TPB research model.

Practically, perceived usefulness of using sUASs for data gathering has a positive influence on attitude toward use which then positively influences the will to use sUASs for data gathering and the actual use of sUASs for data gathering. This makes sense as sUASs used for data gathering provide timely information not readily available from other sources such as aircraft, helicopters, or satellites (Hoffer, Coopmans, Jensen, & Chen, 2014; 2013). Supporting this, most respondents indicated they use sUASs for personal, commercial, or government use rather than just for flying sUASs with no data collection equipment for fun. The most popular application was aerial photography used by 40% of respondents. For stakeholders to increase perceived usefulness, as an example, perhaps improvements to data gathering capability or sUAS design could be made.

Perceived ease of use (PEOU). Perceived ease of use, the degree to which an individual believes that using sUASs for data gathering would be free of effort had a strong positive influence on perceived usefulness. Therefore, the stronger the perceived ease of use is, the stronger perceived usefulness is. Examining the literature reveals support for this relationship. This relationship (PEOU → ATU) like (PU → ATU) is a basic part of the TAM model so it was also expected (Davis, 1989). The relationship has also been verified in many other studies including Choi and Chung (2012), Gong, Xu, and Yu (2004), and others.

Additionally, another PEOU relationship was identified through the SEM model modification indices not in the original model that was supported. Perceived ease of use was found to have a significant positive influence on behavioral intention. This means that the stronger perceived ease of use is, the stronger the intention is to use sUASs for data gathering. Perceived ease of use is like the perceived behavioral control factor. Perceived behavioral control influencing behavioral intention is a basic premise of the TPB model (Ajzen, 1991). As previously stated for the VMUTES model, only perceived ease of use was used to avoid duplication. Therefore, the relationship of perceived ease of use to behavioral intention in the VMUTES model is supported by the literature. Additionally, PEOU was found to have an indirect positive influence on BI which is a basic premise of the TAM model (Davis, 1989). Finally, PEOU was found to have an indirect positive influence on AB as depicted in Lee's (2009) research combined TAM/TPB model.

Practically, perceived ease of use has a positive influence on perceived usefulness of sUASs for data gathering and the will to use sUASs for data gathering as well as a positive influence on actual behavior. In the context of using sUASs for data gathering, elements of perceived ease of use include mental and physical effort, interaction with the sUAS, knowledge and experience, and sUAS interaction difficulty. In an effort to improve perceived ease of use, formal and informal training could be used. Perhaps stakeholders could also provide formal sUAS use for data gathering training through instruction manuals or other media. Additionally, individuals could receive hands-on training from instructors, friends, or peers.

Subjective norms (SN). Subjective norms refer to the perceived social pressure by parents, spouse, friends, etcetera desiring the individual to use or not use sUASs for data gathering. In this study, subjective norms had a significant positive influence on perceived usefulness. This means that the stronger the subjective norms, the stronger the perceived usefulness is for using sUASs for data gathering. This relationship is supported in the literature. One example is the study of intention to use technology among pre-service teachers where this relationship was hypothesized and supported (Teo, 2012). SN was also found to have an indirect positive influence on BI and on AB which is supported by the TPB model (Ajzen, 1991).

From a practical standpoint, the views of family, friends, and significant others is important to individuals when deciding whether to use sUASs for data gathering. Thus, this research provides a new understanding of one of the individual motivations for using sUASs for data gathering. This finding makes sense given that the use of sUASs for data gathering is a relatively new technology that is rapidly emerging, and information is rapidly changing. Therefore, individuals turn to others that are important to them for opinions on using sUASs for data gathering. In essence, use of sUASs for data gathering can be strongly influenced by what others think. Therefore, stakeholders wanting to improve social norms should not only focus on the individual level but also on the organizational and society levels as well.

Knowledge of regulations (KR). Knowledge of regulations is the comprehension of federal, state, and local laws and guidelines that apply to sUAS operations. The original positive hypothesis relating knowledge of regulations to attitude toward use was not supported in the VMUTES model. However, a new relationship was identified by the SEM model modification indices: knowledge of regulations to actual behavior. Knowledge of regulations has a significant positive influence on actual behavior. Therefore, the stronger the knowledge of applicable regulations, the stronger the possibility of individuals actually using sUASs for data gathering. This relationship is also supported in the literature. Concerning literature support, few studies could be found that incorporated the knowledge of regulations variable. The closest variable found was self-reported knowledge about computers (Alshare et al., 2011). However, since knowledge of regulations can be considered an external variable to the TAM and/or TPB models, several studies verified the relationship between an external variable and actual behavior. Some examples include Donald, Cooper, and Conchie (2014) and Venkatesh et al. (2003). Interestingly, additionally, in this study, while KR had a positive direct influence on AB, KR was also found to have an indirect negative influence on BI and an indirect negative influence on AB.

Few studies have incorporated the KR factor. As discussed previously, the closest factor that could be found was self-reported knowledge about computers. Thus, because the KR factor relationship was supported, future research studies involving aviation or higher risk technologies should consider using the VMUTES model or similar model which includes the KR factor.

Practically, research results indicate individuals do not consider knowledge of regulations pertaining to the operation of sUASs for data gathering when forming their attitude toward using sUASs for data gathering. However, knowledge of regulations of sUAS data gathering operations does have a positive effect on actual use of sUASs for data gathering. This makes sense as there are many aspects of regulated flight that must be considered when flying sUASs for data gathering including altitude, airspace, safety, aircraft deconfliction, etcetera (FAA, AC-107-2, 2016). For stakeholders, knowledge of regulations could possibly be improved, for example, by more media campaigns and required testing. The indirect negative effect of knowledge of regulations on the will to use and actual use of sUASs for data gathering could possibly be explained by the feeling of being overregulated or lack of knowledge of regulations reflected in the additional comments of the questionnaire previously discussed in Chapter IV. Finally, as discussed previously, few studies have incorporated the knowledge of regulations factor. Therefore, this aspect of the research is considered another contribution to the body of knowledge.

Perceived risk (PR). Perceived risk, the perception individuals form and revise based on possible dangers of using sUASs for data gathering had a significant negative influence on attitude toward use. This means that the higher the perceived risk, the more likely it is for individuals to have a weaker attitude toward using sUASs for data gathering. Concerning literature support, Lee (2009) in his study of factors influencing the adoption of internet banking, confirmed that some elements of risk did negatively significantly affect attitude toward use, supporting this relationship.

SEM model modification indices also identified another valid perceived risk relationship. Perceived risk was found to have a significant negative influence on perceived usefulness. This means that the higher the perceived risk, the weaker the perceived usefulness of sUASs for data gathering is. This relationship was also tested and proven in a combined TAM/TPB study by Lee (2009). Consistent with a negative influence, PR was also found to have a negative indirect influence on BI and on AB. This relationship is depicted in Lee’s (2009) TAM/TPB research model.

Notably, perceived risk has been used in few aviation studies. However, this study demonstrated the need to include the perceived risk factor in future aviation and other higher risk technology studies using a model such as the VMUTES model.

From a practical standpoint, perceived risk has a negative influence on attitude toward use and perceived usefulness, both of which indirectly affect actual use of sUASs for data gathering. Thus, perceived risk provides a psychological effect on the individual toward using sUASs for data gathering. As discussed previously, the elements of perceived risk include: (a) physical, (b) performance, (c) time, (d) financial, (e) social, (f) security, (h) privacy, and (i) psychological (Featherman & Pavlou, 2003; Lee, 2009). To improve perceived risk, stakeholders must address the perceived risk elements of concern to eliminate or minimize them. For example, in this research, respondents indicated a slight concern for financial risk. Therefore, as an example, manufacturers could attempt to reduce the purchase price and operating costs of the sUAS to reduce financial perceived risk and therefore possibly improve attitude toward use and perceived usefulness, thus, most likely improving actual use as well.

Discriminant validity. Persistent problems of insufficient evidence to determine discriminant validity during the CFA model process was an unexpected result of this study. All CFA model iterations had some degree of this discriminant validity problem. The initial CFA model indicated there was insufficient evidence to determine discriminant validity for all factors except for PR using the Fornell-Larcker criterion. The final CFA model also indicated a lack of evidence to establish acceptable discriminant validity for PU, BI, ATU, and AB. A lack of discriminant validity raises questions about whether statistically significant parameters are really supported (Voorhees, Brady, Calantone, & Ramirez, 2016).

It is not uncommon for the Fornell-Larker approach to fail to provide enough evidence to determine discriminant validity (Hensler, Ringle, & Sarstedt, 2015). This failure is more prevalent when factor loadings are between 0.60 and 0.80, as a large percentage (73%) were in this study (Hair et. al, 2017). Therefore, heterotrait-monotrait (HTMT) ratios were computed as an alternative method with the criteria of values of 0.90 generally suggested with values less than 1 acceptable used (Hult, Ringle, & Sarstedt, 2017). All HTMT ratios met the suggested or acceptable criteria meaning discriminant validity was satisfactory. Another method to solve discriminant validity using second order factors was briefly explored, but not thoroughly vetted in this study since the HTMT ratio approach was successful and using second-order factors would result in the loss of being able to test some hypotheses due to combined factors.

Other studies have exhibited unacceptable discriminant validity or failed to demonstrate the criterion testing. Although the UTAUT model was not used in this study, it is worthy to compare results since the UTAUT incorporates the TAM and TPB elements among others. Techau, in the first-ever use of the UTAUT2 model to study general aviation pilot acceptance and adoption of electronic flight bag technology, experienced unacceptable discriminant validity (Techau, 2018). In his study, deleting three of the model constructs was necessary to meet discriminant validity requirements. Techau (2018) also cites four other studies using the UTAUT2 model where major modifications to the model were required to meet discriminant validity requirements. Highlighting other instances, Voorhees et al. (2016) discovered in their research that 85.3% of the reviewed marketing studies failed to establish discriminant validity. The same authors support the HTMT technique, as used in this study, since it can be applied to large or small sample sizes. Lastly, none of the TAM and/or TPB studies examined in the literature review experienced difficulties. However, in a search for other TAM and/or

TPB with discriminant validity problems, Chan and Bishop (2013) in a study of a moral basis for recycling using a TPB model noted failed discriminant validity. The authors argued that the discriminant validity was acceptable due to the definition being too stringent and unrealistic, and the correlation between two factors was lower than another comparable study.

Given the studies of Techau (2018), Voorhees et al. (2016), and Chan and Bishop (2013), it is evident that many UTAUT, TPB, and TAM studies did not consider the HTMT discriminant methodology, but rather used the Fornell-Larker approach or other rationale which may have resulted in questionable outcomes. Therefore, this research provides another contribution to the body of knowledge as to why the HTMT methodology should be considered especially when factor loadings of 0.6 to 0.8 are more prevalent (Hair et al., 2017).

Research question 1. The first research question was "To what extent does the VMUTES model explain individuals' intentions to use sUASs for data gathering?" The adjusted SEM model fit is the primary source to answer Research Question 1 which was X2 = 1647.774, df = 742, $p < .001$, CMIN/df = 2.221, GFI = .887, AGFI .869, NFI = .907, CFI = .946, and RMSEA = .043. As previously discussed, GFI and AGFI are sensitive to sample size and therefore were deemed acceptable given the 662-case sample size in this study (Hair et al., 2010). Thus, the model fit and therefore the model was judged as good for explaining an individual's intentions to use sUASs for data gathering. Additionally, as discussed in Chapter IV, the overall predictive power of the VMUTES SEM model of the predictors on BI is .896 and on AB is .785, which is strong.

Research question 2. The second research question was “what factors at the .05 significance level influence individuals’ intentions to use sUASs for data gathering?” The factors that influence individuals’ intentions to use sUASs for data gathering include behavioral intention (BI), attitude toward use (ATU), perceived usefulness (PU), perceived ease of use (PEOU), subjective norms (SN), knowledge of regulations (KR), and perceived risk (PR). The TAM and TPB components of the model had the strongest influence while the external variables of KR and PR, while significant, had the weakest influence of the all the relevant factors.

Concerning indirect effects, PU, PEOU, and SN had a positive indirect influence on BI with PU having the strongest positive influence and PR having the strongest negative indirect influence on BI. Additionally, ATU, PEOU, PU, SN, KR, and PR had an indirect influence on AB with ATU having the strongest indirect positive influence and PR having the greatest indirect negative influence on AB. Having the knowledge of these influencing direct and indirect influencing factors allows stakeholders to target them to improve actual use of sUASs for data gathering. Examples of this approach of addressing influential factors to possibly improve actual use were provided in the VMUTES model results section for each factor.

Conclusions

The present study was the first study applying the new VMUTES model to an aviation application. The purpose of the study was twofold: (a) to determine how well the new VMUTES model explained individuals’ intentions to use sUASs for data gathering and (b) to determine the factors that influence individuals’ intentions to use sUASs for data gathering. Persistent problems with discriminant validity required the

HTMT approach to attain satisfactory discriminant validity deserving further research. However, the study intents were met filling a literature gap in the aviation domain while providing an expanded demographic database concerning operating sUASs for data gathering. Additionally, the study highlighted two external factors that should be included in future aviation and other risk technology studies: perceived risk and knowledge of regulations. Therefore, because of the success of this study with a tested model and associated factors, it is theorized then that the VMUTES model through further research and refinement could provide a useful tool to use in the aviation and other higher risk technology domains.

Theoretical implications. First, this study demonstrates that the VMUTES model can be successfully applied to predict individuals' intentions to use and thus actual use of sUASs for data gathering, and advances the understanding of academia, industry, and government agencies. Therefore, a literature gap is filled by creating the new VMUTES model since prior studies and ground theories involving TAM and/or TPB did not include all the specific variables needed to determine intended use of sUASs for data gathering.

The VMUTES model is unique in that it incorporates the factors necessary to study sUAS for data gathering that other models did not, including the UTAUT, TAM, TPB, and TAM/TPB. The VMUTES model incorporates the perceived risk and knowledge of regulations factors which few studies have incorporated representing a significant contribution to the body of knowledge.

More importantly, this study, by validating the usefulness of the VMUTES model, provides a new tool that could be used in studies throughout a broad realm of technology applications beyond the scope of using sUASs for data gathering where previous ground theory models failed to provide the specific factors needed. Examples of technology study possibilities involving higher risk technologies include the automobile and railroad transportation realms and other aviation applications. Additionally, although this study was limited to U.S. users only, the new VMUTES model can be applied similarly to expanded markets overseas as well since the study can be easily duplicated.

Second, the demographic data in this study can be added to the already existing FAA statistics. Additionally, newly derived demographic data provided to the FAA and other stakeholders could expand knowledge of the use of sUASs for data gathering to appropriately focus efforts while saving those entities' resources required to research that information.

Third, the VMUTES model incorporated the perceived risk factor, expanding research knowledge. While perceived risk has been studied in the information technology realm with TAM and/or TPB components, few aviation studies incorporated perceived risk since 1975. By incorporating the perceived risk factor, this research validated the need to include the perceived risk factor and applicable risk elements in higher risk technology applications such as aviation. As previously discussed, the risk elements that should be considered include: (a) physical, (b) performance, (c) time, (d) financial, (e) social, (f) security, (g) privacy, and (h) psychological risk (Featherman & Pavlou, 2003; Lee, 2009). As discussed previously, if the perceived risk factor and associated elements are not included, then a disparity can exist between society and the implementing or organization's level of perceived risk resulting in technology acceptance being slowed or halted (Hunter, 2009; Myers, 2016). However, if the disparity is identified, then the implementing organization can act to reduce the disparity by targeting the relevant perceived elements to reduce the disparity and improve technology acceptance.

Fourth, conducting a pretest and pilot study further reinforced the need for these processes in research. Survey questions were vetted, the research process tested, and skill of using Amazon Mechanical Turk gained. Thus, doing so increased the validity of the research study.

Practical implications. The present research took measures to ensure the generalizability, reliability, and validity of the study. Because of that, these study results can have significant practical implications concerning stakeholders' marketing and sUAS used for data gathering operator behaviors. Three practical implications are discussed.

First, expanded demographic data could provide stakeholders information to make better policy, marketing, and operational decisions. For example, most respondents were male, in the 18-40 years age group, had a bachelor's degree, earned an income of $51,000 to $100,000, are commercial employees or self-employed, are mostly modelers, and have less than 6 months to less than 3 years of experience. Thus, stakeholders can target marketing strategies to these demographics to achieve stated goals while optimizing resources.

Second, by knowing the factors that influence sUAS for data gathering, the FAA, industry, and other stakeholders can understand and as needed, target those factors that facilitate individuals' behavioral intentions toward using a sUAS for data gathering and minimize or eliminate those factors that hinder intended use. For example, concerning knowledge of regulations, the average mean of all knowledge of regulations was 4.81, somewhere between “neutral” and “somewhat agree” meaning most respondents did not feel very strongly that they knew federal, state, or local laws and guidelines or were familiar with the FAA UAS website. The two weakest areas were knowledge of FAA Advisory Circular 91-57A and Public Law 112-95. Perhaps an FAA media campaign targeting UAS local clubs and organizations would help to increase that knowledge. Concerning perceived risk, while it was a significant factor in the model and should be considered, most risk areas fell in the area of between “neutral” and “somewhat disagree” meaning respondents on average were not that concerned about the risks involved with operating sUASs for data gathering. However, of those risks type scored that the FAA and other government entities have an influence over include privacy and security risk. For industry, financial risk was slightly above neutral indicating cost is a consideration in operating sUASs for data gathering.

Similarly, taking note of the factors with the strongest influences of intended or actual use of sUASs for data gathering can aid stakeholders in learning about and targeting sUAS for data gathering operators creating a proactive versus a reactive strategy. For example, perceived usefulness had a strong influence on attitude toward use which was a strong influence on intended use. Thus, industry could possibly survey the 18-40 years of age sUAS operators discussed earlier to determine those operations they deem important to increase perceived usefulness.

Limitations of the study. Five limitations of this study are presented. First, this study only included voluntary users of sUAS for data gathering in the United States. Therefore, generalization of results is applicable to the U.S. population only due to cultural factors that may influence results (Alshare et al., 2011; Choi, 2013). However, using the same methodology, this study could be applied in other countries.

Second, this study examined sUAS use for data gathering during a selected time period and cannot provide generalization of results beyond that era since sUAS technology and use as well as sUAS regulatory guidance is changing rapidly (Babbie, 2016). However, since the study can be easily replicated, more research can be conducted to verify the results of this study.

Third, while discriminant validity was achieved using HTMT ratios, it was not achieved using the Fornell-Larcker approach. As stated previously, this was theorized to be because many of the factor loadings were in the range of 0.60 and 0.80 and only differed slightly. However, it may also mean the new VMUTES model requires more modifications. To determine this, more research is needed as explained in the recommendations section.

Fourth, Amazon Mechanical Turk has been shown to be more representative than and as least as diverse as traditional samples (Buhrmester, Kwang, and Gosling, 2011), and this study generally validated that. However, the sampling frame may miss some sUAS users who do not participate in AMT, but this is the same limitation with the traditional random sampling when we choose a specific sampling frame.

Fifth, this research was focused on individuals' behavioral intentions toward using sUASs for data gathering. While individuals make up society, the population of individuals using sUASs for data gathering in this study represent only a small segment of society. Therefore, conclusions are limited to the sampled population and cannot be generalized to society or organizations without further research.

Recommendations for future research. Nine recommendations are suggested to guide future research of sUASs used for data gathering, other aviation technologies, and other higher risk technologies such as other transportation realms and related new technologies.

First, further research should incorporate Amazon Mechanical Turk workers. Most likely, an adequate number of responses will be attained in a relatively short time period that represents a random-sampled population. However, more research is needed on the interface between Amazon Mechanical Turk and other external survey websites like Survey Monkey to optimize survey construction and logic to minimize non-usable responses and to avoid paying participants who are not deserving.

Second, given that the FC factor lacked acceptable convergent and discriminant validity, it is suggested to further research the question why. To do so, it is suggested that the FC factor include four second-order factors of (1) legal, (2) training, (3) government regulations, and (4) supporting infrastructure. Additionally, survey questions should be added as necessary to measure the four second-order factors. The legal factor should include how well the legal environment facilitates the use of sUASs for data gathering. The training factor should include provided training and/or operating instructions. The government regulations factor should include how well government regulations facilitate the use of sUASs for data gathering. The supporting infrastructure factor should include maintenance, supporting materials and information, and availability of company or personal assistance. Then, the results should be compared between the two studies to evaluate differences and similarities.

Third, since survey questions were deleted because of overlapping or confusion with other questions and AVE was initially low for some factors such as FC indicating more error than variance explained and ultimately requiring deletion, further action is desired. Therefore, the survey items should be refined to improve the VMUTES model robustness for use with other higher risk technologies, to improve validity, and to improve generalizability.

Fourth, further research should be accomplished to verify individual and operational demographic characteristic information collected in this study. While the respondent data generally paralleled FAA and/or census data, there was some noted differences. Additionally, new demographic information generated by this study includes current occupation, sUAS data gathering experience level, sUAS formal training, possession of a 14 CFR Part 62 FAA manned operating certificate, manned operating experience, type of sUAS used, sUAS registration, amount paid for the sUAS, and type of sensor(s) used on sUASs for data gathering. Therefore, it is prudent to conduct more research to verify the demographic data obtained in this study.

Fifth, while the respondents who chose to answer the additional comments question was overwhelmingly small, some areas that may warrant further research include knowledge of and perception of regulations governing individuals using sUASs for data gathering, operational requirements such as formal training, business uses, and registration.

Sixth, while this study provides a firm foundation overall of data for sUASs for data gathering, more research in the sUAS data gathering area is warranted. Demographic type of operation data provided 13 applications of sUASs used for data gathering. Therefore, this same study methodology should be used to further study those applications to derive more detailed data for a particular area of operation to determine the influencing factors and associated risks. This is purposeful, especially if the FAA or another stakeholder entity wishes to increase the number of operators in an area such as agriculture.

Also, new applications using UAS aircraft are on the horizon including home package delivery. Thus, this model should be used to establish a baseline of data in the initial stages of operation as a proactive measure to identify problem areas.

Seventh, the media influence on individuals' behavioral intentions to use sUASs for data gathering was addressed in the survey as part of social perceived risk. However, because media influence was grouped with society influence, more research is required to discern the influences of media versus society.

Eighth, to discern the potential differences in results between modeler, civil, and public user populations, the data should be split according to the three populations, data analysis completed for each population, and the results compared to highlight any differences between populations.

Ninth, stakeholders including the FAA, sUAS users, sUAS vendors, and other higher risk technologies should use this study to their benefit. The FAA and sUAS vendors can use the demographic data to identify a target population and address influencing factors to increase the number of users. For the FAA, valuable new demographic data is added providing a deeper insight including perceived risk areas of concern that could be addressed where applicable to improve safety. For sUAS vendors, the demographic information provides information of where to target marketing information. Additionally, by addressing influencing factors that vendors can influence, such as perceived usefulness, perceived ease of use of sUASs, and the perceived risks of time, performance, financial, and security for example, sales and actual use could possibly be increased. For sUAS users, this study could serve to educate and broaden individual perspectives by providing a community versus individual perspective. For example, as shown in the additional comments section, it could possibly highlight the lack of individual regulatory knowledge, provide a proactive versus reactive individual risk assessment, and provide individuals a community versus individual perspective.

Additionally, stakeholders in other higher risk technology areas such as the automobile and railroad industry as well as other aviation applications should use the same research approach and model given the incorporation of perceived risk which is needed for higher risk technologies. Doing so could possibly provide feedback on problem areas and needed focus on relevant influencing factors, risks, etcetera in a more proactive way.

REFERENCES

Aeronautics and Space, 14 C.F.R. pt. 1 (2017). Retrieved from https://www.ecfr.gov/cgi-bin/text-idx?mc=true&node=pt14.2.107&rgn=div5

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211. doi:10.1016/0749-5978(91)90020-T

Ajzen, I. (2002). Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior. *Journal of Applied Social Psychology*, *32*(4), 665-683. doi:10.1111/j.1559-1816.2002.tb00236.x

Alshare, K. A., Mesak, H. I., Grandon, E. E., & Badri, M. A. (2011). Examining the moderating role of national culture on an extended technology acceptance model. *Journal of Global Information Technology Management, 14*(3), 27-53. doi: 10.1080/1097198X.2011.10856542

Amos for Windows (Version 20) [Computer Software]. Armonk, NY: IBM Corp.

Andersen, M. (2015). Technology device ownership: 2015. *Pew Research Center*. Retrieved from www.pewinternet.org/2015/10/29/technology-device-ownership-2015/

Armitage, C. J., & Conner, M. (2001). Efficacy of the theory of planned behaviour: A meta-analytic review. *British Journal of Social Psychology, 40*, 471-499. doi:10.1348/014466601164939

Arterburn, D., Ewing, M., Prabhu, R., Zhu, F., & Francis, D. (2017). *FAA UAS Center of Excellence task A4: UAS ground collision severity evaluation, revision 2*.

Association for Unmanned Vehicle Systems International (AUVSI). (2017). *State legislation map.* Retrieved from http://cqrcengage.com/auvsi/statelegmap

Ayranci, Z. B. (2017). Use of drones in sports broadcasting. *The Entertainment and Sports Lawyer, 33*(3), 79.

Babbie, E. (2016). *The practice of social research*. (14th ed.). Boston, MA: Cengage Learning.

Babbie, E. (1990). *Survey research methods* (2nd ed.). Belmont, CA: Wadsworth Publishing Company.

Bag, S. (2015). A short review on structural equation modeling: Applications and future research directions. *Journal of Supply Chain Management Systems, 4*(3). doi:10.21863/jscms/2015.4.3.014

Beeman, M. (2017). A unified drone theory. *Indiana Review, 39*(1), 50.

Bennett, C., Khangura, S., Brehaut, J. C., Graham, I. D., Moher, D., Potter, B. K., & Grimshaw, J. M. (2010;2011;). Reporting guidelines for survey research: An analysis of published guidance and reporting practices. *PLoS Medicine, 8*(8), e1001069. doi:10.1371/journal.pmed.1001069

Bickart, B., & Schmittlein, D. (1999). The distribution of survey contact and participation in the United States: Constructing a survey-based estimate. *Journal of Marketing Research,* Spring, 286-294. doi:10.2307/3152100

Bissonnette, G. R. (2016). Eyes in the skies: Regulating drones. *Privacy Journal, 42*(3), 3.

Blitz, M. J., Grimsley, J., Henderson, S. E., & Thai, J. (2015). Regulating drones under the first and fourth amendments. *William and Mary Law Review, 57*(1), 49.

Bloss, R. (2014). Unmanned vehicles while becoming smaller and smarter are addressing new applications in medical, agriculture, in addition to military and security. *The Industrial Robot, 41*(1), 82-86. doi:10.1108/IR-03-2013-410

Blunch, N. J., & ProQuest (Firm). (2008). *Introduction to structural equation modelling using SPSS and AMOS* (2nd ed.). Los Angeles: SAGE. doi:10.4135/9781526402257

Boksberger, P. E., Bieger, T., & Laesser, C. (2007). Multidimensional analysis of perceived risk in commercial air travel. *Journal of Air Transport Management. 13*(2), 90-96. doi:10.1016/j.jairtraman.2006.10.003

Bracken-Roche, C. (2016). Domestic drones: The politics of verticality and the surveillance industrial complex. *Geographica Helvetica, 71*(3), 167-172. doi:10.5194/gh-71-167-2016

Brice, R. G., & Sifferd, K. L. (2017). Domestic drone surveillance: The court's epistemic challenge and Wittgenstein's actional certainty. *Louisiana Law Review, 77*(3), 805.

Broman Toft, M., Schuitema, G., & Thøgersen, J. (2014). Responsible technology acceptance: Model development and application to consumer acceptance of smart grid technology. *Applied Energy, 134*, 392-400. doi:10.1016/j.apenergy.2014.08.048

Buaphiban, T., & Truong, D. (2017). Evaluation of passengers' buying behaviors toward low cost carriers in southeast Asia. *Journal of Air Transport Management, 59*, 124-133. doi:10.1016/j.jairtraman.2016.12.003

Buchan, H. F. (2005). Ethical decision making in the public accounting profession: An extension of Ajzen’s theory of planned behavior. *Journal of Business Ethics*, 61(2), 165-181. doi:10.1007/s10551-005-0277-2

Buhrmester, M., Kwang, T., & Gosling, S. D. (2011). Amazon's mechanical turk: A new source of inexpensive, yet high-quality, data? *Perspectives on Psychological Science, 6*(1), 3-5. doi:10.1177/1745691610393980

Bureau of Labor Statistics, U. D. O. L. (2018). Occupational outlook handbook. Washington, DC: Bureau of Labor Statistics, U.S. Department of Labor. Retrieved from https://www.bls.gov/ooh/transportation-and-material-moving/airline-and-commercial-pilots.htm#tab-4

Byrne, B. M. (2010). *Structural equation modeling with AMOS*. New York: Taylor and Francis Group.

Campolettano, E. T., Bland, M. L., Gellner, R. A., Sproule, D. W., Rowson, B., Tyson, A. M., & Rowson, S. (2017). Ranges of injury risk associated with impact from unmanned aircraft systems. *Annals of biomedical engineering*, *45*(12), 2733-2741.

Casper, E. S. (2007). The theory of planned behavior applied to continuing education for mental health professionals. *Psychiatric Services, 58*(10), 1324-9. doi:10.1176/ ps.2007.58.10.1324

Cayne, B. S. & Lechner, D. E. (Eds.). (1991). *The new lexicon Webster's encyclopedic dictionary of the English language.* New York, NY: Lexicon Publications.

Chan, L., & Bishop, B. (2013). A moral basis for recycling: Extending the theory of planned Behaviour. *Journal of Environmental Psychology*, 36, 96-102. doi:10.1016/j.jenvp.2013.07.010

Chan, K., Prendergast, G., & Ng, Y. (2016). Using an expanded theory of planned behavior to predict adolescents' intention to engage in healthy eating. *Journal of International Consumer Marketing, 28(*1), 16-27. doi:10.1080/089611530.2015. 1089088

Chang, K., & Chang, C. (2009). Library self-service: Predicting user intentions related to self-issue and return systems. *The Electronic Library, 27*(6), 938-949. doi:10.1108/02640470911004048

Chen, M., & Tung, P. (2014). Developing an extended theory of planned behavior model to predict consumers' intention to visit green hotels. *International Journal of Hospitality Management, 36*, 221. doi:10.1016/j.ijhm.2013.09.006

Chen, S. (2016). Using the sustainable modified TAM and TPB to analyze the effects of perceived green value on loyalty to a public bike system. *Transportation Research Part A, 88*, 58-72. doi:10.1016/j.tra.2016.03.008

Cheng, T. C. E., Lam, D. Y. C., & Yeung, A. C. L. (2006). Adoption of internet banking: An empirical study in Hong Kong. *Decision Support Systems, 42*(3), 1558-1572. doi:10.1016/j.dss.2006.01.002

Chirayath, V., & Earle, S. A. (2016). Drones that see through waves – preliminary results from airborne fluid lensing for centimetre-scale aquatic conservation. *Aquatic Conservation: Marine and Freshwater Ecosystems, 26*(S2), 237-250. doi:10.1002/aqc.2654

Choi, S. (2013). Public perception and acceptability of technological risk: Policy implications for governance. *Journal of Convergence Information Technology, 8*(13), 605-615. Retrieved from http://www.globalcis.org/jcit/home/index.html

Choi, G., & Chung, H. (2012). Elaborating the technology acceptance model with social pressure and social benefits for social networking sites (SNSs). *Proceedings of the American Society for Information Science and Technology, 49*(1), 1-3. doi:10.1002/meet.14504901376

Clothier, R. A., Greer, D. A., Greer, D. G., & Mehta, A. M. (2015). Risk perception and the public acceptance of drones. *Risk Analysis, 35*(6), 1167-1183. doi:10.1111/risa.12330

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly, 19*(2), 189-211. doi:10.2307/249688

Connelly, L. M. (2008). Pilot studies. *Medsurg Nursing: Official Journal of the Academy of Medical-Surgical Nurses* 17(6), 411.

Creswell, J. W. (2014). *Research design: Qualitative, quantitative, and mixed methods approaches* (4th ed.). Thousand Oaks, CA: Sage.

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika, 16*(3), 297-334. doi:10.1007/BF02310555

Cruzan, M. B., Weinstein, B. G., Grasty, M. R., Kohrn, B. F., Hendrickson, E. C., Arredondo, T. M., & Thompson, P. G. (2016). Small unmanned aerial vehicles (micro-UAVs, drones) in plant ecology. *Applications in Plant Sciences, 4*(9), 1600041. doi:10.3732/apps.1600041

Cutler, M., McLain, T., Beard, R., & Capozzi, B. (2010). *Energy harvesting and mission effectiveness for small unmanned aircraft.* doi:10.2514/6.2010-8037

Czaja, S. J., Charness, N., Fisk, A. D., Hertzog, C., Nair, S. N., Rogers, W. A., & Sharit, J. (2006). Factors predicting the use of technology: Findings from the center for research and education on aging and technology enhancement (CREATE). *Psychol. Aging, 21*(2), 333-352. doi:10.1037/0882-7974.21.2.333

Czerniak, C. M., & Lumpe, A. T. (1996). Predictors of science fair participation using the theory of planned behavior. *School Science and Mathematics, 96*(7), 355. doi:10.1111/j.1949-8594.1996.tb15853.x

Dalamagkidis, K., Valavanis, K. P., & Piegl, L. A. (2008). On unmanned aircraft systems issues, challenges and operational restrictions preventing integration into the national airspace system. *Progress in Aerospace Sciences, 44*(7), 503-519. doi:10.1016/j.paerosci.2008.08.001

Davis, F. D., (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. doi:/10.2307/249008

Department of Transportation, *Federal Aviation Administration Final Rule*, 14 C.F.R. § 1.1 (2018). Retrieved from https://www.gpo.gov/fdsys/pkg/CFR-2002-title14-vol3/pdf/CFR-2002-title14-vol3-chapI-toc-id4.pdf

Discoverpolicing.org (2018). *Basic requirements*. Retrieved from http://www.discoverpolicing.org/what_does_take/?fa=requirements

Dobbie, M. F., & Brown, R. R. (2014). *A framework for understanding risk perception, explored from the perspective of the water practitioner.* doi:10.1111/risa.12100

Domestic drones: Balancing privacy and safety with innovation and opportunity (2016). Washington: Congressional Digest.

Donald, I. J., Cooper, S. R., & Conchie, S. M. (2014). An extended theory of planned behaviour model of the psychological factors affecting commuters' transport mode use. *Journal of Environmental Psychology, 40*, 39-48. doi:10.1016/j.jenvp.2014.03.003

Drones may search for people lost in the woods. (headline science: April/May 2016, current news in science research). (2016). *The Science Teacher, 83*(4), 17.

Elias, B. (2016). *Unmanned operations in domestic airspace: U.S. policy perspectives and the regulatory landscape*. Congressional Research Service, Washington, D.C. Retrieved from http://nationalaglawcenter.org/wp-content/uploads/assets/crs/R44352.pdf

Embry-Riddle Aeronautical University. (2017*). Institutional Review Board.* Retrieved from http://research.erau.edu/faculty-resources/institutional-review-board/index.html (website)

FAA Modernization and Reform Act of 2012, Pub L. No. 112-95, § 40101 11 Stat. 126. (2012a). Retrieved from https//www.gpo.gov/fdsys/pkg/PLAW-112pub95/htm/PLAW-112publ95.htm

FAA Modernization and Reform Act of 2012, 49 U.S.C. § 40101. (2012b). Retrieved from https://www.gpo.gov/fdsys/pkg/USCODE-2011-title49/html/USCODE-2011-title49.htm

Fan, X., Thompson, B., & Wang, L. (1999). Effects of sample size, estimation methods, and model specification on structural equation modeling fit indexes. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 56-83. doi:10.1080/10705519909540119

Federal Aviation Administration. (2019). *UAS data exchange (LAANC)*. U.S. Department of Transportation, Washington D.C. Retrieved from https://www.faa.gov/uas/programs_partnerships/data_exchange/

Federal Aviation Administration (2018). *The administrator's fact book*. U.S.

Department of Transportation, Washington, D.C. Retrieved from https://www.faa.gov/news/media/2018_administrators_fact_book.pdf

Federal Aviation Administration (2017a). *FAA aerospace forecast fiscal years 2017-2037*. U.S. Department of Transportation, Washington, D.C. Retrieved from https://www.faa.gov/data_research/aviation/aerospace_forecasts/media/FY2017-37_FAA_Aerospace_Forecast.pdf

Federal Aviation Administration. (2017b). *Unmanned aircraft systems*. U.S. Department of Transportation, Washington D.C. Retrieved from https://www.faa.gov/uas/

Federal Aviation Administration. (2017c). *Interpretation of the special rule for model aircraft.* U.S. Department of Transportation, Washington D.C. Retrieved from https://www.faa.gov/uas/media/model_aircraft_spec_rule.pdf

Federal Aviation Administration. (2017d). U.S. civil airmen statistics. U.S. Department of Transportation, Washington, D.C. Retrieved from https://www.faa.gov/data_research/aviation_data_statistics/civil_airmen_statistics

Federal Aviation Administration (2017e). *The administrator's fact book*. U.S. Department of Transportation, Washington, D.C. Retrieved from https://www.faa.gov/news/media/2017_administrators_fact_book.pdf

Federal Aviation Administration (2016a). *Model aircraft operating standards*. (Advisory Circular 91-57A Change: 1). U.S. Department of Transportation, Washington, D.C. Retrieved from https://www.faa.gov/documentLibrary/media/Advisory_Circular/AC_91-57A_Ch_1.pdf

Federal Aviation Administration (2016b). *Small unmanned aircraft systems (sUAS).*

(Advisory Circular 107-2). U.S. Department of Transportation, Washington, D.C. Retrieved from https://www.faa.gov/regulations_policies/advisory_circulars/index.cfm/go/document.information/documentID/1019962

Federal regulation of domestic drones: Control of public, civil, and model aircraft operations. (2016). *Congressional Digest, 95*(6), 7.

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human - Computer Studies, 59*(4), 451-474. doi:10.1016/S1071-5819(03)00111-3

Field, A. (2013). *Discovering statistics using IBM SPSS statistics* (4th ed.). Thousand Oaks, CA: Sage Publishing.

FireRecruite.com. (2018). *What are the requirements to be a firefighter?* Retrieved from https://www.firerecruit.com/articles/1063916-What-are-the-requirements-to-be-a-firefighter

Floreano, D., & Wood, R. J. (2015). Science, technology and the future of small autonomous drones. *Nature, 521*(7553), 460-466. doi:10.1038/nature14542

Foster, R. L. (2013). What a pilot study is and what it is not. *Journal for Specialists in Pediatric Nursing, 18*(1), 1-2. doi:10.1111/jspn.12015

Frew, E. W., & Brown, T. X. (2008). Airborne communication networks for small unmanned aircraft systems. *Proceedings of the IEEE, 96(12),* 2008-2037. doi:10.1109/JPROC.2008.2006127

Furr, M. (2011). *Scale construction and psychometrics for social and personality psychology* (1st ed.). London: SAGE Publications. doi:10.4135/9781446287866

Gallacher, D. (2016). Drones to manage the urban environment: Risks, rewards, alternatives. *Journal of Unmanned Vehicle Systems, 4*(2), 115-124. doi:10.1139/juvs-2015-0040

Ghazizadeh, M., Lee, J. D., & Boyle, L. N. (2012). Extending the technology acceptance model to assess automation. *Cognition, Technology & Work, 14*(1), 39-49. doi:10.1007/s10111-011-0194-3

Gillani, B., & Gillani, R. (2015). From droughts to drones: An after-school club uses drones to learn about environmental science. *Science and Children, 53*(2), 50. doi:10.2505/4/sc15_053_02_50

Gong, M., Xu, Y., & Yu, Y. (2004). An enhanced technology acceptance model for web-based learning. *Journal of Information Systems Education, 15*(4), 365.

Gregory, T. S., Tse, Z. T. H., & Lewis, D. (2015). Drones: Balancing risk and potential. *Science (New York, N.Y.), 347*(6228), 1323-1323. doi:10.1126/ science.347.6228.1323-a an

Grose, T. K. (2016). Flight risk. *ASEE Prism, 25*(8), 30-33.

Groves, R. M., Cialdini, R. B., & Courier, M. P. (1992). Understanding the decision to participate in a survey. *Public Opinion Quarterly, 56,* 475-95. doi:10.1086 269338

Groves, R. M., Fowler Jr., F. J., Couper, M. P., Lepkowsiki, J. M., Singer, E., & Tourangeau, R. (2009). *Survey Methodology* (2nd ed.). Hoboken, NJ: Wiley.

Gupta, N., Fischer, R. H., & Frewer, L. J. (2012). Socio-psychological determinants of public acceptance of technologies: A review. *Public Understanding of Science*, 21(7), 782-795. doi:10.177/0963662510392485

Ha, S., & Stoel, L. (2009). Consumer e-shopping acceptance: Antecedents in a technology acceptance model. *Journal of Business Research, 62*(5), 565-571. doi:10.1016/j.jbusres.2008.06.016

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Upper Saddle River, NJ: Prentice-Hall.

Hair, J. F., Hult, T. M., Ringle, C. M., & Sarstedt, M (2017). A primer on partial least squares structural equation modeling (PLS-SEM) (2nd ed.) Los Angeles, CA: Sage.

Hayat, S., Yanmaz, E., & Muzaffar, R. (2016). Survey on unmanned aerial vehicle networks for civil applications: A communications viewpoint. *IEEE Communications Surveys & Tutorials, 18*(4), 2624-2661. doi:10.1109/ COMST.2016.2560343

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115-135. doi:10.1007/s11747-01 4-0403-8

Hertzog, M. A. (2008). Considerations in determining sample size for pilot studies. *Research in Nursing & Health, 31*(2), 180-191. doi:10.1002/nur.20247

Hill, R. (1998). What sample size is enough in internet survey research? *Interpersonal Computing and Technology: An Electronic Journal for the 21st Century*, 6 (3-4). ISSN: 1064-4326

Hitlin, P. (2017). 8% of Americans say they own a drone, while more than half have seen one in operation. *Pew Research Center.* Retrieved from http://www.pewrearch.org/fact-tank/2017/12/19/8-of-americans-say-they-own-a-drone-while-more-than-half-have-seen-one-in-operation/

Hoffer, N. V., Coopmans, C., Jensen, A. M., & Chen, Y. (2014;2013;). A survey and categorization of small low-cost unmanned aerial vehicle system identification. *Journal of Intelligent & Robotic Systems, 74*(1), 129-145. doi:10.1007/s10846-013-9931-6

Hsieh, P. (2015). Physicians' acceptance of electronic medical records exchange: An extension of the decomposed TPB model with institutional trust and perceived risk. *International Journal of Medical Informatics, 84*(1), 1-14. doi:10.106/j.ijmedinf.2014.08.008

Hu, L., & Bentler, P. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1-55. doi:10.1080/10705519909540118

Hunter, R. (2001). The public perception of risk. *Australasian Science, 22*, 30-32. Retrieved from http://www.australasianscience.com.au

Ison, D. C. (2010). Mitigating online survey nonresponse error in aviation research. *Journal of Aviation/Aerospace Education & Research, 20*(1), 41-57. 3. doi:10.15394/jaaer.2010.1358

Ison, D. C. (2011). Development and validation of an aviation research survey. *Journal of Aviation/Aerospace Education & Research, 21*(1), 45-85. doi:10.15394/jaaer.2011.1339

Jensen, O. B. (2016). New 'foucauldian boomerangs': Drones and urban surveillance. *Surveillance & Society, 14*(1), 20.

Job-applications.com. (2018a). *Facts about working at AT&T.* Retrieved from https://www.job-applications.com/att-job-application/

Job-applications.com. (2018b). *Facts about working at UPS*. Retrieved from https://www.job-applications.com/ups-application/

Johnson, R. (2017). Seeing the big picture. *Land Journal,* 10.

Kansal, P. (2016). Perceived risk and technology acceptance model in self-service banking: A study on the nature of mediation. *South Asian Journal of Management, 23*(2), 51-71.

Kansas State University (2016). *ASSURE UAS research and development program research abstract.* Retrieved from http://www.assureuas.org/projects/funding/A5UASMxConsiderationsAbstract.pdf

King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management, 43*(6), 740. doi:10.1016/j.im.2006.05.003

Klauser, F., & Pedrozo, S. (2017). Big data from the sky: Popular perceptions of private drones in Switzerland. *Geographica Helvetica, 72*, 231-239. doi:10.5194/gh-72-231-20

Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed.). New York, NY: Guilford Press. doi:10.1111/insr.12011_25

Koerner, M. R. (2015). Drones and the fourth amendment: Redefining expectations of privacy. *Duke Law Journal, 64*(6), 1129 -1772. Retrieved from http://scholarship.law.duke.edu/dij/vol64/iss6/3

Kwan, J. L. Y., & Chan, W. (2014). Comparing squared multiple correlation coefficients using structural equation modeling. *Structural Equation Modeling: A Multidisciplinary Journal, 21*(2). 225-238. doi:10.1080/107005511.2014.882673

Lai, Vincent S., & Honglei, Li. (2005). Technology acceptance model for internet banking: An invariance analysis. *Information & Management,* 42, no. 2: 373-386. doi:10.1016/j.im.2004.01.007

Lao, H. C. F., Tao, V. Y. K., & Wu, A. M. S. (2016). Theory of planned behaviour and healthy sleep of college students: TPB and healthy sleep. *Australian Journal of Psychology, 68*(1), 20-28. doi:10.1111/ajpy.12094

LaPorte, T., & Metlay, D. (1975a). Public attitudes toward present and future technologies. *Social Studies of Science, 5*, 373–398. Retrieved from http://www.4sonline.org/

LaPorte, T., & Metlay, D. (1975b). *They watch and wonder. Public attitudes toward advanced technology final report.* (Report No. NASA-CR-149673). Retrieved from National Aeronautics and Space website http://ntrs.nasa.gov/arhive/nasa/casi.ntrs.nasa.gov/19770012010.pdf

Lee, E. J., Shin, S. Y., Ko, B. C., & Chang, C. (2016). Early sinkhole detection using a drone-based thermal camera and image processing. *Infrared Physics & Technology, 78*, 223-232. doi:10.1016/j.infrared.2016.08.009

Lee, J., Cerreto, F. A., & Lee, J. (2010). Theory of planned behavior and teachers' decisions regarding use of educational technology. *Journal of Educational Technology & Society, 13*(1), 152. ISSN-1436-4522

Lee, M. (2009). Factors influencing the adoption of internet banking: An integration of TAM and TPB with perceived risk and perceived benefit. *Electronic Commerce Research and Applications, 8*(3), 130-141. doi:10.1016/j.elerap.2008.11.006

Lee, W. J., & Choi, H. C. (2009). Understanding meeting planners’ internet use behavior:

An extension to the theory of planned behavior. *International Journal of Hospitality and Tourism Administration, 10*(2), 109-128. doi:10.1080/15256480902850968

Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. *Information & Management, 40*(3), 191-204. doi:10.1016/S0378-7206(01)00143-4

Lester, M. (2000). Communicate risk effectively**.** *Chemical Engineering Progress, 96*(6), 79. Retrieved from http://www.aiche.org/resources/publications/cep

Lord, R. (2017). Drones and law enforcement. *Science Scope, 41*(1), 94.

Loukinas, P. (2017). Surveillance and drones at Greek border zones: Challenging human rights and democracy. *Surveillance & Society, 15*(3/4), 439.

Lu, C., Huang, S., & Lo, P. (2010). An empirical study of on-line tax filing acceptance model: Integrating TAM and TPB. *African Journal of Business Management, 4*(5), 800-810. Retrieved from http://www.academic journals.org/AJBM

Mallya, J., & Lakshminarayanan, S. (2017). Factors influencing usage of internet for academic purposes using technology acceptance model. *DESIDOC Journal of Library & Information Technology, 37*(2), 119-124.

Marais, K., Koelling, J., & Ballin, M. (2016). FAA finalizes rules for small drones. *Aerospace America, 54*(11), 27.

Mariani, R. L. (2014). Rise of the drones. *The Brief, 43*(4), 19.

Marshall, D. M., Barnhart, R. K., Hottman, S. B., Shappee, E., & Most, M. T. (2016). *Introduction to unmanned aircraft systems.* Boca Raton, FL: CRC Press Taylor & Francis Group.

Marshall, D. M. (2015). "What a long strange trip it's been": A journey through the FAA's drone policies and regulations. *DePaul Law Review, 65*(1), 123.

Marangunić, N., & Granić, A. (2015). Technology acceptance model: A literature review from 1986 to 2013. *Universal Access in the Information Society, 14*(1), 81-95. doi:10.1007/s10209-014-0348-1

Mason, W., & Suri, S. (2012). Conducting behavioral research on amazon's mechanical turk. *Behavior Research Methods, 44*(1), 1.

Mathieson, K. (1991). Predicting user intentions: Comparing the technology acceptance model with the theory of planned behavior. *Information Systems Research*, *2*(3), 173-191. doi:10.1287/isre.2.3.173

McCormack, E. (2009). Exploring transportation applications of small unmanned aircraft. *Institute of Transportation Engineers. ITE Journal, 79*(12), 32.

Morosan, C. (2014). Toward an integrated model of adoption of mobile phones for purchasing ancillary services in air travel. *International Journal of Contemporary Hospitality Management, 26*(2), 246-271. Retrieved from http://search.proquest. com.ezproxy.libproxy.db.erau.edu/docview/1469873649?accountid=27203

Morris, M. G., Venkatesh, V., & Ackerman, P. L. (2005). Gender and age differences in employee decisions about new technology: An extension to the theory of planned behavior. *IEEE Transactions on Engineering Management, 52*(1), 69-84. doi:10.1109/TEM.2004.839967

Motlagh, N. H., Bagaa, M., & Taleb, T. (2017). UAV-based IoT platform: A crowd surveillance use case. *IEEE Communications Magazine, 55*(2), 128-134. doi:10.1109/MCOM.2017.1600587CM

Moussaïd, M. (2013). Opinion formation and the collective dynamics of risk perception. *PLoS One, 8*(12). doi:10.1371/journal.pone.0084592

Myers, P. L. (2016). SMS derived vs. public perceived risk in aviation technology acceptance (Literature Review). *International Journal of Aviation, Aeronautics, and Aerospace, 3*(4). doi:10.15394/ijaaa.2016.1141

National Science Foundation. (2018). *Proposal and award policies and procedures guide.* Retrieved from https://www.nsf.gov/pubs/policydocs/pappg18_1.pdf

Olson, K. (2010). An examination of questionnaire evaluation by expert reviewers. *Field Methods, 22*(4), 295-318. doi:10.1177/1525822X10379795

Pai, F., & Huang, K. (2011). Applying the technology acceptance model to the introduction of healthcare information systems. *Technological Forecasting & Social Change, 78*(4), 650-660. doi:10.1016/j.techfore.2010.11.007

Pan, J. Y., & Truong, D. (2018). Passengers' intentions to use low-cost carriers: An extended theory of planned behavior model. *Journal of Air Transport Management*, 69, 38-48. doi:10.1016/j.jairtraman.2018.01.006

Park, E., & Kim, K. J. (2014). Driver acceptance of car navigation systems: Integration of locational accuracy, processing speed, and service and display quality with technology acceptance model. *Personal and Ubiquitous Computing, 18*(3), 503-513. doi:10.1007/s00779-013-0670-2

Parker, D., Manstead, A. R., Stradling, S. G., Reason, J. T., & Baxter, J. S. (1992). Intention to Commit Driving Violations: An Application of the Theory of Planned Behavior. *Journal of Applied Psychology*, *77*(1), 94-101. doi:10.1037/0021-9010.77.1.94

Parnell, G. S., Driscoll, P. J., & Henderson, D. L. (2011). *Decision making in systems engineering and management*. (2nd ed.). Hoboken, NJ: Wiley and Sons. doi:10.1002/9780470926963

Paulson, C. A., Sóbester, A., & Scanlan, J. P. (2017). The rapid development of bespoke small unmanned aircraft: A proposed design loop. *The Aeronautical Journal, 121(1235),* 1683. doi:10.1017/aer.2017.99

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce, 7*(3), 101-134.

Perritt, H. H., & Plawinski, A. J. (2016). Making civilian drones safe: Performance standards, self-certification, and post-sale data collection. *Northwestern Journal of Technology and Intellectual Property, 14*(1), 1.

Perritt, H. H., Jr, & Sprague, E. O. (2015). drones. *Vanderbilt Journal of Entertainment and Technology Law, 17*(3), 673.

Pickett, L. L., Ginsburg, H. J., Mendez, R. V., Lim, D. E., Blankenship, K. R., Foster, L. E., . . . Sheffield, S. B. (2012). Ajzen's theory of planned behavior as it relates to eating disorders and body satisfaction. *North American Journal of Psychology, 14*(2), 339-354. Retrieved from http://najp.us/

Pöllänen, R., Toivonen, H., Peräjärvi, K., Karhunen, T., Ilander, T., Lehtinen, J., Rintala, K., Katajainen, T., Niemelä, J. & Juusela, M. (2009). Radiation surveillance using an unmanned aerial vehicle. *Applied Radiation and Isotopes, 67*(2), 340-344. doi:10.1016/j.apradiso.2008.10.008

Ramadan, Z. B., Farah, M. F., & Mrad, M. (2017; 2016). An adapted TPB approach to consumers' acceptance of service-delivery drones. *Technology Analysis & Strategic Management, 29*(7), 817-12. doi:10.1080/09537325.2016.1242720

Ratcliffe, M., Burd, C., Holder, K., & Fields, A. (2016). *Defining rural at the U.S. Census Bureau. ACSGEO-1, U.S. Census* Bureau, Washington, D.C. Retrieved from https://www2.census.gov/geo/pdfs/reference/ua/Defining_Rural.pdf

Rivis, A., Sheeran, P., Armitage, C. J., (2009). Expanding the affective and normative components of the theory of planned behavior: a meta-analysis of anticipated affect and moral norms. J. *Applied Social Psychology, 39*(12), 2985. doi:10.1111/j.1559-1816.2009.00558.

Rule, T. A. (2015). Airspace in an age of drones. *Boston University Law Review, 95*(1), 155. *S. 631 Drone Aircraft Privacy and Transparency Act of 2017, 115th Cong. § 3, 4, 5*. (2017). Retrieved from https://www.congress.gov/115/bills/s631/BILLS-115s631is.pdf

SAS (2013). *Data mining using SAS Enterprise Miner: A case study approach* (3rd ed.). SAS Documentation Retrieved from https://erau.instructure.com/courses /58758/pages/1-dot-2-guided-support?module_item_id=2959732

Sabatini, R., Cappello, F., Ramasamy, S., Gardi, A., & Clothier, R. (2015). An innovative navigation and guidance system for small unmanned aircraft using low-cost sensors. *Aircraft Engineering and Aerospace Technology, 87*(6), 540-545.

Scobie, C. A., & Hugenholtz, C. H. (2016). Wildlife monitoring with unmanned aerial vehicles: Quantifying distance to auditory detection. *Wildlife Society Bulletin, 40*(4), 781-785. doi:10.1002/wsb.700

Shaunnessey, T. (2015). Drones & disasters. *Professional Safety, 60*(7), 12.

Shultz, D. (2015). How lawmakers aim to protect you from a drone invasion. *Science.* doi:10.1126/science.aaa7814

Simon, M. K., & Goes, G. (2018). *Dissertation and scholarly research: Recipes for Success* (2018 ed.). Seattle, WA: Dissertation Success, LLC.

Sjöberg, L. (2000). Factors in risk perception. *Risk Analysis*, *20*(1), 1-12. doi:10.1111/0272-4332.00001

Smith, R. E. (2017). Legal remedies against drones? *Privacy Journal, 43*(9).

Soper, D. (2017). A-priori sample size calculator for structural equation models. Retrieved from https://www.danielsoper.com/statcalc/calculator.aspx?id=89

Stansbury, R.S. (2018). Unmanned aircraft systems make research and business advances. *Aerospace America*, 56(11), 78.

Stolzer, A. J., & Goglia, J. J. (2015). *Safety management systems in aviation* (2nd ed.). Burlington, VT: Ashgate.

Straub, J., Vacek, J., & Nordlie, J. (2014). Considering regulation of small unmanned aerial systems in the united states. *Air and Space Law, 39*(4), 275-293.

Takahashi, T. T. (2012). Drones in the national airspace. *Journal of Air Law and Commerce, 77*(3), 489.

Tate, A. (2015). Miley Cyrus and the attack of the drones: The right of publicity and tabloid use of unmanned aircraft systems. *Texas Review of Entertainment and Sports Law, 17*(1), 73.

Tauro, F., Porfiri, M., & Grimaldi, S. (2016). Surface flow measurements from drones. *Journal of Hydrology, 540*, 240-245. doi:10.1016/j.jhydrol.2016.06.012

Techau, T. E. (2018). *General aviation pilot acceptance and adoption of electronic flight* *bag technology* (Unpublished doctoral dissertation). Embry-Riddle Aeronautical University, Daytona Beach, FL.

Teo, T. (2012). Examining the intention to use technology among pre-service teachers: An integration of the technology acceptance model and theory of planned behavior. *Interactive Learning Environments, 20*(1), 3-18. doi:10.1080/10494821003714632

Teo, T., Lee, C. B., & Chai, C. S. (2008). Understanding pre-service teachers' computer attitudes: Applying and extending the technology acceptance model. *Journal of Computer Assisted Learning, 24*(2), 128-143. doi:10.1111/ j.1365-2729.2007.00247.x

Teo, T., Ursavaa, A. F., & Bahcekapili, E. (2011). Efficiency of the technology acceptance model to explain pre-service teachers E14 intention to use technology. A Turkish study. *Campus-Wide Information Systems, 28*(2), 93-101. doi:10.1108/10650741111117798

Terwilliger, B., Vincenzi, D., Ison, D., Witcher, K., Thirtyacre, D., & Khalid., A. (2015). Influencing factors for use of unmanned aerial systems in support of aviation accident and emergency response. *Journal of Automation and Control Engineering*, 3(3), 246-252. doi:10.12720/joace.3.3.246-252

Terwilliger, B., Ison, D. C., Robbins, J., & Vincenzi, D. A. (2017). *Small unmanned aircraft systems guide: Exploring designs, operations, regulations, and economics*. Newcastle, Washington: Aviation Supplies & Academics, Inc.

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal computing: Toward a conceptual model of utilization. *MIS Quarterly, 15*(1), 125-143. doi:10.2307/24944

Turner, M., Kitchenham, B., Brereton, P., Charters, S., & Budgen, D. (2010). Does the technology acceptance model predict actual use? A systematic literature review. *Information and Software Technology, 52*(5), 463. doi:10.106/ j.infsof.2009.11.005

U.S. Census Bureau. (2016). *Quick facts United States.* Retrieved from https://www.census.gov/quickfacts/fact/table/US/PST045216

U.S. Census Bureau. (2018). *U.S. geographic regions*. Retrieved from https://www.census.gov/geo/reference/webatlas/regions.html

van Birgelen, M., Semeijn, J., & Behrens, P. (2011). Explaining pro-environment consumer behavior in air travel. *Journal of Air Transport Management, 17*(2), 125-128. doi:10.1016/j.jairtraman.2010.12.013

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478. Retrieved from http://misq.org/

Venkatesh, V., Thong, J., & Xu, X (2012). Consumer acceptance and use of information technology. Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157.

Villasenor, J. (2014). "Drones" and the future of domestic aviation [point of view]. *Proceedings of the IEEE, 102*(3), 235-238. doi:10.1109/JPROC.2014.2302875

Vogt, W. P., Gardner, D. C., & Haeffele, L. M. (2012). *When to use what research design*. New York, USA: The Guilford Press.

Vogt, W. P., Vogt, E. R., Gardner, D. C., & Haeffele, L. M. (2014). *Selecting the right analysis for your data: Quantitative, qualitative, and mixed methods.* New York: NY: Guilford Press.

Voorhees, C. M., Brady, M. K., Calantone, R., & Ramirez, E. (2016). Discriminant validity testing in marketing: An analysis, causes for concern, and proposed remedies. *Journal of the Academy of Marketing Science*, 44(1), 119-134. doi:10.1007/s11747-015-0455-4

Wang, S. W., & Hsu, M. K. (2016). Airline co-branded credit cards—An application of the theory of planned behavior. *Journal of Air Transport Management, 55*, 245-254. doi:10.1016/j.jairtraman.2016.06.007

Waraich, Q. R., Mazzuchi, T. A., Sarkani, S., & Rico, D. F. (2013). Minimizing human factors mishaps in unmanned aircraft systems. *Ergonomics in Design: The Quarterly of Human Factors Applications, 21*(1). Doi:10.177/ 1064804612463215

Weissbach, D., & Tebbe, K. (2016). Drones in sight: Rapid growth through M&A's in a soaring new industry. *Strategic Direction, 32*(6), 37-39. doi:10.1108/ SD-04-2016-0044

Werner, D. (2014a). Easing small drones into U.S. skies. *Aerospace America, 52*(6), 9.

Werner, D. (2014b). A drone's day in court. *Aerospace America, 52*(4), 8.

Werner, D. (2017). FAA pushes tech breakthroughs, safety in drone planning. *Aerospace America, 55*(5), 29.

Westland, J. C. (2010). Lower bounds on sample size in structural equation modeling. *Electronic Commerce Research and Applications, 9*(6), 476-487.

Whitfield, S. C., Rosa, E. A., Dan, A., & Dietz, T. (2009). The Future of Nuclear Power: Value Orientations and Risk Perception. *Risk Analysis: An International Journal*, *29*(3), 425-437. doi:10.1111/j.1539-6924.2008.01155.x

Wildavsky, A., & Dake, K. (1990). Theories of risk perception: Who fears what and why? *Daedalus, 119*(4), 41. Retrieved from http://www.jstor.org/stable/20025337

Williams, J. (2017). Tips from the FAA's drone pioneer. *Aerospace America, 55*(5), 34.

Woodley, X. M., & Lockard, M. (2016). Womanism and snowball sampling: Engaging marginalized populations in holistic research. *The Qualitative Report*, 21(2), 321.

Wolinsky, H. (2017). Biology goes in the air. *EMBO Reports, 18*(8), 1284-1289. doi:10.15252/embr.201744740

Wu, I., Li, J., & Fu, C. (2011). The adoption of mobile healthcare by hospital's professionals: An integrative perspective. *Decision Support Systems, 51*(3), 587. doi:10.1016/j.dss.2011.03.003

Young, S. L., & Laughery, K. R., (1994). Components of perceived risk: A reconciliation of previous findings. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, October 1994; vol. 38: pp. 888-892.* doi:10.1177/154193129403801420

Yucel, U. A., & Gulbahar, Y. (2013). Technology acceptance model: A review of the prior predictors. *Egitim Bilimleri Fakultesi Dergisi, 46*(1), 89. doi:10.1501/Egifak_0000001275

APPENDIX A

Permission to Conduct Research

Embry-Riddle Aeronautical University
Application for IRB Approval
Determination Form

Principal Investigator: Dothang Truong

Other Investigators: Paul L. Myers III

Role: Student **Campus:** Worldwide **College:** Aviation/Aeronautics

Project Title: A Behavioral Research Model for Small Unmanned Aircraft Systems for Data Gathering Operations

Review Board Use Only

Initial Reviewer: Teri Gabriel **Date:** 07/12/2018 **Approval #:** 19-003

Determination: Exempt

Dr. Beth Blickensderfer
IRB Co-Chair Signature: Elizabeth L. Blickensderfer, Ph.D. Digitally signed by Elizabeth L. Blickensderfer, Ph.D. Date: 2018.07.24 14:19:12 -04'00' **Date:** 07/24/2018

Brief Description:

The overarching goal of this project is focused on developing and testing a new behavioral research model for sUAS use for data gathering operations. The model called Viti/Myers, Mashburn/Uland/Truong/ERAU/Sullenger (VMUTES) will be tested using large scale survey data obtained from sUAS users. The survey purpose is to learn about the factors that influence individuals' intention to use sUAS for data gathering. This proposed study will increase the knowledge base of demographic information of sUAS users. The research will take place using an online survey.

This research falls under the **EXEMPT** category as per 45 CFR 46.101(b) under:

☐ (1) Research, conducted in established or commonly accepted educational settings, that specifically involves normal educational practices that are not likely to adversely impact students' opportunity to learn required educational content or the assessment of educators who provide instruction. This includes most research on regular and special education instructional strategies, and research on the effectiveness of or the comparison among instructional techniques, curricula, or classroom management methods.

☑ (2) Research that only includes interactions involving educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures (of adults), interview procedures (of adults), or observation of public behavior if at least one of the following criteria is met:

(i) The information obtained is recorded by the investigator in such a manner that the identity of the human subjects cannot readily be ascertained, directly or through identifiers linked to the subjects;

(ii) Any disclosure of the human subjects' responses outside the research would not reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, educational advancement, or reputation.

☐ (4) Research involving the collection or study of **existing** data, documents, records, pathological specimens, or diagnostic specimens, if these sources are publicly available or if the information is recorded by the investigator in such a manner that subjects cannot be identified, directly or through identifiers linked to subjects.

☐ (6) Taste and food quality evaluation and consumer acceptance studies:

(i) If wholesome foods without additives are consumed, or

(ii) If a food is consumed that contains a food ingredient at or below the level and for a use found to be safe, or agricultural chemical or environmental contaminant at or below the level found to be safe, by the Food and Drug Administration or approved by the Environmental Protection Agency or the Food Safety and Inspection Service of the U.S. Department of Agriculture.

EMBRY-RIDDLE
Aeronautical University
FLORIDA | ARIZONA | WORLDWIDE

11 July 2018

Human Subject Protocol Application

Campus:	**Worldwide**	College:	COA
Other Institution Name & Address:			
Applicant:	**Paul Myers III**	Degree Level:	**Doctorate**
ERAU ID:	**0115531**	ERAU Affiliation:	**Student**
Project Title:	**A Behavioral Research Model for Small Unmanned Aircraft Systems for Data Gathering Operations**		
Principal Investigator:	**Dothang Truong**		
Other Investigators:	**Paul L. Myers III**		

Submission Date:	**05/10/2018**		
Beginning Date:	**07/16/2018**	Expected End Date:	
Type of Project:	**Survey**		
Type of Funding Support (if any):	**No**		

Questions:

1. Background and Purpose: Briefly describe the background and purpose of the research.

Background. Society as a stakeholder can induce undesired results when millions are spent during the technology development process, but when a system is deployed, society greatly slows growth or rejects it. Introduction of recent technology such as sUASs (small unmanned aircraft systems) by a commercial company or government agency involves some level of defined risk to society along with other factors that are viewed as acceptable by the organization. However, society may perceive the organizational defined risk and benefit of the technology at a more negative level than the implementing organization, creating a disparity. While perceived risk and other factors are recognized to some degree as influencing technology acceptance and intended use in society today, the problem is that technology implementation is often attempted concurrently with addressing society's concerns in a reactive versus proactive approach such as the case of the use of sUASs for data gathering operations. This reactive approach coupled with not grasping the magnitude of the impact of perceived risk and other influencing factors on technology acceptance and behavioral intention has resulted in undesired end-states.

Applying this philosophy to sUAS use, no studies to date were found focusing on identifying relevant factors of behavioral intention toward using a sUAS for data gathering operations encompassing the factors proposed in this study, nor a Structural Equation Model (SEM) showing relevant factors and associated relationships. Additionally, few studies were found that applied behavioral research models to aviation studies other than those focused on airline passengers. Thus, more knowledge is needed in this area and a behavioral research model is needed by academia, industry, and government agencies that can be used to identify relevant factors to enhance behavioral intention by society as well as correcting or minimizing factors that threaten safety, and/or efficiency of operation.

Purpose. According to the National Science Foundation (2018), the purpose of intellectual merit is to advance the knowledge of academia, industry, and government agencies. Thus, the overarching goal of this project is focused on developing and testing a new behavioral research model for sUAS use for data gathering operations. The newly developed model will fill the gap in the technology acceptance literature including the lack of proper and validated combination of technology acceptance model (TAM) and theory of planned behavior (TPB) theories and the neglect of perceived risks' impact; these issues are not addressed in current studies. The model, so called VMUTES (Viti / Myers, Mashburn / Uland / Truong / ERAU / Sullenger), uses a combined TAM/TPB model with an added perceived risk factor, and will be tested using large scale survey data obtained from sUAS users. The VMUTES model identifies influencing factors and examines the relationships among these factors on society's behavioral intention and thus actual use of sUAS for data gathering operations. The findings will allow industry and government agencies implementing technology to use the model as a baseline. Knowing the influencing factors, as derived from the VMUTES model, provides the FAA, industry, and other stakeholders with essential information to understand and, if needed, to target factors that facilitate behavioral intention toward using a sUAS for data gathering operations and to eliminate or minimize those factors that hinder intended use. Another intellectual benefit is the possibility that the developed model could be applied by academia, industry, and government agencies to other future aviation technology intention-to-use research studies and possibly to other technology areas such as automobile and railroad technology. Lastly, the FAA has published little demographic data for sUAS users. Therefore, this proposed study will also increase the knowledge base of demographic information of sUAS users.

The National Science Foundation defines broader impacts as those that include the potential of the proposed study to benefit society and contribute to achievement of specific, desired societal outcomes. Society and user benefits of this project could include possible renewed interest and growth of sUAS for data gathering operations as well as enhanced safety and improved security. First, if the research findings support, findings could aid the FAA in developing regulations that support growth of the use of sUASs for data gathering operations. These revised regulatory areas could better support sUAS users, facilitate more commercial use of sUAS, provide increased training for sUAS operators, and establish a protective legal environment that describes sUAS liabilities or requires insurance. Second, if research findings support, stakeholder safety could possibly be enhanced by establishing regulations and/or procedures to reduce the physical risk posed to sUAS operators and/or residents, and establishing more regulatory guidance, or developing software to prevent a conflict with manned aircraft. Third, if research findings support, security enhancement might be achieved through software and/or procedures that prevent jamming and/or interference of sUAS operations for unlawful or terrorist operations and establishing regulatory standards to minimize invasion of privacy violations by sUAS users. Finally, sUAS use for data gathering operations is a cornerstone to future aviation advancement providing added security, disaster assistance, and geological applications. Identifying the factors that influence society's behavioral intention toward using a sUAS could allow the FAA and industry to make informative decisions to facilitate the implementation and increase the growth of sUAS, which will lead to further aviation advancement and possibly aid in expanding commercial applications.

Practically, this proposed study fills an aviation research knowledge gap for sUAS use for data gathering. It also provides a research model and identifies influencing factors of behavior intention related to sUAS for data gathering. Thus, it is theorized the developed model incorporating new variables can be used for further sUAS research and provide an adaptable model for aviation and other technology areas to predict and facilitate new technology implementation where current models fall short.

2. Design, Procedures, Materials and Methods: Describe the details of the procedure to be used and the type of daa that will be collected.

The research is taking place online using an online survey. The proposed study uses two sampling methods: Amazon Mechanical Turk (MTurk) and a chain referral snowball sampling method. MTurk participants will be provided a link to the electronic survey integral to the MTurk Human Intelligence Task (HIT) posting. The proposed snowball sampling email that will be sent to applicable participants is included in the email invitation attachment. The email will contain a link to the online survey.
Electronic survey data including general demographic data and individual data related to operation of a sUASs for data gathering operations will be recorded electronically through Survey Monkey. No personal, other than general demographic data, will be recorded in the online survey. Finally, commercial companies and government agencies will be used in the study, but because the study remains anonymous, no permission is required.

3. Measures and Observations: What measures or observations will be taken in the study?

Data being collected is demographic data and data concerning operation of a small UAS for data gathering operations using an online survey. The sample unit is the individual sUAS user. The 78-question survey instrument is attached and uses a multiple-choice format for the filter and demographic data and a seven-point Likert scale for measurement of the observed variables related to each of the nine constructs. The Survey Monkey link to the online survey will be provided to participants through two methods; Amazon Mechanical Turk and chain referral snowball sampling using email. Survey results from the online survey will be transferred to an Excel spreadsheet for data analysis.

3b. If any questionnaires, tests, or other instruments are used, provide a brief description.

The survey contains a preamble and main body of questions. The survey preamble contains information for respondents to review before beginning the survey. These sections consist of study leadership and topic, purpose, eligibility, procedures, voluntary participation, risks and benefits, safeguarding policy, further information, and consent. The main body of the survey consists of 5 filter questions, 20 demographic questions, and 53 questions to determine the factors affecting an individual's intentions to use a sUAS for data gathering.

4. Risks and Benefits: Describe any potential risks to the dignity, rights, health or welfare of the human subjects. Assess the potential benefits to be gained by the subjects as well as to society in general as a result of this project. Briefly assess the risk-benefit ratio.

Potential risks and benefits are described in the introductory portion of the survey. There is no anticipated physical, psychological, financial, or reputational harm anticipated in this proposed study. Harm is unlikely in this proposed online survey study when collecting data. However, awareness of harm factors was considered when constructing the survey questions. One possible inconvenience to the participant is that they may spend less time on other activities because of participating in the survey. Concerning benefits, those participants using Amazon Mechanical Turk® will be paid the required fee. For those participants contacted through email, as an incentive to participate in the survey, an iPhone 8 will be awarded to one participant who was contacted through email in the snowball sampling process after the survey data has been collected. Participation in the drawing is voluntary. The chance to win is 1 in approximately 300. To participate in the drawing, the participant must send an email to the research team using myersllp@my.erau.edu with their organization to verify they were contacted using email. Each participant who was contacted through email and contacts the research team will be assigned a number. A random number generator will be used to select the winning number/survey respondent. Another benefit conveyed to respondents is that by participating in the survey process, respondent participation will also promote the understanding of individual's intention to use sUAS for data gathering.

5. Informed Consent: Describe the procedures you will use to obtain informed consent of the subjects and the debrief/feedback that will be provided to participants. See Informed Consent Guidelines for more information on Informed Consent requirements.

The informed consent portion is included in the consent section at the end of the survey preamble section before the filter questions. Clicking the consent box signifies the respondent understands the information presented in the survey preamble sections and agrees to participate in the survey.

6. Anonymity: Will participant information be anonymous (not even the researcher can match data with names), confidential (Names or any other identifying demographics can be matched, but only members of the research team will have access to that information. Publication of the data will not include any identifying information.), or public (Names and data will be matched and individuals outside of the research team will have either direct or indirect access. Publication of the data will allow either directly or indirectly, identification of the participants.)?

Anonymous

6b. Justify the classification and describe how privacy will be ensured/protected.

Responses from the self-administered Survey Monkey online survey are considered anonymous as the researcher has no way to match respondent names to a specific survey submission or responses to individual questions. No personal identifiers and only generic demographic information which cannot be tied to an individual will be required during the data collection process. For the initial respondents contacted by the research team through snowball sampling, for respondents who send an email to ask questions of the proposed research team or contact the research team to enter the drawing for the iPhone device, as a by-product of the methods used, the proposed research team will have personal identifying information including the name, organization, and email address of the individual. However, the personal identifying information will be masked or deleted from the study. The survey administrator will keep the personal identifying data as confidential information in password-protected computer systems and perturbation will be used for the personal identifying information.

7. Privacy: Describe the safeguards (including confidentiality safeguards) you will use to minimize the risks. Indicate what will happen to data collected from participants that choose to "opt out" during the research process. If video/audio recordsings are part of the research, please describe how that data will be stored or destroyed.

Those respondents who do not complete the survey completely, except for the optional general comments section, will be considered non-respondents. The data from those incomplete surveys will be used to compare available demographic data between the respondent and non-respondent groups to test for non-response bias. No video or audio recording is planned.

8. Participant Population and Recruitment Procedures: Who will be recruited to be participants and how will they be recruited. Note that participants must be at least 18 years of age to participate. Participants under 18 years of age much have a parent or guardian sign the informed consent document.

For this proposed study, the target population consists U.S. citizens who use model, civil, or public small unmanned aircraft for data gathering operations. To participate in the survey, besides being U.S. citizens, respondents must be eighteen years of age or older, and have voluntarily flown a sUAS for the purposes of transmitting or recording photos, video, audio, or collecting other data in the last two years. The target population of 460 will be focused more on modelers since 85.5% of those who have registered a UAS are modelers consistent with FAA data. The remaining target population of approximately (14%) will be split as equally as possible between civil and public users which is also consistent with FAA data. In the context of this proposed research, a U.S. citizen is defined as a person who was born in the U.S., a naturalized citizen, or a lawful permanent resident (green card holder).

For Amazon Mechanical Turk workers, qualifications for survey participants will be described in the Human Intelligence Task (HIT) as a screening mechanism. For the second sampling method, the snowball sampling email will be distributed to and further respondents identified through: (a) members of model aircraft organizations, (b) civil users such as educational institutions including instructors who teach UAS courses, and commercial companies that use sUASs, (c) government agencies that use sUASs, and (d) UAS/sUAS conference attendees. Those respondents will then in turn forward the survey request to other respondents they know using a chain referral method. Additionally, an introductory letter from the research team will be included in the email as shown in the attachment below.

9. Economic Considerations: Are participants going to be paid for their participation?

Yes

9b. If yes, describe your policy for dealing with participants who 1) Show up for research, but refuse informed consent; 2) Start but fail to complete research.

By design, Amazon Mechanical Turk requires workers (survey participants) to be paid a monetary amount to complete the task. The average wage for a laboratory participant ranges from $1.38 to $4.80 per hour. Past researchers advise to start payment at an amount less than this expected rate and then increase the wage if the rate of completed work (number of respondents) is too low. Since the estimated time to complete the online survey is approximately 40 minutes, the adjusted rate is $.92 to $3.19 per hour. Therefore, payment will start less than $.92 and increased as necessary up to the maximum amount to increase response rate as necessary with all participants receiving the same amount.

Participants in the chain referral snowball sampling process will be given the opportunity to email the proposed research team after completing the online survey to enter a random drawing for one participant to win an iPhone 8 as an incentive to complete the survey. Doing so can increase response rates. All respondents who email the research team to enter the drawing will be assigned a number and a random number generator will select the winner. Therefore, each respondent will have an equal chance of winning the device. The chance to win is approximately 1 in 300.

10. Time: Approximately how much time will be required of each participant?

The estimated time required for the participant to complete the survey is approximately 40 minutes which is described in the introductory portion of the survey.

By submitting this application, you are signing that the Principal Investigator and any other investigators certify the following:
1. The information in this application is accurate and complete
2. All procedures performed during this project will be conducted by individuals legally and responsibly entitled to do so
3. I/we will comply with all federal, state, and institutional policies and procedures to protect human subjects in research
4. I/we will assure that the consent process and research procedures as described herein are followed with every participant in the research
5. That any significant systematic deviation from the submitted protocol (for example, a change in the principal investigator, sponsorship, research purposes, participant recruitment procedures, research methodology, risks and benefits, or consent procedures) will be submitted to the IRB for approval prior to its implementation
6. I/we will promptly report any adverse events to the IRB

Electronic Signature:

Paul L Myers III

APPENDIX B

Data Collection Device

APPENDIX B

Data Collection Device

General Information Part 1

STUDY LEADERSHIP AND TOPIC. You are invited to participate in a survey, which is part of a research project that examines sUAS users' intention to use a sUAS for data gathering. The topic of the study is A Behavioral Model For Small Unmanned Aircraft Systems for Data Gathering Operations.

PURPOSE. The survey purpose is to learn about the factors that influence individuals' intention to use a sUAS for data gathering.

ELIGIBILITY. To be in this study, you must be: (a) 18 years or older, (b) a U.S. citizen, naturalized citizen, or have a green card, and (c) must have voluntarily flown a sUAS for the purpose data gathering (transmitting or recording audio, video, photography or collecting other data using a sUAS) in the last two years.

PROCEDURES. This survey is a self-administered survey. Survey responses are anonymous and cannot be attributed to an individual. The survey should take approximately 40 minutes to complete.

VOLUNTARY PARTICIPATION. It is preferred that responses are provided to all items. However, your participation in this study is completely voluntary and you are free to decline to participate, without consequence, at any time prior to or during the survey. You are also free to skip any question in the questionnaire that you feel uneasy to give an answer to.

RISKS AND BENEFITS. There are no known risks to you as a person taking this survey, beyond those risks experienced in everyday life. One possible inconvenience to you is that you may spend less time on other activities because of participating in the survey. Concerning benefits, those participants using Amazon Mechanical Turk® will be paid the required fee. For those participants contacted through email, as an incentive to participate in the survey, an iPhone 8 will be awarded to one participant who was contacted through email after the survey data has been collected. Participation in the drawing is voluntary. The chance to win is 1 in approximately 300. To participate in the drawing, you must send an email to the research team using myersllp@my.erau.edu with your organization to verify you were contacted using email. Each participant who was contacted through email and contacts the research team will be assigned a number. A random number generator will be used to select the winning number/survey respondent. Your participation will also promote the understanding of individual's intention to use sUAS for data gathering.

SAFEGUARDING PRIVACY. The participation is anonymous. No personal information will be collected other than basic demographic descriptors from the actual survey. The questions are designed such that no personal identification will be included. All information collected from you will be maintained in a secure manner. For those individuals contacted by email, personal information will not be included in the study and kept confidential by the research team.

General Information Part 2

FURTHER INFORMATION.
Definitions - In the context of the survey questions: (a) Data gathering means transmitting or recording pictures, audio, video or collecting other data. (b) A small UAS is one that weighs <55 pounds. (c) A modeler is an individual flying an unmanned aircraft under the Special Rule for Model Aircraft Public Law 112-95 for recreational purposes only. (d) A civil user is an individual using sUASs for non-government personal or commercial flights which do not fall in the model aircraft category. (e) Commercial use is for profit or furtherance of a business without compensation. (f) A public user operates unmanned aircraft performing non-commercial governmental functions such intelligence missions, firefighting, search-and-rescue, law enforcement, aeronautical research, or biological or geological resource management. (g) A military user operates a sUAS for the United States Army, Air Force, Navy, Marines, or Coast Guard. (h) Voluntary means flying the sUAS for data gathering is not legally binding. You have the option to not perform the required activity or quit your job if your personal values do not support performing the action. The results from this study will be published in a dissertation and journal article. Both will be available to the public. If you have any questions about the survey or would like additional information about this study, please contact Paul Myers at myersllp@my.erau.edu

CONSENT. Please click "Yes" below to indicate that you understand the information on this form and that you agree to participate in this survey.

* 1. CONSENT

- ○ Yes, I would like to parcipate in the survey (Thank you and please start the survey)
- ○ No, I would not like to participate in the survey (Thank you, please exit the survey)

Section 1. Filter Questions.

1. Are you a U.S. citizen, naturalized citizen, or have a green card?

- ◯ Yes (Please continue the survey)
- ◯ No (Please withdraw from the survey)

2. Are you eighteen years or older?

- ◯ Yes (Please continue the survey)
- ◯ No (Please withdraw from survey)

3. Have you flown a sUAS for the purposses of transmitting or recording, pictures, audio, video, or gathering other data in the last two years?

- ◯ Yes (Please continue survey)
- ◯ No (Please withdraw from survey)

4. Use of a sUAS for the purposes of transmitting or recording pictures, audio, video, or collecting other data has been voluntary. (voluntary means flying the sUAS for gathering is not legally binding. You have the option to not perform the required activity or quit your job if your personal values do not support performing the action.)

- ◯ Yes (Please continue survey)
- ◯ No (Please withdraw from survey)

5. Are you currently using a sUAS for military use only? (military users are those that fly sUASs for the United States Army, Air Force, Navy, Marines, or Coast Guard)

- ◯ Yes (Please withdraw from survey)
- ◯ No (Please continue survey)

Section 2. Demographics.

1. Gender

- ◯ Male
- ◯ Female

2. Age

- ◯ 18-20 years
- ◯ 21-30 years
- ◯ 31-40 years
- ◯ 41-50 years
- ◯ 51-60 years
- ◯ Older than 60 years

3. Highest Education Level

- ◯ Attending high school
- ◯ High school diploma
- ◯ Bachelor's degree
- ◯ Master's degree
- ◯ Higher than Master's degree

4. Annual Income

- ◯ Less than $30,000
- ◯ $30,000 to $50,000
- ◯ $51,000 to $100,000
- ◯ $101,000 to $150,000
- ◯ $151,000 to $200,000
- ◯ More than $200,000

5. Current occupation (Select all that apply)

- ☐ Student
- ☐ Commercial company employee
- ☐ Self-employed
- ☐ Government Employee
- ☐ Unemployed
- ☐ Business Owner
- ☐ Other

6. I voluntarily use a sUAS for data gathering as a a _______________.

- modeler user only (one who uses a sUAS for hobby or recreational use only)
- civil user only (using sUASs for non-government personal or commercial flights which do not fall in the model aircraft category)
- public user only (non-commercial government agency)
- modeler and civil user
- modeler and public user
- modeler and military user (military user - one who operates a sUAS for the United States Army, Air Force, Navy, Marines, or Coast Guard)
- civil and military user

7. My experience level using a sUAS for data gathering is _______________.

- less than six months
- six months to < one year
- one to < two years
- two to < three years
- three to < four years
- four to < five years
- five years to < ten years
- ten years or greater

8. The region of the United States I primarily operate a sUAS is the ___________ region.

- Northeast
- West
- Midwest
- South

U.S. Census Bureau

9. I primarily operate a sUAS in a _____________.

- urban metro area (population >= 50,000 people)
- urban micro area (population >= 10,000 to < 50,000 people)
- rural area (population < 10,000 people)

10. I possess a remote pilot certificate.

- Yes
- No

11. The type of operation I primarily use a sUAS for is _____________ (please only check one)

- ◯ Insurance purposes
- ◯ Agriculture
- ◯ Aerial photography
- ◯ Movie filming
- ◯ Real estate
- ◯ Wildlife monitoring
- ◯ Education purposes
- ◯ Environmental (chemical, biological, or natural resources monitoring)
- ◯ Emergency management / humanitarian / disaster response
- ◯ Construction / roadway, industrial, or utility inspections
- ◯ Law or border enforcement
- ◯ Sports or media broadcasting
- ◯ Other

12. I have had formal training on how to use a sUAS.

- ◯ Yes
- ◯ No

13. I have a 14 CFR Part 61 FAA manned aircraft operating certificate.

- ◯ Yes
- ◯ No

14. My experience level operating a manned aircraft is _______________.

- ◯ none
- ◯ less than six months
- ◯ six months to < one year
- ◯ one year to < two years
- ◯ two to < three years
- ◯ three to < four years
- ◯ four to < five years
- ◯ five to < ten years
- ◯ ten years to < twenty years
- ◯ twenty years or greater

15. Please indicate the most frequently used type of sUAS your fly for data gathering.

- ◯ Fixed wing
- ◯ Vertical Takeoff and Landing (VTOL)
- ◯ Other

16. Indicate the type(s) of FAA waiver(s) most frequently requested. If none have been requested, please check none.

- ◯ 14 CFR Section 107.25 - Operation from a moving vehicle or aircraft
- ◯ 14 CFR Section 107.29 - Daylight operation
- ◯ 14 CFR Section 107.31 - Visual line of sight operation
- ◯ 14 CFR Section 107.33 - Visual observer
- ◯ 14 CFR Section 107.35 - Operation of multiple small unmanned aircraft systems
- ◯ 14 CFR Section 107.37 - Yielding the right of way
- ◯ 14 CFR Section 107.39 - Operation over people
- ◯ 14 CFR Section 107.41 - Operation in certain airspace
- ◯ 14 CFR Section 107.51 - Operating limitations for small unmanned aircraft
- ◯ Other
- ◯ None

17. The sUAS I fly for data gathering is registered.

- ◯ Yes
- ◯ No

18. How much did you pay for the most expensive model aircraft or sUAS you own?

- ◯ < $200
- ◯ > $200 and < $500
- ◯ $500 to $1,000
- ◯ > 1,000 to $2,000
- ◯ > $2,000 to $5,000
- ◯ > 5,000 to $10,000
- ◯ > $10,000
- ◯ Unknown, the company or agency paid for the sUAS

19. What type of sensor(s) is used on your model aircraft or sUAS for data gathering? (select all that apply)

- ☐ Camera
- ☐ Infared
- ☐ Video
- ☐ RGB Camera
- ☐ Sythetic Aperture Radar
- ☐ LiDAR (light detection and ranging)
- ☐ Multispectral
- ☐ Thermal
- ☐ Other

Section 3. Factors Affecting Individual's Intentions to use a sUAS for Data Gathering

1. FC1 When I need help to use a sUAS for data gathering, guidance is available to me.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

2. FC2 When I need help to use a sUAS for data gathering, a specific person or company is available to provide assistance.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

3. FC3 I have adequate supporting materials and information available to me for effective use of a sUAS for data gathering.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

4. FC4 Current U.S. government regulations facilitate my operation of a sUAS for data gathering.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

5. FC5 If my sUAS breaks, it is easy to find help and/or replacement parts to fix it.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

6. FC6 Training provided and/or operating instructions provided with the sUAS was sufficient to safely operate my sUAS for data gathering.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

7. FC7 The legal environment facilitates me using a sUAS for data gathering.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

8. PEOU1 Using a sUAS for data gathering does not require a lot of mental effort.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree

9. PEOU2 I think it is easy to use a sUAS for data gathering to accomplish my data gathering tasks.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree

10. PEOU3 My interaction with a sUAS for data gathering is clear and understandable.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree

11. PEOU4 I find it easy when using a sUAS for data gathering to get the sUAS to do what I want it to do.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree

12. PEOU5 It is easy to become skillful at using a sUAS for data gathering.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree

13. PEOU6 I have sufficient knowledge and experience to use a sUAS for data gathering.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree

14. PU1 I think that using a sUAS for data gathering would enable me to accomplish data gathering tasks more quickly.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree

15. PU2 I think that using a sUAS for data gathering would make it easier for me to carry out my tasks.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree

16. PU3 Using a sUAS for data gathering will enhance my productivity.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

17. PU4 I think using a sUAS for data gathering is valuable to me.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

18. PU5 Overall, I find using a sUAS for data gathering useful.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

19. SN1 People who are important to me would think I should use a sUAS for data gathering.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

20. SN2 People who influence me would think I should use a sUAS for data gathering.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

21. SN3 People whose opinions I value will encourage me to use a sUAS for data gathering.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

22. SN4 People who are important to me will support me using a sUAS for data gathering.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

23. SN5 My individual values/beliefs morally support me using a sUAS for data gathering.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

24. BI1 I would use a sUAS for my data gathering needs.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

25. BI2 I will use a sUAS for data gathering in the future.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

26. BI3 I plan to use a sUAS for data gathering at least every 90 days.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

27. BI4 When choosing data gathering task methods, use of a sUAS is my first choice.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

28. BI5 I would recommend using a sUAS for data gathering to my relatives and friends.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

29. ATU1 I think using a sUAS for data gathering is a good idea.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

30. ATU2 In my opinion, it is desirable to use a sUAS for data gathering.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

31. ATU3 Using a sUAS for data gathering is fun.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

32. ATU4 Using a sUAS for data gathering makes my work more interesting.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

33. ATU5 I like the idea of using a sUAS for my data gathering needs.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

34. PR1 Using a sUAS for data gathering is physically threatening to myself and/or others in society.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

35. PR2 Using a sUAS for data gathering is physically threatening to other aircraft.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

36. PR3 My sUAS may not perform data gathering well.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

37. PR4 The costs of procuring, operating, and maintaining a sUAS for data gathering is concerning.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

38. PR5 It would take me lots of time to learn how to use a sUAS for data gathering.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

39. PR6 Security is a concern when using a sUAS for data gathering because other people may be able to intercept my information or affect the operation of the sUAS.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

40. PR7 Legal liability is a concern when using my sUAS for data gathering.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

41. PR8 The media and/or society influence my perceived risk level of using a sUAS for data gathering.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

42. PR9 Others in society using a sUAS for data gathering will lead to a loss of privacy for me.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

43. PR10 Using a sUAS for data gathering will not fit well with my self-image or self-concept.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

44. KR1 I am familiar with state laws that apply to my sUAS operations or have determined that there are no state laws that apply.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

45. KR2 I am familiar with local laws that apply to my sUAS operations or have determined that there are no local laws or guidelines that apply.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

46. KR3 I am familiar with FAA Advisory Circular 91-57A as a model aircraft operator or FAA Advisory Circular 107-2 as a non-model sUAS operator.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

47. KR4 I am familiar with Public Law 112-95 as a model aircraft (recreational) category operator or 14 CFR Part 107 as a non-model sUAS operator.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

48. KR5 I have viewed, and I am familiar with the contents of the FAA website regarding UAS operations.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

49. AB1 I have used a sUAS for data gathering purposes.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

50. AB2 I used a sUAS for data gathering purposes this year.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

51. AB3 I have frequently used a sUAS for data gathering.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

52. AB4 I have used a sUAS for data gathering more than once in the past two years.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

53. AB5 When I needed data gathering tasks completed, I used a sUAS.

Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
○	○	○	○	○	○	○

Section 4. Additional Comments.

1. Additional Comments

Thank you for participating in the survey! For those participants who are amazon turk workers, please enter code 8100ER to receive payment.

APPENDIX C

Tables

C1 Input Variables – Questions and Sources for the VMUTES Model

Table C1

Input Variables - Questions and Sources for the VMUTES Model

Variables	Statements	Source
Facilitating Conditions (FC)	FC1. When I need help to use a sUAS for data gathering, guidance is available to me.	Modified from Teo (2012) & Thompson Higgings and Howell (1991).
	FC2. When I need help to use a sUAS for data gathering, a specific person or company is available to provide assistance.	Modified from Teo (2012) & Thompson Higgings and Howell (1991).
	FC3. I have adequate supporting materials and information available to me for effective use of a sUAS for data gathering.	Created from Groves and Zemel (2000) as cited by Choi and Chang (2012).
	FC4. The U.S. government facilitates my operation of a sUAS for data gathering.	Created from Dalamagkidis, Valavanis and Piegl (2008).
	FC5. If my sUAS breaks, it is easy to find help and/or replacement parts to fix it.	Created from Mariani (2014).
	FC6. Training provided and/or operating instructions provided with the sUAS was sufficient to safely operate my sUAS for data gathering.	Created from Groves and Zemel (2000) as cited by Choi and Chang (2012).

	FC7. The legal environment facilitates me using a sUAS for data gathering.	Created from Klauser and Pedrozo (2017), Tate (2015) & Vlliasenor (2014).
Perceived Ease of Use (PEOU)	PEOU1. I think that interaction with using a sUAS for data gathering does not require a lot of mental effort.	Modified from Lee (2009) & Cheng et al. (2006).
	PEOU2. I think it easy to use a sUAS for data gathering to accomplish my data gathering tasks.	Modified from Lee (2009) & Cheng et al. (2006).
	PEOU3. My interaction with a sUAS for data gathering is clear and understandable.	Modified from Teo (2012), Davis (1989) & Cheng et al. (2006).
	PEOU4. I find it easy when using a sUAS for data gathering to get the sUAS to do what I want it to do.	Modified from Teo (2012), Davis (1989) & Cheng et al. (2006).
	PEOU5. It is easy to become skillful at using a sUAS for data gathering.	Modified from Lu, Huang, and Lo (2010).
	PEOU6. I have sufficient knowledge and experience to use a sUAS for data gathering.	Created from Dobbie and Brown (2014).
Perceived Usefulness (PU)	PU1. I think that using a sUAS for data gathering would enable me to accomplish data gathering tasks more quickly.	Modified from Lee (2009) & Cheng et al. (2006).
	PU2. I think that using a sUAS for data gathering would make it easier for me to carry out my tasks.	Modified from Lee (2009) & Cheng et al. (2006).
	PU3. Using a sUAS for data gathering will enhance my productivity.	Modified from Teo (2012) & Davis (1989).

	PU4. I think using a sUAS for data gathering is valuable to me.	Modified from Lu, Huang, and Lo (2010).
	PU5. Overall, I find using a sUAS for data gathering useful.	Modified from Lu, Huang, & Lo (2010) & Cheng et al. (2006).
Subjective Norms (SN)	SN1. People who are important to me would think that I should use a sUAS for data gathering.	Modified from Lee (2009) & Wu and Chen (2005).
	SN2. People who influence me would think that I should use a sUAS for data gathering.	Modified from Lee (2009), Wu & Chen (2005) & Chen (2016).
	SN3. People whose opinions I value will encourage me to use a sUAS for data gathering.	Modified from Teo (2012), Ajzen (1991), Davis et al. (1989) & Chen (2016).
	SN4. People who are important to me will support me using a sUAS for data gathering.	Modified from Teo (2012), Ajzen (1991) & Davis et al. (1989).
	SN5. My individual values/beliefs morally support me using a sUAS for data gathering.	Created from Sjoberg, (2000), Whitfield et al. (2009) & Rivis, Sheeran, & Armitage (2009).
Behavioral Intention (BI)	BI1. I would use sUAS for my data gathering needs.	Modified from Lee (2009) & Cheng et al. (2006).
	BI2. I will use a sUAS for data gathering in the future.	Modified from Teo (2012) & Davis et al. (1989).

	BI3. I plan to use a sUAS for data gathering at least every 90 days.	Modified from Teo (2012) & Davis et al. (1989).
	BI4. When choosing data gathering task methods, use of a sUAS is my first choice.	Modified from Lu, Huang, and Lo (2010).
	BI5. I would recommend a sUAS for data gathering to my relatives and friends.	Modified from Lu, Huang, and Lo (2010).
Attitude Toward Use (ATU)	ATU1. I think using a sUAS for data gathering is a good idea.	Modified from Lee (2009) & Cheng et al. (2006).
	ATU2. In my opinion, it is desirable to use a sUAS for data gathering.	Modified from Lee (2009) & Cheng et al. (2006).
	ATU3. Using a sUAS for data gathering is fun.	Modified from Teo (2012) & Compeau and Higgins (1995).
	ATU4. Using a sUAS for data gathering makes my work more interesting.	Modified from Teo (2012) & Compeau and Higgins (1995).
	ATU5. I like the idea of using a sUAS for my data gathering needs.	Modified from Lu, Huang, and Lo (2010).
Perceived Risk (PR)	PR1. Using a sUAS for data gathering is threatening to myself and/or others in society.	Modified from Clothier et al. (2015) &

	Featherman and Pavlou (2003).
PR2. Using a sUAS for data gaterhing is physically threatening to other aircraft.	Created from Grose (2016) & Featherman and Pavlou (2003).
PR3. A sUAS may not perform well by failing to transmit or record video, audio, photography, or gather other data correctly	Created from Lee (2009).
PR4. The costs of procuring, operating, and maintaining a sUAS for data gathering is concerning.	Created from Lee (2009).
PR5. It would take me lots of time to learn how to use a sUAS for data gathering.	Created from Lee (2009) & Featherman and Pavlou (2003).
PR6. Security is a concern when using a sUAS for data gathering because other people may be able to intercept my information or affect the operation of the sUAS	Created from Gallacher (2017).
PR7. Being held legally liable for damage to property or injuries to persons is a concern.	Created from Mariani (2014).
PR8. The media and/or family and friends have a strong influence on my perceived risk level.	Created from Slovic (1991).
PR9. Others in society using a sUAS for data gathering will lead to a loss of privacy for me.	Modified from Featherman & Pavlou (2003).

	PR10. Using a sUAS for data gathering will not fit well with my self-image or self-concept.	Modified from Featherman & Pavlou (2003).
Knowledge of Regulations (KR)	KR1. I am familiar with state laws that apply to my sUAS operations or have determined that there are no state laws that apply.	Created based on FAA AC-107-2, (2016) & Elias, (2016)
	KR2. I am familiar with local laws that apply to my sUAS operations or have determined there are no local guidelines or laws that apply.	Created based on Elias (2016)
	KR3. I am familiar with FAA Advisory Circular 91-57A as a model aircraft operator or FAA Advisory Circular 107-2 as a non-model sUAS operator.	Created based on FAA AC-91-57A (2016a)
	KR4. I am familiar with Public Law 112-95 as a model aircraft (recreational) operator or 14 CFR Part 107 as a non-model sUAS operator.	Created based on Aeronautics and Space, 14 C.F.R. pt. 1 (2017)
	KR5. I have viewed, and I am familiar with the contents of the FAA website regarding UAS operations.	Created based on FAA (2017b)
Actual Behavior (AB)	AB1. I have used a sUAS for data gathering purposes.	Modified from Lu, Huang and Lo (2010).
	AB2. I used a sUAS for data gathering purposes this year.	Modified from Lu, Huang and Lo (2010), Davis et al. (1989) & Compeau and Higgins (1995).
	AB3. I have frequently used sUAS for data gathering.	Created from Lu, Huang and Lo (2010).
		Created from Lu, Huang and Lo (2010),

AB4. I have used a sUAS for data gathering more than once in the past two years.	Davis et al. (1989) & Compeau and Higgins (1995).
AB5. When I needed data gathering tasks completed, I used a sUAS.	Created from Lu, Huang and Lo (2010).

APPENDIX D

Figures

D1 Amazon Mechanical Turk HIT

.

1 Enter Properties | 2 Design Layout | 3 Preview and Finish

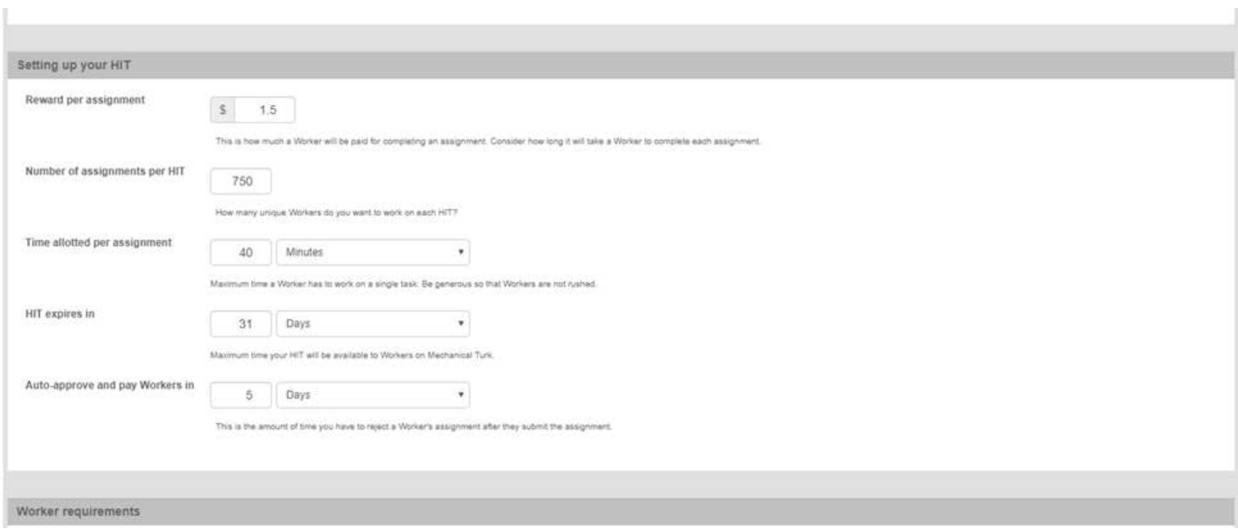
Project Name: sUAS Main Study
This name is not displayed to Workers.

Describe your HIT to Workers

Title
Small Unmanned Aircraft Behavioral Research Model Pilot Study
Describe the task to Workers. Be as specific as possible, e.g. "answer a survey about movies", instead of "short survey", so Workers know what to expect.

Description
The survey purpose is to learn about the factors that influence individuals' intention to use a small
Give more detail about this task. This gives Workers a bit more information before they decide to view your HIT.

Keywords
survey, unmanned aircraft, aviation,
Provide keywords that will help Workers search for your HITs.



Setting up your HIT

Reward per assignment
$ 1.5
This is how much a Worker will be paid for completing an assignment. Consider how long it will take a Worker to complete each assignment.

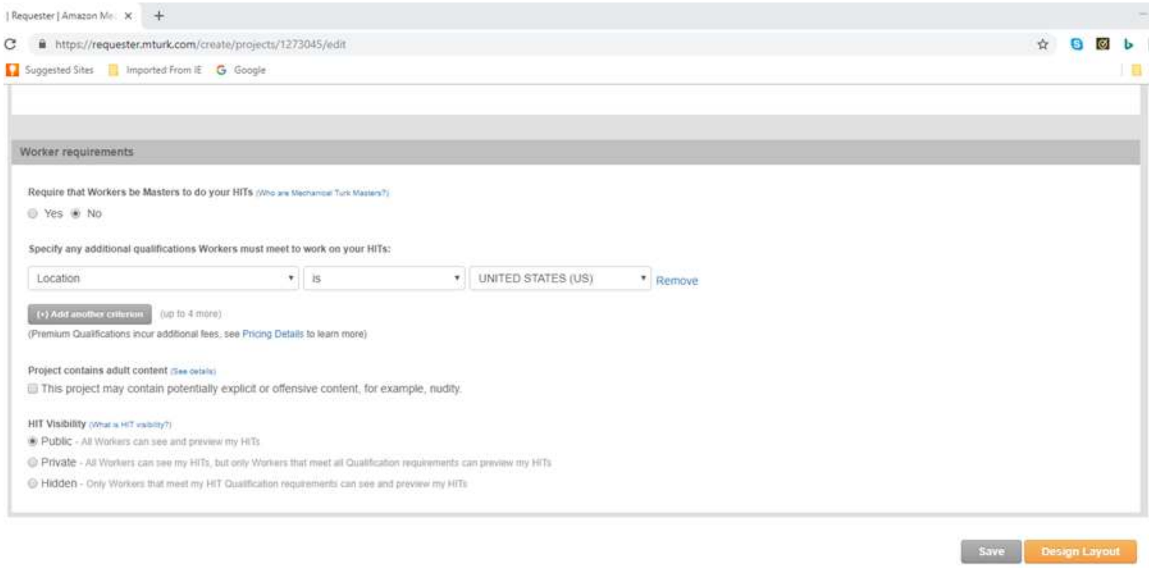
Number of assignments per HIT
750
How many unique Workers do you want to work on each HIT?

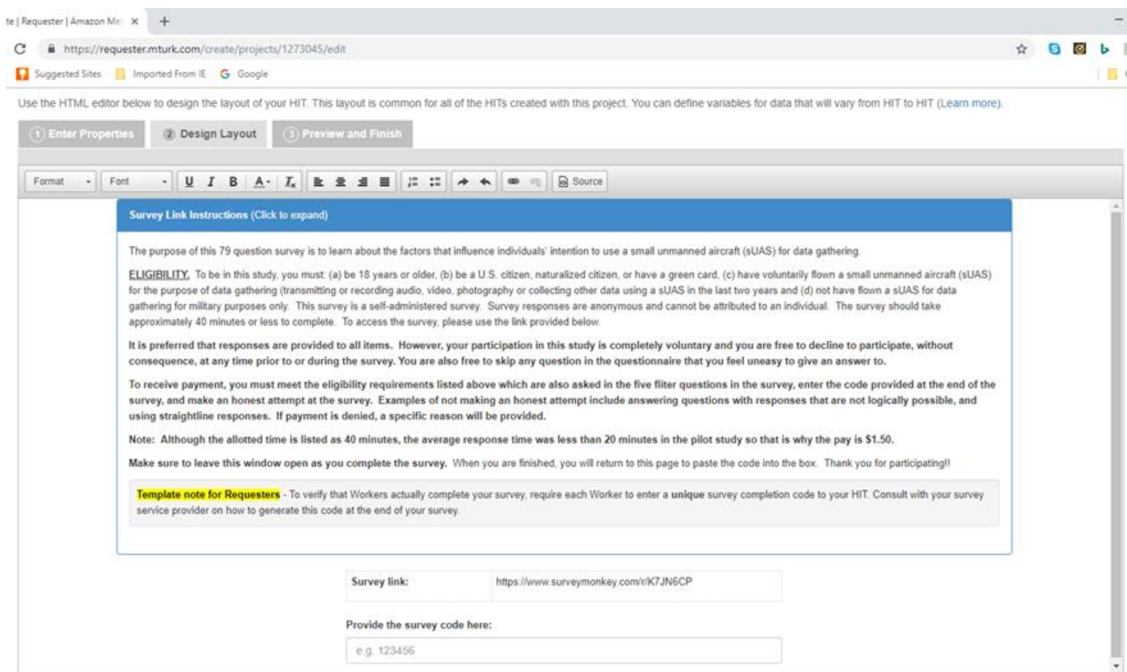
Time allotted per assignment
40 Minutes
Maximum time a Worker has to work on a single task. Be generous so that Workers are not rushed.

HIT expires in
31 Days
Maximum time your HIT will be available to Workers on Mechanical Turk.

Auto-approve and pay Workers in
5 Days
This is the amount of time you have to reject a Worker's assignment after they submit the assignment.

Worker requirements


| Requester | Amazon Me
https://requester.mturk.com/create/projects/1273045/edit
Suggested Sites
Imported From IE
Google
Worker requirements
Require that Workers be Masters to do your HITs (Who are Mechanical Turk Masters?)
Yes No
Specify any additional qualifications Workers must meet to work on your HITs:
Location
is
UNITED STATES (US)
Remove
(+) Add another criterion
(up to 4 more)
(Premium Qualifications incur additional fees, see Pricing Details to learn more)
Project contains adult content (See details)
This project may contain potentially explicit or offensive content, for example, nudity.
HIT Visibility (What is HIT visibility?)
Public - All Workers can see and preview my HITs
Private - All Workers can see my HITs, but only Workers that meet all Qualification requirements can preview my HITs
Hidden - Only Workers that meet my HIT Qualification requirements can see and preview my HITs
Save
Design Layout


te | Requester | Amazon Me
https://requester.mturk.com/create/projects/1273045/edit
Suggested Sites
Imported From IE
Google
Use the HTML editor below to design the layout of your HIT. This layout is common for all of the HITs created with this project. You can define variables for data that will vary from HIT to HIT (Learn more).
1 Enter Properties
2 Design Layout
3 Preview and Finish
Format
Font
Source
Survey Link Instructions (Click to expand)
The purpose of this 79 question survey is to learn about the factors that influence individuals' intention to use a small unmanned aircraft (sUAS) for data gathering.
ELIGIBILITY. To be in this study, you must: (a) be 18 years or older, (b) be a U.S. citizen, naturalized citizen, or have a green card, (c) have voluntarily flown a small unmanned aircraft (sUAS) for the purpose of data gathering (transmitting or recording audio, video, photography or collecting other data using a sUAS in the last two years and (d) not have flown a sUAS for data gathering for military purposes only. This survey is a self-administered survey. Survey responses are anonymous and cannot be attributed to an individual. The survey should take approximately 40 minutes or less to complete. To access the survey, please use the link provided below.
It is preferred that responses are provided to all items. However, your participation in this study is completely voluntary and you are free to decline to participate, without consequence, at any time prior to or during the survey. You are also free to skip any question in the questionnaire that you feel uneasy to give an answer to.
To receive payment, you must meet the eligibility requirements listed above which are also asked in the five fliter questions in the survey, enter the code provided at the end of the survey, and make an honest attempt at the survey. Examples of not making an honest attempt include answering questions with responses that are not logically possible, and using straightline responses. If payment is denied, a specific reason will be provided.
Note: Although the allotted time is listed as 40 minutes, the average response time was less than 20 minutes in the pilot study so that is why the pay is $1.50.
Make sure to leave this window open as you complete the survey. When you are finished, you will return to this page to paste the code into the box. Thank you for participating!!
Template note for Requesters - To verify that Workers actually complete your survey, require each Worker to enter a unique survey completion code to your HIT. Consult with your survey service provider on how to generate this code at the end of your survey.
Survey link:
https://www.surveymonkey.com/r/K7JN6CP
Provide the survey code here:
e.g. 123456