Summer 2022

Behavioral Intention Factors for Prescription Deliveries by Small Unmanned Aircraft in Rural Communities

Sarah M. Talley
Embry-Riddle Aeronautical University, vanhob92@my.erau.edu

Behavioral Intention Factors for Prescription Deliveries by Small Unmanned Aircraft in Rural Communities

Sarah Michelle Talley

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

July 2022

Behavioral Intention Factors for Prescription Deliveries by Small Unmanned Aircraft in Rural Communities

By

Sarah Michelle Talley

This dissertation was prepared under the direction of the candidate's Dissertation Committee Chair, Dr. Robert E. Joslin, 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.

Robert E. Joslin Digitally signed by Robert E. Joslin Date: 2022.09.09 16:42:16 -04'00'

Robert E. Joslin, Ph.D.
Committee Chair

Kristy Kiernan Digitally signed by Kristy Kiernan Date: 2022.09.13 10:11:45 -05'00'

Kristy Kiernan, Ph.D.
Committee Member

Dothang Truong Digitally signed by Dothang Truong Date: 2022.09.14 17:07:17 -04'00'

Dothang Truong, Ph.D.
Committee Member

Committee Member

Paul L. Myers III Digitally signed by Paul L. Myers III Date: 2022.09.14 09:32:48 -05'00'

Paul L. Myers III, Ph.D.
Committee Member (External)

Steven Hampton Digitally signed by Steven Hampton Date: 2022.09.17 11:52:17 -04'00'

Steven Hampton, Ed.D.
Associate Dean, School of Graduate Studies, College of Aviation

Alan J. Stolzer Digitally signed by Alan J. Stolzer Date: 2022.09.19 09:03:22 -04'00'

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

Lon Moeller Digitally signed by Lon Moeller Date: 2022.09.19 11:13:03 -04'00'

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

08/31/2022

Signature Page Date

Abstract

Researcher: Sarah Michelle Talley

Title: Behavioral Intention Factors for Prescription Deliveries by Small Unmanned Aircraft in Rural Communities

Institution: Embry-Riddle Aeronautical University

Degree: Doctor of Philosophy in Aviation

Year: 2022

Nearly half of the U.S. population regularly use and depend on prescription medications; however, pharmacy availability and access to pharmacy services are often lacking, particularly in rural communities. In an effort to meet local healthcare needs, delivery by sUAS is proposed to ensure the nearly 60 million rural residents have access to their prescription medications.

As an emerging technology with little research into home delivery applications, the successful implementation of sUAS for prescription medication delivery requires public acceptance and positive behavioral intention toward its use. At the time of the current research, no prior studies have specifically focused on the individual factors that impact the behavioral intention of using sUAS for prescription medication delivery.

This dissertation developed a modified behavioral research model to determine the factors that influenced individual's behavioral intention to use sUAS for prescription medication delivery and the relationships between those factors. The model integrated factors from the technology acceptance model (TAM) and the theory of planned behavior (TPB) and added the factors of perceived risk and trust. Using random sampling through Amazon MTurk, participants accessed an online cross-sectional survey for data collection. Data analysis included descriptive statistics assessment, CFA analysis, and the full SEM process.

Results indicated the research model had strong predictive power of sUAS use for prescription medication delivery with eight of the ten hypotheses supported. One new relationship was identified of subjective norms having a positive influence on perceived risk, though not supported by current literature. Further investigation into the relationship is warranted to better understand the impact. Additionally, all model factors were found to have a direct or indirect impact on behavioral intention, with perceived usefulness, trust, and subjective norms having the strongest effects.

The current research filled a gap in existing literature by exploring factors associated with behavioral intention to use sUAS for prescription medication delivery. Additionally, a new research model was provided for identifying influencing factors for behavioral intention of this sUAS application and the nature of the relationships among the factors. Thus, this new model can be used for further sUAS research and may provide an adaptable model for other industries to facilitate new technology implementation.

Keywords: behavioral intention, public acceptance, sUAS, prescription medication delivery.

Dedication

To my husband, Trip, who always supported me on this journey. You celebrated beside me when it was exciting. You stood behind me when it was demanding. You believed in me from the very beginning, and I wouldn't have made it this far without you. You have always been the glue that held our family together. Thank you for carrying the torch when I couldn't. I love you.

To my kids, who motivated me to be the best that I can in everything I do. Despite the challenges and the hurdles, you pushed me to reach the stars. I hope to always be your guiding light and give you the strength and courage to chase your dreams. No matter what I do in life, you will always be my greatest achievement. I'm so proud to be your mom.

To my cohort, my partners in crime, my lifeline. You kept me laughing while I endured the roughest roads. You kept me smiling, beaming with pride at our every accomplishment. Most of all, you kept me going when I felt overwhelmed and alone. I am honored to be welcomed among such remarkable people and astute scholars. We did it!

Acknowledgments

This project was only made possible by the unwavering support I received from the beginning. I would like to thank my Dissertation Chair, Dr. Robert Joslin, for guiding me every step of the way. Your input and expertise kept me in line and on track. You gave me the schedule and deadlines that I needed to keep moving forward. I am deeply grateful for all of your support and encouragement.

I would also like to thank my Dissertation Committee Members, Dr. Dothang Truong, Dr. Paul Myers III, and Dr. Kristy Kiernan. Your attention to detail and your expertise helped me ensure I had the latest information on the ever-changing regulations on sUAS operations. I especially appreciate the time and effort Dr. Truong spent helping me work through my validity and instrument issues. Your guidance was truly enlightening.

Finally, I would like to extend a special ‘thank you’ to Dr. Stephanie Fussell. From the first day of our first residency, you have been an absolute pillar of support. You have always been available when I had questions, when I was stuck on a problem, when I needed direction through the process, or when I just needed an outlet. You reminded me that I’m not saving the world and that I can make it through to the end, one step at a time. You have been a true partner, friend, and mentor, and I am so glad to have you in my life. Cheers to our success, and on to the next adventure!

Table of Contents

List of Tables

List of Figures

Chapter I: Introduction

This dissertation research focused on small unmanned aircraft systems (sUAS) and their potential use in commercial aviation for residential deliveries of medicines. It defined the current issues surrounding home delivery of filled prescriptions, including the lack of pharmacies in rural U.S. communities relative to urban areas. The theoretical foundation that guided the current research pertains to the role of public acceptance of new technologies and behavioral intent to use such technologies.

Chapter I presents the background of the problem of interest, the purpose of the study, research questions, hypotheses, and significance grounded in the primary literature. These sections are followed by research delimitations, limitations, and assumptions. This chapter concludes with a list of terms and acronyms to aid the readers' understanding.

Background of the Study

Pharmacy availability for filling medical prescriptions is a critical component of healthcare in the U.S., with nearly half of the population regularly using pharmaceuticals (Martin et al., 2019). Pharmacy availability refers to the direct or immediate physical access to such pharmacy services. Syed et al. (2016) researched the relationship between physical distance to a pharmacy and compliance with medical prescriptions by individuals being treated for diabetes mellitus in urban populations. Although the authors found adherence to medication prescriptions was not associated with the distance to a pharmacy, they found evidence that mail-order pharmacy services improved compliance. Generalizing Syed et al.'s finding to rural populations would indicate a critical need for greater availability of pharmacy services for filling prescriptions.

A policy brief by the National Rural Health Association (NRHA, 2009) identified multiple issues impacting access to pharmacies in rural communities. The NRHA noted access was hindered by deficiencies in pharmacy staffing and relief coverage, alternative methods of providing pharmacy services, and the financial viability of rural pharmacies. Despite these issues, the number of pharmacies per 10,000 people varies greatly depending on geographical location, ranging from 0 per capita in some rural areas to 13.6 per capita (NRHA, 2009). The national average in 2015 was only 2.11 pharmacies per 10,000 people; hence, a significant portion of the U.S. population is impacted by a lack of timely access to prescription medications (Qato et al., 2017).

In addition to a lack of roadway infrastructure, rural communities are also hampered with exclusion from many transportation services, such as overnight and expedited delivery options. In some cases, the USPS does not deliver mail to rural areas because the residences do not have a typical address or the location is too remote (CDC, 2019). Instead, those residents must travel to their post office (PO) box to pick up mail. United States Zip Codes (2021) reports 9,468 zip codes that only offer USPS mail delivery to a post office box and not to individual residencies. Based on 2010 census data, these zip codes represent approximately 5.5 million U.S. residents. Residents who live in rural U.S. communities often lack efficient or convenient pharmacy services, if any at all (Qato et al., 2017).

To meet local healthcare needs, some pharmacies offer a variety of accommodations to facilitate access to medical prescriptions. One such accommodation is the option for home delivery of prescription medications. In 2018, the National Community Pharmacists Association (NCPA) and Cardinal Health published the annual NCPA Digest, a report aiming to quantify and articulate the factors that make community pharmacies successful and that differentiate them from online or mail-order pharmacies. Hoey (2018) reported 71% of locally owned community pharmacies could provide same-day home delivery services. However, the study only included independent community pharmacies, comprising only 35% of all U.S. retail pharmacies.

Home deliveries of medicines are typically sent by U.S. Postal Service (USPS) to an individual's residence or their post office box or by a commercial carrier to their residence. Couriers such as United Parcel Service (UPS), Federal Express (FedEx), and Amazon offer home delivery options for prescription medications through their pharmacy programs or their home-healthcare delivery partners (Livingston, 2020; Thomason, 2018). Nonetheless, pharmacies offering home delivery services may not be able to provide timely or expedient deliveries to many rural residents. Postal deliveries to rural homesteads are often significantly delayed due to extended or irregular routes (SJ Consulting Group, Inc., 2011). Homes in remote or rural areas that do not have a mailing address can only receive mail at a post office box (Centers for Disease Control and Prevention [CDC], 2019), further hindering the availability of delivery of prescriptions. The solution proposed by Gatteschi et al. (2015a) for deliveries of prescription medications to rural residents is the use of sUAS. The authors claim the benefits of remotely controlled sUAS home deliveries over conventional gas-driven car/truck delivery options include financial savings, less energy consumption, better time management and efficiency, and increased safety. However, Sah et al. (2020) point out issues with potential safety hazards from defective or malfunctioning sUAS equipment, privacy concerns about sUAS cameras, mistrust in the novel technology, and security breaches in a package's chain-of-custody.

The public acceptance of new technology can significantly impact implementation, governance, and policy development (Gray, 2020). Lack of consumer or public acceptance may result in the failed execution of operations. To achieve success in implementation, public support and approval are necessary. In the case of utilizing sUAS technology for prescription deliveries in rural communities, public intent to use the technology is required for success. Therefore, behavioral intentions were modeled in this present research to determine if rural residents are willing to use the technology.

Research studies on sUAS applications in the medical community by Claesson et al. (2016), Kim et al. (2017), Lin et al. (2018), and Truog et al. (2020) addressed:

- delivery of emergency medical supplies (Claesson et al., 2016),
- regulatory considerations in using sUAS for prescription deliveries (Kim et al., 2017),
- optimal number and location of sUAS center locations for efficient pickup and delivery routes (Lin et al., 2018), and
- optimizing costs of existing sUAS operations for simultaneous medication delivery and test kit pickups (Truog et al., 2020).

Significant findings of these studies include:

- delivery of automated external defibrillators to rural out-of-hospital cardiac arrest patients in Sweden using sUAS resulted in significantly lowered response times (Claesson et al., 2016),
- placing sUAS center of operations in strategic locations within rural areas based on patient residences could potentially reduce delivery times and out-

of-pocket expenses for patients receiving regular medication deliveries for chronic conditions (Lin et al., 2018),

- existing regulations may limit the full potential of sUAS integration into the pharmacy industry for prescription medication deliveries to rural residents (Kim et al., 2017), and
- the use of sUAS for delivering medical supplies to remote rural health clinics in East Africa is more efficient and quicker than using ground vehicles for delivery (Truog et al., 2020).

These studies did not investigate the factors contributing to rural U.S. residents' behavioral intention to use sUAS for prescription deliveries. As first defined by Ajzen (1985), behavioral intent is key to determining the likelihood of an individual's behavior toward a given subject. A research gap exists within current literature with regard to predictive modeling of behavioral intention toward specific sUAS applications.

The research gap in predicting rural U.S. residents' intent to use sUAS for home deliveries of prescriptions by modeling the factors that influence behavioral intentions was addressed in the current research. The theory of planned behavior (TPB) is a research model composed of multiple constructs relating to behavioral intent. Used in many research applications since its introduction by Ajzen (1991), the TPB encompasses several model constructs to study, predict, and explain human behavior based on indicators that identify the intent to perform the studied behavior. Furthermore, several recent studies have noted the impact of trust on intended behaviors (Akbari et al., 2019; Cheung et al., 2017; Manganelli et al., 2020; Vempati, 2020). Existing literature lacks focus on identifying relevant factors associated with rural residents' behavioral intentions to use sUAS for prescription deliveries in the U.S. Also, no existing theoretical model defines these factors and their associated relationships. The current study sought to explain how the TPB model could be expanded and applied to sUAS operations and public acceptance studies. By expanding the TPB model, the research identified specific contributing factors of behavioral intent to use sUAS-delivered prescriptions and defined relationships among those variables. These constructs provided valuable insight into the behavioral intentions of rural residents to accept or reject prescription deliveries by sUAS.

Additionally, the insight the TPB model provides on predictor variables for behavioral intention may also be applied to other industries that utilize sUAS for deliveries, such as commerce, agriculture, and food. The theories used to develop the research model for the current study are discussed further in Chapter II. Furthermore, the research provided insight and value in the use of sUAS for deliveries of Coronavirus-2019 (Covid-19) related items, such as at-home tests (self-diagnostic kits), to not only facilitate the accessibility of pharmaceutical supplies but also support Covid-19 social distancing guidelines (CDC, 2020; Urban Air Mobility News, 2020; Ward, 2020). The International Transport Forum (ITF) (2020) reported several benefits drones have been providing during the Covid-19 pandemic, namely contact-free deliveries, surveillance, enforcement, and other hygiene applications. The ITF study also noted a potential positive shift in public attitudes toward drones due to positive experiences with such deliveries, which might indicate broadening acceptance of sUAS operations.

Public acceptance of sUAS operations for prescription deliveries could significantly impact the implementation and ongoing innovation of this new technology (Winickoff, 2017). Some potential benefits include accessibility for previously unreachable locations, improved delivery times, and consumer convenience. Furthermore, prescription medication deliveries via sUAS will promote existing recommendations for social distancing, limiting virus exposure; thus decreasing the risk of contracting or transmitting a deadly virus. Public acceptance of sUAS operations for prescription deliveries could also potentially improve medication adherence, as suggested by Syed et al. (2016). Specifically, research indicates that cost and availability are contributing factors to prescription nonadherence (Ho et al., 2009). People's willingness to accept prescription medication deliveries by sUAS may impact pharmacies' decisions to offer the service. With this remote delivery option, pharmacies will be able to serve customers with mobility limitations (Tabatabai, 2020). Alternatively, without public acceptance, new technology implementations often fail (Gray, 2020). Such consequences could lead to continued long delivery times, lack of available pharmacies for filling medically necessary prescriptions in rural communities, and increased risk for virus transmission due to social interactions (Leventhal & Bryan, 2020).

Statement of the Problem

The U.S. Census Bureau (2017) estimates one in five residents live in rural communities, which are most affected by the disparity between pharmacy availability and local population needs (see also Ratcliffe et al., 2016). With nearly half of the U.S. population requiring pharmacies for prescription medications, access is a crucial component of the healthcare industry (CDC, 2019). Due to the lack of available or timely pharmacy services in rural U.S. communities and the extended delivery times by traditional ground transportation, these areas could greatly benefit from improved methods for prescription deliveries.

One possible solution for poor pharmacy access to rural residents is the option to have pharmacies deliver prescription medications by sUAS. However, the successful implementation of this new technology requires public acceptance (Clothier et al., 2015). For the current research, the definition for public acceptance is adopted from Otway and Winterfeldt's (1982) study on risk perception and social acceptability of technology:

> The acceptance of risks is implicitly determined by the acceptance of technologies which, in turn, depends upon the information people have been exposed to, what information they have chosen to believe, the values they hold, the social experiences to which they have had access, the dynamics of stakeholder groups, the vagaries of the political process, and the historical moment in which it is all happening. (p. 254)

Few studies have been conducted to determine the public acceptance of this technology and the behavioral factors influencing the intention to use sUAS for prescription medication deliveries. For the purposes of the current study, behavioral intention is defined as the level of effort an individual is willing to expend to use sUAS for prescription medication deliveries. For example, Boucher (2016) investigated the strategies for managing public acceptance of civil sUAS use in the United Kingdom and Italy but did not review factors associated with behavioral intention. Additionally, Boucher did not examine the impact of trust or behavioral intent of recipients of services provided by sUAS technology. Furthermore, Cameron (2014) conducted a quantitative analysis of survey data on various aspects of sUAS usage in law enforcement activities but did not investigate the intention to use sUAS in other industries. Cameron's research also lacked structural modeling or factor analysis of constructs impacting behavioral intent. Other studies have investigated public acceptance of sUAS for deliveries in e-commerce, deliveries in emergency medical supplies, construction, law enforcement, and emergency response operations (Cameron, 2014; Claesson, et al., 2016; Graham, 2016; Terwilliger et al., 2015; Yoo et al., 2018).

Similarly, Myers and Truong (2020) developed and tested a new model using comprehensive constructs including actual use to measure the predictive ability for sUAS data gathering applications. Based on the existing need for pharmacy access, the proposed solution for sUAS deliveries, and the lack of current literature support, the current research included variables relevant to behavioral intention not found in grounded theories of existing technology acceptance and planned behavior.

Purpose Statement

The purpose of the current research was to utilize a comprehensive behavioral research model to identify the factors that influence rural residents' behavioral intentions to accept prescription deliveries by sUAS. Furthermore, the research examined the relationships among the relevant factors to theoretically explain rural residents' acceptance and intent to use sUAS deliveries for prescription medication.

Significance of the Study

The significance of the current research is to support the body of aviation knowledge by identifying and mapping the relationships of variables influencing prescription deliveries by sUAS. Specifically, the study focused on rural U.S. areas where access to a pharmacy or services is not available or not timely. The research objective is to test a new behavioral research model encompassing trust as a construct, which has not been modeled with the TPB in research studies for sUAS for prescription medication delivery, thus contributing intellectual merit to the field of aviation. It also expands how TPB and other extended or combined theoretical models may be applied to other uses of sUAS technology. New factors and hypothesized relationships were included to investigate sUAS application for prescription medication delivery. The research sought to fill the gap in the aviation literature on technology acceptance, planned behavior, behavioral intent, and perceived risks and trust of sUAS for home deliveries of pharmaceuticals. Researching constructs provided insight into factors that influence and hinder a rural resident's intent to rely on sUAS deliveries. A validated prediction model using the combined factors to study this problem has not been found in the published aviation literature.

Research Question and Hypotheses

This research sought to investigate the following research questions:

- RQ_1: What factors influence rural residents' intentions to use sUAS for prescription deliveries?
- RQ_2: How do these factors impact rural residents' intentions to use sUAS for prescription deliveries?

Ten hypotheses were proposed based on the TPB and related theories and validated models from several studies (Abkari et al., 2019; Carfora et al., 2019; Cheung et al., 2017; Manganelli et al., 2020; Myers, 2019) as well as the extended TPB:

- H_1: Subjective norms positively influence perceived usefulness.
- H_2: Perceived usefulness positively influences attitude toward use.
- H_3: Subjective norms positively influence attitude toward use.
- H_4: Subjective norms positively influence behavioral intention.
- H_5: Attitude toward use positively influences behavioral intention.
- H_6: Perceived risk negatively influences attitude toward use.
- H_7: Trust positively influences perceived usefulness.

- H_8: Trust positively influences attitude toward use.
- H_9: Trust positively influences subjective norms.
- H_{10}: Trust positively influences behavioral intention.

Delimitations

The current research was delimited to participants 18 years and older who currently live or have lived in rural U.S. communities, as defined by the U.S. Census Bureau. Additionally, the study was limited to sUAS capable of vertical take-off and landing (VTOL) as defined by the Federal Aviation Administration (FAA). The FAA requires sUAS to be in visual line of sight (VLOS) for approved operations, unless a waiver is obtained. Large UAS and manned platforms or technologies were not included in the current research. The context of the study focused on domestic sUAS commercial operations for work or business, as defined by the FAA. Therefore, only 14 C.F.R. Part 107 and Part 135 sUAS operations using certificated remote pilots were of interest in the research. Recreational, government, and educational sUAS operators were not included in the current study.

Another delimitation of the current research includes deliveries of non-emergent, non-time-critical, non-refrigerated prescription medications, including consumables, inhalants, and wearables, prescribed by a licensed physician. Over-the-counter (OTC) medicines and medical supplies were not included in the current study. The U.S. Food and Drug Administration (FDA) defines prescription medications as a “substance intended for the use in the diagnosis, cure, mitigation, treatment, or prevention of disease” (FDA, 2017, p. 248) and must be prescribed by a licensed doctor and procured at a pharmacy. Additionally, the prescription medication payload must be 5 lbs (2.3 kg) or less based on recent FAA approvals for sUAS delivery operations of packages weighing 5 pounds or less

(Palmer, 2020). Finally, this study did not include operational factors such as noise or distance in the sUAS concept of operations.

Limitations and Assumptions

A limitation of the study was only including small unmanned aircraft systems, as defined by 14 C.F.R. Part 107.3. This regulation limits unmanned aircraft systems to a weight of 55 lbs (24.9 kg), including the payload (FAA, 2020d). Flight operations during twilight hours and night time operations are only permitted with appropriate anti-collision lighting. Additionally, weather conditions must allow minimum visibility of 3 mi (4.8 km) from the control station. Airspace is limited to a maximum altitude of 400 ft (122 m) above ground level (AGL). The maximum altitude may be higher if the aircraft remains within 400 ft (122 m) of a structure. The speed of the aircraft cannot exceed 100 mph (160 kph). Finally, the research was limited to the 2010 U.S. Census data, as the 2020 Census data was not published at the time of the current research.

Per 14 C.F.R. Part 107, it was assumed that businesses utilizing sUAS for prescription medication deliveries have obtained appropriate training and certification for night operations, operations in overpopulated areas, and operations beyond visual line of sight (BVLOS). Also, it was assumed that businesses have obtained a waiver for the operation of multiple sUAS, per 14 C.F.R. 107.35. The FAA has established a partnership with the aviation industry under the FAA UAS Data Exchange umbrella, called the Low Altitude Authorization and Notification Capability (LAANC). This collaboration supports UAS integration into the airspace and authorizes sUAS operations into controlled airspace at or below 400 ft (122 m). It also provides awareness of where sUAS pilots can and cannot fly as well as visibility of sUAS operations for air traffic controllers (ATC) (FAA, 2019b). For this study, it was assumed that businesses conducting sUAS operations for prescription medication deliveries are utilizing LAANC services for authorization to operate in controlled airspace in the vicinity of airports (FAA, 2019b). It was also assumed that the chain of custody of all prescription medications adheres to current handling regulations established in 21 C.F.R. Part 1306, Prescriptions (2020) and the Drug Supply Chain Security Act (FDA, 2014). Furthermore, it was assumed that research participants would have a safe area for sUAS deliveries (drop-off area clear of obstacles, animals, and people).

Summary

The current research sought to explore and investigate factors that influence U.S. rural residents' attitudes toward sUAS deliveries of prescriptions and their specific intent to use sUAS for such purposes. Chapter I provided an overview of the background of the study, including the lack of available pharmacies and limited postal delivery services in rural communities. It defined the problem of interest, research purpose, the significance of the study, research questions, and hypotheses. Finally, this chapter presented the current research's delimitations, limitations, and assumptions.

Chapter II will review the relevant literature associated with the concept of public acceptance, sUAS applications for commercial delivery, and the research models and grounded theories, and provide the theoretical framework upon which the current research is based.

Definitions of Terms

Actual Use	The use of sUAS for prescription medication deliveries existing in reality as opposed to theory or possibility (Ajzen, 1991).

Attitude Toward Use	An individual’s positive or negative evaluation of using sUAS for prescription medication deliveries (Ajzen, 1991).
Behavioral Intention	The level of effort an individual is willing to expend to use sUAS for prescription medication deliveries (Ajzen, 1991).
Beyond Visual Line of Sight	The operation of a UAS beyond the capability of the flight crew members (i.e., the remote pilot in command), the person manipulating the controls, and visual observer, if used, to see the aircraft with vision unaided by any device other than corrective lenses (spectacles and contact lenses) (FAA, 2018).
Drone	An unmanned aircraft (FAA, 2016).
Facilitating Conditions	External factors or environmental circumstances that positively impact an individual’s intent to use sUAS for prescription medication deliveries (Teo et al., 2008).
Knowledge of Regulations	A certified remote pilot’s awareness and understanding of the federal, state, and local

	regulations that govern sUAS operations (FAA, 2016).
Perceived Ease of Use	The degree to which an individual believes using sUAS for prescription medication delivery is relatively free of effort (Davis, 1989).
Perceived Risk	The potential risks or threats that an individual associates with using sUAS for prescription medication delivery (Lee, 2009).
Perceived Usefulness	The degree to which an individual believes using sUAS for prescription medication delivery will be beneficial or significantly improve his or her circumstances (Davis, 1989).
Prescription Medications	Substances intended for the use in the diagnosis, cure, mitigation, treatment, or prevention of disease" (FDA, 2017, p. 248) and must be prescribed by a licensed doctor and procured at a pharmacy. Items included can be consumables, inhalants, wearables, and self-administered test kits.

Small Unmanned Aircraft	An unmanned aircraft weighing less than 55 lb (24.9 kg) on takeoff, including everything onboard or otherwise attached to the aircraft (FAA, 2016).
Small Unmanned Aircraft System	A small unmanned aircraft and its associated elements (including communication links and the components that control the small unmanned aircraft) as required for its safe and efficient operation in the national airspace system (Small Unmanned Aircraft Systems, 2017).
Subjective Norms	The social pressures experienced or perceived by an individual to use sUAS for prescription medication delivery (Ajzen, 1991).
Trust	An individual’s willingness to accept a technology, which is based on their expectations of the technology’s predictability, reliability, and performance of its intended function (Lippert, 2001).
Unmanned Aircraft System	An unmanned aircraft and its associated elements (including communication links and

the components that control the unmanned aircraft) as required for the remote pilot to operate it safely and efficiently in the national airspace system (FAA, 2018).

List of Acronyms

AB	Actual Behavior
AC	Advisory Circular
AGFI	Adjusted Goodness of Fit Index
AGL	Above Ground Level
AMOS	Analysis of a Moment Structures
ANSI	American National Standards Institute
ATC	Air Traffic Controller
ATU	Attitude Toward Use
AVE	Average Variance Extracted
BI	Behavioral Intention
BTS	Bureau of Transportation Statistics
BVLOS	Beyond Visual Line of Sight
C-TAM/TPB	Combined TAM/TPB model
CDC	Centers for Disease Control
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
C.F.R.	Code of Federal Regulations
CMIN/df	Chi-Square Fit Statistics/Degrees of Freedom

Covid-19	Coronavirus 2019
CR	Construct Reliability
CSOP	Certification Service Oversight Process
df	Degrees of Freedom
DOT	Department of Transportation
DSCSA	Drug Supply Chain Security Act
EASA	European Aviation Safety Agency
EFA	Exploratory Factor Analysis
ERAU	Embry-Riddle Aeronautical University
FAA	Federal Aviation Administration
FC	Facilitating Conditions
FDA	Food and Drug Administration
FedEx	Federal Express
GFI	Goodness of Fit Index
HIT	Human Intelligence Task
HTMT	Heterotrait-Monotrait Ratio of Correlations
HTMT2	Modified Heterotrait-Monotrait Ratio of Correlations
ICAO	International Civil Aviation Organization
IRB	Institutional Review Board
IT	Information Technology
ITF	International Transport Forum
IPP	Integration Pilot Program

KMO	Kaiser-Meyer-Olkin Measure of Sampling Adequacy
KOR	Knowledge of Regulations
LAANC	Low Altitude Authorization and Notification Capability
MLE	Maximum Likelihood Estimate
MSV	Maximum Shared Variance
MTurk®	Amazon® Mechanical Turk®
NAS	National Air Space
NCPA	National Community Pharmacists Association
NFI	Normed Fit Index
NRHA	National Rural Health Association
OTC	Over the Counter
PASI	Pre-application Statement of Intent
PEOU	Perceived Ease of Use
PR	Perceived Risk
PU	Perceived Usefulness
RMSEA	Root Mean Square Error of Approximation
SAS	Safety Assurance System
SEM	Structural Equation Modeling
SN	Subjective Norms
SPSS	Statistical Package for the Social Science
SRW	Standardization Regression Weights

sUA	Small Unmanned Aircraft
sUAS	Small Unmanned Aircraft System
TAM	Technology Acceptance Model
TRA	Theory of Reasoned Action
TPB	Theory of Planned Behavior
UAS	Unmanned Aircraft System
UASSC	Unmanned Aircraft Systems Standardization Collaborative
UAV	Unmanned Aerial Vehicle
UPS	United Parcel Service
USC	United States Code
USPS	United States Postal Service
UTAUT	Unified Theory of Acceptance and Use of Technology
VLOS	Visual Line of Sight
VMUTES	Viti, Myers/Mashburn, Uland, Truong, ERAU, Sullenger
VTOL	Vertical Take-Off and Landing

Chapter II: Review of the Relevant Literature

This chapter presents the relevant literature associated with the problem of interest, research constructs, and theoretical foundation. It begins with a review of public acceptance and its importance in successful technology implementation. This is followed by an overview of current sUAS technology and its various applications. It provides the definition, significance, origin, and measurement of perceived risk, reviews the acceptance models and grounded theories underpinning this research, and provides the background for the theoretical framework and support for the research hypotheses.

Definition and Background of sUAS

The type and number of aircraft operating in U.S. airspace are becoming increasingly diverse, and the airspace is becoming more congested with the introduction of sUAS operations by commercial, hobby/recreational, and public operators. Researchers project the volume of sUAS commercial operations to continue to grow throughout the next decade (Lee, 2016). Additionally, the FAA published a forecast that describes steady growth in sUAS activity, anticipating sales and subsequent operations to more than triple in size before the end of 2021 (FAA, n.d.). As defined by the FAA (2020j), an sUAS is a small unmanned aircraft (sUA) and all of the components needed for its safe and efficient operation. The FAA (2020j) defines an sUA as an aircraft weighing less than 55 lbs (24.9 kg) on takeoff, including everything that is on board or otherwise attached to the aircraft, that can be operated without possible direct human intervention either from within or on the aircraft. The system aspect of an sUAS may include any hardware, software, communication links, and any other component necessary that controls the sUA (FAA, 2016). These aircraft are often referred to as drones or unmanned aerial vehicles (UAV). For simplicity, the term sUAS denotes this classification of aircraft in the current study.

To further define these systems, the FAA divides sUAS users into one of four subcategories: recreational flyers and modeler community-based organizations, certified remote pilots/commercial operators, public safety/government users, and educational users (FAA, 2020h). Public safety, government, and educational users are provided rules governing safe and lawful operations. Regulated and enforced by the FAA, local law enforcement and other public safety agencies help monitor UAS operations and assist the FAA with criminal penalties, when necessary. Regardless, all of these agencies are subject to FAA regulations and limited authority in operations (FAA, 2019a).

14 C.F.R. Part 107 Small Unmanned Aircraft Systems

Certificated remote pilots are authorized to operate sUA weighing less than 55 lbs (24.9 kg) for work or other business under the 14 C.F.R. Part 107 regulation. UAS operators become FAA-certified remote pilots with a small unmanned aircraft system rating by passing a knowledge test. To be eligible, applicants must be at least 16 years old, able to effectively communicate in English, and be in sound mental and physical condition to safely operate a UAS. Once the Remote Pilot Certificate is obtained, the sUAS must be registered with the FAA and marked appropriately for identification. Though flight operations are closely governed by the rules listed in 14 C.F.R. Part 107, some operations are not covered and may require a waiver, per the provisions in 14 C.F.R. §107.200 and 14 C.F.R. §107.205; examples include operations from a moving vehicle or aircraft or beyond visual line of sight operations (FAA, 2016).

However, 14 C.F.R. Part 107 does permit the transportation of property by sUAS for compensation or hire. Although the regulation currently does not allow operations to be conducted between states, U.S. territories, across the Hawaiian Islands, or through the airspace of Washington, D.C., companies are permitted to transport property via sUAS as part of business operations within a confined area and within the operating restrictions defined in the federal regulations. Transport operations by sUAS are limited to flights within the Visual Line of Sight (VLOS) of the remote pilot unless a waiver has been granted. However, Beyond Visual Line of Sight (BVLOS) operations for delivery are addressed under 14 C.F.R. Part 135 regulations. Operations also cannot be conducted from a moving vehicle or aircraft for property transport by sUAS for compensation or hire. The sUA and its payload may not exceed 55 lbs (24.9 kg) and must be visible and locatable by the remote pilot at all times. Furthermore, the remote pilot must be able to determine altitude, attitude, and direction throughout the entire duration of the flight, must yield the right-of-way to other aircraft, and be able to see and avoid other aircraft during flight operations (FAA, 2016).

14 C.F.R. Part 135 Air Carrier and Operator Certification

The 14 C.F.R. Part 135 UAS operations are subject to the same safety compliance regulations as manned Part 135 flight operations. Part 135 certification is the only authorized avenue for package delivery operations by UAS beyond visual line of sight (BVLOS) for compensation (FAA, 2020d). Companies interested in conducting delivery operations via UAS must complete the existing five-phase Part 135 certification process as prescribed by the FAA. Phase 1 identifies the steps for the pre-application process. Four main actions must be completed in this first phase:

- applicants must request access to the FAA Safety Assurance System (SAS) External Portal,
- applicants must submit the FAA Form 8400-6 Pre-application Statement of Intent (PASI) to the local Flight Standards District Office through the SAS External Portal,
- the FAA office manager will initiate the Certification Service Oversight Process (CSOP) once the PASI is accepted, and
- the applicant and any additional key management personnel must attend a Pre-application Meeting with the Certification Team assigned to their project (FAA, 2020c).

The formal application of the FAA Part 135 certification process is completed in Phase 2. Applicants must provide the assigned Certification Team with all required documents. The packet must include the formal application letter, a schedule of events, a compliance statement, company manuals, training curricula, management qualification attachments, documents of purchase, SAS element design assessment tools, proposed operations specifications, and flight attendant materials, if required. A Formal Application Meeting will then be held to conclude Phase 2 of the certification process and allow any questions or issues to be resolved (FAA, 2020c).

Phases 3 and 4 of the certification process consists of the Design and Performance assessments, respectively. The Certification Team reviews and analyzes the documents provided in the formal application to ensure compliance with regulations and safety practices. The team then determines if the proposed procedures, operations, and training programs are effective. Once approved, applicants may then move to Phase 5 of the certification process. The final phase consists of the administrative functions necessary for the FAA to issue the certificate and operations specifications to the applicant (FAA, 2020c).

Title 14 C.F.R. Part 135 operating certificates may be obtained for a single-pilot operator, a single pilot in command (PIC) operator, a basic operator, or a standard operator. The FAA issued the first Part 135 single-pilot air carrier certificate to Wing Aviation, LLC in April 2019 for UAS operations. Wing Aviation later obtained a standard Part 135 air carrier certificate and delivers both food and OTC pharmaceuticals to residences in Christiansburg, VA. Another commercial operator, UPS Flight Forward also obtained a standard Part 135 air carrier certificate in September 2019 to conduct UAS delivery operations for medical supplies in Raleigh, NC (FAA, 2020c). In August 2020, Amazon became the third recipient of a standard Part 135 air carrier certificate to deliver packages to customers via UAS (Cozzens, 2020).

UAS Integration Pilot Program

The FAA began encouraging the introduction of drones into everyday air traffic through the implementation of the UAS Integration Pilot Program (IPP). Working with state, local, and tribal governments as well as private sectors in the aviation industry, the FAA is fostering awareness of the benefits of UAS innovation while articulating the development of future regulations (FAA, 2020d). The UAS IPP was initiated in 2017 with the intent of testing and evaluating the integration of UAS into the National Airspace System (NAS) and concluded the initiative on October 25, 2020. The program had the intent to identify methods of balancing local and national interests as they relate to UAS integration, improve communication with governing entities regarding UAS operations, address any security and privacy risks associated with UAS integration, and accelerate the approval of UAS operations which currently require special authorizations. The leading program participants evaluated an array of conceptual operations. Several of these concepts included night operations, flights over people, operating BVLOS, and package delivery operations. Industries identifying an immediate benefit to these concepts included commerce, emergency management, infrastructure inspections, agricultural support, and photography (FAA, 2020f; Gabrlik et al., 2018; Padró et al., 2019).

Under the UAS IPP, several lead participants completed projects that included UAS operations for package delivery that are relevant to this research. The city of San Diego, CA, completed a project that focused on food deliveries via UAS and other applications. The program investigated various landing stations and ports for the aircraft and employed a variety of communication technologies to improve UAS tracking and ID systems (FAA, 2020f).

The Center for Innovative Technology in Herndon, VA, also partnered with the FAA under the UAS IPP. Their project included package delivery operations via UAS in both rural and urban environments, utilizing various collision avoidance, tracking, and identification technologies. Similarly, the North Carolina Department of Transportation worked to test package delivery operations via UAS in local communities by establishing dedicated delivery stations. Their project specifically sought to support small businesses by enabling them to utilize UAS delivery platforms for commercial purposes (FAA, 2020f).

Most notably, the City of Reno, NV, was a lead participant in the UAS IPP with a project focused on time-sensitive deliveries of life-saving medical equipment. This project supported both urban and rural communities experiencing emergencies and who were in dire need of medical equipment such as defibrillators. The project detailed options for commercial medical partners and included a delivery model which was scalable across the nation (FAA, 2020f).

Upon its conclusion, the UAS IPP provided valuable insight and data supporting increased UAS operations within the existing NAS framework. The lessons learned allowed FAA and U.S. Department of Transportation (DOT) policymakers to further develop appropriate regulations, policies, and guidelines regarding advanced UAS operations. The UAS IPP was so successful, the FAA decided to continue the partnerships under the newly established program called BEYOND. As of October 26, 2020, the purpose of BEYOND is to continue investigating the challenges identified in UAS integration that were not fully explored through UAS IPP. Specifically, its purpose is to examine:

- BVLOS operations that support infrastructure inspection, public operations, and small package delivery,
- societal and economic benefits of UAS operations by leveraging existing industry operations to better analyze and quantify advantages, and
- community engagement efforts to collect, analyze, and address local concerns regarding UAS operations (FAA, 2020h).

The BEYOND program is going to examine UAS operation concepts that operate under established regulations, as opposed to those requiring waivers. Through these efforts, the FAA is going to gather data with the intent to develop performance-based standards, analyze community feedback to further understand potential benefits to society, and restructure the process for approving UAS integration to be more efficient (FAA, 2020g).

Low Altitude Authorization and Notification Capability (LAANC)

The FAA UAS Data Exchange is an industry collaboration between the U.S. government and private aviation sectors to facilitate sharing of airspace data. One of the partnerships supported under this innovation is the Low Altitude Authorization and Notification Capability (LAANC). This effort directly supports the safe and efficient integration of UAS into the airspace. Specifically, LAANC allows UAS pilots to have access to controlled airspace at 400 ft (122 m) or below, provides information on boundaries for where pilots can and cannot operate their UAS, and gives air traffic controllers visibility on UAS locations within the airspace. Also, UAS service providers are companies authorized by the FAA to offer these LAANC services. These companies utilize desktop applications and mobile applications to provide near real-time data and approvals for pilots applying for airspace authorization (FAA, 2019b).

Prescription Dependencies in the U.S.

According to a 30-day study conducted by the CDC (2019), 45.8% of the U.S. population regularly used prescription drugs between 2015 and 2016. The data also show prescription drug use increases with age and reported medical conditions, particularly chronic diseases. Georgetown University Health Policy Institute (n.d.) reported 89% of patients diagnosed with arthritis use prescription medications, and 98% of diabetes patients use prescription medications. The CDC (2019) study also found the top three types of prescription drugs used by the U.S. population during 2015 and 2016 varied by age. The most commonly used prescription drug types in the past 30 days during the study were bronchodilators for children aged 0–11 years (4.3%), central nervous system stimulants for adolescents aged 12–19 (6.2%), antidepressants for adults aged 20–59 (11.4%), and lipid-lowering drugs for adults aged 60 and over (46.3%) (CDC, 2019).

With uses including pain management, anxiety, panic, sleep disorders, cardiovascular disease, and central nervous system treatments, more than 4.3 billion prescriptions are filled annually at pharmacies throughout the U.S. (Fuentes et al., 2018). In addition to the commonly prescribed medications, the FDA has also approved new methods, called medication-assisted treatments, to treat substance abuse such as alcohol and opioid addictions (Substance Abuse and Mental Health Services Administration, 2020). Based on published data, the number of medication prescriptions dispensed by pharmacies has been steadily increasing over the last decade, and numbers are expected to continue to rise (Shahbandeh, 2020).

Pharmacy Services in Rural Areas

Few research studies in the available literature have focused on access to pharmacy services in rural communities, even though such services are an integral aspect of rural health policy issues (Casey et al., 2002). Analyzing survey information, licensure data, and interview responses from more than 500 rural pharmacies in Minnesota, North Dakota, and South Dakota, Casey et al. found most residents within 20 miles of a pharmacy have adequate geographic access to pharmacy services but struggle with financial resources. These financial challenges are particularly impactful on elderly and uninsured patients. The perspective of that study as well as the responses were solicited from pharmacists, pharmacy employees, and public health staff rather than the area residents. Additionally, many independent and rural pharmacies closed following the implementation of Medicare Part D in 2006 (Klepser, 2010).

Chisholm-Burns et al. (2017) conducted a study in Shelby County, Tennessee, to investigate the disparities in drug pricing, pharmacy services, and access to community pharmacies for populations consisting of predominantly minorities. Despite geographic access to a pharmacy being widely available in the 25 zip codes included in the study, Chisholm-Burns et al. found the areas with higher minority populations had fewer pharmacies per 10,000 residents. Additionally, their research revealed pricing was generally lower for specific medications in areas with lower employment rates, and pharmacies located in areas with lower average income levels, lower employment rates, and higher crime risks were less likely to offer home medication delivery services.

Public AcceptanceError! Bookmark not defined.

If the users of a new technology perceive the introduced equipment as disruptive or inefficient or even a waste of resources, then the successful implementation of that technology could be significantly hindered (Kasperson et al., 2013). Thus, public acceptance is critical for new technologies. *Public acceptance* has been accepted in research as a "positive attitude towards an idea or product at the specific time of introduction" (Talley, 2020, p. 49). Cohen et al. (2014) discuss three aspects of public acceptance within the general framework of the abstract model. Supported by Wüstenhagen et al. (2007), these aspects exist in the form of socio-political acceptance, community acceptance, and market acceptance. The socio-political aspect encompasses technologies and policies, and is typically influenced by politicians, stakeholders, and the public (Sonnberger & Ruddat, 2017). Community acceptance is also known as local acceptance. Much like socio-political acceptance, the objects are technology projects, only on a local level. The resident citizens affected are the primary influencers of this aspect of acceptance (Roddis et al., 2020).

Market acceptance refers to the consumer adoption of technologies, specifically by the investors and the public sector that utilize the technologies (van Rijnsoever et al., 2015). Each of these facets of public acceptance is critical for the successful implementation of new technologies into society.

Perceived risks and other factors associated with the new technology could impact public acceptance of the technology. The introduction of sUAS in any industry includes some level of acceptable defined risk to users. However, the level of perceived risk may greatly vary between members of the public and the institutions which have developed and implemented sUAS. The general public tends to place greater concern on long-term risks associated with new technologies; yet new technologies are often implemented before or along with the implementation of risk management efforts (Renn, 2004). Implementing new technologies concurrently with risk management, such as deploying sUAS for prescription deliveries in rural areas of the U.S., have generated public concerns regarding perceived risk and other factors influencing behavioral intentions to accept the technology (Choi, 2013).

Vincenzi et al. (2013) conducted a study consisting of a comprehensive literature review on existing publications of UAS technology and operations within the NAS. The researchers also administered a survey to people among the U.S. population selected from a public opinion data vendor to study the public opinion of UAS operations. The survey assessed the participants' familiarity with UAS operations, comfort level for various platforms, as well as different uses and demographics. Although the sample size was small (n = 223), rendering the results non-generalizable to the overall population, the data collected were valid and indicative of public opinions on UAS operations. The study revealed a general awareness of UAS operations and equipment by the public, but 95% of respondents associated UAS platforms and missions with military operations. Participants agreed with existing UAS uses which provided a service or benefit to the community, such as firefighting and weather monitoring. However, they expressed concerns with UAS uses in law enforcement, surveillance, and crowd control-type missions.

A similar study was conducted with a survey design project administered to 400 U.S. residents over the age of 18 and 14 C.F.R. Part 135 stakeholders of the UAS industry, including pilots and airline industry employees (Reddy & DeLaurentis, 2016). Specifically focusing on identifying factors reducing uncertainty among the general public on UAS platforms and operations, this study found similar results in that the public is generally familiar with UAS operations but only considers them acceptable under certain circumstances. Results indicate participants generally approve of UAS operations in support of public service missions and scientific applications. Both the citizens and stakeholders expressed concern regarding the potential risks associated with UAS operations.

A more recent study was conducted to assess public opinion regarding policies and regulations governing UAS operations as well as the placement of responsibility for developing and enforcing those regulations (West et al., 2019). This study focused on public opinion regarding UAS from a political standpoint, analyzing data collected from the 2016 pre-election Cooperative Congressional Election Study survey. The sample population included 1,000 U.S. adults whom answered questions primarily focused on UAS use by law enforcement, commercial firms, and private citizens. As seen in previous studies, respondents showed a general knowledge and awareness of UAS technology. Results also indicated that the public is supportive of comprehensive UAS regulation, specifically regarding privacy protection. The study also found that respondents were divided in their support of other aspects of UAS regulations, such as military operations utilizing UAS as well as recreational use.

In an exploratory study conducted in Europe and Australia, Macias et al. (2019) state social acceptance is necessary for the successful integration of drones within the current airspace. The researchers further suggested the benefits that an emerging technology can provide must outweigh its potential issues, as perceived by society, for the technology to avoid being rejected by society. This study also identified crucial factors of acceptance including transparency, inclusiveness, and the ability of law enforcement agencies to mitigate negative impacts of the new technology and for violators of policy to be penalized. Three overall indicators of public acceptance were reviewed in the study: safety, economic benefit, and political considerations. Utilizing a survey approach, the results revealed significant decreases in a member of society's willingness to accept the technology as the environmental complexities increased. However, within the parameters of the proposed airspace environment detailed jointly by the European Commission (the executive branch of the European Union) and the European Union Aviation Safety Agency (EASA), members of society appear to be more willing to accept UAS technology implementation with accompanying procedures and services designed to render operations more safe, efficient, and secure (Macias et al., 2019).

Boucher (2016) utilized semi-structured focus groups to conduct an exploratory study of public acceptance of civil applications of drone operations in Italy. Boucher prompted small groups of participants with open-ended questions regarding civil drones and allowed conversations to naturally evolve to identify which issues are important to the population. Participants identified boundaries for acceptable and unacceptable civil uses for drones and largely sided on accepting applications where a significant social benefit was perceived. However, this study did not apply any of the identified factors to an acceptance model and primarily focused on organizing the thoughts and insights solicited from the focus groups.

Cameron (2014) conducted a study on the public acceptance of sUAS for U.S. law enforcement operations. The research employed a survey tool distributed to the general U.S. public via email, online forums, survey distribution sites, and social media. The participants partially consisted of the researcher’s personal contacts, therefore, the sample was not an accurate representation of the population. Although the analysis was completed on the survey results utilizing statistical software, the data were not modeled, and the researcher did not explicitly identify relevant factors influencing behavioral intent to use sUAS operations. Furthermore, the study focused specifically on sUAS applications in law enforcement so does not provide specific insight for potential sUAS use for prescription medication deliveries.

A study conducted by Clothier et al. (2015) on the public acceptance of sUAS in Australia investigated whether the public believes sUAS are riskier than existing manned aircraft and what broader concerns influence public acceptance of sUAS. This study surveyed 200 Australian citizens with both scaled and open-ended questions. The researchers found the respondents held a fairly neutral opinion regarding sUAS. Survey results indicated citizens felt sUAS provided more benefit to society as a whole rather than to an individual. The results also indicated respondents perceived a comparable safety risk with sUAS as with other technologies capable of performing the same tasks. Although this study investigated public opinion and acceptability of sUAS and included perceived risk as a factor, the sample included both rural and urban residents and did not model contributing factors of behavioral acceptance.

The acceptance of sUAS applications in other industries (e.g., agriculture) has been investigated. Efron (2015) proposed a study to combat food shortages and inefficiencies in farming practices in Sub-Saharan Africa. The researcher investigated how sUAS technology could increase agricultural output and considered factors that could influence the acceptance of sUAS in that industry. Using a mixed-method approach and based on a review of existing literature and consultation with subject matter experts, Efron determined sUAS technology could assist with pest control, so she developed a framework for decision-makers to use in assessing sUAS acceptance. The researcher identified various contributing factors but did not use a validated model to analyze the factors or explore any relationships among the study variables.

Khan et al. (2019) investigated consumer acceptance of purchases delivered by sUAS in the retail industry in Pakistan. Utilizing a survey tool, the researchers sampled middle- and upper-class residents from two major cities regarding factors contributing to the acceptance of sUAS for retail deliveries. The researchers analyzed the data using descriptive statistics and conducted correlation, regression, and cluster analyses. They determined consumer privacy is a major concern of residents. This study finding provides valuable insight into consumer acceptance of sUAS, but the factors of acceptance and behavioral intention to use the technology were not modeled.

sUAS Technology Applications

Walgreens and CVS, two of the largest pharmacy chains in the U.S., recently launched a pilot program to test sUAS deliveries of convenience items such as snacks and over-the-counter medications (Reader, 2019). Partnering with UPS, FedEx, and Wing, a sister company of Google, pharmacies are testing these deliveries as a way to remain competitive in the e-commerce market. Other applications of the pilot program include prescription drug deliveries from pharmaceutical manufacturers directly to doctors and independent pharmacies (Reader, 2019). The sUAS businesses are exploring solutions for areas with poor infrastructure or dilapidated roadways. For example, Zipline is capitalizing on the transportation benefits of sUAS to deliver medical supplies to healthcare clinics in Rwanda and Ghana (Kolodny, 2019).

Retailers in the U.S. have also considered the use of sUAS for parcel deliveries. In a study conducted by Yoo et al. (2018), factors affecting the public's attitude and intention to adopt sUAS for parcel deliveries were investigated. Using an online survey, a sample of U.S. consumers responded to questions about perceived advantages and risks and innovativeness, attitude, and intention toward parcel deliveries by sUAS. The researchers proposed a theoretical model based on the diffusion of innovation theory (Rogers, 2003) and the TAM (Davis, 1989). The data were analyzed by linear regression. The results indicated relative advantages of parcel deliveries by sUAS positively impacted users' attitude toward sUAS as well as their intentions to adopt the technology. Also, perceived risks were found to negatively impact attitudes toward sUAS deliveries. This study provided insight into factors impacting consumers' intent to use sUAS for deliveries, but it did not focus on sUAS deliveries in rural communities or for prescription medications.

The American National Standards Institute (ANSI) released a Standardization Roadmap for UAS in June 2020, prepared by the Unmanned Aircraft Systems Standardization Collaborative (UASSC), updating the 2018 version. This roadmap identifies current and in-progress standards for UAS operations, assesses gaps in regulations, and offers priority recommendations for additional standardization based on feedback and collaboration with industry stakeholders in both the public and private sectors. Section 8.4.1. specifically addresses commercial package delivery via UAS. The current assessment of existing operations identifies a need for more specific and rigorous regulations regarding commercial delivery operations via UAS before such business models can be implemented. Recommendations for standardization include how packages are carried on the aircraft, which types of materials can be delivered, mechanisms and procedures for package release at the point of delivery, determination of safety and security for landing at the point of delivery, testing and evaluation of safety features, and so forth (ANSI UASSC, 2020; Mascarello et al., 2017).

Other research has investigated the overall security of the cargo itself for medical deliveries via UAS. Royall and Courtney (2019) studied the safety and quality implications of medical products being delivered by UAS and reviewed the existing framework of regulations that assess and assure that safety and quality. The study identified the unique stresses encountered during UAS delivery, including vibration, g-force, rapid changes in pressure, humidity, and temperature excursions, which need to be further investigated for potential negative impacts to the medicines being transported.

A similar study was conducted to evaluate the quality impact on insulin when transported to a location by UAS (Hii et al., 2019). Insulin is sensitive to sunlight so needs to be transported in appropriate containers and the temperature kept between 2°C to 8°C to maintain potency and reduce damage (Bahendeka et al., 2019). The Hii et al. study involved the transportation of Actrapid, an injectable solution containing insulin, subjecting the medication to temperature and vibration impacts during UAS flight. The researchers found no evidence of significant negative impacts to the medication from UAS transport and recommended the following five aspects be considered when transporting medication via UAS: (a) safe flight time and range, (b) quality of the medication post-flight, (c) conditions the medications are exposed to onboard, (d) security of the supply chain process, and (e) impacts of potential delivery failure by either damaging the medication during transport or disruption in its delivery (Hii et al., 2019; Scalea et al., 2018).

Perceived Risk

Although the TAM is widely used and accepted as a valid and reliable tool to assess consumer acceptance, the factor of perceived risk is not included in the model. *Risk* is defined as expected loss coupled with the probability of loss or the undesirable changes in technical performance, cost, or schedule due to a probabilistic event (Parnell et al., 2010; Stolzer & Goglia, 2016). The perceived risk in the technology acceptance model incorporates numerous factors, including financial risk, performance risk, physical risk, security risk, and social risk, and is ultimately the overall perception of the possible danger or hazard presented by a technology (Jacoby & Kaplan, 1972; Myers, 2016; Vassie, 2005).

Lee (2009) further defined each construct of perceived risk. *Financial risk* is defined as the probability of monetary loss. *Performance risk* is defined as the probability of system failure. *Physical risk* is defined as the probability of harm or damage to people or property. *Security risk* is defined as the probability of a threat to personal security or safety. *Social risk* is defined as the probability of public discontentment. Based on the prevalence of this factor in individual acceptance, Myers (2016) argues perceived risk should be included as a construct in the analysis of TAM and the UTAUT model.

Trust

Trust is a component of social behavior that has been studied in a range of applications, including e-commerce, grocery shopping, and food consumption (Cheung & To, 2017; Hameed et al., 2019; Qi & Ploeger, 2019; Spence et al., 2018). Trust plays a significant role in counteracting negative social acceptance notions as well as reducing perceived risk (Gefen, 2004). Furthermore, trust has been shown to increase the assumption of a positive result thus influencing behavioral intent within the social framework (Grabner-Kraeuter, 2002; Luhmann, 2018). Absent the positive influence of trust, studies have found reduced levels of behavioral intent as well as actual behaviors (Kim et al., 2004; Pavlou & Gefen, 2004). Trust can be increased through familiarity and understanding of a situation or concept. Research has also found that first impressions and personal interactions have a positive influence on building trust by developing cognitive categorizations and perceptions of control (Brewer & Silver, 1978; Luhmann, 2018; Meyerson et al., 1996).

Trust can be associated with current TPB theories based on the examination of aspects in which trust is hypothesized to also influence attitude toward use, subjective norms, and behavioral intent. Trust is also a construct related to theories supporting various aspects of technology acceptance models, such as perceived usefulness (Gefen, 2004; McKnight & Chervany, 2001). Pavlou (2003) posits that trust is identified as a principal behavioral belief which categorically impacts attitude toward behavior. Davis et al. (1989) and Bandura (1986) further support the notional theory that trust directly impacts attitude toward behavior. The social cognitive theory relates the expectation of behavior leading to a particular outcome with attitude toward behavior (Bandura, 1986). Trust, therefore, is assumed to have a significant impact on attitude and behavior.

Research by Nelson and Cooprider (1996) and Taylor and Todd (1995) has shown trust and influence, or the capacity to have an impact over a person's behavior, are highly correlated in social contexts, indicating trust's effect in the subjective norm construct. These studies also indicate the influences of peers and superiors regarding the determination and acceptance of subjective norms. Thus, as a derivative result, it can be hypothesized that trust plays a significant role in determining subjective norms. Indeed, as it relates to behavioral intent and perceived usefulness, trust has been studied in multiple contexts as a direct influence of both constructs (Gefen, 2004; Gefen et al., 2003; Pavlou, 2003; Saeed et al., 2003).

Trust is also an aspect of reliance on automation or systems, as stated by Hoff et al. (2015). Trust is described as having a significant role in determining a user's willingness to rely on an automated system in scenarios considered uncertain. Specifically, trust in automation or technology depends on the purpose and performance of the system (Lee et al., 1992). Though trust is a dynamic concept with different meanings based on applications, it can account for an individual's overall interactive experience with automation (Yang et al., 2017).

Current Technology Acceptance and Behavior Theories

Research by Aydin (2019), Flynn (2007) Kasperson and Ram (2013), and Stelter et al. (2020) identified a need for public acceptance for new technology to be successfully introduced into society. Specifically, they found implementation success hinges on acceptance. This revelation is supported by various models that include influencing factors of behavioral intention, such as the technology acceptance model (TAM), theory of planned behavior (TPB), combined TAM/TPB model (C-TAM/TPB), unified theory of acceptance and use of technology (UTAUT) model, and the comprehensive VMUTES model (Viti, Myers/Mashburn, Uland, Truong, ERAU, Sullenger) that combines the TPB and TAM models with several additional external factors (Myers, 2019). However, the reviewed research shows that although these models are effective in exploring some factors influencing technology acceptance, further research is needed to address their inadequacies to expand their explanatory capabilities and broaden their practical applications.

The TAM has evolved since its development and has become a widely accepted model for use in information technology (IT) acceptance studies. It has been a key factor in determining and evaluating predictors of human behavior related to accepting or rejecting the introduction of new technologies (Marangunić & Granić, 2014). However, it has not been effective in measuring or predicting intent or actual use (Turner et al., 2010).

Similarly, the TPB model evaluates intention to perform a behavior based on attitude toward the behavior, subjective norms, and perceived behavioral control (Mathieson, 1991). An extension of Ajzen's TAM model, the TPB model explores the impact of perceptions of behavioral control as a factor in predictive modeling of behavioral intent (Madden et al., 1992). Although this model is effective in predicting the actual use of new technologies, it fails to capture all of the relevant factors needed to evaluate intent to use aviation technologies. Ajzen (1991) found that perceived behavioral control varies greatly from one industry or application to another. Therefore, the TPB model alone cannot extensively evaluate an individual's behavioral intention to use sUAS for prescription medication deliveries.

The C-TAM/TPB model has been used to exploit the strengths of both C-TAM and TPB models. Taylor and Todd (1995) posited societal factors and perception of control were key components of predicting behavior, which are factors the TAM does not include. Pynoo et al. (2012) and Chen (2013) used the C-TAM/TPB model in their empirical research evaluating users' behaviors in accepting new computer technologies. However, these studies did not include all potentially relevant factors relating to behavioral intentions toward using sUAS for prescription medication deliveries.

After an extensive literature review and synthesis of existing theoretical models for predicting behavioral intent, Venkatesh et al. (2003) proposed an alternative approach for evaluating user acceptance of new IT inventions. Their UTAUT model attempts to explain much of the variance between use and intent to use. However, it does not theorize all potential relationships among constructs and has not been modified to incorporate all relevant factors relating to behavioral intentions toward using sUAS for prescription medication deliveries. Similarly, the VMUTES model includes and combines factors from various models, but it targets a different population than the population targeted in the study. Also, three constructs in the model—actual use (AU), knowledge of regulations (KOR), and facilitating conditions (FC)—were not relevant to investigating the hypotheses proposed in the current research.

Models Selected for this Grounded Study

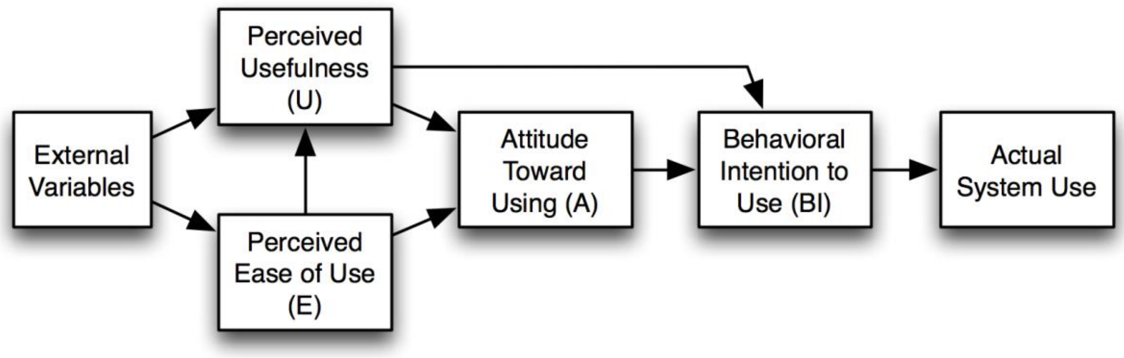
The selection of four theoretical models for this present research were based on their prior validation and wide use in academic research. The following sections explain how the theoretical models and several validated adaptations and extensions of these models applied to the study.

TAM Model

The TAM model is a commonly employed method in social sciences for studying acceptance due to its reliability and validity (King & He, 2006). In summary, the TAM model is designed to evaluate the perceived usefulness (PU) and perceived ease of use (PEOU) for a given technology. *Perceived usefulness* is a model construct generally defined as the degree to which an individual user perceives the technology as being able to improve performance (Davis, 1989). Davis also defines *perceived ease of use* as the degree to which an individual user perceives the usability of the technology as being without difficulty. Together, the model is then used to forecast an individual's intent to use the technology from the predicting factors PU and PEOU. The model is also used to assess an individual's actual usage of the technology. The information systems theory underpinning the TAM model provides a framework for quantifying and evaluating the behavioral factors which influence a user's willingness to accept new technology. An expansion of Ajzen and Fishbein's theory of reasoned action (TRA), which correlates the relationship between an individual's actions and the behaviors and attitudes which influenced those actions, the TAM is the most extensively recognized model of technology acceptance (Venkatesh, 2000). Figure 1 depicts the TAM model developed by Davis et al. (1989).

Figure 1

Components and Relationships of the Technology Acceptance Model



Note. Adapted from "User Acceptance of Computer Technology: A Comparison of Two Theoretical Models," by F. D. Davis, R. P. Bagozzi, and P. R. Warshaw (1989), *Management Science*, *35*(8), p. 984. https://doi.org/10.1287/mnsc.35.8.982. Copyright 1989 by the Institute of Management Sciences.

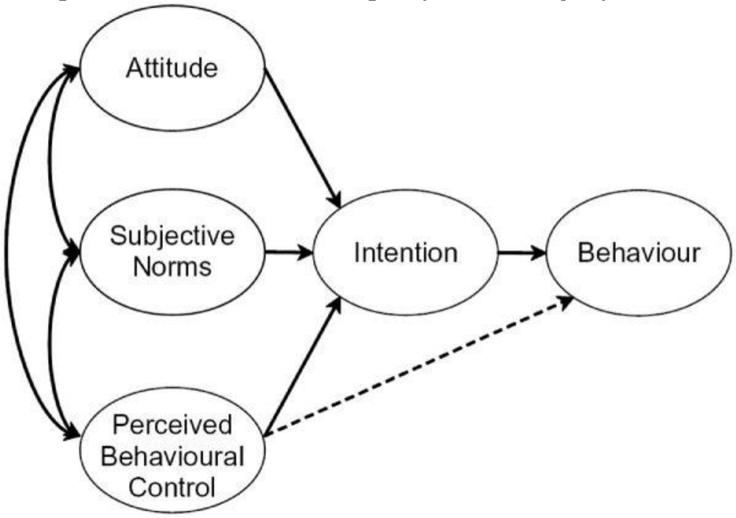
The TAM also includes an individual's attitude and general acceptance of a technology as well as the individual's intent to use the technology. Combined with PU and PEOU as predictor variables, the model provides a comprehensive review of acceptance. Utilizing self-reported usage data by research participants, an individual's attitude toward a new technology is measured and analyzed. Correspondingly, research participants provide self-predicted future usage of a technology. This data is used to measure and analyze behavioral intentions (King & He, 2006). Once all datapoints are collected, each is assigned a corresponding value by means of a validated survey tool. Using a Likert scale, the values are measured and evaluated for TAM research studies. Regarded as one of the most inclusive and dynamic predictor models for technology acceptance, the TAM has endured extensive and rigorous testing to measure validity and reliability (Legris et al., 2003).

TPB Model

The TPB model is an expansion of the TRA model. It infers behavior is governed by intention to perform that behavior and that intention is a function of attitude toward the behavior and subjective norms (Ajzen & Fishbein, 1980). Similarly, the TPB models attitude, behavior, and intentions, serving to predict an individual's intent to accept a given technology (Ajzen, 1991). However, unlike TAM which aims to predict acceptance of technology, the TPB model theorizes behavior is determined by behavioral intention (BI), which in turn is determined by attitude (A), subjective norms (SN), and perceived behavioral control (PBC) (Seyal & Rahman, 2017). Thus, an individual's behavior is determined by their intention to perform such behavior (Mathieson, 1991). Figure 2 depicts the TPB developed by Ajzen (1991).

Figure 2

Components and Relationships of the Theory of Planned Behavior



Note. Adapted from "The Theory of Planned Behavior" by Ajzen (1991), *Organizational Behavior and Human Decision Processes, 50*, 179-211. https://doi.org/10.1016/0749-5978(91)90020-t. Copyright 1991 by Elsevier Inc.

C-TAM/TPB Model

Although both TAM and TPB have validity and reliability, many studies have combined them to minimize the limitations of solely using one or the other (Myers, 2019). Mathieson (1991) made a comprehensive comparison of the two models and determined that a successful merge of the TAM and TPB provides sufficient modeling for researchers to investigate behavioral intention while also considering SN and PBC as control variables. Empirical research has been conducted, and researchers determined the combined TAM and TPB (C-TAM/TPB) model is effective in explaining an individual's behaviors toward using new technology (Chen, 2013).

Similarly, the UTAUT is another example of several merged models, including the TAM and the TPB as well as six other previously studied models. Venkatesh et al. (2003)

determined that any other single model could only explain 30% to 60% of an individual's behavioral intention to use new technology. Therefore, eight models were combined to create the UTAUT model, which explains 70% of an individual's behavioral intention to use new technology (Venkatesh et al., 2012). Although the UTAUT model has been shown to account for 70% of behavioral intent, additional precision is needed for this present investigation of the acceptance of prescription medication deliveries by sUAS.

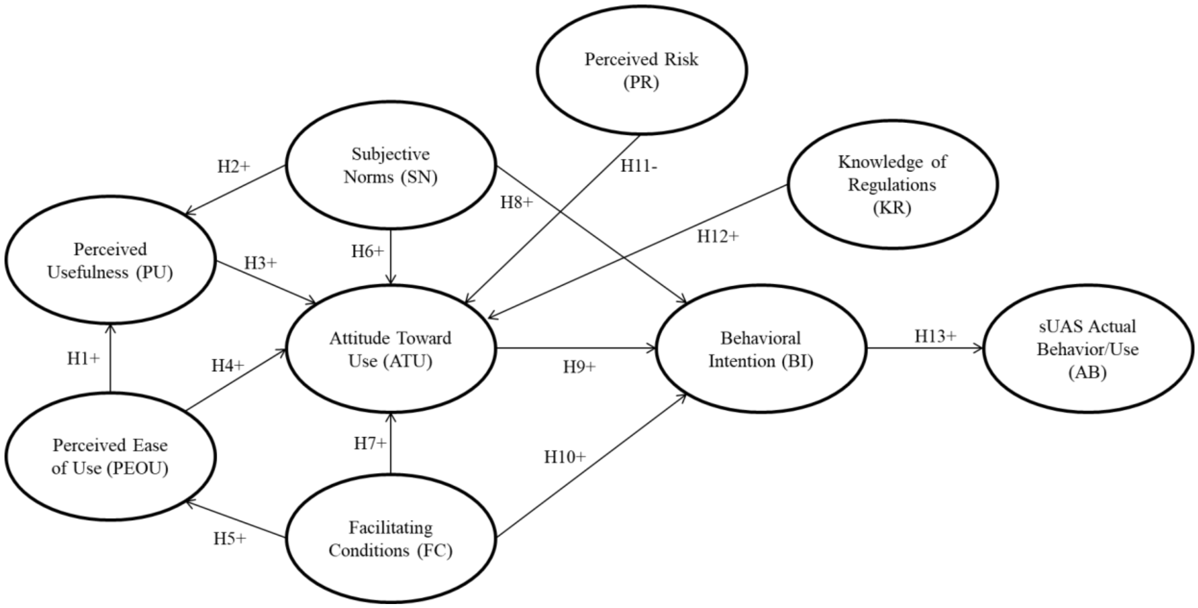
VMUTES Model

The VMUTES model is also composed of multiple constructs relating to behavioral intent. First used in research of sUAS applications by Myers (2019), this model is a combination of other existing research models consisting of the TPB, TAM, and the addition of two external factors of perceived risk (PR) and knowledge of regulations (KOR). The model consists of nine specific constructs, all derived from previously reviewed and validated models. The nine constructs are perceived usefulness (PU), perceived ease of use (PEOU), subjective norms (SN), attitude toward use (ATU), facilitating conditions (FC), perceived risk (PR), knowledge of regulations (KOR), behavioral intention (BI), and actual behavior/use (AB) (Myers, 2019).

To effectively capture each of these contributing factors to determine behavioral intention to accept new technology, the framework from previously validated technology acceptance models was combined to form the VMUTES model. However, the results of the empirical study conducted by Myers and Truong (2020) led to the removal of the FC construct to improve the overall model fit. Similar studies using this construct also recommend the removal of the FC construct in modeling behavioral intentions to accept a new technology (Davis, 1989; Techau, 2018; Teo, 2012). The VMUTES model framework is depicted in Figure 3. Table C2 presents relevant research and major findings related to the constructs that have been included in the VMUTES model as well as the relevant research references.

Figure 3

Theoretical Framework Presented in the VMUTES Model



Note. H = hypothesis. Adapted from "A Behavioral Research Model for Small Unmanned Aircraft Systems for Data Gathering Operations" by P. Myers and D. Truong (2020), *Journal of Intelligent & Robotic Systems*, 100, 1617–1634. https://doi.org/10.1007/s10846-020-01232-x.

Gaps in the Literature

As shown in the reviewed literature, numerous studies have been conducted using the TAM, TPB, UTAUT, C-TAM/TPB, and several other derivative models. In each study, constructs relevant to an individual's behavioral intent to accept a new technology were used. For example, PU and PEOU have consistently been validated and shown to have a significant impact on ATU and BI. These models have all been successfully applied to studies in a variety of industries looking to introduce new technology. However, the extant literature does not include research on behavioral intention to use sUAS for prescription medication deliveries in rural communities using a comprehensive model, as investigated in this study.

Constructs for the Theoretical Model

The model used in the research is a modification of the original TPB model that also incorporates constructs from the TAM as well as other external factors. The previous studies outside of the aviation discipline show the new constructs are directly related to attitude and behavior. They were adapted for this present research to fill gaps in existing literature regarding the public's acceptance of sUAS for prescription medication deliveries in rural communities. The constructs included are attitude toward use (ATU), behavioral intent (BI), perceived risk (PR), perceived usefulness (PU), subjective norms (SN), and trust (TR). Table 1 provides the research supporting these constructs as well as the relevant findings indicating relationships for each factor. Table C1 reviews extant literature detailing similar studies. This literature review also shows a gap in research studies available to the public using the existing model for investigating behavioral intention to use sUAS for prescription medication delivery.

Table 1

Sources and Relevant Findings for the Model Constructs

Construct	Major Finding	Research
Attitude Toward Use (ATU)	Helps determine BI	Lu et al. (2010)
	Affected by PU	Chang & Chang (2009)
Behavioral Intent (BI)	Influenced by ATU	Gong et al. (2004)
Perceived Risk (PR)	Direct effect on BI	Pavlou (2003)
	Negative effect on BI	Teo (2012)
Perceived Usefulness (PU)	Predictor of ATU	Ha & Stoel (2009); Morosan (2014)
	Significant effect on BI	Choi & Chung (2012); Park & Kim (2014); Teo (2012)
Subjective Norms (SN)	Direct effect on attitude	Teo et al. (2008)
	Significant effect on BI	Teo (2012)
	Significant effect on PU	Teo (2012)
	Positively related to ATU	Lu et al. (2010)
	Influences intention and behavior	Ajzen (1991); Casper (2007)
Trust (TR)	Positively influences SN	Manganelli (2020); Wu & Chen (2005)
	Positively influences ATU	Akbari et al. (2019); Cheung & To (2017); Manganelli et al. (2020); Saeri et al. (2014); Wu & Chen (2005)
	Positively influences PU	Manganelli (2020); Wu & Chen (2005)
	Positively influences BI	Akbari et al. (2019); Carfora et al. (2019); Cheung & To (2017)

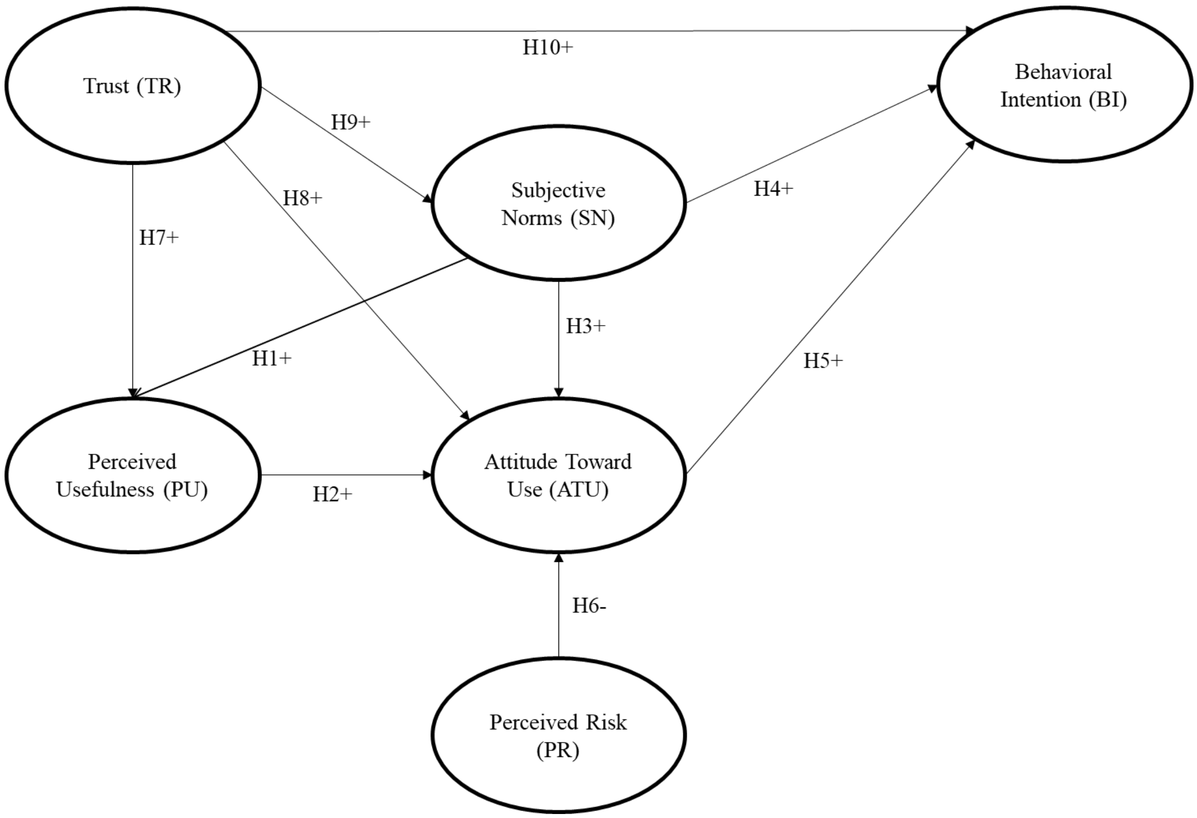
Note. ATU = attitude toward use; BI = behavioral intention; PU = perceived usefulness; SN = subjective norms.

Theoretical Framework

The review of relevant literature was used to determine constructs to include in the theoretical framework and to hypothesize relationships between the chosen variables of interest. Rural residents' behavioral intention to use sUAS for prescription medication deliveries is the outcome variable. The predictor variables are attitude toward use, perceived risk, perceived usefulness, subjective norms, and trust (Ajzen, 1991; Manganelli, 2020; Myers, 2019; Saeri et al., 2014; Wu & Chen, 2005). These variables are included in the research model based on the constructs included in the TAM and TPB models, and perceived risk and trust are included based on their theoretical support in the reviewed literature. The framework proposes the relationships between the predictor variables and an individual's intentions to use sUAS for prescription medication delivery. The theoretical framework and hypothesized relationships are depicted in Figure 4.

Figure 4

Theoretical Framework for the Proposed Research Model



Note. H = hypothesis. Theoretical framework and relationships to the research hypotheses.

This model does not include other factors which may influence a user's behavioral intent to use sUAS for prescription medication delivery. Furthermore, due to the limited scope of the current research, factor and path selections in the model were restricted to those derived from the literature review. Based on the grounded theories detailed in the literature review, the research model provided a strong theoretical basis for studying the behavioral intent to use sUAS technology for prescription medication deliveries in rural communities.

Hypotheses and Support

This section provides the hypothesis statements for the research model. It includes support for the 10 hypotheses and their constructs.

H_1: Subjective norms positively influence perceived usefulness. The subjective norm construct was found to have a significant positive influence over perceived usefulness in previous studies using a C-TAM/TPB approach (Teo, 2012). Similar observations were made in studies using an extended TAM approach to study behavioral intention to accept or use new technology (Choi & Chung, 2012). These two studies did not focus on behavioral intention to use sUAS technology, but the relationship is consistent with that presented in the proposed model. Therefore, the subjective norms construct is hypothesized to positively influence perceived usefulness. It is expected that others who may benefit from the use of sUAS for prescription medication delivery will support the sUAS user.

H_2: Perceived usefulness positively influences attitude toward use. Previous studies using a C-TAM/TPB approach revealed perceived usefulness as having a positive influence on attitude toward the use of new technology (Chang & Chang, 2009; Lee, 2009; Lu et al., 2010; Teo, 2012). Because sUAS for prescription medication delivery may offer users benefits that other methods of delivery may not, such as faster delivery or better access to medications, it is anticipated that users will perceive sUAS as useful. Therefore, it is expected that the perceived usefulness construct will positively influence attitudes toward the use of sUAS.

H_3: Subjective norms positively influence attitude toward use. This hypothesis is similar to the theory that subjective norms have a positive influence over perceived usefulness. Therefore, it is hypothesized that the subjective norms construct will have a positive influence over attitude toward use. It is expected that others who may benefit from sUAS use for prescription medication delivery will support the user. It is therefore expected that the user's attitude toward the use of sUAS for prescription medication delivery will become more positive. This theory is supported by previous studies using the extended TPB approach and the C-TAM/TPB approach (Lao et al., 2016; Lu et al., 2010).

H_4: Subjective norms positively influence behavioral intention. Similar to the theory that subjective norms have a positive influence over perceived usefulness and attitude towards use, it is also hypothesized that the subjective norms construct will have a positive influence over behavioral intent. It is expected that others who may benefit from sUAS use for prescription medication delivery will support the user. Therefore, it is also expected that the user's behavioral intention to use sUAS for prescription medication delivery will increase. This expectation is supported in the literature review on similar studies (Lee, 2009; Lu et al., 2010; Teo, 2012).

H_5: Attitude toward use positively influences behavioral intention. It is hypothesized that attitude toward use construct positively influences users' behavioral intention to use sUAS for prescription medication delivery. This theory is supported by other studies using the TAM approach and the C-TAM/TPB approach (Lee, 2009; Lu et al., 2010; Teo, 2012).

H_6: Perceived risk negatively influences attitude toward use. Perceived risk is a significant factor in behavioral intention. It has been theorized as having negative effects on attitude toward use, and many studies incorporating a variety of potential risks have supported the theory (Clothier et al., 2015; Featherman & Pavlou, 2003; Lee, 2009; Myers, 2019; Park, 2009; Venkatesh & Davis, 1996). If the perceived risk is too high, it is expected that an individual's intentions to use sUAS for prescription medication delivery will be hindered or stopped altogether. This theory is further supported by a study conducted by Ramadan, Farah, and Mrad (2017) on consumer acceptance of service-delivery drones.

Based on the theories presented in the literature review, it is hypothesized that the perceived risk construct will have a negative influence on attitude toward use.

H_7: Trust positively influences perceived usefulness. The literature review details the importance of trust in both technology acceptance models as well as projected behavior models (Manganelli et al., 2020; Wu & Chen, 2005). In studies regarding trust and consumer behavior, trust is described as the belief that the responsible party will not only behave dependably but will not venture to capitalize on the vulnerabilities of the user (Schnall et al., 2015). Trust is evident in the credibility of the responsible party as well as the integrity of the medium being used. This notion is further supported by research indicating trust is associated with perceived usefulness in a system (Donmez et al., 2008). If users have greater trust in sUAS operations for prescription delivery, it is expected that users will have an increased perception of usefulness. Therefore, it is hypothesized that trust will have a positive effect on perceived usefulness.

H_8: Trust positively influences attitude toward use. Existing literature supports the theory that trust positively influences a person's attitude toward the use of a new item or service (Akbari et al., 2019; Cheung & To, 2017; Manganelli et al., 2020; Saeri et al., 2014). As a component of Ajzen's (1991) original TPB model, attitude toward use has a significant impact on a user's behavior. Previous studies have investigated the impact of trust as a predictor of attitude and found that trust is a significant precursor of attitude (Teng & Wang, 2015; Ricci et al., 2018). If users have greater trust in sUAS operations for prescription delivery, it is expected that users will have an improved attitude toward the use of sUAS for prescription medication delivery. Therefore, it is hypothesized that trust will positively influence attitude toward use.

H_9: Trust positively influences subjective norms. Subjective norms refer to the social impact of people's perceptions about a behavior (Wu & Chen, 2005). The perceived social pressure from others with influence over a user significantly can impact a user's behavior. The greater trust a user has in those individuals, the more likely they are to exhibit the same behaviors (Cheung & To, 2017). Therefore, it is hypothesized that trust will positively influence subjective norms.

H_{10}: Trust positively influences behavioral intention. Existing literature supports the theory that trust is directly related to a user's behavioral intention to use a system or service (Akbari et al., 2019; Carfora et al., 2019; Cheung & To, 2017). Research also shows trust plays a significant role in a user's decision-making process regarding purchasing options (Del Guidice et al., 2018). Lobb et al. (2007) found that a user's trust in an institution predicted intent to purchase from that institution. Furthermore, it can be implied that trust in the sUAS for prescription deliveries will likely impact a user's intent to use sUAS for prescription deliveries. Therefore, it is hypothesized that trust will positively influence behavioral intention.

Summary

This chapter provided a comprehensive review of the primary literature supporting public acceptance of the new technology application under investigation. The founding theories used for the current study were described with relevant supporting research, thereby providing the foundation for the methodology of this research. Furthermore, the theoretical framework for the research model was detailed, along with research and justification for each construct included in the model, providing context for the problem investigated and the specific research question.

An overview of sUAS technology, commercial operations under 14 C.F.R. Part 107 and 14 C.F.R. Part 135, and current sUAS technology applications were provided in this chapter. Additionally, prescription dependencies in the U.S. were discussed, and relevant supporting statistics were reviewed as they relate to the problem being studied. The literature review provided the background for public acceptance and trust and the role they play in the successful implementation of new technologies. Current technology acceptance theories were reviewed as well as the grounded theories supporting the model used in the current study. Finally, gaps in existing research and the theoretical framework for the model in this research were detailed.

Chapter III details the research methodology and design for the study. It describes the population of interest, data sampling, measurement instruments, treatment of the data, and ethical considerations.

Chapter III: Methodology

This chapter presents the research approach and justifies the methodology chosen for answering the research questions and hypotheses. To enable replication of the methodology, it describes in detail the research design, population and sample, instrument and its theoretical constructs, ethical considerations, data collection and analysis procedures, and the reliability and validity assessments.

Research Method Selection

Vogt et al. (2012) articulate effective scenarios for research designs to use an experimental approach. Experimental designs are appropriate for studies if participants can be randomly assigned, variables can be manipulated, or if randomized control trials are effective for the study. However, none of these stipulations were valid for this research; therefore, a non-experimental approach was appropriate. Additionally, a survey approach was used to collect data concerning participant intention and attitude. Groves et al. (2009) define a survey as an organized approach for researchers to collect data from a sample group to construct quantitative descriptors for the larger population. Surveys are effective in collecting data for analysis on a population too large to include in a study and are commonly used for research in behavioral and social sciences (Vogt et al., 2012).

The current research used a cross-sectional approach to investigate a sample of the target population at a single point in time (Babbie, 2016). Data was collected one time, so it is only relevant for the period being studied and cannot be used for studying change over time (Vogt et al., 2012). The survey was voluntary, and participants were able to withdraw at any time without consequence. All data was self-reported by the participants, and it was assumed that all survey responses were truthful and accurate. The collection of personal data was limited to information that is relevant to the research questions. To maintain privacy and anonymity, all personally identifiable information was kept secure, and it was not published or conveyed to others by this researcher.

The study employed a non-experimental survey approach and quantitative data analysis. The data analysis relied on structural equation modeling (SEM) to examine the structural relationships between the measured variables and latent constructs. The SEM analysis was appropriate for the current research to effectively describe all of the relationships between variables and constructs as well as represent any unobserved interrelationships within the model. The SEM analysis was also able to account for error measurements in the estimation process (Hair et al., 2010). The SEM approach utilized statistical methodologies and hypothesis testing to evaluate the structural theory of a given problem. More specifically, it graphically modeled relationships between variables using causal methods that were categorized by a sequence of structural equations, allowing the theory to be visually conceptualized. Once developed, the SEM was then analyzed for relationships among variables, as hypothesized using the model fit (Byrne, 2010). Furthermore, confirmatory factor analysis (CFA) was used to test how well the measured variables represent the constructs. The CFA was a critical component of the SEM process because it confirmed the theoretical foundation (Hair et al., 2010). Therefore, the CFA process was completed before testing the hypotheses. Using SEM and CFA was appropriate because this study incorporated unvalidated factors, and they were used to test the theoretical framework.

Population/Sample

This section identifies the target population, sampling parameters, and strategies for sampling the target population. From the 2010 census data, the U.S. Census Bureau reported 19.3% of the U.S. population, approximately 59.6 million people, reside in rural areas (Ratcliffe et al., 2016). These residents were counted from the 704 counties that were identified as mostly or completely rural.

Population and Sampling Frame

According to Groves et al. (2009), a target population is the group of elements from which the researcher obtains sample statistics to make inferences. The target population for this research was U.S. citizens 18 years or older who currently live or who have lived in rural communities, as defined by the U.S. Census Bureau rural-urban commuting area codes (RUCA). A RUCA is assigned to a geographical region determined by the census tracks in each state and county.

The sampling frame is the list of members within a population (Vogt et al., 2012). The sampling frame was users of Amazon® Mechanical Turk®, and the sampling unit was individual persons. The U.S. Census Bureau classifies U.S. census tracts and assigns a RUCA of urban or rural based on measures of population density, urbanization, and daily commuting using the most recently published census. Census tracts are small, relatively permanent statistical subdivisions of a county (Census Bureau, 2018). These criteria provided the basis of the preliminary qualifying questions that serve to grant or deny respondents access to the survey as valid participants.

Sample Size

Vogt et al. (2012) identify the representativeness of the sample population as being more important than the size of the sample. However, the larger the sample, the more accurate the results of the research will represent the target population. Westland (2010) identifies two lower bounds on sample size for SEM-based studies. The first is based on the ratio of indicator variables to latent variables. The second is a function of minimum effect, power, and significance. Equation 1 details Westland's recommended formula to determine the minimum sample size:

$$n = \frac{1}{2H}\left(A\left(\frac{\pi}{6} - B + D\right) + H + \sqrt{\left[A\left(\frac{\pi}{6} - B + D\right) + H\right]^2 + 4AH\left(\frac{\pi}{6} + \sqrt{A} + 2B - C - 2D\right)}\right) \quad (1)$$

where:

$A = 1 - \rho^2$

$B = \rho\, arcsin\left(\frac{\rho}{2}\right)$

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

$D = \frac{A}{\sqrt{3 - A}}$

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

ρ = correlation for a bivariate Normal random vector

δ = effect size

z = standard normal score

α = probability level

β = Type II error rate

An online a-priori sample size calculator for SEM studies that uses Westland's formula (https://www.danielsoper.com/statcalc/calculator.aspx?id=89) was used to determine the appropriate sample size for the current research. The effect size was set at 0.2, the statistical power level was set at 0.8, six latent variables and 30 observable variables were included, and the probability level for the model was set at 0.05. Using these parameters, the appropriate minimum sample size for the model was 403 participants with valid responses who meet the criteria of a rural resident and submit a complete survey (Soper, 2021).

Sampling Strategy

Non-stratified convenience sampling, a form of nonprobability sampling (Lavrakas, 2008), was chosen for the current study. Although probability sampling generally leads to higher quality findings due to the unbiased representation of the population, convenience sampling employing the crowdsourcing model available through Amazon® Mechanical Turk® (MTurk®) was ideal for the research. Crowdsourcing is a sourcing model for obtaining information or services by enlisting the paid services of a large number of people, usually via the internet (Chambers & Nimon, 2019). Using MTurk® as the platform for participant recruitment and survey distribution provided a means of quickly obtaining a large number of samples that are similar in quality to lab-based collected samples (Rice et al., 2017). Internet-based sampling techniques have demonstrated convergent validity with other samples collected in a lab, inferring data share similar psychological and social constructs (Chandler & Shapiro, 2016; Cunningham et al., 2017).

The use of this online platform as a crowdsourcing database could have introduced the possibility of sampling bias due to the impact of the selection limitation imposed by the

MTurk® workers (survey participants). For example, they could have chosen to participate or not participate in a study based on the type of survey design, compensation awarded for completing the survey, civic duty or community service aspect that participation offers, and other factors (Hunt-White, 2014). Cheung et al. (2017) also identified numerous factors with the potential to impact the validity of research using MTurk® as a crowdsourcing platform (see also Stritch et al., 2017). Selection bias, demand characteristics, range restrictions, and sample representativeness pose a potential threat to the external, internal, and construct validity of a research project. To limit possible impacts to validity, Cheung et al. (2017) recommend not revealing details of the study before a worker elects to participate, ensuring characteristics of the obtained sample are representative of the target population by evaluating demographics and limiting restrictions for participant eligibility to ensure appropriate participation is achieved. Ward et al. (2021) also found that convenience sampling using MTurk® may impose potential bias due to the general population of MTurk® workers differing from the general population, but this limitation is somewhat mitigated from research stating the data obtained is useful (Litman et al., 2017). Buhrmester et al. (2011) found MTurk® participants represented more population diversity than would be available through random sampling of an in-person setting compared to its virtual setting.

MTurk® uses human intelligence tasks (HIT) to identify work opportunities on this Amazon® internet platform, including survey participation tasks. *Requestors* are defined as the researchers posting HIT for completion and identifying how many respondents are needed. *Workers* are defined as participants completing the HIT for compensation. Amazon® provides the overall account management, including payment accounts for both requestors and workers, and it manages the platform for developing and distributing HIT opportunities (MTurk, 2018). Requestors create and upload the HIT to be completed, set the required number of workers, set the rate of compensation, and deposit the funds into the Amazon® payment account. The HIT is then initiated and available for workers to complete. Once a worker completes the HIT, his or her Amazon® account is credited automatically with the payment. Workers received $0.75 for participation in the survey.

MTurk® also allows requestors to restrict HIT participation based on specific qualifications or demographics of workers. Amazon® collects nationality information during the account registration process for tax and legal purposes (MTurk, 2018). The target population for this study consisted of U.S. residents 18 years or older who currently live or who have lived in rural communities. Therefore, the HIT settings for the survey for the current research limited distribution to U.S. MTurk® workers.

An additional feature offered by MTurk® is the ability for requestors to limit workers based on qualifications such as the number of previous tasks the worker has completed and the percent of completed HITs that have been accepted by other requestors (Sheehan, 2017). The current research limited participation to workers who have completed at least 100 HITs with a 95% approval rating or better from previous requestors. These restrictions aimed to exclude or avoid participation by low-rated workers who were more likely to provide false information or not follow all instructions (Litman et al., 2017).

Data Collection Process

As noted in Babbie (2013), survey administration may occur through a variety of avenues, including online distribution platforms. Data collection in the current study used a survey instrument administered through MTurk®, an online, self-administered recruitment platform. Researchers have found MTurk® participants to be more representative and as diverse as other internet-based population samples (Buhrmester et al., 2011). However, research also indicates that U.S. users of MTurk® are generally more educated and more likely to be unemployed than the general population (Goodman et al., 2013). Additionally, the range of ages and socioeconomic status could be more limited compared to the general population (McDuffie, 2019). Nevertheless, MTurk® has been found to meet or exceed existing psychometric standards defined by Eignor (2011) and related to published scientific research (Mason & Suri, 2011).

Design and Procedures

The research design employed a non-experimental survey approach with quantitative data analysis. The theoretical model was an extension of existing behavioral research models, including the TAM and TPB, to better assess an individual's behavioral intentions to accept the use of sUAS deliveries of medical prescriptions. The selection of the model factors was based on extensive research to ensure the theoretical framework of the data collection instrument was appropriate for this research (Babbie, 1990; Groves et al., 2009). The survey items were modeled from similar studies (Davis et al., 1989; Elias, 2016; Lee, 2009; Lu et al., 2010; Myers, 2019; Teo, 2012) and were tailored to specifically assess the constructs concerning sUAS prescription medication deliveries (Vogt et al., 2014). Survey items were grouped by model construct and were direct and easily comprehendible. Demographic information was collected, but no personally identifiable demographics were collected, and all survey responses were anonymous.

The relationship of the indicator variables to and between the constructs was evaluated through CFA. The reliability of the indicator variables and constructs was tested using Cronbach's alpha. Fit statistics were evaluated for acceptability. The model fit of the

CFA was analyzed using the comparative fit index (CFI), and a value of 0.93 or greater was considered acceptable and a good fit of the target model (Hair et al., 2010). Evaluation for the goodness of fit (GFI) and adjusted goodness of fit (AGFI) was considered acceptable if the value was 0.90 or greater (Kline, 2016). The normed fit index (NFI) details the model's measure of fit and was considered acceptable if the value was 0.90 or greater. Evaluation of the minimum discrepancy over degrees of freedom (CMIN/df) was considered acceptable if the value was equal to 3 or less (Hair et al., 2010). Lastly, evaluation of the root mean square error of approximation (RMSEA) was considered acceptable if the value was 0.06 or less (Byrne, 2010; Hair et al., 2010).

Pilot Study. Following the development of the survey instrument, the IRB was consulted for approval to engage human participants. After approval, a pilot study was conducted to validate the survey instrument and demonstrate reliability. Connelly (2008) suggests a pilot study should incorporate a sample size that is 10% of the projected sample size of the larger study. However, the literature further states that determining the sample size of a pilot study is not as simple or straightforward and must consider other factors, such as confidence interval and effect size (Aberson, 2019; Hertzog, 2008). Thabane et al. (2010) argue that the sample size of a pilot study should be large enough to be able to provide relevant information about the instrument being assessed.

Thabane et al. (2010) also recommend using a confidence interval approach to estimate the required sample size of a pilot study to establish the feasibility of the instrument. Using this approach, a confidence interval of 95% was chosen for the proportion of eligible participants who completed the pilot survey. Based on a margin of error of 0.05, a lower bound of the confidence interval of 0.70 and a 75% anticipated completion rate, the pilot study required at least 75 participants (Thabane et al., 2010). To ensure enough data was collected to validate the survey instrument, a minimum sample size of 100 participants was chosen for the pilot study.

For the pilot study, reliability and convergent validity were confirmed. However, not enough evidence existed after thorough analysis to support discriminant validity. Therefore, the survey was modified. After the revised survey was approved by the Institutional Review Board (IRB), a second pilot study was conducted. After reliability and validity were confirmed for the second pilot study, no necessary adjustments were made to the survey instrument prior to its full distribution. The survey was then administered to volunteer participants via MTurk®, and data were collected. Data analysis was completed for hypothesis testing.

Apparatus and Materials

The survey instrument for this research was only able to be accessed through the MTurk® online survey tool. MTurk® was chosen as the recruitment and distribution platform for the survey instrument due to its widespread use in research studies as well as its ability to effectively reach a diverse sample of participants (Buhrmester et al., 2011; Rice et al., 2017). The survey included filter and demographic questions designed to ensure each participant was a member of the target population, and it included multiple items to examine each input variable for the model constructs. Additionally, the survey included a brief background of the research, instructions for completing the survey successfully, and a consent form completed by each participant.

Sources of the Data

The sources of the data analyzed were items on a social survey, and those items were the primary source of information; there were no secondary data sources. The data were collected through an online instrument administered through the MTurk® platform that was acceptable and appropriate for administration (Babbie, 2013). Survey designs are appropriate due to their relatively low cost for administration and data collection, ease of distribution, and widespread reach of participants (Vogt et al., 2012). The online data collection device for the current research is provided in Appendix B.

Ethical Consideration

Human participation was required to collect the survey data. Therefore, this study required IRB approval. Due to the nature of survey research and the limited direct contact with participants, ethical concerns were considered relatively minor (Vogt et al., 2012). The research also included ethical choices built into the design, as is standard for survey research designs (Vogt et al., 2012). However, because survey research requested participants to provide perspectives and information about themselves which was not otherwise available, the current study addressed ethical considerations from the following five aspects.

1. Voluntary consent: All participants were provided a written consent statement detailing the purpose of the research. This statement was provided at the beginning of the survey instrument, and participants were required to read it and provide consent before accessing the survey. If at any time a participant no longer wished to continue in the research, they were free to opt-out of the survey or end their participation by exiting the online survey.

2. Protection from harm: This research was not anticipated to cause any harm to participants as a survey design examining participants' attitudes and behavioral intentions toward acceptance of using sUAS for prescription medication deliveries. Sensitivity and consideration were used in the wording of the survey items to avoid information bias from negative phrasing that could be misconstrued or biased language that could impact the nature or directionally of the results. Furthermore, the design ensured no reasonable potential for any physical or psychological harm to the participants.
3. Privacy: It is critical to ensure privacy when administering a survey research design. This research did not collect any personally identifiable information from participants. Because participation was anonymous, the relevant demographic data that was recorded and used in the data analysis cannot be traced back to specific respondents. If any participant contacts the researcher directly, any personally identifiable information obtained through that communication will be kept confidential and will not be made available to the public.
4. IRB: Participation in any research study involving a survey design requires IRB approval. The IRB process outlined and administered by Embry-Riddle Aeronautical University (ERAU) was strictly followed to ensure participant rights and safety were protected throughout each step of the research. Appendix A provides the IRB application, informed consent statement, and other supporting documents relevant to the IRB process. This researcher completed the Collaborative Institutional Training Initiative (CITI) training required by the university, and no special actions were required of the survey participants.

5. Integrity of the study: Results of the research were reported as fairly and accurately as possible. Data was presented and discussed without bias or prejudice by the researcher. Both positive and negative results were presented without any predisposition. The research did not include any falsified results, data, authorship, or conclusions.

Measurement Instrument

The current research utilized an online survey instrument to collect data from participants. The survey instrument included a total of 38 items in addition to the survey consent form. The first section of the survey contained the purpose of the research, a consent form, and several screening questions to determine participant eligibility. The second section contained five items regarding participant demographics. Demographic data included gender, age, education level, annual income, and occupation. The third section of the survey contained 30 items designed to assess the latent constructs that may influence participants' intentions to use sUAS for prescription medication deliveries as well as factors impacting attitude and behavioral intention. At least three items should be used to accurately measure each construct (Hair et al., 2010). Using previous studies as a model for designing the items, each construct contained a minimum of five survey items for measurement. The full survey instrument is provided in Appendix B.

Constructs

This study proposed to explore the six constructs in the model using various indicator variables. Research suggests using at least three measurement instruments (items) to assess each construct (Hair et al., 2010). The research used a minimum of five items for each construct assessment. Table 2 lists the constructs and the number of associated indicator variables used in this research.

Table 2

Constructs and Indicator Variables

Construct	Number of Indicator Variables
Perceived Usefulness (PU)	5
Subjective Norms (SN)	5
Behavioral Intent (BI)	5
Attitude Toward Use (ATU)	5
Perceived Risk (PR)	5
Trust (TR)	5

The survey items were adapted from previously validated instruments in literature, specifically from the original study that employed the VMUTES model (Myers, 2019) as well as other studies conducted using a modified TPB model (Cheung & To, 2017; Gefen et al., 2003; Hsiao & Yang, 2010; Ibrahim et al., 2020; Rehman et al., 2019; Sadiq et al., 2021). Furthermore, the items were modified to reflect the focus of the current research: sUAS for prescription medication delivery. A detailed list of each survey item on the data collection device is in Appendix B.

The review of relevant literature, including previous similar studies, was used to develop the indicator variables and conceptual framework of the model used to answer the research questions and identify the relationships theorized among and between the constructs. Each of the constructs chosen for this study was supported by relevant literature and was appropriate for research in the field of aviation, specifically UAS applications. Table 3 provides the operational definition of each construct, variable type, and the primary supporting literature. These constructs have been previously tested in similar studies focused on UAS applications. However, none of the studies specifically targeted prescription medication deliveries via UAS in rural communities. Therefore, to address the gaps in the literature and answer the research questions, 10 hypotheses were tested using the six model constructs identified in Table 3.

Table 3

Constructs, Variable Type, Operational Definition, Primary Support

Construct	Operational Definition	Primary Support
Perceived Usefulness (PU)	The degree to which an individual believes using sUAS for prescription medication deliveries will be beneficial or significantly improve his or her circumstances.	Davis (1989)
Subjective Norms (SN)	The social pressures experienced or perceived by an individual to use sUAS for prescription medication deliveries.	Ajzen (1991)
Behavioral Intent (BI)	The level of effort an individual is willing to expend to use sUAS for prescription medication deliveries.	Ajzen (1991)
Attitude Toward Use (ATU)	An individual's positive or negative evaluation of using sUAS for prescription medication deliveries.	Ajzen (1991)
Perceived Risk (PR)	The potential risks or threats that an individual associates with using sUAS for prescription medication deliveries.	Lee (2009)
Trust (T)	The degree to which an individual is willing to accept sUAS for prescription medication deliveries based on expectations of predictability, reliability, and performance of its intended function.	Lippert (2001)

Variables and Scales

The constructs used were assessed using 3 to 10 indicator variables, provided in Table 1, with responses measured on a 7-point Likert scale, with 1 representing "*strongly disagree*" and 7 representing "*strongly agree*." The Likert response format is a psychometric scale widely used in research studies due to its ability to provide numeric response options for participants that can be easily analyzed (Babbie, 2016; Carifio & Perla, 2007). When originally developed, the Likert response format treated scale data as interval values, with every single variable being measured within a larger construct (Likert, 1932). Although the term “scale” is used, the data were not continuous and were considered interval.

A 7-point Likert scale was an appropriately sized measurement instrument. Psychometric literature suggests the effectiveness of scales increases as the number of points increases until the point of diminishing returns is reached around 11 points (Nunnally & Bernstein, 1978). A scale with 7 points gives respondents enough points of discrimination to reduce measurement error without overwhelming them with an excessive number of options. Although no consensus exists in existing literature regarding a single ideal number for scales, Allen and Seaman (2007) suggest 7-point Likert scales could demonstrate greater reliability than those with fewer points. According to Likert (1932), scales may be used as widely as necessary for research because points can be collapsed or condensed into consolidated categories, if necessary, while smaller point scales cannot be expanded into extended categories.

Data Analysis Approach

The survey collected the following demographic information: gender, age, education level, annual income, and occupation. Therefore, descriptive statistics checked normality, a critical assumption in SEM. A profile of demographic responses ensured appropriate and proportionate representation of the target population was achieved. The software chosen to identify missing values and outliers in the data set was the IBM® Statistical Package for the

Social Sciences (SPSS) Statistics (Version 28). Values were considered outliers if they differed substantially from other values in the data set (Byrne, 2010). Examination of the identified outliers was performed using IBM® SPSS® Analysis of a Moment Structures (AMOS) software using the Mahalanobis D-square values and by reviewing the descriptive statistics. Following Kline (2016), any outlier valued at 100 or more was evaluated for removal.

The analysis procedure included reviewing all values for removal, retainment, or transformation, if necessary (Aberson, 2019; Kline, 2016). Removal was necessary for any data recorded erroneously or for any data that did not meet model fit statistics (Hair et al., 2010; Kline, 2016). Data required transformation if normality assumptions were not met or if the data set was not normally distributed. The transformation was accomplished by applying a mathematical function to each participant's data value to ensure normal distribution (Lee, 2020; Stevens, 2009). According to Byrne (2010), both multivariate and univariate normality assumptions should be met. The skewness could impact the test of means for the CFA model, as well as kurtosis potentially impacting the tests of means, variances, and covariances. Using Byrne's model, the CFA model's kurtosis and the critical ratio were checked for acceptability. Kurtosis values less than 3 were acceptable, although data values less than 5 that display normality were allowable (Byrne, 2010). Furthermore, critical ratio values below 1.96 were not statistically significant at the .05 significance level and, therefore, cannot support the hypothesis (Hair et al., 2010).

The SEM data analysis process was used to test the full structural model. Full structural modeling detailed the relationships between measured variables and latent constructs according to the grounded theory (Byrne, 2010; Myers, 2019). The SEM data analysis process utilized a CFA path diagram to detail relationships between exogenous (i.e., independent) and endogenous (i.e., dependent) variables using arrows. The model was then tested for reliability and validity before the full structural analysis. Finally, model fit statistics were evaluated (Hair et al., 2010). The model results were then analyzed for hypothesis testing.

Non-Response Bias Analysis

Creswell (2014) defines response bias as “the effect of nonresponses on survey estimates” (p. 162). Such bias in data may occur if the data collected from non-respondents would cause a substantial change to the overall results of the research. Respondents who answered less than 50% of the questions or who gave straight-line responses were considered non-respondents. A chi-square test was used to determine bias or a significant difference between the data collected from respondents and non-respondents. If significant bias was noted, additional data was collected. The probability level was $p < .05$ significance, and any values greater than this measurement were considered insignificant. These measures were combined to ensure the research was valid, generalizable, and added useful information to the body of knowledge.

Reliability Assessment Method

The reliability of the survey instrument was evaluated to ensure the tool will yield the same results over multiple trials. A pilot study was employed to test the reliability of the survey instrument. Reliability of an instrument refers to the degree to which it yields consistent results over multiple applications as well as the instrument’s stability over time (Creswell, 2014). Instrument reliability was addressed with several approaches. First, the survey questions were written in simple, easy-to-understand English language to avoid confusion or ambiguity (Babbie, 2016; Eignor, 2001). The Johns Hopkins Medicine IRB recommends the informed consent document and survey items be written no higher than an 8th-grade level (2016). Items were also ordered by construct and based on previously validated survey instruments, thus increasing the reliability of the instrument. Additionally, each construct was assessed using multiple survey items due to the subjective nature of the measurements (Groves et al., 2009). Finally, construct reliability was assessed using Cronbach's alpha, a commonly used method for assessing the consistency of the instrument's scale. Hair et al. (2010) recommend a value of 0.7 as the lower limit of acceptability, with any items valued below 0.7 recommended for transformation or removal. Construct reliability (CR) was also evaluated for an acceptable value of 0.5 or greater. Hair et al. (2010) also note that values of 0.7 or greater are ideal. The formula for calculating this value is shown in Equation 2.

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

where:

n = number of indicators for the construct

i = indicator

λ = standardized factor loading for item i

δ = error variance for item i

Validity Assessment Method

The validity of the survey instrument was evaluated to ensure the tool measured what it was designed to measure. The pilot study was also used to test the validity of the survey instrument. Instrument validity refers to the degree to which it accurately measures the items it is designed to measure (Creswell, 2014; Groves et al., 2009). Content, construct, and criterion validity were all considered when assessing the survey instrument. Content validity indicates the extent to which the measures represent what the researcher intends to measure (Vogt et al., 2014). The quality of an indicator should make it seem like a reasonable measure of the variable being assessed. The empirical measures may or may not match commonly accepted agreements on a concept and are therefore accepted at face value (Babbie, 2016).

Construct validity refers to the extent to which the latent variables accurately represent the associated construct and produces a result distinct from results produced by other construct measurements. Construct validity was assessed using various methods including correlation tests and factor analysis (Babbie, 2016; Hair et al., 2010). It can also be based upon findings from the extant relevant public acceptance and behavioral intention research for further validation. Construct validity is important, as the CFA process is used to confirm the measurement model (Brown, 2006). Finally, criterion-related validity, sometimes referred to as predictive validity, is the degree to which the instrument's scores can predict future behavior (Babbie, 2016). A common method to measure this type of validity is the correlation coefficient between two numerical and continuous measures.

Byrne (2010) identifies convergent validity as the extent to which measures of a construct are related to one another. Hair et al. (2010) indicate the average variance extracted (AVE) as the common methodology for evaluating convergent validity. A measure of AVE ≥ 0.5 is considered an adequate value for convergence. Factor loadings below this value should be considered for removal based on literature support to improve convergent validity (Byrne, 2010). In this research, factor loadings were assessed using the computed value for AVE, shown in Equation 3.

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

where:

n = number of indicators for the construct

i = indicator

L = standardized factor loading

Additionally, discriminant validity within the context of social sciences is defined as the extent to which a construct is distinct from other constructs in the model (Fornell & Larcker, 1981). The Fornell-Larcker method of reviewing discriminant validity involves comparing the AVE value of one construct with the correlation estimates between that construct and the other constructs of the model (Hair et al., 2010). Commonly, the maximum shared variance (MSV) values identified for each factor are compared to the AVE value for that factor. The discriminant validity is considered acceptable if the AVE of one factor is greater than the MSV of the corresponding factors (Hair et al., 2010). Much of existing research in social sciences recommends using the Fornell-Larcker method and/or cross-loadings. Table C3 details prior research recommending one or both of these methods.

Few research studies identify alternative methods for determining discriminant validity, such as assessing the correlations between latent variables and running an isolated CFA prior to completing variance-based structural equation modeling (Milberg et al., 2000; see also Cording et al., 2008; Pavlou et al., 2007). More recently, studies have suggested that the Fornell-Larcker method is not always effective, indicating a potential weakness in the evaluation (Henseler et al., 2015). Instead, the heterotrait-monotrait ratio of correlations

(HTMT) or the modified heterotrait-monotrait ratio of correlations (HTMT2) is recommended to assess discriminant validity in variance-based structural equation modeling (Henseler, 2015; Roemer et al., 2021). This method was also used to assess discriminant validity.

Data Analysis Process/Hypothesis Testing

The hypotheses in the current research were tested using IBM® SPSS® AMOS software, and the values including standardization regression weights (SRW), *t*-values (CR), and significance levels were evaluated. The SRW values were compared between individual constructs to assess the strength of correlations within the model. The *t*-values must be higher than 1.96 with *p* values below 0.05 to retain (accept) a hypothesis. Each hypothesis was tested and then either rejected or failed to be rejected based on the results. Additionally, the SEM approach in the study further demonstrated whether the observed data fit in the proposed model by determining the strength of relationships of constructs.

Summary

This chapter presented the research methodology proposed to investigate the research questions. The approach was described and supported by the relevant literature to better understand factors that influence rural residents' attitudes toward and intentions to accept the use of sUAS for prescription medication deliveries. The research method, population, sample, data collection process, ethical considerations, measurement instrument, and data analysis approach were described in detail to enable near replication of this research.

Chapter IV presents the results of the research and the analysis of the data.

Chapter IV: Results

The current study investigated the extent to which the modified TPB model explained individual's behavioral intentions to use sUAS for medication deliveries, the factors that influence an individual's intentions to receive medication deliveries via sUAS, and the relationships among those factors. This chapter presents significant findings in all areas of analysis along with a summary of the chapter.

Pilot Study 1

The pilot study was conducted using Amazon MTurk®. The survey was distributed to workers fitting the target population, and responses were collected and validated. Based on the calculated sample size for the full study, a sample size of at least 100 was determined to be sufficient for the pilot study. A total of 186 responses were received for the pilot study, with 156 complete and valid responses. The data was prepared, the CFA model was constructed and executed, and the reliability analysis was completed.

All of the item questions showed factor loadings of greater than 0.5, indicating acceptability for the model (Byrne, 2010). Additionally, composite reliability was used to evaluate the extent to which each item question represented its corresponding construct (Hair et al., 2010). Hair et al. (2010) also note that ideal values should be greater than 0.7.

Reliability assessment for the pilot study model showed acceptable CR values for each construct. Cronbach's alpha was also used as an additional method to evaluate reliability for each construct. A value of 0.7 or greater is considered acceptable (Hair et al., 2010). All of the constructs demonstrated acceptable reliability based on the Cronbach's alpha values.

Finally, the average variance extracted (AVE), which measures the variance captured by a construct in relation to the amount of variance due to the measurement error, was evaluated for convergent validity (Hair, Black, Babin & Anderson, 2010). Typically, an AVE value of 0.5 or greater is acceptable (Hair et al., 2010). However, Fornell and Larcker (1981) note that AVE is a more conservative assessment of validity and should be taken into consideration when evaluating the overall model. However, not enough evidence existed to confirm discriminant validity.

Additional data were collected for analysis to determine if a larger sample would improve the discriminant validity results. The survey used for this pilot study is shown in Appendix B. A total of 682 responses were received with 575 valid responses used for further analysis. Descriptive statistics were reviewed to assess the effect of each construct in the model. Reliability and validity were also evaluated to determine the usefulness of the model. The larger sample of data indicated similar results, showing acceptable reliability and convergent validity. However, again not enough evidence existed to confirm discriminant validity.

In an effort to evaluate the model for appropriate relationships, a factor analysis was conducted. Techniques for factor analysis aim to evaluate a large number of variables and categorize similar items together into a single factor. Typically, this process uses the maximum common variance from each variable to pair them with other common variables. Various assumptions must be met prior to completing factor analysis to ensure valid results. Two common methods used in social sciences are confirmatory factor analysis (CFA) and exploratory factor analysis (EFA). When a model is developed based on pre-established theories, CFA determines the factor and factor loading of measured variables to confirm what is expected of the model. When variables are not already assigned to an established model, EFA assumes that any variable may be associated with a given factor. It allows the model to be built based on observations of common variance (Hair et al., 2010).

Since the model did not display sufficient evidence to confirm discriminant validity, a respecified CFA model was evaluated using a second-order factor to combine similar factors. The constructs PU and ATU were combined in a second-order factor, and data analysis was completed. However, no significant improvements were achieved for discriminant validity. The CFA model was then revised to create a second-order factor combining constructs PU, SN, and ATU. The analysis was completed against the new model, but again no significant improvements were achieved for discriminant validity.

Before revising the original model further, the EFA process was explored in SPSS to determine if variables should be recategorized under newly established constructs. The dataset was first reviewed to ensure appropriate assumptions were met. First, Bartlett's Test of Sphericity was used to test the null hypothesis that the correlation matrix derived from the dataset is an identity matrix. If found to be true, then the results would indicate that the variables are not related and therefore unsuitable for common factor detection. However, if Bartlett's Test of Sphericity is significant at $p < .05$, then the correlation matrix is found to not be an identity matrix, and the null hypothesis can be rejected (Abu-Bader, 2016).

Additionally, the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) test was conducted. This measure is also used to determine the suitability of the dataset for structure detection. The statistic is used to specify the proportion of variance among the variables which may be caused by underlying factors. Values greater than .50 generally indicate that factor analysis will be useful with ideal values being closer to 1.00 (Abu-Bader, 2016). The KMO and Bartlett's tests both indicate acceptable assumptions for the dataset, meeting the inter-correlation requirement. The anti-image matrices were then examined to evaluate the individual measure of sampling adequacy for each variable.

Next, the EFA process was conducted to review factor analysis. The first analysis was conducted in SPSS including all 35 variables using the Principal Components extraction method. Values were extracted based on Eigenvalues greater than 1 with a Varimax rotation solution. The Total Variance Explained identified three factors through the analysis with a cumulative variance of 55.514%. One item, TR4, was found to have insufficient factor loading. It was removed from the analysis, and the EFA was completed again.

In both the rotated and unrotated solutions, the variance between factors was not evenly distributed. The Scree plot also identified three factors for the dataset, based on where the slope of the plot suddenly changes. Based on the results, the three variables identified in the Rotated Component Matrix, all items have acceptable factor loadings. However, the items are not evenly distributed within the matrix. Factor 1 consists of 20 items, factor 2 consists of 10 items, and factor 3 consists of 3 items.

The recommended factor structure also did not group together measurement items of similar nature. For example, factor 1 included items from questions designed to assess perceived usefulness, subjective norms, behavioral intent, and attitude toward use. Factor 2 included measurement items designed to assess perceived risk. Factor 3 included items designed to measure trust. Though factors 2 and 3 could easily be understood and named appropriately, factor 1 does not encompass like items and does not make sense as an overall factor. Additionally, the factor structure identified in the EFA process does not support the intended research investigation. Appendix C details supporting tables of the first pilot study data analyses. Therefore, it was determined that the survey should be modified to reword questions according to their intended factor's operational definition and conduct a new CFA analysis.

Pilot Study 2

The data collection survey was modified to reword questions for clarity. Each measurement item was written to be more consistent and brief and to better capture the intent of the construct's operational definition. The modified data collection survey can be found in Appendix B. The second pilot study was conducted using Amazon MTurk®. The survey was distributed to workers fitting the target population, and responses were collected and validated. Based on the calculated sample size for the full study, a sample size of at least 100 was determined to be sufficient for the pilot study. A total of 211 responses were received for the pilot study, with 151 complete and valid responses. The data was prepared, the CFA model was constructed and executed, and the reliability analysis was completed. Table 4 details the analysis results. Reliability was assessed and determined to be acceptable.

Table 4

Reliability Assessment for Pilot Study

Construct	Item Question	Factor Loading	CR (≥0.7)	Cronbach's Alpha (≥0.7)	AVE (≥0.5)
Perceived Usefulness	PU1	.743	.831	.917	.687
	PU2	.810			
	PU3	.838			
	PU4	.874			
	PU5	.873			
Subjective Norms	SN1	.811	.791	.924	.722
	SN2	.887			
	SN3	.918			
	SN4	.816			
	SN5	.811			
Behavioral Intent	BI1	.865	.841	.946	.780
	BI2	.890			
	BI3	.893			
	BI4	.896			
	BI5	.872			
Attitude Toward Use	ATU1	.877	.811	.905	.661
	ATU2	.826			
	ATU3	.762			
	ATU4	.688			
	ATU5	.893			
Perceived Risk	PR1	.885	.696	.877	.589
	PR2	.870			
	PR3	.703			
	PR4	.732			
	PR5	.611			
Trust	TR1	.867	.852	.936	.745
	TR2	.811			
	TR3	.917			
	TR4	.862			
	TR5	.856			

All of the item questions show factor loadings of greater than 0.5, indicating acceptability for the model (Byrne, 2010). Additionally, composite reliability was used to evaluate the extent to which each item question represented its corresponding construct (Hair et al., 2010). Hair et al. (2010) also note that ideal values should be greater than 0.7, which is achieved for all factors except PR (.696). However, this value was very nearly at the minimum recommended threshold and was considered acceptable for the model. Reliability assessment for the pilot study model showed acceptable CR values for each other construct. Cronbach's alpha was also used as an additional method to evaluate reliability for each construct. A value of 0.7 or greater was considered acceptable (Hair et al., 2010). All of the constructs demonstrated acceptable reliability based on the Cronbach's alpha values.

Finally, the average variance extracted (AVE), which measures the variance captured by a construct in relation to the amount of variance due to the measurement error, was evaluated for convergent validity (Hair, Black, Babin & Anderson, 2010). Typically, an AVE value of 0.5 or greater is acceptable (Hair et al., 2010). However, Fornell and Larcker (1981) note that AVE is a more conservative assessment of validity and should be taken into consideration when evaluating the overall model. Nonetheless, the AVE values for each construct exceeded the 0.5 recommended value. Additionally, the MSV values were calculated and compared to the AVE values for each construct. Though not all values yielded acceptable results to confirm discriminant validity, they were considered acceptable enough to continue with the full survey data collection. Based on the high values of CR and Cronbach's alpha for each of the constructs, as well as the small sample size of the pilot study, the reliability was assessed as acceptable.

Survey Responses and Sample

Data was collected for the full study using Amazon MTurk®. The survey shown in Appendix B was set up as a HIT and released to workers on Amazon MTurk®. Participants were limited to those fitting the target population requirements. Once accepting the HIT, research participants were directed to Survey Monkey where they were presented with the Informed Consent. After accepting the Informed Consent, participants were then presented with the research survey. In order to achieve the minimum of 403 valid survey responses, 800 responses were solicited using Amazon MTurk®. Of the responses collected, 782 were complete and valid. Including those from the pilot study, 903 survey responses were complete and valid. Participants were required to complete the full survey on Survey Monkey and retrieve a completion code to then enter into the HIT. Upon entering the appropriate survey code, participants were approved for payment. Participants who did not accept the Informed Consent, skipped, or did not pass any of the survey qualification filter questions, or exited the survey before completion did not receive the survey code for compensation.

The 1,067 total Survey Monkey survey responses between the pilot study and the full study, collected within a timeframe of approximately 72 hours, were first exported into Excel® and then to SPSS for review. After screening and cleaning the data, 903 valid cases remained which well exceeded the minimum of 403 valid responses for data analysis. The valid responses collected from the total solicited responses showed a response rate of 84.6%. Because a sufficient number of valid responses were collected using Amazon MTurk®, no other forms of sampling were required or attempted. Table 5 details the number of responses removed during the data screening process and why they were removed.

Table 5

Summary of Case Deletion

Rationale	Number of Cases
Total responses received	1,067
Respondents did not qualify based on filter questions	119
Respondents answered filter questions and no survey items	15
Respondents provided straight-line responses	30
Remaining valid responses	903

Demographics Results

The demographic data collected for the research included participant gender, age, highest education completed, annual income, and occupation. Table 6 highlights the basic demographic attributes of the survey participants. The results of the demographic data collected are discussed below.

Table 6

Basic Demographic Attributes of Participants

Attribute	Subgroup Categories	Frequency (*N* = 903)	Percentage
Gender	Female	349	38.6
	Male	554	61.4
Age	18-24 years	26	2.9
	25-29 years	177	19.6
	30-34 years	239	26.5
	35-39 years	140	15.5
	40-44 years	130	15.1
	45-49 years	62	6.9
	50-54 years	53	5.9
	55-59 years	37	4.1
	60-64 years	25	2.8
	65-69 years	12	1.3
	70-74 years	1	0.1
	75 years or older	1	0.1
Highest education level	Attending high school	1	0.1

	High school graduate	47	5.2
	Associate's degree	47	5.2
	Bachelor's degree	580	64.2
	Master's degree	178	19.7
	Doctoral degree	2	0.2
	Professional degree	5	0.6
	Some college, no degree	43	4.8
Annual income	Less than $15,000	41	4.5
	$15,000 to $24,999	69	7.6
	$25,000 to $34,999	143	15.8
	$35,000 to $49,999	218	24.1
	$50,000 to $74,999	227	25.1
	$75,000 to $99,999	124	13.7
	$100,000 to $149,999	59	6.5
	$150,000 to $199,999	19	2.1
	$200,000 or more	3	0.3
Occupation*	Student	37	4.1
	Commercial company employee	504	55.8
	Self-employed	351	38.9
	Government employee	69	7.6
	Unemployed	29	3.2
	Business owner	74	8.2
	Other	13	1.4

Note: *Respondents allowed to select more than one response, so percentage exceeds 100%.

Results indicated that among all respondents who provided valid responses, 38.6% were female and 61.4% were male. The gender ratio for participants in the research was different from the U.S. population, which indicated that 50.8% were female and 49.2% were male (U.S. Census Bureau, 2019a). Nearly half of all respondents fell into two age groups encompassing 30-34 years (26.5%) and 25-29 years (19.6%). The U.S. Census Bureau (2019a) reports 61.2% of the population is between the ages of 18 and 65. However, the census statistics also include those under the age of 18 (22.8%) which were not included in this research.

Regarding education level, most respondents indicated having completed a bachelor's degree (64.2%) followed by a master's degree (19.7%). The U.S. Census Bureau (2019a) reports 88% of the population as having a high school diploma or higher, which is in line with the demographics reported in the current study. Although, it seems evident that the research participants have an overall higher post-graduate education level than the U.S. population.

Concerning annual income, most respondents were included in four groups which included $50,000 to $74,999 (25.1%), followed by $35,000 to $49,999 (24.1%), $25,000 to $34,999 (15.8%), and 75,000 to $99,999 (13.7%). The U.S. Census Bureau (2019a) reports the median income of the population to be $55,000, which is in line with the data reported in the current research.

Regarding the occupation of research participants, a majority of respondents indicated being an employee of a commercial company (55.8%), followed closely by self-employed (38.9%). Participants were given the option to select more than one occupation, so percentages in total exceed 100%.

In summary, the demographic information reported by the survey participants generally reflected data reported by the U.S. Census Bureau (2019a), with minor differences. The most notable differences were in the gender ratios between the research participants and the average U.S. population. However, the variations were not large enough to consider the research results nonrepresentative. The research results on age groups generally matched the U.S. Census Bureau data as well as the education levels. Although, research participants indicated a slightly higher education level than the average U.S. population sampled by the census. Additional data was collected on participant occupation, which is new to the general demographic profile. Participants were allowed to select multiple options as a response.

Descriptive Statistics

Descriptive statistics of the data collected for each of the constructs were run in SPSS, shown in Table 7. Seven-point Likert response items were used for survey question answers, ranging from “strongly disagree” (1) to “strongly agree” (7). Descriptive statistics include the mean, standard deviation (SD), skewness, and kurtosis of the item questions for each of the model constructs.

Table 7

Descriptive Statistics Scores of the Model Constructs

Construct	Item Question	Mean (N=903)	SD	Skewness	Kurtosis
PU	PU1	5.447	1.179	-1.048	1.419
	PU2	5.505	1.285	-1.085	1.465
	PU3	5.268	1.372	-1.076	1.286
	PU4	5.362	1.337	-1.123	1.385
	PU5	5.323	1.297	-1.056	1.228
SN	SN1	4.966	1.462	-0.835	0.357
	SN2	4.790	1.722	-0.790	-0.286
	SN3	4.857	1.677	-0.826	-0.110
	SN4	5.163	1.399	-0.907	0.767
	SN5	4.788	1.867	-0.821	-0.448
BI	BI1	5.045	1.535	-0.981	0.496
	BI2	5.119	1.534	-1.034	0.747
	BI3	4.968	1.595	-0.914	0.302
	BI4	5.037	1.624	-0.970	0.308
	BI5	5.159	1.479	-1.098	0.963
ATU	ATU1	5.411	1.336	-1.095	1.271
	ATU2	5.330	1.398	-1.044	1.018
	ATU3	5.215	1.357	-0.924	0.763
	ATU4	5.659	1.218	-1.238	1.907
	ATU5	5.472	1.297	-1.136	1.501
PR	PR1	4.669	1.584	-0.619	-0.399
	PR2	4.707	1.685	-0.580	-0.559
	PR3	4.863	1.541	-0.716	-0.010
	PR4	4.761	1.619	-0.571	-0.518
	PR5	4.833	1.631	-0.646	-0.379
TR	TR1	5.279	1.319	-1.084	1.231
	TR2	5.284	1.348	-0.930	0.858
	TR3	5.214	1.510	-0.994	0.568
	TR4	5.256	1.381	-0.980	0.829
	TR5	5.347	1.343	-1.035	1.174

Note. PU = Perceived Usefulness; SN = Subjective Norms; BI = Behavioral Intent; ATU = Attitude Toward Use; PR = Perceived Risk; TR = Trust.

Attitude Toward Use (ATU) had the highest mean item average (5.417) of all the constructs with an average standard deviation of 1.321. In other words, respondents reported a positive evaluation of using sUAS for prescription medication deliveries with average scores between “somewhat agree” (5) and “agree” (6). All five of the item measurements for the ATU construct indicated a similar result.

Perceived Usefulness (PU) had the second highest mean item average (5.381) of all of the constructs with an average standard deviation of 1.294. Like ATU, many respondents supported the idea that using sUAS for prescription medication deliveries would be beneficial or would significantly improve his or her circumstances, reporting responses on average between “somewhat agree” (5) and “agree” (6). Additionally, all five of the item measurements for the PU construct indicated a similar result.

Trust (TR), or the degree to which respondents are willing to accept sUAS for prescription medication deliveries based on expectations of predictability, reliability, and performance, had a mean average item score of 5.276 and an average standard deviation score of 1.380. This indicates that many respondents were positive with average scores between “somewhat agree” (5) and “agree” (6), much like PU and ATU. All four of the item measurements for the TR construct indicated a similar result.

Behavioral Intent (BI), or the level of effort respondents are willing to expend to use sUAS for prescription medication deliveries, had an average mean score of 5.065 and an average standard deviation score of 1.553. This indicates that many participants reported positive responses with average scores between “somewhat agree” (5) and “agree” (6). Each of the five item measurements for the BI construct also indicated a similar result.

Subjective Norms (SN), or the social pressures experienced or perceived by respondents to use sUAS for prescription medication deliveries, had an average mean score of 4.913 with an average standard deviation score of 1.625. This indicates that many participants reported positive responses with average scores between “somewhat agree” (5) and “agree” (6). Each of the five item measurements for the SN construct also indicated a similar result.

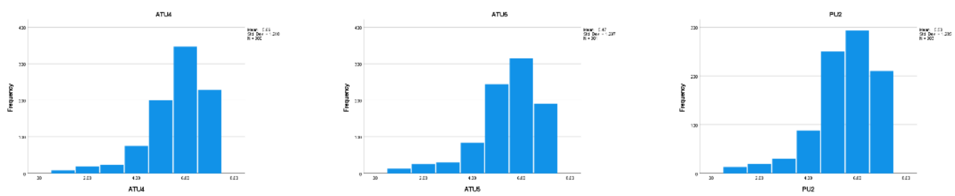
Finally, Perceived Risk (PR), or the potential risks or threats that respondents associate with using sUAS for prescription medication deliveries, had an average mean score of 4.767 with an average standard deviation score of 1.612. This means the overall opinion of many respondents was between “somewhat agree” (5) and “agree” (6). However, three of the ten item measurements (PR1, PR9, and PR10) indicate an average mean of below 5, meaning many of the responses were between “neither agree nor disagree” (4) and “agree” (6).

Normality was assessed using the Kolmogorov-Smirnov and Shapiro-Wilk tests in SPSS. Though the Shapiro-Wilk test is generally more appropriate for smaller sample sizes, literature supports using this method for sample sizes up to 2,000 (Lærd Statistics, n.d.; Mishra et al., 2019). The Kolmogorov-Smirnov test for normality is also appropriate for sample sizes greater than 50. However, Field (2013) indicates these tests tend to be significant with larger sample sizes and recommends assessing normality through other testing. Therefore, the data was assessed for normality using alternative methods.

From the data shown in Table 17, all items exhibited a negatively skewed distribution with the highest value being ATU4 (-1.238). Regarding kurtosis, all items displayed a leptokurtic value (positive kurtosis). The histograms of each item reflected the same results. Though it was not practical to depict the histogram for each of the 34 response items, the three variables with the highest kurtosis values (ATU4, ATU5, and PU2) are shown in Figure 5.

Figure 5

Histograms for ATU4, ATU5, and PU2



Note. ATU4, ATU5, and PU2 displayed the highest kurtosis values.

The ideal value for normality in both skewness and kurtosis is zero, but values between -1 and 1 are considered acceptable (Hair et al., 2017). For skewness, 17 values were within the acceptable range, while 13 values were just slightly outside of the acceptable range. For kurtosis values, 19 items were within the acceptable range, while 11 items were slightly outside of the acceptable range. ATU4 displayed the highest kurtosis value (1.907). The items with skewness and kurtosis values outside of the acceptable range were examined individually using boxplots. Most items had multiple outliers which likely caused the excessive values. Normality assessment with and without these outliers revealed little difference in skewness and kurtosis values, so the outliers were kept within the data set (Byrne, 2010).

Non-Response Bias Testing

Bias was assessed to determine if the responses of non-respondents would have significantly altered the overall results of the research. Participants who answered less than 50% of the Likert response items or those who gave straight line responses to the survey questions were categorized as non-respondents. Non-respondents in this research were the 15 participants who answered 50% or less of the Likert response items and the 30 respondents who provided straight-line answers to the Likert response items. A Chi-square test was used to identify bias, if any, in demographics between the respondent and non-respondent groups. The results of the Chi-square tests with the probability significance set to $p < .05$ were reviewed. None of the five demographic variables examined in the research exhibited significant differences between respondents and non-respondents, indicating the sample was free of non-response bias. Therefore, the sample collected and utilized for the survey was deemed representative of the target population.

Confirmatory Factor Analysis

The confirmatory factor analysis steps included assessment of normality, missing data, outliers, model fit statistics with respecification if necessary, reliability, and validity (Hair et al., 2010).

Normality

The CFA process requires several assumptions to be met to determine the factor structure of the dataset. The first assumption that must be met is normality (Hair et al., 2010). Normality was checked using SPSS as described in Chapter 3 as well as in AMOS. According to Byrne (2010), normality assumptions are determined by observing the kurtosis values. Kurtosis values less than 3.0 are ideal; however, values less than 5.0 are also acceptable to assess normality. One item question had a kurtosis value of 1.907 (indicator ATU4), while all other values were measured below 1.5. Thus, the normality assumption for the CFA was met.

Missing Data

Upon examination of the dataset during the data cleaning process, several points of data were found to be missing. The SPSS missing data analysis identified 103 missing values from the 27,090 Likert-scale response items. The missing values represented less than one percent of the total dataset. Additionally, each variable was assessed with the missing values, and it was found that each had less than two percent data missing. Since less than 10% of the data was missing at random, Hair et al. (2010) state any method for eliminating the data is acceptable. The Missing Completely at Random (MCAR) test was completed in SPSS and found not to be significant, suggesting the missing data was not associated with any pattern (Hair et al., 2010). Therefore, no cases or variables were deleted from the dataset. Instead, missing values were imputed using the Multiple Imputation method in SPSS. All datasets produced from the Multiple Imputation process displayed similar results for the model fit. Therefore, dataset one of the Multiple Imputation process was selected.

Outliers

Outliers were examined using the Mahalanobis D-square values in SPSS. Values over 100 are considered extreme and should be further reviewed. The dataset revealed nine values over 100, which meet the definition of an extreme outlier (Kline, 2016). Hair et al. (2010) notes that not all outliers should be removed, as their absence may impact generalizability of the model and instead recommends running the model with and without the outliers to compare the effects. Therefore, two distinct datasets were created: Imputation Dataset 1 with outliers and Imputation Dataset 1 without outliers. To determine the best dataset for analysis, the CFA process was accomplished without a post-hoc analysis to assess model fit statistics, reliability, convergent validity, and discriminant validity. Results are detailed in Table 8. The results indicate very little difference between datasets regarding reliability and both convergent and discriminant validity. Since no significant differences exist, the dataset with the outliers excluded was chosen as the dataset for analysis in order to limit any impacts to model fit.

Table 8

Comparison of Datasets With and Without Outliers

Dataset	Model Fit		Reliability	Convergent Validity	Discriminant Validity
Imputation Dataset 1 with outliers	CFI GFI AGFI NFI CMIN/df RMSEA	.943 .890 .869 .926 4.002 .058	Acceptable - all CR values above 0.7	Acceptable - AVE value for all factors above 0.5, all factor loadings acceptable at 0.5 or above	Unacceptable - MSV value for 7 correlations are above AVE, 8 are below
Imputation Dataset 1 without outliers	CFI GFI AGFI NFI CMIN/df RMSEA	.947 .892 .872 .930 3.868 .057	Acceptable - all CR values above 0.7	Acceptable - AVE value for all factors above 0.5, all factor loadings acceptable at 0.5 or above	Unacceptable - MSV value for 7 correlations are above AVE, 8 are below

Model Fit and Respecification

According to literature, sample sizes in research greater than 400 may skew the accuracy of goodness of fit measures (Hair et al., 2010). Specifically, the Goodness of Fit Index (GFI) and the Adjusted Goodness of Fit Index (AGFI) may become more sensitive to the larger sample size and suggest a poor fit for the model. Since the sample size for this research is well over 400, an alternative model fit approach will be utilized. The Maximum Likelihood Estimate (MLE) is an approach that provides stable and accurate results when normality assumptions for a dataset are met (Hair et al., 2010). The MLE and acceptable values for the Imputation Dataset 1 with outliers excluded were chosen for the model fit parameters. The GFI and AGFI values were included but used as secondary measures for the model fit.

The initial model did not have all acceptable model fit values, as evident by the CMIN/df value, so the model was respecified through post hoc analyses. This process included reviewing the modification indices in the CFA output and systematically making adjustments one at a time. Table 9 details the model fit indices for both the initial model and the respecified model.

Table 9

Model Fit Indices for Initial and Respecified CFA Models

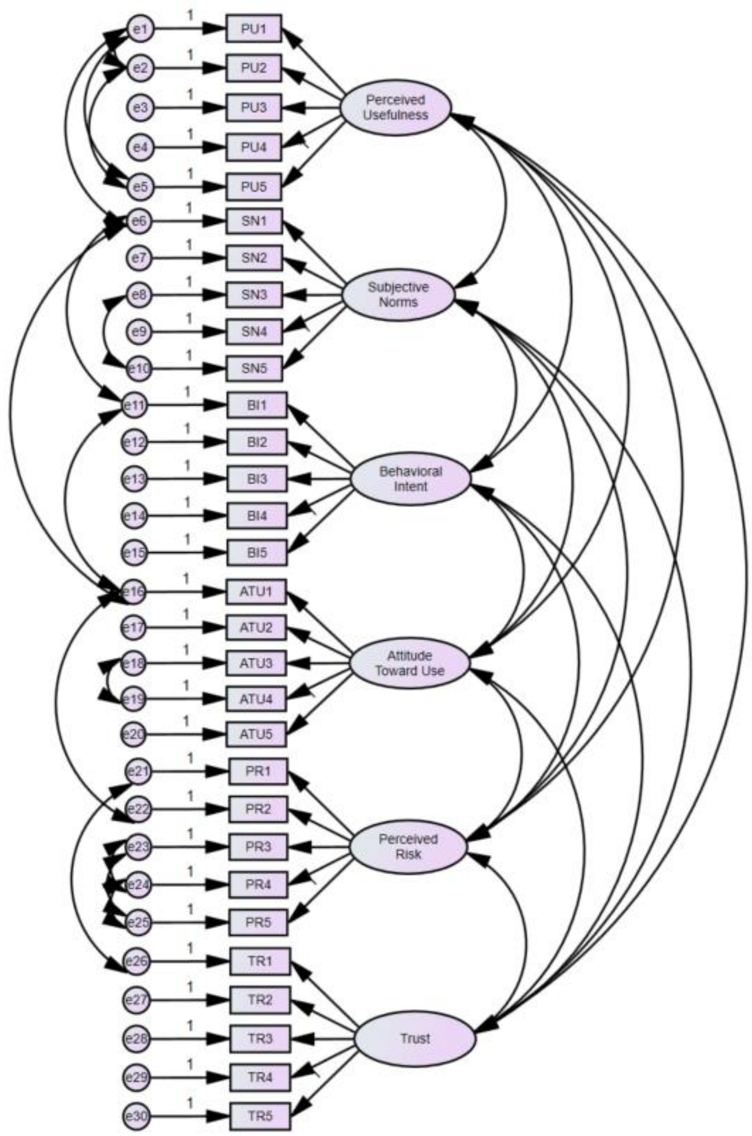
Model Fit Indices	Acceptance Value	Initial CFA Model	Respecified CFA Model
X^2	-	1508.426**	1122.349**
df	-	390	376
CMIN/df	≤ 3	3.868	2.985
GFI	> .90*	.892	.923
AGFI	> .90*	.872	.905
NFI	> .90	.930	.948
CFI	> .93	.947	.964
RMSEA	< .06	.057	.047

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

While the fit parameters in the respecified model appear to indicate an acceptable model fit, the modification indices indicate cross loadings and covariances between items of different factors. Figure 6 depicts the respecified model. Therefore, the model was then examined for reliability and validity in order to determine the next course of action.

Figure 6

Respecified CFA Model



Note. Respecified model not yet fully reviewed for reliability and validity.

Reliability and Validity Testing Results

As with the pilot study, the CFA model was analyzed for reliability and validity by examining individual factor loadings, construct reliability, Cronbach's alpha, and the average variance extracted (AVE). Table 10 details the reliability assessment for the CFA model using Imputation Dataset 1 with outliers excluded.

Table 10

Reliability Assessment for Respecified CFA Model

Construct	Item Question	Factor Loading	CR (≥0.7)	Cronbach's Alpha (≥0.7)	AVE (≥0.5)
Perceived Usefulness	PU1	.695	.806	.883	.576
	PU2	.691			
	PU3	.777			
	PU4	.818			
	PU5	.804			
Subjective Norms	SN1	.819	.816	.919	.698
	SN2	.862			
	SN3	.864			
	SN4	.798			
	SN5	.831			
Behavioral Intent	BI1	.850	.844	.927	.720
	BI2	.848			
	BI3	.832			
	BI4	.858			
	BI5	.853			
Attitude Toward Use	ATU1	.843	.801	.873	.578
	ATU2	.784			
	ATU3	.676			
	ATU4	.653			
	ATU5	.825			
Perceived Risk	PR1	.873	.692	.868	.540
	PR2	.838			
	PR3	.654			
	PR4	.673			
	PR5	.579			

	TR1	.830			
	TR2	.787			
Trust	TR3	.833	.837	.905	.658
	TR4	.798			
	TR5	.806			

All of the item questions showed factor loadings of greater than 0.5, indicating acceptability for the model (Byrne, 2010), with the exception of PR (.692). However, based on reviewing the model fit statistics after removing PR5 due to its low factor loading, CR does not improve. Therefore, no items were removed from the construct. Additionally, composite reliability was used to evaluate the extent to which each item question represented its corresponding construct (Hair et al., 2010). The factor loadings and construct reliability were expected to be acceptable based on the pilot study results. No changes were necessary to the pilot study, indicating results should be similar for the CFA model. Hair et al. (2010) also state that ideal values should be greater than 0.7. Reliability assessment for the CFA model showed acceptable CR values for each construct. Cronbach's alpha was also used as an additional method to evaluate the reliability for each construct. A value of 0.7 or greater is considered acceptable (Hair et al., 2010). All of the constructs demonstrated acceptable reliability based on Cronbach's alpha values.

Finally, the average variance extracted (AVE), which measures the variance captured by a construct in relation to the amount of variance due to the measurement error, was evaluated for convergent validity (Hair, Black, Babin, & Anderson, 2010). Typically, an AVE value of 0.5 or greater is acceptable (Hair et al., 2010). However, Fornell and Larcker (1981) note that AVE is a more conservative assessment of the validity and should be taken into consideration when evaluating the overall model. However, all constructs demonstrated an AVE above the acceptable value, thus, reliability was assessed as acceptable.

Discriminant validity was first reviewed using the Fornell and Larker method. The MSV values were calculated and compared to the AVE values. However, the results did not indicate acceptable results. Discriminant validity was then reviewed using the HTMT approach. Table 11 details the HTMT values calculated for the CFA model. Henseler et al. (2015) state that values of .90 or below are acceptable and establish discriminant validity. Based on the values shown in the HTMT assessment, not enough evidence was found to achieve discriminant validity between two factors (PU and ATU, and SN and BI). However, the values are close enough to the acceptable cut off value. Based on the HTMT values between the remaining factors, discriminant validity is considered marginally achieved. Thus, the respecified model shown in Figure 6 is accepted as the final CFA model.

Table 11

HTMT Values for Respecified CFA Model

	PU	SN	BI	ATU	PR	TR
PU						
SN	.752					
BI	.888	.910*				
ATU	.917*	.692	.817			
PR	.050	.331	.182	.010		
TR	.847	.736	.834	.883	.049	

Note. *values do not establish discriminant validity.

Full Structural Model Assessment

The final step is testing the full structural model. These steps included model construction from the final specified CFA model, model fit assessment and any appropriate respecifications, and reliability and validity assessment (Hair et al., 2010).

Model Construction, Model Fit, and Respecification

The final CFA model specified in Figure 7 was transformed into the full SEM using AMOS to remove covariances between factors, add one-way arrows between factors to represent the hypotheses, and create residual error terms to endogenous factors. The full structural model is depicted in Figure 6. Upon reviewing the model fit statistics for the full structural model, indicators revealed similar results as the final specified CFA model indicating an acceptable model fit. Table 12 details the model fit indices for the full structural model. Based on these values, no model respecifications were necessary.

Table 12

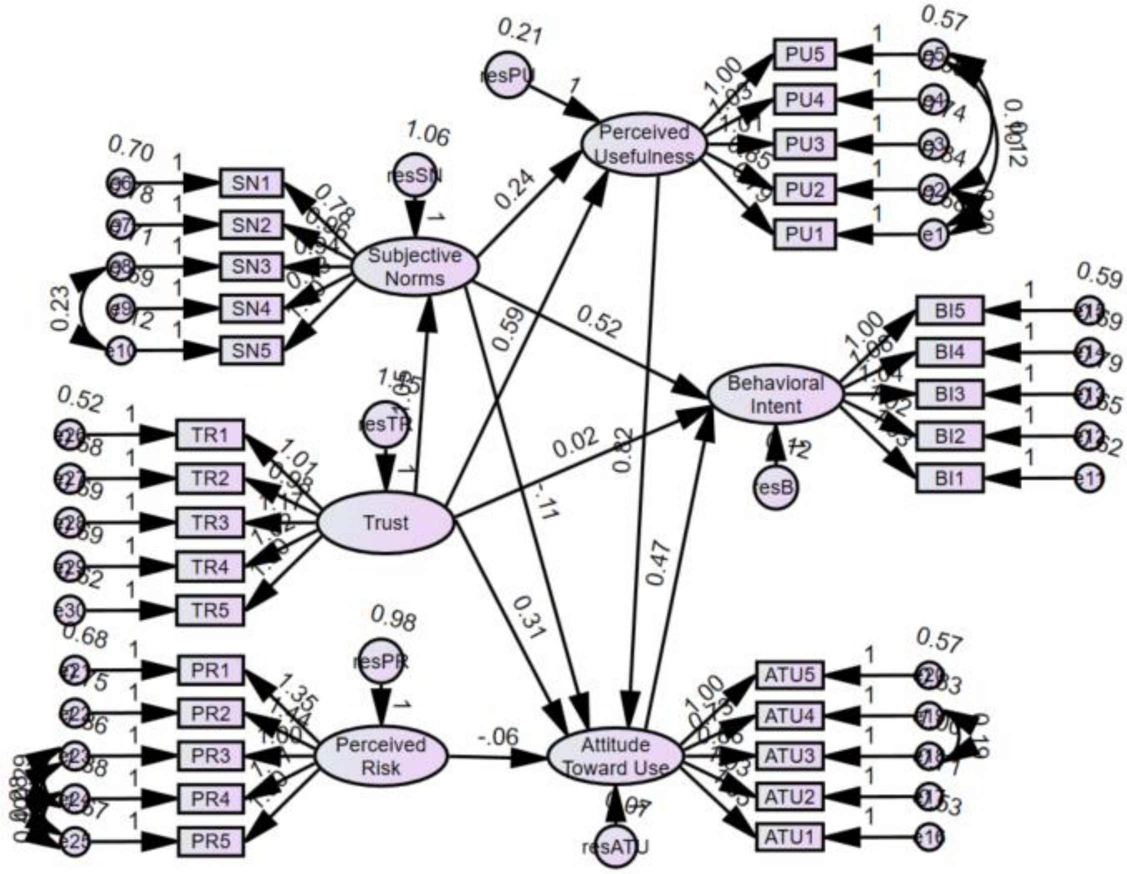
Model Fit Indices for Full Structural Model

Model Fit Indices	Acceptance Value	Full Structural Model
X^2	-	1507.250**
df	-	387
CMIN/df	≤ 3	3.895
GFI	> .90*	.895
AGFI	> .90*	.874
NFI	> .90	.930
CFI	> .93	.947
RMSEA	< .06	.057

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

Figure 7

Full Structural Model



Note. Regression weights are displayed.

Hypothesis Testing Results

None of the constructs or item measurements were removed from the model; therefore, all hypotheses were able to be tested. Results of the hypothesis testing are detailed in Table 13.

Table 13

Hypothesis Testing of Full Structural Model

Hypothesis/Relationship	SRW	*t*-value	*p*-value	Result
H_1: SN positively influences PU	.354	9.368	***	Supported
H_2: PU positively influences ATU	.804	11.069	***	Supported
H_3: SN positively influences ATU	-.155	-3.890	***	Not supported
H_4: SN positively influences BI	.625	19.281	***	Supported
H_5: ATU positively influences BI	.390	7.857	***	Supported
H_6: PR negatively influences ATU	-.060	-3.206	.001	Supported
H_7: TR positively influences PU	.606	14.706	***	Supported
H_8: TR positively influences ATU	.313	5.694	***	Supported
H_9: TR positively influences SN	.739	20.378	***	Supported
H_{10}: TR positively influences BI	.021	.413	.680	Not supported

Note. *** indicates significance at $p < .001$. The critical ratio *t*-values should be above 1.96 with *p* values below .05 to indicate support for a hypothesis. SRW = standardized regression weight.

Hypothesis 1 (H_1) is supported, indicating that SN positively influences PU. The hypothesis has a statistically significant value ($p < .001$) and a *t*-value greater than 1.96. This means that if SN increases by one point, PU will subsequently increase by .354.

Hypothesis 2 (H_2) is supported, indicating that PU positively influences ATU. The hypothesis has a statistically significant value ($p < .001$) and a *t*-value greater than 1.96, which implies ATU will increase by .804 for every point that PU increases

Hypothesis 3 (H_3) is not supported, indicating that SN does not positively influence ATU. The hypothesis has a statistically significant value ($p < .001$) and a *t*-value greater than 1.96, but the relationship is negative. This indicates a significant relationship, but not a positive relationship. Therefore, H_3 is not supported.

Hypothesis 4 (H_4) is supported, indicating SN positively influences BI. The hypothesis has a statistically significant value ($p < .001$) and a t-value greater than 1.96. This implies that if SN increases by one point, so too will BI increase by .625.

Hypothesis 5 (H_5) is supported, indicating that a change to ATU will positively impact BI. The relationship is significant ($p < .001$), and as ATU changes by one point, the high t-value means that BI will change by .390.

Hypothesis 6 (H_6) is supported, indicating PR has a negative impact ATU. The relationship is significant ($p < .001$) and displayed a t-value greater than 1.96. In other words, as PR increases by one point, ATU will decrease by .060.

Hypothesis 7 (H_7) is supported with a significance of $p < .001$, indicating TR positively influences PU. The hypothesis is further supported by a t-value greater than 1.96. As TR increases by one point, PU will subsequently increase by .606.

Hypothesis 8 (H_8) is supported, indicating TR positively influences ATU. The relationship is statistically significant at $p < .001$ with a high t-value. This means that if TR increases by one point, ATU will subsequently increase by .313.

Hypothesis 9 (H_9) is supported, indicating that a change to TR will positively impact SN. The hypothesis has a statistically significant value ($p < .001$). With a high t-value, a one point increase to TR will increase SN by .739.

Hypothesis 10 (H_{10}) is not supported, as indicated by the non-significant p value ($p = .680$). The results indicate there is insufficient evidence to conclude that TR has a positive influence on BI. The t-value was also less than 1.96 at $t = .413$, further indicating the lack of support for this hypothesis.

New Relationship Identified

The SEM model was reviewed for model fit, reliability, and validity. No issues were found, and all indicators were acceptable; therefore, no changes were made to the model. Following the hypothesis testing, the post hoc analysis was performed to review the modification indices for high regression weights which might indicate a potential new relationship in the model. CFA and SEM are theory-driven research methods; therefore, any potential relationship must first be reviewed for supporting literature before it can be added to the model (Hair et al., 2010). Based on the modification indices, one possible new relationship was identified for review and potential inclusion into the existing research model. The modification indicator between SN→PR demonstrated a regression weight value of M.I. = 96.031, signifying a possible significant relationship.

Though SN and PR are extremely common in current research on behavioral intention, particularly studies utilizing TAM and TPB, these factors have not previously been modeled in the context shown in the SEM results of this research. In a similar study, Sarosa (2022) investigated a hypothesis of PR having a negative impact on SN (specifically defined as the perception of social pressure in committing a behavior). However, the results did not support the hypothesis, and thus it was rejected. Additionally, Xie et al. (2017) investigated predictors for individuals to adopt e-government services and hypothesized that PR will have a negative impact on SN. The study utilized a SEM analysis but ultimately found the hypothesis to not be supported.

Ho et al. (2017) researched the causal effects of PR and SN on a user's trust intention to adopt cloud technology. However, the research focused on these constructs as moderators of perceived behavioral control and trust intention. The research model did not test or support a direct relationship between SN and PR. Lee (2009) defined PR in terms of five subcomponents, one of which included social risk. The social risk included the potential loss of status an individual may experience from a social group as a result of adopting a particular service. In this study, the model theorized that the social risk aspect of PR would have a negative impact on SN. This notion is similarly supported by Featherman and Fuller (2002). In both studies, the hypothesis was supported. However, the operational definition does not fit that of PR in this study. Furthermore, no indication is referenced that SN has any impact on PR. Based on the lack of support in existing literature, further investigation into the relationship between SN and PR is recommended.

Summary

Chapter IV detailed the results of both the statistical and analytical aspects of the research to determine behavioral intention factors of rural residents to use sUAS for prescription medication delivery. An initial pilot study was conducted with the full survey collection completed without amendments. The minimum required sample (403) was exceeded using Amazon MTurk® and SurveyMonkey with an initial sample size of 682 and a final sample size of 575. Following the reliability and validity assessments, a second pilot study was deemed necessary with an altered survey instrument. The second pilot study revealed acceptable reliability and validity, and full data collection was completed. The second survey collection also surpassed the minimum required sample (403) using Amazon Mturk® SurveyMonkey with an initial sample size of 1,067 and a final sample size of 903. Descriptive statistics were used to summarize the demographics of participant responses.

The CFA process was used to complete the measurement model assessment of the research. The first model did not achieve acceptable results in terms of model fit, cross-loadings, and validity and was revised for the second research. The second CFA model displayed better results, though initial discriminant validity was not achieved. It was deemed necessary to use HTMT ratios as an alternative method for assessing discriminant validity. Once acceptable results were achieved, the final respecified CFA model displayed acceptable model fit statistics, reliability, and validity.

The full structural model assessment was performed next. As expected, the SEM model fit was comparable to the results achieved in the final respecified CFA model. Thus, no model respecification was required. One new potential relationship was discovered (SN→PR), though literature review did not support including the relationship in the full structural model. Additional research is suggested to further investigate the potential association. The full SEM analysis tested the 10 hypotheses, eight of which were supported at a statistically significant level of $p < .001$ (H_1, H_2, H_4, H_5, H_6, H_7, H_8, and H_9). Two of the hypotheses were not supported (H_3 and H_{10}). Since no additional iterations were completed on the original SEM model, no items or constructs were removed. All factors were relevant components to determine behavioral intention for rural residents to use sUAS for prescription medication delivery. Four constructs had a direct, positive influence on ATU, BI, or both. Chapter V discusses the results of the research, including literature support for the theoretical framework used in the research. Conclusions are drawn from the research results, and recommendations are provided for future research opportunities.

Chapter V: Discussion, Conclusions, and Recommendations

Chapter V discusses the results of the statistical analyses presented in the previous chapter. The two research questions are reviewed, and the conclusions are presented. Furthermore, the theoretical and practical significance of the findings are discussed. Finally, this chapter presents suggestions for future research opportunities and recommendations.

Discussion

Model Modification and Results

The original CFA presented validity results during the initial analysis and required modifications to improve model fit. Using systematic changes one at a time, the model was revised using post-hoc analysis respecification with new model fit values reviewed after each iteration. Several cross-loading and covariance issues were noted in the original model. Following the post-hoc analysis of the CFA model with the revised survey instrument, many of these issues were eliminated. It was determined that no factors or constructs required removal.

Discriminant validity of the model was first assessed using the Fornell-Larcker (1981) approach followed by the heterotrait-monotrait ratio of correlations (HTMT; Henseler et al., 2015). This assessment is a critical facet of the CFA and SEM analysis as it reviews the intercorrelations of factors and ensures sufficient differentiation among them. If factors do not display adequate differences from others, the discriminant validity is not considered acceptable (Kline, 2016). Hair et al. (2010) state factor loadings between 0.60 and 0.80 may have an unfavorable impact on the Fornell-Larcker (1981) approach when assessing AVE. Therefore, the HTMT approach was applied to confirm the discriminant validity values were acceptable. This approach was also utilized by Myers (2019) and Fussell (2021).

The final model included all five original predictor variables and one outcome variable: perceived usefulness (PU), attitude toward use (ATU), subjective norms (SN), perceived risk (PR), trust (TR), and behavioral intention (BI, outcome variable). Each of these variables were derived from relevant research using the TAM, TPB, VMUTES, and other combined models.

Discussion of the Research Questions

Two research questions were explored, both of which are discussed below. Each of the proposed hypotheses are further discussed in the following section.

RQ1. The first research question was, “What factors influence rural residents’ intentions to use sUAS for prescription deliveries?” The original CFA model identified six latent constructs, all derived from the literature review. All six were included in the final SEM, with five identified as direct or indirect influencers of BI. The between-factor strengths are detailed in rank order for both positive and negative associations in Table 14.

PU had the strongest positive influence on ATU, which is a relationship identified in the TAM and is supported by literature (Davis et al., 1989). Also identified in literature, as well as displayed in the SEM results of this research, ATU had a strong, positive influence on BI. The other factors that influence ATU and BI are SN and PR. Interestingly, SN had a positive influence on BI but showed a negative influence on ATU. A similar result was noted by Fussell (2021) with the relationship between self-efficacy (SE) and BI and ATU. TR was also hypothesized to influence BI; however, the relationship between TR and BI revealed negligible results and thus was not sufficient to support the hypothesis.

The predictive power of the overall model was relatively strong. The squared multiple correlation coefficient (R squared) describes the measurement of the total variance proportion in the dependent variables that is accounted for, or predictable, by the indicator variables in the model (Kwan & Chan, 2014). The predictive power of the research model indicated a squared multiple correlation coefficient value of .972 for behavioral intention and .939 for attitude toward use.

Table 14

Rank-Ordered Strength of Between-Factor Relationships

Hypothesis/Relationship	Positive Rank-Ordered Strength	Negative Rank-Ordered Strength
H_2: PU positively influences ATU	.804	-
H_9: TR positively influences SN	.739	-
H_4: SN positively influences BI	.625	-
H_7: TR positively influences PU	.606	-
H_5: ATU positively influences BI	.390	-
H_1: SN positively influences PU	.354	-
H_8: TR positively influences ATU	.313	-
H_{10}: TR positively influences BI	.021	-
H_3: SN positively influences ATU	-	-.155
H_6: PR negatively influences ATU	-	-.060

RQ2. The second research question asked, “How do these factors impact rural residents’ intentions to use sUAS for prescription deliveries?” Hypothesis testing revealed that PU and TR have a direct, positive impact on ATU and an indirect, positive influence on BI. Based on the strength of the between-factor relationships, PU had a significantly stronger effect on ATU than TR. The factor of SN directly, positively influences BI. This relationship is also relatively strong, based on the value of the between-factor relationship. However, SN was shown to negatively influence ATU directly, though with a much smaller

effect. As hypothesized, PR displayed a direct, negative influence on ATU. Interestingly, the value of the effect was very small and represented the lowest strength in impact among all hypothesized relationships. Understanding which factors influence rural residents to use sUAS for prescription medication delivery and which factors undermine efforts to use sUAS can allow stakeholders to target how sUAS is implemented into home delivery services.

Discussion of the Hypotheses

Ten hypotheses were investigated using the full structural model, all of which were derived from previously validated research models including TAM, TPB, VMUTES, and various combined models. Each of the hypotheses were supported by literature. The factors and hypothesized relationships of the research focused on a user's behavioral intention as opposed to analyzing actual use. Though one new relationship was discovered during the model analysis, the literature review did not support it and thus was not added to the final model.

Hypothesis 1: Subjective norms positively influence perceived usefulness. The results indicate that sufficient evidence exists to support the hypothesis that SN positively influences PU, which is also supported in literature. Teo (2012) proposed and validated the relationship between SN and PU based on previously confirmed research models that studied these constructs. This was subsequently confirmed by Myers (2019). In the current study, SN refers to the social pressures one experiences from friends or family to use sUAS for prescription medication delivery. The supported hypothesis means that the stronger the subjective norms, the stronger the perceived usefulness of sUAS for prescription medication delivery.

Practical implications of this finding suggest that the personal views of one’s friends and family is important when deciding whether to use sUAS for prescription medication deliveries. Thus, this research offers new understanding and insight into one factor which motivates individuals to use this technology. The finding makes practical sense, as sUAS applications are relatively new and information is rapidly changing. Therefore, potential users turn to those who have influence on their decisions and perceptions for opinions on using sUAS for prescription medication deliveries. In other words, the perceived usefulness of sUAS for prescription medication deliveries can be strongly influenced by what others think. Therefore, stakeholders who wish to elevate social norms of this sUAS application should not only focus on the individual perception, but also the broader societal acceptance.

Hypothesis 2. Perceived usefulness positively influences attitude toward use. The results indicate there is sufficient evidence to conclude that PU positively influences ATU, which is also supported throughout the literature. A key component of the TAM proposed by Davis (1989), this relationship has been further validated by numerous researchers including Chang and Chang (2009), Ha and Stoel (2009), Morosan (2014), and Myers (2019). The relationship between PU and ATU in each of these studies indicated a strong, positive connection, which was also displayed in the SEM results of this study. From a practical standpoint, an individual’s perceived usefulness of sUAS for prescription medication delivery directly impacts the attitude toward using it. The higher the perceived usefulness, the more positive the attitude toward use.

Hypothesis 3. Subjective norms positively influences attitude toward use. Results indicate there is not sufficient evidence to conclude that SN positively influences ATU. Contrarily, the results indicate there is a negative relationship between SN and ATU. The implication of SN having a negative impact on ATU suggests the more favorable family and friends find sUAS, the less favorable an individual may feel about it. Though this relationship is not generally seen in technology studies using Ajzen's (1991) TPB model, it has been observed in other organizational studies. Titah and Barki (2009) referenced negative connotations with subjective norms and attitude toward use in a study focused on human resource firms hired to represent large oil conglomerates. Though the firms held negative beliefs regarding the oil companies' operations and subsequent impacts to the environment, they maintained their positive associations with upholding their professional responsibilities. However, Teo et al. (2008) and other subsequent studies have found that SN has a positive impact on attitude. Though for the current research, SN did not prove to have a positive influence over ATU, but results revealed SN has a negative influence over ATU.

Hypothesis 4. Subjective norms positively influences behavioral intent. Results indicate there is sufficient evidence to conclude that SN positively influences BI, which is also supported throughout the literature. Originally shown as an indirect influence on BI, SN is an important component of Ajzen's (1991) TPB model. Later modified and observed as a direct influence by Teo (2012) and others, this research further validates the positive influence that SN has over BI. The views and opinions of family, friends, and others considered important to an individual carry significant weight when influencing one's decisions. Thus, the study offers new insights into one of the motivating factors for individuals to use sUAS for prescription medication delivery.

Hypothesis 5. Attitude toward use positively influences behavioral intent. Results indicate there is sufficient evidence to conclude that ATU positively influences BI, which is also supported throughout literature. In terms of the research, the more favorable one's attitude, the higher the intention to use sUAS for prescription medication delivery. As an original component of the TAM (Davis, 1989), it was expected that ATU display a positive influence over BI. Several other studies throughout literature further validate this relationship (Choi & Chung, 2012; Mallya, & Lakshminarayanan, 2017; Myers, 2019).

In application, attitude toward using sUAS for prescription medication delivery is a positive influence on the desire or intent to follow through with the behavior of using sUAS for prescription medication delivery. This is differentiated from other influencers such as social pressures or practicality, as it establishes a positive relationship between one's attitude and one's choice to use sUAS. In the context of prescription medication deliveries, stakeholders should seek to improve the factors which positively influence one's attitude.

Hypothesis 6. Perceived risk negatively influences attitude toward use. Results indicate there is sufficient evidence to conclude that PR negatively influences ATU. In other words, the higher the perceived risk one associates with sUAS for prescription medication delivery, the less likely one is to develop a positive attitude toward use. Pavlou (2003) postulated that PR has a direct effect on BI, and Teo (2012) further delineated that influence to be negative. Literature also suggests that BI is influenced by ATU (Gong et al., 2004), indicating PR would similarly influence one's attitude toward using sUAS for prescription medication delivery in a negative manner. Myers (2019) also found a direct, negative correlation between PR and ATU, supporting this relationship. From a practical standpoint, stakeholders should focus on reducing the perceived risk of sUAS for prescription medication delivery in order to improve one's attitude toward using the technology.

Hypothesis 7. Trust positively influences perceived usefulness. Results indicate there is sufficient evidence to conclude that TR positively influences PU, which is also supported throughout literature. Wu and Chen (2005) investigated and validated this relationship in a study focused on the technological adoption of an online tax service. Manganelli et al. (2020) further validated the relationship in a study focused on factors influencing organic food purchases. These studies proposed and confirmed the relationship that TR has a positive influence on PU. Though trust is a broad concept on its own, trust in technology can be further delineated into the expectation of a certain outcome or performance. As shown in the SEM results, PU has a positive influence on ATU. Therefore, TR has an indirect influence on ATU through the construct of PU. Stakeholders who wish to promote sUAS for prescription medication delivery should focus on improving one's trust in the technology.

Hypothesis 8. Trust positively influences attitude toward use. Results indicate there is sufficient evidence to conclude that TR positively influences ATU, which is also supported throughout literature. Wu and Chen (2005) found that trust has a greater impact on attitude than either perceived usefulness or perceived ease of use from the original TAM model. Subsequent studies throughout the literature further validated the relationship that TR has a positive influence on ATU (Akbari et al., 2019; Cheung & To, 2017, Manganelli et al., 2020, Saeri et al., 2014). As with PU, ATU has shown to have a positive influence on BI. Therefore, TR has an indirect influence on BI through the construct of ATU.

Hypothesis 9. Trust positively influences subjective norms. Results indicate there is sufficient evidence to conclude that TR positively influences SN, which is also supported throughout literature. Wu and Chen (2005) hypothesized that trust would have an impact on social pressures of using online tax services. The model results confirmed the positive relationship between TR and SN. This relationship was further validated by Manganelli et al. (2020) in a study regarding organic food purchases. The research postulated that a positive association exists between TR and SN. Specifically, a person with a higher degree of trust in buying organic food products would more heavily rely on the normative belief influenced by social pressures. The research sustained the hypothesis that TR has a positive effect on SN.

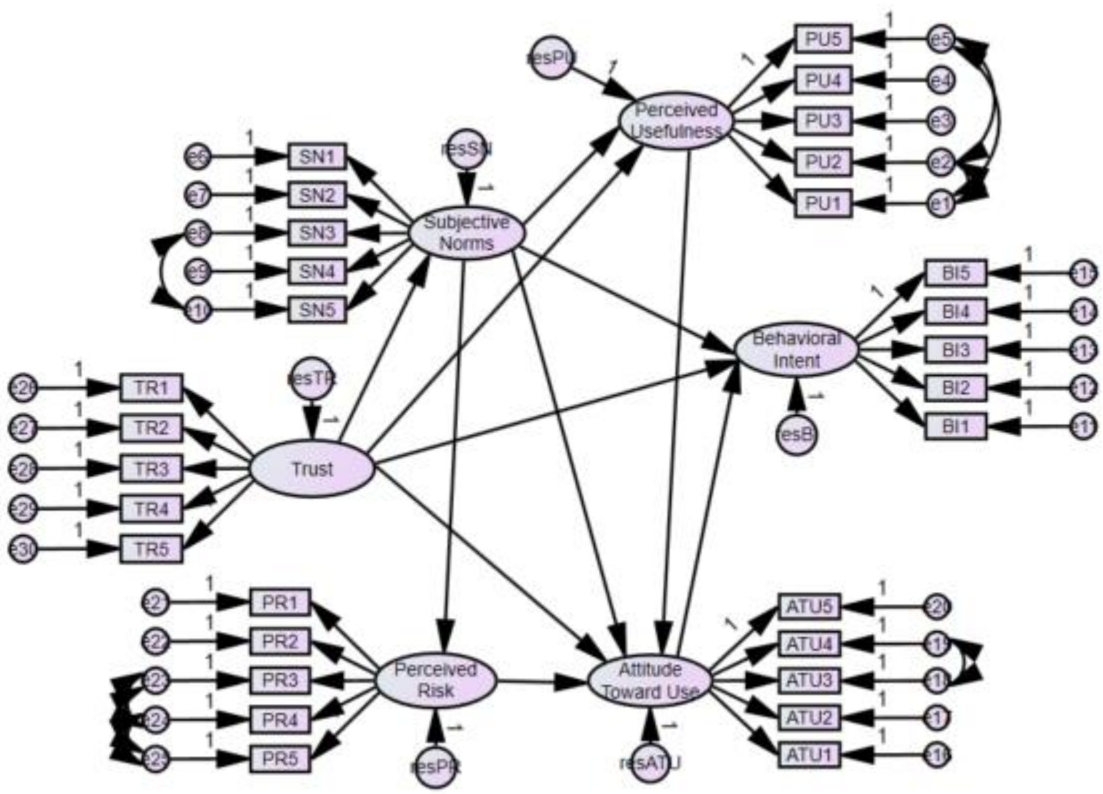
Hypothesis 10. Trust positively influences behavioral intent. Results indicate there is not sufficient evidence to conclude that TR positively influences BI. Though the SEM results detail a positive association between the constructs, the relationship was not significant. This was not the same result observed in other research studies including Akbari et al. (2019), Carfora et al. (2019), and Cheung and To (2017). These studies found that trust positively influenced behavioral intent in either a direct or indirect capacity. This is further supported by literature suggesting that trust is an important motivational factor in the cognitive decision-making process (Hobbs & Goddard, 2015). However, the relationship was not found to be significant in this research regarding sUAS for prescription medication delivery.

New Hypothesis. Subjective Norms Positively Influence Perceived Risk. The new relationship identified in the structural model assessment indicated a previously unresearched connection between SN and PR. Zhong et al. (2021) researched the cultural impacts of social pressures, or subjective norms, on perceived physical and psychological risks. Specifically, the notion of collectivism, or individuals acting in the interest of a group as opposed to oneself, generates interesting behavioral patterns and motivations when dining out in restaurants. Using a questionnaire, participants in Korea and China provided responses that were analyzed in a full structural model. Researchers found that subjective norms had a statistically significant impact on both perceived physical and psychological risks. In other words, when people who hold influence over an individual believe dining out is safe, that individual is likely to perceive less risks toward dining out. This relationship was found to indirectly impact behavioral intention and revealed participants were more willing to dine out when friends and family stated it was safe. Implications of this finding could mean that the perceptions of friends and family could impact an individual's perceived risk of using sUAS for prescription medication deliveries. In other words, if the influencing opinions of others identify sUAS as safe or as having low risk, individuals may also perceive low risk.

The study conducted by Zhong et al. (2021) did not model behavioral intention factors as they relate to using sUAS or other aviation technologies. However, the results did provide a foundation for exploring the possible implications that subjective norms directly have on perceived risks as well as the indirect impact on behavioral intention. Though the findings were related to the new relationship found in this study, the literature did not provide sufficient support for adding the relationship to the existing model at this time. However, it could be theorized in future research initiatives. Figure 8 depicts the theorized model with a relationship between SN and PR.

Figure 8

Theorized Structural Model



Note. Regression weights are not displayed.

Conclusions

The purpose of this research was to determine factors that influence rural residents' behavioral intention to use sUAS for prescription medication delivery. The model used was a modified version of the combined TAM and TPB, used for the first time in conjunction with behavioral intention research into sUAS use for prescription medication delivery. The research specifically sought to investigate what factors influence rural residents' intentions to use sUAS for this application and how those factors impact behavioral intention. The model fit indices denoted the research model was adequate in identifying those factors and evaluating the extent of their impact. Continual concerns with discriminant validity required an alternative approach to evaluation, the HTMT method, in order to obtain acceptable validity results. The root cause of the original discriminant validity problems may be further investigated in future research.

Once validity issues were resolved, the research was conducted and successfully achieved research initiatives and contributed to academia by filling a gap in the literature in the aviation domain. The research also provided an expanded demographic catalog for research concerning sUAS for prescription medication delivery. Furthermore, the research offered new insights into the impacts of perceived risk and trust in combination with the widely validated TAM and TPB models. Research results imply these two factors have significant impact on a user's behavioral intention directly or indirectly through attitude toward use.

Four factors (SN, PU ATU, TR) were found to either directly or indirectly positively impact BI, as hypothesized. PR was also found to negatively impact ATU directly, which negatively impacts BI indirectly, as hypothesized. Two other factors associated with behavioral intention of sUAS use for prescription medication delivery, SN and TR, had hypothesized unsupported relationships. Given these factors have both been successfully included and validated in other modified TAM and TPB models, it is evident they are important components to understanding behavioral intention and may require further investigation for the sUAS prescription medication delivery environment. The success of the research indicates that the finalized model, with additional research and refinement, could be a useful tool for research in the aviation technology domain and beyond.

Furthermore, the implication of the results of H3 (subjective norms demonstrated a negative impact on attitude toward use) and the new identified relationship (subjective norms demonstrated a positive impact on perceived risk) may be correlated. It was hypothesized that SN would have a positive influence on ATU, however the opposite was observed. Specifically, the negative implication seen in H3 may explain the new relationship found in the model evaluation. When people of influence have a negative evaluation of sUAS for prescription medication deliveries, residents may subsequently perceive higher risks. In terms of participants' perceptions of sUAS for prescription medication deliveries, social pressures may imply an unexplored association with attitude and risk. This potential relationship could prove relevant when assessing public perception and influencing factors for sUAS applications.

Theoretical Contributions

The research results provide theoretical contributions to the literature in several ways. First, the overall research offers additional insights and information to the existing body of knowledge surrounding sUAS applications, specifically prescription medication delivery. The model validated that several well-established factors of the TAM and TPB may be combined with other external factors and applied to sUAS technology, prescription medication delivery, and the use of sUAS for prescription medication delivery. These factors went beyond the scope of the ground theories used to offer additional understanding of each construct and how it influences, positively or negatively, rural residents' behavioral intention to use sUAS for prescription medication delivery. The validated model may be further modified and adapted to be applied to other aviation technologies as well as other medication delivery applications.

Second, the modified model used in the research is unique in that it incorporates additional factors not generally included in combined TAM/TPB models. It includes additional, relevant constructs needed to thoroughly investigate behavioral intention to use sUAS for prescription medication delivery that other models did not incorporate, including the TAM, TPB, C-TAM/TPB, and VMUTES models. The research model used in this research included the perceived risk and trust factors, which have not been widely used in other sUAS studies, thus representing a significant contribution to the existing body of knowledge.

Also relevant, the study provides a new tool for use in future research endeavors throughout the aviation domain and beyond by validating the usefulness of the model. Other possible research applications involving higher risk technologies that could implement this model include urban air mobility, railroad and automobile transportation, or other applications within the aviation industry. Furthermore, this model can be extended to other populations outside of the rural U.S. studied in the current research and expanded into other easily replicated studies.

Third, the demographic data collected in the research can be added to existing databases or combined with the statistics of other similar studies. Additionally, this newly collected information on rural U.S. demographics could offer stakeholders and future research initiatives an expanded insight into the use of sUAS for prescription medication delivery while also saving time and resources required to collect that data.

Fourth, the model used in the research incorporated the perceived risk and trust factors, which further expands the existing body of knowledge. Though these constructs have been incorporated in modified TAM and TPB studies within commercial aviation and retail domains, not many research efforts have incorporated perceived risk and/or trust regarding sUAS applications in a structured model. By including perceived risk and trust as constructs, this research tested and validated the necessity of incorporating the perceived risk and trust factors in behavioral intention studies regarding new technologies. As confirmed in Myers' (2019) research, identifying a disparity between societal expectations and actual implementation of a new technology through targeted perceived risk research can greatly improve technology acceptance.

Fifth, the negative relationship between subjective norms and attitude toward use is a discovery that is not supported by the theorized relationship. However, the negative association observed in this study has not been previously explored in a study focused on sUAS for prescription medication delivery. The negative influence subjective norms showed to have on attitude toward use is novel and unique for the existing body of knowledge. The unsupported hypothesis also adds value to the literature by providing new insight to future researchers wishing to explore behavioral intention factors associated with accepting sUAS.

Sixth, through the pilot study and subsequent modification of the research instrument, the need for the process of research validation was reinforced. Through the initial pilot study, the research questions were vetted and found to require modification for acceptable validity. Furthermore, the use of Amazon MTurk® as a crowdsourcing platform was confirmed as an acceptable method for data collection and was confirmed to be representative of the target population.

Finally, the research fills several gaps in the existing literature. Though researchers have recently investigated the potential acceptance of sUAS medication delivery, the specific application in rural communities has not yet been studied. Prescription patients living outside the convenience of local pharmacies and home-delivery services have not been widely considered in the existing sUAS application studies, which is a clear gap in the aviation domain where new and more innovative technologies are regularly adopted. Additionally, not many studies have considered the behavioral intention of users to adopt a new technology using a model that includes the perceived risk and trust factors; thus, factors that impact the behavioral intention to use sUAS for prescription medication delivery has not previously been extensively explored. Relevant findings pursuant to these issues have been presented.

Practical Contributions

The research focused on prescription medication deliveries using sUAS to rural U.S. residents. Research parameters were designed to ensure generalizability, reliability, and validity of the results. As a result, the research data can provide significant practical implications for stakeholders wishing to implement sUAS for prescription medication delivery in rural communities. Four notable practical contributions of the research are discussed.

First, the research provided practical benefits to the existing body of knowledge by expanding upon the current known demographic profile for rural residents. The data may offer further insight for stakeholders to create better guidelines, advertising strategies, and functional decisions for future operations. For instance, the majority of survey participants were male, between the ages of 30 and 34, hold a Bachelor’s degree, have a household income between $50,000 and $74,999, and are employed at a commercial company. Using this information, stakeholders can specifically target the majority demographic to accomplish relevant objectives while using resources efficiently.

Second, by establishing the factors that impact behavioral intention to use sUAS for prescription medication delivery, pharmacies, industry, and other stakeholders have a better understanding on how to strategically target those factors that have a positive influence on behavioral intention. Furthermore, they can either avoid the factors that hinder behavioral intention or work to address the underlying causes for negative associations. For example, regarding perceived risk, the mean score for all related survey items was 4.77, meaning the average response was between "neither agree nor disagree" and "somewhat agree." These responses indicate participants found relevant physical, financial, and legal risks associated with sUAS use for prescription medication delivery. The highest risk scored was with the perceived costs associated with sUAS, followed closely by the potential loss of privacy and the possible legal liabilities with using sUAS for prescription medication delivery. Transportation companies could market affordable costs of delivery or work with pharmacies to incorporate operating costs within the overall infrastructure of their negotiated distribution framework. Similarly, strategies to manage the privacy and legal concerns can be addressed through targeted media campaigns and social education.

Third, focusing on the factors that had the strongest impact on behavioral intention to use sUAS for prescription medication delivery can assist stakeholders in learning about users and targeting their intentions by creating a proactive approach to implementing the technology. For example, the perceived usefulness factor displayed the strongest impact on attitude toward use which also had a significant influence on behavioral intention. Based on the research results, stakeholders could administer additional surveys to the primary demographic, which is rural residents between the ages of 30 and 34, to determine what aspects of sUAS prescription medication delivery they deem important to improve perceived usefulness.

By understanding the impacts affecting behavioral intention, stakeholders and industry professionals can work to address negative factors in conjunction with advancing positive factors for sUAS prescription medication delivery. The significance of the current research is in furthering initiatives to offer pharmacy services to rural residents who may otherwise not have access to their much needed prescription medications.

Finally, the research model may be adapted by other investigators. The survey instrument and methodology could offer additional information into residents' attitude toward and behavioral intention to use sUAS for other applications. The survey items can be reworded for better adaptation to studies focused on similar technologies or applications of sUAS in other domains. The survey instrument and methodology could also be used by researchers for other users or service recipients, as the behavioral intention factors also apply to sUAS applications outside the prescription medication delivery environment.

Limitations of the Findings

Four notable limitations exist for this study. First, the research investigated sUAS for prescription medication delivery at a single point in time and thus can be generalized to that period. The applications of sUAS and existing regulations governing operations are rapidly evolving and may not generate the same responses in future studies (Babbie, 2016). However, the research can be replicated without difficulty and additional data can be collected to confirm the results provided in the current research.

Second, the discriminant validity of the research was not achieved by the standard Fornell-Larker method and was instead achieved using the HTMT approach. It was theorized that the Fornell-Larker method was not achieved due to the low average scores of the factor loadings. All factor loadings fell in the range of 0.66 and 0.88 and did not display much variation. The factor loadings should be consistently higher in general for the Fornell-Larker method to display acceptable discriminant validity. Though the HTMT method successfully achieved discriminant validity for the model, further modifications may be required to improve the overall model.

Third, the current research validated the representativeness of the workers on Amazon MTurk® to the general population in terms of diversity in sampling (Buhrmester et al., 2011). Based on the demographic information analyzed in the research data, this study confirmed that crowdsourcing through Amazon MTurk® provides sampling with population representation at least as diverse as traditional sampling. The limitation exists where many rural residents, the target population, may not be registered workers for Amazon MTurk®. However, similar limitations are noted in studies with traditional random sampling for a specific sampling frame.

Finally, this research investigated factors that impact behavioral intentions of rural residents to use sUAS for prescription medication delivery. Though the target population is a significant part of the population, the U.S. Census Bureau (2017) estimates one in five residents live in rural areas. Therefore, the research results are limited to approximately one-fifth of the U.S. population and cannot be generalizable to the remaining population or overall society without further research.

Recommendations

Several recommendations are discussed for future research as it pertains to the current research. Suggested steps are provided for stakeholders, future research methodology, and additional research efforts regarding sUAS for prescription medication delivery and other aviation technologies.

Recommendations for the Stakeholders

The results of this study may be particularly relevant to stakeholders looking to grow the sUAS industry, particularly for distribution and delivery operations. The data may also be useful to policymakers, possibly in conjunction with stakeholders, to target specific populations or demographics for capitalization on influencing factors of technology acceptance. Feedback collected and survey data gathered can be analyzed to address areas of concern in both social education as well as written policies and guidelines.

Furthermore, valuable demographic data can be used to increase understanding into the factors impacting behavioral intention of the current target population as well as expand research into new populations. This data can offer insight into targeted marketing and media strategies to positively influence factors that impact behavioral intention which may in turn increase the likelihood of acceptance.

Additionally, stakeholders in other higher risk technology environments as well as those in other areas within the aviation domain can use this research approach and model to investigate the factors that impact a user's behavioral intention to use the technology. Specifically, the inclusion of perceived risk and trust in the research could potentially provide important insights into problem areas and allow stakeholders to focus on addressing influencing factors of behavioral intention in a more targeted approach.

Recommendations for Future Research Methodology

The research factors included in the model should be thoroughly reviewed and revised as appropriate for future studies. Specifically, subjective norms should be investigated further based on the unexpected output seen in the SEM results. Though the factor was not removed from the model, it displayed an unexpected relationship with attitude toward use. Stakeholders may be unaware of a potential negative association between subjective norms and attitude toward use, thus indirectly with behavioral intention, and should further investigate any underlying causes. It is suggested that deeper analysis should be conducted, particularly once sUAS technology is in more widespread application. Comparisons of the results between the current research and a study in which participants have a better understanding of the social impacts of sUAS may yield new considerations which could impact the use of sUAS for prescription medication delivery.

Additionally, the trust construct displayed negligible results in the research as it directly impacts behavioral intention. Though trust showed a significant positive influence on perceived usefulness, attitude toward use, and subjective norms, further investigation into the relationship between trust and behavioral intention is warranted. Trust has been used in a wide variety of studies with varying operational definitions (Gefen, 2004). Despite what was displayed in the current research, trust has previously been shown to have significant positive impacts on behavior and intention (Luhmann, 2018; Pavlou, 2003; Saeed et al., 2003). Based on the contradicting results shown in the current study, further research modeling may provide additional insights into the relationship between trust and behavioral intention.

Finally, future research methodologies should further investigate the relationship between subjective norms and perceived risks. Though insufficient literature existed to add it to the current model and conduct additional analysis, the data implied subjective norms have a positive influence on perceived risk. Zhong et al. (2021) recently investigated the nature of this relationship in a study focused on cultural implications on dining out during the pandemic. Their research model analyzed survey participants' responses regarding the impact of opinions of family and friends. The data revealed individuals are more willing to dine out during the pandemic because they perceive fewer associated risks when friends and family say it is safe. Future research methodologies can further expand this insight by investigating the impact of subjective norms on perceived risk regarding sUAS applications.

Recommendations for Future Research

Future research initiatives should utilize Amazon MTurk® as a crowdsourcing platform for sampling to further validate the representativeness of respondents to a targeted population. The platform should also be paired with other external survey websites such as Survey Monkey and Google Forms to optimize survey development and interface with Amazon MTurk®. These inter-platform collaborations may also assist in refining the logic for developing survey items to minimize redundancies and non-useful or irrelevant questions. Furthermore, screening options available with these online services can help eliminate participants who are not qualified or who may otherwise introduce bias to the research data.

Additionally, further research could be conducted into the framework of the research model and the wording of the associated survey questions. The original research instrument in this study was modified due to issues achieving discriminant validity. Several original survey items also displayed low factor loadings and AVE values. Additional investigation is warranted into why the original survey items, which were developed from previously validated survey tools, did not display acceptable validity. With additional research, the survey can be further refined to improve the research model in future research studies with increased validity and generalizability.

Finally, new research should be conducted to validate participant demographic data collected in this study. Though respondent information generally correlated with U.S. Census Bureau demographics for the population, some variances were observed. Most notably, the male to female ratio observed from participant data did not closely match the ratio expected based on census data. Additional research should be conducted to determine if any disparities exist in the existing research and future studies with participants who more closely mirror expected population demographics. Also, this research introduces a new demographic profile for current occupation. Therefore, future research should be conducted and include this demographic to verify the data collected in the current study.

References

Aberson, C. L. (2019). *Applied power analysis for the behavioral sciences* (2nd ed.). Routledge. https://doi.org/10.4324/9781315171500

Abu-Bader, S. H. (2016). *Using statistical methods in social science research: With a complete SPSS guide* (Second ed.). Oxford University Press.

Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In J. Kuhl & J. Beckman (Eds.), *Action-control: From cognition to behavior* (pp. 11–39). Springer. https://doi.org/10.1007/978-3-642-69746-3_2

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

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. Prentice-Hall.

Akbari, M., Fozouni Ardekani, Z., Pino, G., & Maleksaeidi, H. (2019). An extended model of theory of planned behavior to investigate highly-educated Iranian consumers' intentions towards consuming genetically modified foods. *Journal of Cleaner Production*, *227*, 784–793. https://doi.org/10.1016/j.jclepro.2019.04.246

Allen, E. I., & Seaman, C. A. (2007, July). Likert scales and data analysis. *Quality Progress*, *40*(7), 64-65.

American Association for Public Opinion Research. (2014). *AAPOR guidance for IRBs and survey researchers*. https://www.aapor.org/Standards-Ethics/Institutional-Review-Boards/Full-AAPOR-IRB-Statement.aspx

American National Standards Institute Unmanned Aircraft Systems Standardization Collaborative. (2020, June). *Standardization roadmap for unmanned aircraft systems – V2*. https://share.ansi.org/Shared%20Documents/Standards%20Activities/UASSC/ANSI_UASSC_Roadmap_V2_June_2020.pdf

Aydin, B. (2019). Public acceptance of drones: Knowledge, attitudes, and practice. *Technology in Society*, 59. Article 101180. https://doi.org/10.1016/j.techsoc.2019.101180

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

Bahendeka, S., Kaushik, R., Swai, A. B., Otieno, F., Bajaj, S., Kalra, S., Bavuma, C. M., & Karigire, C. (2019). EADSG guidelines: Insulin storage and optimization of injection technique in diabetes management. *Diabetes Therapy*, *10*(2), 341–366. https://doi.org/10.1007/s13300-019-0574-x

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice-Hall.

Boucher, P. (2016). 'You wouldn't have your granny using them': Drawing boundaries between acceptable and unacceptable applications of civil drones. *Science and Engineering Ethics, 22*(5), 1391–1418. https://doi.org/10.1007/s11948-015-9720-7

Brewer, M. B., & Silver, M. (1978). Ingroup bias as a function of task characteristics. *European Journal of Social Psychology*, *8*(3), 393–400. https://doi.org/10.1002/ejsp.2420080312

Brown, T. A. (2006). *Confirmatory factor analysis for applied research*. Guilford Press.

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. https://doi.org/10.1016/j.jairtraman.2016.12.003

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. https://doi.org/10.1177/1745691610393980

Bureau of Transportation Statistics. (2020, June 10). *Preliminary air traffic data, April 2020: 96% reduction in U.S. airline passengers from 2019.* https://www.bts.gov/newsroom/preliminary-air-traffic-data-april-2020-96-reduction-us-airline-passengers-2019

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

Cameron, E. D. (2014). *Unmanned aircraft systems: Factors that affect the acceptance of unmanned aircraft usage within the United States National Airspace System.* [Master's thesis, University of North Dakota]. ProQuest Dissertations & Theses Global. https://doi.org/10.1007/978-1-4020-8672-4_4

Carfora, V., Cavallo, C., Caso, D., Del Giudice, T., De Devitiis, B., Viscecchia, R., Nardone, G., & Cicia, G. (2019). Explaining consumer purchase behavior for organic milk: Including trust and green self-identity within the theory of planned behavior. *Food Quality and Preference, 76*, 1–9. https://doi.org/10.1016/j.foodqual.2019.03.006

Carifio, J., & Perla, R. J. (2007). Ten common misunderstandings, misconceptions, persistent myths and urban legends about Likert scales and Likert response formats and their antidotes. *Journal of Social Sciences*, *3*(3), 106–116. https://doi.org/10.3844/jssp.2007.106.116

Casey, M. M., Klingner, J., & Moscovice, I. (2002). Pharmacy services in rural areas: Is the problem geographic access or financial access? *The Journal of Rural Health, 18*(3), 467–477. https://doi.org/10.1111/j.1748-0361.2002.tb00911.x

Casper, E. S. (2007). The theory of planned behavior applied to continuing education for mental health professionals. *Psychiatric Services, 58*(10), 1324–1329. https://doi.org/10.1176/ps.2007.58.10.1324

Centers for Disease Control and Prevention. (2019). *Prescription drug use in the United States, 2015–2016* (NCHS Data Brief No. 334). National Center for Health Statistics.

Centers for Disease Control and Prevention. (2020, September 14). *Public health guidance for potential COVID-19 exposure associated with international or domestic travel.* https://www.cdc.gov/coronavirus/2019-ncov/php/risk-assessment.html

Chambers, S., & Nimon, K. (2019). Conducting survey research using MTurk. In *Crowdsourcing: Concepts, methodologies, tools, and applications* (pp. 410–439). IGI Global. https://doi.org/10.4018/978-1-5225-8362-2.ch022

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

Chen, C. C. (2013). The exploration on network behaviors by using the models of theory of planned behaviors (TPB), technology acceptance model (TAM) and C-TAM-TPB. *African Journal of Business Management*, *7*(30), 2976–2984. https://doi.org/10.5897/ajbm11.1966

Cheung, J. H., Burns, D. K., Sinclair, R. R., & Sliter, M. (2017). Amazon Mechanical Turk in organizational psychology: An evaluation and practical recommendations. *Journal of Business and Psychology*, *32*(4), 347–361. https://doi.org/10.1007/s10869-016-9458-5

Cheung, M. F. Y., & To, W. M. (2017). The influence of the propensity to trust on mobile users’ attitudes toward in-app advertisements: An extension of the theory of planned behavior. *Computers in Human Behavior*, *76*, 102–111. https://doi.org/10.1016/j.chb.2017.07.011

Chisholm-Burns, M. A., Spivey, C. A., Gatwood, J., Wiss, A., Hohmeier, K., & Erickson, S. R. (2017). Evaluation of racial and socioeconomic disparities in medication pricing and pharmacy access and services. *American Journal of Health-System Pharmacy, 74*(10), 653–668. https://doi.org/10.2146/ajhp150872

Choi, A. S., Ritchie, B. W., & Fielding, K. S. (2016). A mediation model of air travelers' voluntary climate action. *Journal of Travel Research, 55*(6), 709–723. https://doi.org/10.1177/0047287515581377

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. https://doi.org/10.1002/meet.14504901376

Choi, S. (2013). Public perception and acceptability of technological risk: Policy implications for governance. *Journal of Convergence Information Technology, 8*(13), 605–615.

Claesson, A., Fredman, D., Svensson, L., Ringh, M., Hollenberg, J., & Nordberg, P. (2016). Unmanned aerial vehicles (drones) in out-of-hospital-cardiac-arrest. *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine, 24*(1), 124–124. https://doi.org/10.1186/s13049-016-0313-5

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. https://doi.org/10.1111/risa.12330

Cohen, J. J., Reichl, J., & Schmidthaler, M. (2014). Re-focusing research efforts on the public acceptance of energy infrastructure: A critical review. *Energy, 76*, 4–9. https://doi.org/10.1016/j.energy.2013.12.056

Connelly, L. M. (2008). Pilot studies. *Medsurg Nursing, 17*(6), 411–412.

Cording, M., Christmann, P., & King, D. R. (2008). Reducing causal ambiguity in acquisition integration: Intermediate goals as mediators of integration decisions and acquisition performance. *Academy of Management Journal, 51*(4), 744-767.

Cozzens, T. (2020, September 2). FAA gives go-ahead for Amazon drone-delivery tests. *GPS World*. https://www.gpsworld.com/faa-gives-go-ahead-for-amazon-drone-delivery-tests/

Creswell, J. W. (2014). *Research design: Qualitative, quantitative, and mixed methods approaches* (4th ed.). Sage Publications. https://doi.org/10.5539/elt.v12n5p40

Cunningham, J. A., Godinho, A., & Kushnir, V. (2017). Using Mechanical Turk to recruit participants for internet intervention research: Experience from recruitment for four trials targeting hazardous alcohol consumption. *BMC Medical Research Methodology, 17*(1–7). https://doi.org/10.1186/s12874-017-0440-3

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

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, *35*(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982

Del Giudice, T., Cavallo, C., & Vecchio, R. (2018). Credence attributes, consumers trust and sensory expectations in modern food market: Is there a need to redefine their role? *International Journal on Food System Dynamics*, *9*(4), 307–313.

Donmez, B., Boyle, L., & Lee, J. D. (2008, May 27–30). Associations between trust and perceived usefulness as drivers adapt to safety systems. *Proceedings of the 10th International Conference on Applications of Advanced Technologies in Transportation, Athens, Greece.* http://web.mit.edu/~bdonmez/www/Donmez_Boyle_Lee_AATT_2008_Trust.pdf

Efron, S. (2015). *The use of unmanned aerial systems for agriculture in Africa* (Publication No. 3664426) [Doctoral dissertation, Pardee RAND Graduate School]. ProQuest Dissertations & Theses Global.

Eignor, D. R. (2001). Standards for the development and use of tests: The standards for educational and psychological testing. *European Journal of Psychological Assessment*, *17*(3), 157–163. https://doi.org/10.1027//1015-5759.17.3.157

Elias, B. (2016, January 27). *Unmanned operations in domestic airspace: U.S. policy perspectives and the regulatory landscape*. Congressional Research Service. http://nationalaglawcenter.org/wp-content/uploads/assets/crs/R44352.pdf

FAA Reauthorization Act of 2018, Public L. No. 115-2018, § 341 et seq. https://www.congress.gov/115/bills/hr302/BILLS-115hr302enr.pdf

Featherman, M., & Fuller, M. (2003, January 6-9). *Applying TAM to e-services adoption: The moderating role of perceived risk* [Paper presentation]. 36th Annual Hawaii International Conference on System Sciences, Big Island, HI. https://doi.org/10.1109/HICSS.2003.1174433

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. https://doi.org/10.1016/s1071-5819(03)00111-3

Federal Aviation Administration. (2016, June 21). *Small unmanned aircraft systems (sUAS).* (Advisory Circular 107-2). U.S. Department of Transportation. https://www.faa.gov/regulations_policies/advisory_circulars/index.cfm/go/document.information/documentID/1019962

Federal Aviation Administration. (2018, September 26). *Volume 16 unmanned aircraft systems* (Report No. 8900.1 CHG 625). https://fsims.faa.gov/PICDetail.aspx?docId=8900.1%2cVol.16%2cCh1%2cSec2

Federal Aviation Administration. (2019a, April 10). *Public safety and government.* https://www.faa.gov/uas/public_safety_gov/

Federal Aviation Administration. (2019b, October 15). *UAS data exchange (LAANC).* https://www.faa.gov/uas/programs_partnerships/data_exchange/

Federal Aviation Administration. (2020a, February 18). *Recreational flyers & modeler community-based organizations.* https://www.faa.gov/uas/recreational_fliers/

Federal Aviation Administration. (2020b, April 1). *14 C.F.R. Part 135 certification process.* https://www.faa.gov/licenses_certificates/airline_certification/135_certification/cert_process/

Federal Aviation Administration. (2020c, April 21). *Educational users.* https://www.faa.gov/uas/educational_users/

Federal Aviation Administration. (2020d, May 12). *Package delivery by drone (Part 135).* https://www.faa.gov/uas/advanced_operations/package_delivery_drone/

Federal Aviation Administration. (2020e, July 22). *Certified remote pilots including commercial operators.* https://www.faa.gov/uas/commercial_operators/

Federal Aviation Administration. (2020f, July 28). *Integration pilot program lead participants.* https://www.faa.gov/uas/programs_partnerships/integration_pilot_program/lead_participants/

Federal Aviation Administration. (2020g, September 22). *UAS by the numbers.* https://www.faa.gov/uas/resources/by_the_numbers/

Federal Aviation Administration. (2020h, October 30). *BEYOND.* https://www.faa.gov/uas/programs_partnerships/beyond/

Federal Aviation Administration. (2020i, October 30). *UAS integration pilot program.* https://www.faa.gov/uas/programs_partnerships/integration_pilot_program/

Federal Aviation Administration. (2020j). *Unmanned aircraft systems (UAS).* https://www.faa.gov/uas/

Federal Aviation Administration. (n.d.) Aerospace forecast, fiscal years 2020–2040. https://www.faa.gov/data_research/aviation/aerospace_forecasts/media/FY2020-40_FAA_Aerospace_Forecast.pdf

Field, A. (2013). *Discovering statistics using IBM SPSS Statistics* (4th ed.). Sage Publishing.

Flynn, R. (2007). Risk and the public acceptance of new technologies. In *Risk and the public acceptance of new technologies* (pp. 1–23). Palgrave Macmillan. https://doi.org/10.1057/9780230591288_1

Food and Drug Administration. (2017, November 13). *Prescription drugs and over-the-counter (OTC) drugs: Q & A.* https://doi.org/10.1007/0-387-25733-0_10

Food and Drug Administration. (2014, December 16). *Title II of the Drug Quality and Security Act.* https://www.fda.gov/drugs/drug-supply-chain-security-act-dscsa/title-ii-drug-quality-and-security-act

Fornell, C., & Larcker, D.F. (1981). Evaluating structural equations with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Fuentes, A. V., Pineda, M. D., & Nagulapalli-Venkata, K. C. (2018, May 14). Comprehension of top 200 prescribed drugs in the U.S. as a resource for pharmacy teaching, training and practice. *Pharmacy (Basel) 6*(2), 43–53. https://doi.org/10.3390/pharmacy6020043

Fussell, S. G. (2020). *Determinants of aviation students' intentions to use virtual reality for flight training* (Publication No. 28150209) [Doctoral dissertation, Embry-Riddle Aeronautical University]. ProQuest Dissertations & Theses Global. http://ezproxy.libproxy.db.erau.edu/login?url=https://www.proquest.com/dissertations-theses/determinants-aviation-students-intentions-use/docview/2459162236/se-2?accountid=27203

Gabrlik, P., Cour-Harbo, A. l., Kalvodova, P., Zalud, L., & Janata, P. (2018). Calibration and accuracy assessment in a direct georeferencing system for UAS photogrammetry. *International Journal of Remote Sensing*, *39*(15–16), 4931–4959. https://doi.org/10.1080/01431161.2018.1434331

Gatteschi, V., Lamberti, F., Paravati, G., Sanna, A., Demartini, C., Lisanti, A., & Venezia, G. (2015). New frontiers of delivery services using drones: A prototype system exploiting a quadcopter for autonomous drug shipments. In *2015 IEEE 39th Annual Computer Software and Applications Conference* (Vol. 2, pp. 920–927). IEEE. https://doi.org/10.1109/compsac.2015.52

Gefen, D. (2004). What makes an ERP implementation relationship worthwhile: Linking trust mechanisms and ERP usefulness. *Journal of Management Information Systems*, *21*(1), 263–288. https://doi.org/10.1080/07421222.2004.11045792

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Inexperience and experience with online stores: The importance of TAM and trust. *IEEE Transactions on Engineering Management, 50*(3), 307–321. https://doi.org/10.1109/tem.2003.817277

Gefen, D., Karahanna, E., & Straub, D. W. (2003b). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, 51–90. https://doi.org/10.2307/30036519

Georgetown University Health Policy Institute. (n.d.) *Prescription drugs.* https://hpi.georgetown.edu/rxdrugs/#

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

Goldman, G. H. (2016). Acoustic detection results for a small unmanned aircraft system extrapolated over range. *Journal of the Acoustical Society of America, 140*(4), 3120–3120. https://doi.org/10.1121/1.4969771

Gong, M., Xu, Y., & Yu, Y. (2004). An enhanced technology acceptance model for web-based learning. *Journal of Information Systems Education, 15*(4), 365–374.

Grabner-Kraeuter, S. (2002). The role of consumers' trust in online–shopping. *Journal of Business Ethics, 39*(1/2), 43–50. https://doi.org/10.1023/A:1016323815802

Graham, G. (2016). *Factors influencing and risk associated with the use of drones by specialty construction companies in the United States of America* (Publication No. 28006492) [Doctoral dissertation, Indiana State University]. ProQuest Global Dissertations & Theses Global.

Gray, S. S. (2020). *Environmental management and policy decisions: Understanding the influences on public acceptance* (Publication No. 2405329278). [Doctoral dissertation, University of Michigan] ProQuest Dissertations & Theses Global.

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

Ha, S., & Stoel, L. (2009). Consumer e-shopping acceptance: Antecedents in a technology acceptance model. *Journal of Business Research, 62*(5), 565–571. https://doi.org/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.). Prentice-Hall.

Hameed, I., Waris, I., & Amin Ul Haq, M. (2019). Predicting eco-conscious consumer behavior using theory of planned behavior in Pakistan. *Environmental Science and*

Pollution Research International, *26*(15), 15535–15547. https://doi.org/10.1007/s11356-019-04967-9

Harris, J. M., Nelson, J. A., Rieucau, G., & Broussard, W. P. (2019). Use of drones in fishery science. *Transactions of the American Fisheries Society (1900)*, *148*(4), 687–697. https://doi.org/10.1002/tafs.10168

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. https://doi.org/10.1007/s11747-014-0403-8

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

Hii, M. S. Y., Courtney, P., & Royall, P. G. (2019). An evaluation of the delivery of medicines using drones. *Drones*, *3*(3), 52.

Ho, M. S., Ocasio-Velazquez, M., & Booth, C. (2017). Trust or consequences? Causal effects of perceived risk and subjective norms on cloud technology adoption. *Computers & Security, 70*, 581-595. https://doi.org/10.1016/j.cose.2017.08.004

Ho, P. M., Bryson, C. L., & Rumsfeld, J. S. (2009). Medication adherence: Its importance in cardiovascular outcomes. *Circulation*, *119*(23), 3028–3035. https://doi.org/10.1161/circulationaha.108.768986

Hobbs, J. E., & Goddard, E. (2015). Consumers and trust. *Food Policy*, *52*, 71-74.

Hoey, B. D. (2018, November 29). 2018 NCPA digest: A roadmap for independent community pharmacies. *Cardinal Health*. https://www.cardinalhealth.com/en/essential-insights/2018-ncpa-digest.html

Hoff, K. A., & Bashir, M. (2015). Trust in automation: Integrating empirical evidence on factors that influence trust. *Human Factors*, *57*(3), 407-434. https://doi.org/10.1177/0018720814547570

Hsiao, C., & Yang, C. (2010). Predicting the travel intention to take high speed rail among college students. *Transportation Research*. *Part F*, *Traffic Psychology and Behaviour*, *13*(4), 277–287. https://doi.org/10.1016/j.trf.2010.04.011

Hunt-White, T. (2014, May). *The influence of selected factors on student survey participation and mode of completion*. National Center for Education Statistics. http://sitesusa.s3.amazonaws.com/wp-content/uploads/sites/242/2014/05/2007FCSM_Hunt-White-III-C.pdf

Ibrahim, A. N. H., Borhan, M. N., & Rahmat, R. A. O. (2020). Understanding users' intention to use park-and-ride facilities in Malaysia: The role of trust as a novel construct in the theory of planned behaviour. *Sustainability*, *12*(6), 1–14. https://doi.org/10.3390/su12062484

International Civil Aviation Organization. (n.d.) *Economic impacts of COVID-19 on civil aviation.* https://www.icao.int/sustainability/Pages/Economic-Impacts-of-COVID-19.aspx\

International Transport Forum. (2020, June 19). *Covid-19 transport brief: Drones in the era of coronavirus.* https://www.itf-oecd.org/sites/default/files/drones-covid-19.pdf

Jacoby, J., & Kaplan, L. B. (1972, November 3–5). The components of perceived risk. In Venkatesan (Ed.), *SV – Proceedings of the Third Annual Conference of the Association for Consumer Research, Chicago, IL* (pp. 382–393). https://www.acrwebsite.org/volumes/12016/volumes/sv02/SV02

Johns Hopkins Medicine. (2016, April). *Informed consent guidance - How to prepare a readable consent form*. https://doi.org/10.1007/springerreference_83181

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.

Kasim, K. (2018). Assessment of small unmanned aerial systems operations in the National Airspace System. *Journal of Aviation Technology and Engineering*, *7*(2), 67–73 https://doi.org/10.7771/2159-6670.1161

Kasperson, R. E., & Ram, B. J. (2013). The public acceptance of new energy technologies. *Daedalus*, *142*(1), 90–96. https://doi.org/10.1162/daed_a_00187

Khan, R., Tausif, S., & Malik, A. (2019). Consumer acceptance of delivery drones in urban areas. *International Journal of Consumer Studies*, *43*(1), 87–101. https://doi.org/10.1111/ijcs.12487

Kim, H. W., Xu, Y., & Koh, J. (2004). A comparison of online trust building factors between potential customers and repeat customers. *Journal of the Association for Information Systems*, *5*(10), 392–420. https://doi.org/10.17705/1jais.00056

Kim, S. H. (2020). Third-party risk analysis of small unmanned aircraft systems operations. *Journal of Aerospace Information Systems*, *17*(1), 24–35. https://doi.org/10.2514/1.i010763

Kim, S. J., Lim, G. J., Cho, J., & Côté, M. J. (2017). Drone-aided healthcare services for patients with chronic diseases in rural areas. *Journal of Intelligent & Robotic Systems*, *88*(1), 163–180. https://doi.org/10.1007/s10846-017-0548-z

King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management*, *43*(6), 740–755. https://doi.org/10.1016/j.im.2006.05.003

Klepser, D. G., Xu, L., Ullrich, F., & Mueller, K. J. (2011). Trends in community pharmacy counts and closures before and after the implementation of Medicare Part D. *The Journal of Rural Health*, *27*(2), 168–175. https://doi.org/10.1111/j.1748-0361.2010.00342.x

Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed.). Guilford Publications.

Kolodny, L. (2019, May 17). *Zipline, which delivers lifesaving medical supplies by drone, now valued at $1.2 billion*. CNBC. https://www.cnbc.com/2019/05/17/zipline-medical-delivery-drone-start-up-now-valued-at-1point2-billion.html

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

Lærd Statistics. (n.d.). *Testing for normality using SPSS Statistics.* https://statistics.laerd.com/spss-tutorials/testing-for-normality-using-spss-statistics.php

Lankton, N., McKnight, D. H., & Thatcher, J. B. (2014). Incorporating trust-in-technology into expectation disconfirmation theory. *The Journal of Strategic Information Systems*, *23*(2), 128–145. https://doi.org/10.1016/j.jsis.2013.09.001

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. https://doi.org/10.1111/ajpy.12094

Lavrakas, P. J. (2008). *Encyclopedia of survey research methods* (Vols. 1–0). Sage Publications. https://dx.doi.org/10.4135/9781412963947

Lee, B. R. (2016, December). *Protection, profit, or privacy: Exploring strategic solutions for integrating unmanned aerial systems (UAS) and the delicate balance between commercial opportunity and public safety* [Master's thesis, Naval Postgraduate School]. Homeland Security Affairs. https://www-proquest-com.ezproxy.libproxy.db.erau.edu/docview/2206253996?pq-origsite=summon

Lee D. K. (2020). Data transformation: A focus on the interpretation. *Korean Journal of Anesthesiology*, *73*(6), 503–508. https://doi.org/10.4097/kja.20137

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. https://doi.org/10.1016/j.elerap.2008.11.006

Lee, J., & Moray, N. (1992). Trust, control strategies and allocation of function in human-machine systems. *Ergonomics*, *35*(10), 1243-1270.

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. https://doi.org/10.1016/s0378-7206(01)00143-4

Leventhal, J., & Bryan, D. N. (2020, May 12). During a pandemic, using drones to deliver medical supplies and prescription drugs makes great sense. *The Bridge*. https://www.mercatus.org/bridge/commentary/during-pandemic-using-drones-deliver-medical-supplies-and-prescription-drugs-makes

Likert, R. (1932). A technique for the measurement of attitudes. *Archives of Psychology, 22*(140), 5–55.

Lin, C. A., Shah, K., Mauntel, L. C. C., & Shah, S. A. (2018). Drone delivery of medications: Review of the landscape and legal considerations. *The Bulletin of the American Society of Hospital Pharmacists*, *75*(3), 153–158. https://doi.org/10.2146/ajhp170196

Lippert, S. K. (2001). *An exploratory study into the relevance of trust in the context of information systems technology* (Publication No. 3004032) [Doctoral dissertation, George Washington University]. ProQuest Dissertations & Theses Global.

Litman, L., Robinson, J., & Abberbock, T. (2017). TurkPrime.com: A versatile crowdsourcing data acquisition platform for the behavioral sciences. *Behavior Research Methods*, *49*(2), 433–442. https://doi.org/10.3758/s13428-016-0727-z

Livingston, M. (2020, November 18). The best prescription delivery services in 2021: Amazon, CVS, PillPack and more. *CNET Health and Wellness*. https://www.cnet.com/health/personal-care/best-prescription-delivery-services/

Lobb, A. E., Mazzocchi, M., & Traill, W. B. (2007). Modeling risk perception and trust in food safety information within the theory of planned behaviour. *Food Quality and Preference*, *18*(2), 384–395. https://doi.org/10.1016/j.foodqual.2006.04.004

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.

Luhmann, N. (2018). *Trust and power*. John Wiley & Sons.

Macias, M., Barrado, C., Pastor, E., & Royo, P. (2019, September 8–12). *The future of drones and their public acceptance* [Paper presentation]. 2019 IEEE/AIAA 38th Digital Avionics Systems Conference (DASC), San Diego, CA. https://doi.org/10.1109/dasc43569.2019.9081623

Madden, T. J., Scholder, E. P., & Ajzen, I. (1992). A comparison of the theory of planned behavior and the theory of reasoned action. *Personality & Social Psychology Bulletin*, *18*(1), 3–9. https://doi.org/10.1177/0146167292181001

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.

Manganelli, A. M., Bobbio, A., & Canova, L. (2020). Buying organic food products: The role of trust in the theory of planned behavior. *Frontiers in Psychology*, 11, 575820–575820. https://doi.org/10.3389/fpsyg.2020.575820

Marangunić, N., & Granić, A. (2014). Technology acceptance model: A literature review from 1986 to 2013. *Universal Access in the Information Society*, *14*(1), 81–95. https://doi.org/10.1007/s10209-014-0348-1

Martin, C. B., Hales, C. M., Gu, Q., & Ogden, C. L. (2019). *Prescription drug use in the United States, 2015-2016*. National Center for Health Statistics. https://www.cdc.gov/nchs/data/databriefs/db334-h.pdf

Mascarello, L., & Quagliotti, F. (2017). Challenges and safety aspects of a disaster relief exercise. *Journal of Intelligent & Robotic Systems*, *88*(2–4), 737–749. https://doi.org/10.1007/s10846-017-0518-5

Mason, W., & Suri, S. (2012). Conducting behavioral research on Amazon's Mechanical Turk. *Behavior Research Methods*, *44*(1), 1–23. https://doi.org/10.3758/s13428-011-0124-6

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

McDuffie, D. (2019, January 30). *Using Amazon's Mechanical Turk: Benefits, drawbacks, and suggestions*. Association for Psychological Science. https://www.psychologicalscience.org/observer/using-amazons-mechanical-turk-benefits-drawbacks-and-suggestions

McKnight, D. H., & Chervany, N. L. (2001). What trust means in e-commerce customer relationships: An interdisciplinary conceptual typology. *International Journal of*

Electronic Commerce, *6*(2), 35–59. https://doi.org/10.1080/10864415.2001.11044235

Meyerson, D., Weick, K. E., & Kramer, R. M. (1996). Swift trust and temporary groups. In R. M. Kramer & T. R. Tyler (Eds.), Trust in organizations: *Frontiers of theory and research* (pp. 166–195). Sage. https://doi.org/10.4135/9781452243610.n9

Milberg, S. J., Smith, H. J., & Burke, S. J. (2000). Information privacy: Corporate management and national regulation. *Organization Science (Providence, R.I.), 11*(1), 35-57. https://doi.org/10.1287/orsc.11.1.35.12567

Mishra, P., Pandey, C., Singh, U., Gupta, A., Sahu, C., & Keshri, A. (2019). Descriptive statistics and normality tests for statistical data. *Annals of Cardiac Anaesthesia*, *22*(1), 67-72. https://doi.org/10.4103/aca.ACA_157_18

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. https://doi.org/10.1108/ijchm-11-2012-0221

MTurk. (2018). *Amazon Mechanical Turk FAQs.* https://www.mturk.com/help

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), 1–19. https://doi.org/10.15394/ijaaa.2016.1141

Myers, P. L., III. (2019). *A behavioral research model for small unmanned aircraft systems for data gathering operations* (Publication No. 13856256) [Doctoral dissertation, Embry-Riddle Aeronautical University]. ProQuest Dissertations & Theses Global.

Myers, P., & Truong, D. (2020). A new research model for higher risk activities applied to the use of small unmanned aircraft for data gathering operations. *Journal of Intelligent & Robotic Systems*, 100, 1617–1634. https://doi.org/10.1007/s10846-020-01232-x

National Rural Health Association. (2009, May). *Pharmacy*. https://doi.org/10.1111/j.1748-0361.1997.tb00946.x

Nelson, K. M., & Cooprider, J. G. (1996). The contribution of shared knowledge to IS group performance. *MIS Quarterly*, 409–432. https://doi.org/10.2307/249562

Nunnally, J. C., & Bernstein, I. H. (1978). *Psychometric theory.* McGraw-Hill.

Otway, H. J., & Von Winterfeldt, D. (1982). Beyond acceptable risk: On the social acceptability of technologies. *Policy Sciences*, *14*(3), 247-256. https://doi.org/10.1007/BF00136399

Padró, J., Carabassa, V., Balagué, J., Brotons, L., Alcañiz, J. M., & Pons, X. (2019). Monitoring opencast mine restorations using unmanned aerial system (UAS) imagery. *The Science of the Total Environment*, *657*, 1602–1614. https://doi.org/10.1016/j.scitotenv.2018.12.156

Palmer, A. (2020, August 31). Amazon wins FAA approval for Prime Air drone delivery fleet. *CNBC*. https://www.cnbc.com/2020/08/31/amazon-prime-now-drone-delivery-fleet-gets-faa-approval.html

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. https://doi.org/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. https://doi.org/10.1007/s00779-013-0670-2

Park, S. Y. (2009). An analysis of the technology acceptance model in understanding university students' behavioral intention to use e-learning. *Educational Technology & Society*, *12*(3), 150–162.

Parnell, G. S., Driscoll, P. J., & Henderson, D. L. (2010). *Decision making in systems engineering and management* (2nd ed.). Wiley.

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. https://doi.org/10.1080/10864415.2003.11044275

Pavlou, P. A., & Gefen, D. (2004). Building effective online marketplaces with institution-based trust. *Information Systems Research*, *15*(1), 37–59. https://doi.org/10.1287/isre.1040.0015

Pavlou, P. A., Liang, H., & Xue, Y. (2007). Understanding and mitigating uncertainty in online exchange relationships: A principal-agent perspective. *MIS Quarterly*, *31*(1), 105-136. https://doi.org/10.2307/25148783

Prescriptions, 21 C.F.R. § 1306 (2020).

Pynoo, B., Tondeur, J., van Braak, J., Duyck, W., Sijnave, B., & Duyck, P. (2012). Teachers' acceptance and use of an educational portal. *Computers and Education*, *58*(4), 1308–1317. https://doi.org/10.1016/j.compedu.2011.12.026

Qato, D., Zenk, S., Wilder, J., Harrington, R., Gaskin, D., & Alexander, G. (2017). The availability of pharmacies in the United States: 2007–2015. *PLOS ONE, 12*(8), 1–13, Article e0183172. https://doi.org/10.1371/journal.pone.0183172

Qi, X., & Ploeger, A. (2019). Explaining consumers' intentions towards purchasing green food in Qingdao, China: The amendment and extension of the theory of planned behavior. *Appetite, 133,* 414–422. https://doi.org/10.1016/j.appet.2018.12.004

Ramadan, Z. B., Farah, M. F., & Mrad, M. (2017). An adapted TPB approach to consumers' acceptance of service-delivery drones. *Technology Analysis & Strategic Management*, *29*(7), 817–828. https://doi.org/10.1080/09537325.2016.1242720

Ratcliffe, M., Burd, C., Holder, K., & Fields, A. (2016). *Defining rural at the U.S. Census Bureau: American community survey and geography brief.* U.S. States Census Bureau, Department of Commerce. https://www2.census.gov/geo/pdfs/reference/ua/Defining_Rural.pdf

Reader, R. (2019, October 21). *Drones from CVS and Walgreens are finally here—and they're bringing Band-Aids.* Fast Company. https://www.fastcompany.com/90419596/cvs-and-walgreenss-drones-are-finally-here-and-theyre-bringing-bandaids

Reddy, L. B., & DeLaurentis, D. (2016). Opinion survey to reduce uncertainty in public and stakeholder perception of unmanned aircraft. *Transportation Research Record, 2600*(1), 80–93. https://doi.org/10.3141/2600-09

Rehman, S. U., Bhatti, A., Mohamed, R., & Ayoup, H. (2019). The moderating role of trust and commitment between consumer purchase intention and online shopping behavior in the context of Pakistan. *Journal of Global Entrepreneurship Research, 9(*1), 1–25. https://doi.org/10.1186/s40497-019-0166-2

Renn, O. (2004). Perception of risks. *Toxicology Letters*, *149*(1–3), 405–413. https://doi.org/10.1016/j.toxlet.2003.12.051

Ricci, E. C., Banterle, A., and Stranieri, S. (2018). Trust to go green: An exploration of consumer intentions for eco-friendly convenience food. *Ecological Economics, 148,* 54–65. https://doi.org/10.1016/j.ecolecon.2018.02.010

Rice, S., Winter, S. R., Doherty, S., & Milner, M. (2017). Advantages and disadvantages of using internet-based survey methods in aviation-related research. *Journal of Aviation Technology and Engineering*, *7*(1), 58–65. https://doi.org/10.7771/2159-6670.1160

Roddis, P., Roelich, K., Tran, K., Carver, S., Dallimer, M., & Ziv, G. (2020). What shapes community acceptance of large-scale solar farms? A case study of the UK's first 'nationally significant' solar farm. *Solar Energy*, *209*, 235-244. https://doi.org/10.1016/j.solener.2020.08.065

Roemer, E., Schuberth, F., & Henseler, J. (2021). HTMT2 - an improved criterion for assessing discriminant validity in structural equation modeling. *Industrial Management + Data Systems*, *121*(12), 2637-2650. https://doi.org/10.1108/IMDS-02-2021-0082

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.

Royall, P. G., & Courtney, P. (2019, November 20). *Medicine delivery by drone – implications for safety and quality*. European Pharmaceutical Review. https://www.europeanpharmaceuticalreview.com/article/103799/medicine-delivery-drone-safety-and-quality/

Sadiq, M., Dogra, N., Adil, M., & Bharti, K. (2021). Predicting online travel purchase behavior: The role of trust and perceived risk. *Journal of Quality Assurance in Hospitality & Tourism*, 1–27. https://doi.org/10.1080/1528008X.2021.1913693

Saeed, K. A., Hwang, Y., & Mun, Y. Y. (2003). Toward an integrative framework for online consumer behavior research: A meta-analysis approach. *Journal of Organizational and End User Computing*, *15*(4), 1–26. https://doi.org/10.4018/joeuc.2003100101

Saeri, A. K., Ogilvie, C., La Macchia, S. T., Smith, J. R., & Louis, W. R. (2014). Predicting Facebook users' online privacy protection: Risk, trust, norm focus theory, and the theory of planned behavior. *The Journal of Social Psychology*, *154*(4), 352–369. https://doi.org/10.1080/00224545.2014.914881

Sah, B., Gupta, R., & Bani-Hani, D. (2020). Analysis of barriers to implement drone logistics. *International Journal of Logistics Research and Applications*, 1–20. https://doi.org/10.1080/13675567.2020.1782862

Sarosa, S. (2022). The effect of perceived risks and perceived cost on using online learning by high school students. *Procedia Computer Science*, *197*, 477-483.

Scalea, J. R., Restaino, S., Scassero, M., Blankenship, G., Bartlett, S. T., & Wereley, N. (2018). An initial investigation of unmanned aircraft systems (UAS) and real-time organ status measurement for transporting human organs. *IEEE Journal of Translational Engineering in Health and Medicine, 6*, 1–7. https://doi.org/10.1109/jtehm.2018.2875704

Schnall, R., Higgins, T., Brown, W., Carballo-Dieguez, A., & Bakken, S. (2015). Trust, perceived risk, perceived ease of use and perceived usefulness as factors related to mHealth technology use. *Studies in Health Technology and Informatics*, *216*, 467–471. doi: 10.3233/978-1-61499-564-7-467

Seyal, A. H., & Rahman, M. N. (2017). *Theory of planned behavior: New research*. Nova Science Publishers.

Shahbandeh, M. (2020, August 28). *Total number of retail prescriptions filled annually in the United States from 2013-2025 (in billions)*.* Statista Research Department [Data set]. https://www.statista.com/statistics/261303/total-number-of-retail-prescriptions-filled-annually-in-the-us/

Sheehan, K. B. (2017, July 4). Crowdsourcing research: Data collection with Amazon's Mechanical Turk. *Communication Monographs, 85*(1), 140–156. https://doi.org/10.1080/03637751.2017.1342043

SJ Consulting Group, Inc. (2011). *Report on measuring the benefits of rural postal service for Postal Regulatory Commission.* https://www.prc.gov/sites/default/files/archived/Rural_Service_Report.pdf

Small Unmanned Aircraft Systems, 14 C.F.R. § 107 (2017).

Sonnberger, M., & Ruddat, M. (2017). Local and socio-political acceptance of wind farms in Germany. *Technology in Society, 51*, 56-65. https://doi.org/10.1016/j.techsoc.2017.07.005

Soper, D. S. (2021). *A-priori sample size calculator for structural equation models* (Version 4.0) [Computer software]. http://www.danielsoper.com/statcalc

Spence, M., Stancu, V., Elliott, C. T., & Dean, M. (2018). Exploring consumer purchase intentions towards traceable minced beef and beef steak using the theory of planned behavior. *Food Control, 91*, 138–147. https://doi.org/10.1016/j.foodcont.2018.03.035

Stelter, A., Kaping, C., Oschinsky, F. M., & Niehaves, B. (2020, June 15–19). Theoretical foundations on technology acceptance and usage in public administrations: Investigating bounded acceptance and usage of new technology by employees. In S-J. Eom & J. Lee (Eds.), *The 21st Annual International Conference on Digital Government Research, Seoul Republic of Korea* (pp. 344–345). ACM Digital Library. https://doi.org/10.1145/3396956.3397004

Stevens, J. (2009). *Applied multivariate statistics for the social sciences* (5th ed.). Routledge

Stolzer, A. J., & Goglia, J. J. (2016). *Safety management systems in aviation* (2nd ed.). Routledge. https://doi.org/10.4324/9781315607504

Stritch, J. M., Pedersen, M. J., & Taggart, G. (2017). The opportunities and limitations of using Mechanical Turk (MTURK) in public administration and management scholarship. *International Public Management Journal, 20*(3), 489–511. https://doi.org/10.1080/10967494.2016.1276493

Substance Abuse and Mental Health Services Administration. (2020, September 1). *Medication-assisted treatment (MAT*). U.S. Department of Health & Human Services. https://www.samhsa.gov/medication-assisted-treatment

Syed, S. T., Sharp, L. K., Kim, Y., Jentleson, A., Lora, C. M., Touchette, D. R., & Gerber, B. S. (2016). Relationship between medication adherence and distance to dispensing pharmacies and prescribers among an urban Medicaid population with diabetes mellitus. *Pharmacotherapy, 36*(6), 590–597. https://doi.org/10.1002/phar.1757

Tabatabai, M. (2020, January 29). *Drone-to-door–the ascent of the airborne pharmacy*. Magellan Health Insights. https://magellanhealthinsights.com/2020/01/27/drone-to-door-the-ascent-of-the-airborne-pharmacy/

Talley, S. M. (2020). Public Acceptance of AI Technology in Self-Flying Aircraft. *Journal of Aviation/Aerospace Education & Research*, *29*(1). https://doi.org/10.15394/jaaer.2020.1822

Taylor, S., & Todd, P. (1995). Assessing IT usage: The role of prior experience. *MIS Quarterly, 19*(4), 561–570. https://doi.org/10.2307/249633

Taylor, S., & Todd, P. A. (1995b). Understanding information technology usage: A test of competing models. *Information Systems Research, 6*(2), 144–176. https://doi.org/10.1287/isre.6.2.144

Techau, T. E. (2018). *General aviation pilot acceptance and adoption of electronic flight bag technology* (Publication No. 10975712) [Doctoral dissertation, Embry-Riddle Aeronautical University]. ProQuest Dissertations & Theses Global.

Teng, C. C., & Wang, Y. M. (2015). Decisional factors driving organic food consumption: Generation of consumer purchase intentions. *British Food Journal*, *117*, 1066–1081. DOI 10.1108/BFJ-12-2013-0361

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. https://doi.org/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. https://doi.org/10.1111/j.1365-2729.2007.00247.x

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. https://doi.org/10.12720/joace.3.3.246-252

Thabane, L., Ma, J., Chu, R., Cheng, J., Ismaila, A., Rios, L. P., & Goldsmith, C. H. (2010). A tutorial on pilot studies: The what, why and how [Commentary]. *BMC Medical Research Methodology, 10*(1), 1–10. doi:10.1186/1471-2288-10-1

Thomason, B. (2018, May 9). *If UPS and FedEx 98.5 percent effective, why are so many patients not getting their specialty medication on time?* Parcelshield. https://bit.ly/3mmg8fl

Titah, R., & Barki, H. (2009). Nonlinearities between attitude and subjective norms in information technology acceptance: A negative synergy? *MIS Quarterly, 33*(4), 827-844. https://doi.org/10.2307/20650329

Truog, S., Maxim, L., Matemba, C., Blauvelt, C., Ngwira, H., Makaya, A., Moreira, S., Lawrence, E., Ailstock, G., Weitz, A., West, M., & Defawe, O. (2020). Insights before flights: How community perceptions can make or break medical drone deliveries. *Drones (Basel), 4*(3), 51. https://doi.org/10.3390/drones4030051

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), 463–479. https://doi.org/10.1016/j.infsof.2009.11.005

United States Census Bureau. (2017, August 9). *One in five Americans live in rural areas*. America Counts Staff. https://www.census.gov/library/stories/2017/08/rural-america.html

United States Census Bureau. (2018, December 23). *Census tracts* [PowerPoint slides]. https://www2.census.gov/geo/pdfs/education/CensusTracts.pdf

United States Census Bureau. (2019a, July 1). *QuickFacts* [Data set]. https://www.census.gov/quickfacts/fact/table/US/PST045219

United States Census Bureau. (2019b, October 18). *It takes extra effort by the U.S. Census Bureau to reach people far outside urban areas*. https://www.census.gov/library/stories/2019/12/counting-people-in-rural-and-remote-locations.html

United States Zip Codes. (2021). *ZIP code database* [Data set]. https://www.unitedstateszipcodes.org/zip-code-database/

Urban Air Mobility News. (2020, March 25). *Swoop Aero "first to operate delivery drones from overseas to fight Covid-19."* https://bit.ly/3DfApdD

van Rijnsoever, F. J., van Mossel, A., & Broecks, K. P. F. (2015). Public acceptance of energy technologies: The effects of labeling, time, and heterogeneity in a discrete choice experiment. *Renewable & Sustainable Energy Reviews, 45*, 817-829. https://doi.org/10.1016/j.rser.2015.02.040

Vassie, L. (2005). Facts and fears: Understanding perceived risk (1979) [Supplement]. *Policy and Practice in Health and Safety, 3*(2), 65–102. https://doi.org/10.1080/14774003.2005.11667668

Vempati, L. (2020). *Pilots' willingness to operate in unmanned aircraft system integrated airspace* [Doctoral dissertation, Embry-Riddle Aeronautical University]. ProQuest Dissertations & Theses Global.

Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research*, *11*(4), 342–365. https://doi.org/10.1287/isre.11.4.342.11872

Venkatesh, V., & Davis, F. D. (1996). A model of the antecedents of perceived ease of use: Development and test. *Decision Sciences*, *27*(3), 451–481. https://doi.org/10.1111/j.1540-5915.1996.tb00860.x

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. https://doi.org/10.2307/30036540

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), 157–178. https://doi.org/10.2307/41410412

Vincenzi, D., Ison, D., & Liu, D. (2013). Public perception of unmanned aerial systems (UAS): A survey of public knowledge regarding roles, capabilities, and safety while operating within the National Airspace System (NAS). *Aviation and Safety Scholarly Commons*, *2*(2) 1076-1087. https://commons.erau.edu/cgi/viewcontent.cgi?article=1733&context=publication

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

Ward, K. A., Winter, S. R., Cross, D. S., Robbins, J. M., Mehta, R., Doherty, S., & Rice, S. (2021). Safety systems, culture, and willingness to fly in autonomous air taxis: A multi-study and mediation analysis. *Journal of Air Transport Management, 91*, 1–9. Article 101975. https://doi.org/10.1016/j.jairtraman.2020.101975

Ward, T. (2020, September 22). *Walmart now piloting drone delivery of Covid-19 at-home self-collection kits.* Walmart. https://corporate.walmart.com/newsroom/2020/09/22/walmart-now-piloting-drone-delivery-of-covid-19-at-home-self-collection-kits

West, J. P., Klofstad, C. A., Uscinski, J. E., & Connolly, J. M. (2019). Citizen support for domestic drone use and regulation. *American Politics Research, 47*(1), 119–151. https://doi.org/10.1177/1532673X18782208

Westland, C. J. (2010). Lower bounds on sample size in structural equation modeling. *Electronic Commerce Research and Applications, 9*(6), 476–487. https://doi.org/10.1016/j.elerap.2010.07.003

Winickoff, D. E. (2017, September). Public acceptance and emerging production technologies. In A. Nolan (Ed.), *The Next Production Revolution: Implications for Governments and Business* (pp. 277–298). OECD Publishing. https://doi.org/10.1787/9789264271036-12-en

Wu, I., & Chen, J. (2005). An extension of trust and TAM model with TPB in the initial adoption of on-line tax: An empirical study. *International Journal of Human-Computer Studies*, *62*(6), 784–808. https://doi.org/10.1016/j.ijhcs.2005.03.003

Wu, I., Li, J., & Fu, C. (2011). The adoption of mobile healthcare by hospital's professionals: An integrative perspective. *Decision Support Systems, 51*(3), 587–596. https://doi.org/10.1016/j.dss.2011.03.003

Wüstenhagen, R., Wolsink, M., & Bürer, M. J. (2007). Social acceptance of renewable energy innovation: An introduction to the concept. *Energy Policy, 35*(5), 2683–2691. https://doi.org/10.1016/j.enpol.2006.12.001

Xie, Q., Song, W., Peng, X., & Shabbir, M. (2017). Predictors for e-government adoption: Integrating TAM, TPB, trust and perceived risk. *The Electronic Library, 35*(1), 2-20. https://doi.org/10.1108/EL-08-2015-0141

Yang, X., Unhelkar, V., Li, K., & Shah, J. (2017). Evaluating effects of user experience and system transparency on trust in automation. Paper presented at the 2017 12th ACM/IEEE International Conference on Human-Robot Interaction 408-416. https://doi.org/10.1145/2909824.3020230

Yao, X., Wu, Y., Liu, H., Zhao, X., Bian, Y., & Qu, W. (2019). Analysis of psychological influences on navigation use while driving based on extended theory of planned behavior. *Transportation Research Record*, *673*(9), 480–490. https://doi.org/10.1177/0361198119845666

Yoo, W., Yu, E., & Jung, J. (2018). Drone delivery: Factors affecting the public's attitude and intention to adopt. *Telematics and Informatics, 35*(6), 1687–1700. https://doi.org/10.1016/j.tele.2018.04.014

Zhong, Oh, S., & Moon, H. C. (2021). What Can Drive Consumers' Dining-Out Behavior in China and Korea during the COVID-19 Pandemic? *Sustainability (Basel, Switzerland), 13*(4), 1724. https://doi.org/10.3390/su13041724

Appendix A

Permission to Conduct Research

This appendix includes the informed consent for the study as well as the ERAU Institutional Review Board approval.

Informed Consent Form

INFORMED CONSENT FORM
Willingness to Use sUAS for Prescription Medication Delivery

Purpose of this research: I am asking you to take part in a research project for the purpose of assessing your willingness to use sUAS for prescription medication delivery. During this study, you will be asked to complete an online survey. You will be presented with 3 qualifying questions. If you are eligible to participate in the survey, you will be presented with 5 demographic questions followed by 49 statements regarding sUAS for prescription medication deliveries. You will be asked to rate how strongly you agree or disagree with the statements. The completion of the survey is expected to take approximately 15 minutes.

Eligibility: To be in this study, you must understand written English, be a resident of the United States, currently live or previously have lived in a rural community as defined by the US Census Bureau, a registered user of Amazon Mechanical Turk ® with 100 completed tasks and a 95% approval rate, and be at least 18 years of age.

Risks or discomforts: It is anticipated that this study will pose no greater risk than you would experience through normal daily activities.

Benefits: There are no known benefits to your participation other than knowing you have contributed to the advancement of scientific knowledge by helping to improve assessments of public acceptance.

Confidentiality of records: The data collected during this study will be anonymous and confidential. MTurk does not share any information about your account or identity with us, and we have no way of learning your identity. MTurk may use your IP address to verify your country of origin for eligibility purposes but will not otherwise record the address.

Compensation: You will be compensated 75 cents for your time via Amazon's Mechanical Turk.

Contact: If you have any questions about this research project, you can contact Sarah Talley, principal investigator, at vanhob92@my.erau.edu, or the faculty member overseeing this project, Dr. Robert Joslin, at joslinr@erau.edu. For any concerns or questions as a participant in this research, contact the Institutional Review Board (IRB) at 386-226-7179 or via email at teri.gabriel@erau.edu.

Voluntary participation: Your participation in this study is completely voluntary. You may discontinue your participation at any time without penalty or loss of benefits to which you are otherwise entitled. Should you wish to discontinue the research at any time, no information collected will be used.

CONSENT. By checking AGREE below, I certify that I am a resident of the United States, understand the information on this form, and voluntarily agree to participate in the study.

If you do **not** wish to participate in the study, simply close the browser or check DISAGREE which will direct you out of the study.

Please print a copy of this form for your records. A copy of this form can also be requested from Sarah Talley, vanhob92@my.erau.edu.

0 AGREE
0 DISAGREE

Permission for Behavioral Intention Factors for Prescription Deliveries by Small Unmanned Aircraft in Rural Communities

Embry-Riddle Aeronautical University
Application for IRB Approval
EXEMPT Determination Form

Principal Investigator: Sarah M. Talley

Other Investigators: Dr. Robert Joslin

Role: Student **Campus:** Daytona Beach **College:** Aviation/Aeronautics

Project Title: Behavioral Intention Factors for Prescription Deliveries by Small Unmanned Aircraft in Rural Communities

Review Board Use Only

Initial Reviewer: Teri Gabriel **Date:** 10/01/2021 **Approval #:** 22-029

Determination: Exempt

Dr. Beth Blickensderfer
IRB Chair Signature: Elizabeth L. Blickensderfer Digitally signed by Elizabeth L. Blickensderfer Date: 2021.10.08 15:04:46 -04'00'

Brief Description:

This research seeks understanding about public acceptance of prescription medication deliveries via sUAS in rural US communities. Specifically, the research uses a survey tool to assess the factors that may impact participant's willingness to use sUAS for prescription medication deliveries. The study will investigate this willingness through modeling of behavioral intentions.

This research falls under the **EXEMPT** category as per 45 CFR 46.104:

☑ (2) Research that only includes interactions involving educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior (including visual or auditory recording) if at least one of the following criteria is met: (Applies to Subpart B [Pregnant Women, Human Fetuses and Neonates] and does not apply for Subpart C [Prisoners] except for research aimed at involving a broader subject population that only incidentally includes prisoners.)

Permission for Modified Behavioral Intention Factors for Prescription Deliveries by Small Unmanned Aircraft in Rural Communities

EMBRY-RIDDLE
Aeronautical University
FLORIDA | ARIZONA | WORLDWIDE

23 February 2022

Modification of Previously Approved IRB

Campus:	Daytona Beach	College:	COA
Applicant:	Sarah Talley	Degree Level:	Doctorate
ERAU ID:	1314942	ERAU Affiliation:	Student
Project Title:	Behavioral Intention Factors for Prescription Deliveries by Small Unmanned Aircraft in Rural Communities		
Principal Investigator:	Sarah Talley		
Sumbission Date:	02/23/2022		
Beginning Date:	10/01/2021		
IRB Approval #:	22-029		

Modification of Approved IRB
APPROVAL

✓ Validated to meet the criteria for Exempt or Expedited Status.

IRB Approver Signature: Teri Gabriel, IRB Director

Date of Approval: February 24, 2022

Questions

1. **Change of Protocol due to:**

   Revised survey/questionnaire

   The pilot study from my original survey revealed discriminant validity data for my CFA model. Rather than conducting EFA analysis and revising my entire research model, it was determined that modifying the survey items to be more clear and collect additional data would be the better course of action. Four survey questions were deleted completely, as they were redundant and/or difficult to read. The remaining survey items were re-worded to be much more simplistic and distinguishing.

2. **Have you started the recruitment process?**

   Yes

   Will the Informed Consent Form change?

   No

3. **Have you received any complaints or experienced unanticipated problems with this project?**

   No

Appendix B

Data Collection Device

B1 Original Data Collection Survey

B2 Modified Data Collection Survey

B1 Data Collection Survey

Section 1 – Filter Questions

1. Are you a U.S. citizen, naturalized citizen, or have a green card?
2. Are you eighteen (18) years or older?
3. Do you currently live or previously lived in a rural community as defined by the U.S. Census Bureau (see definition below)?

   The Census Bureau identifies two types of urban areas:
   - *Urbanized Areas (UAs) of 50,000 or more people;*
   - *Urban Clusters (UCs) of at least 2,500 and less than 50,000 people.*

   "Rural" encompasses all population, housing, and territory not included within an urban area.

Section 2 – Demographics

1. Gender (Male/Female)
2. Age (18-24 years/ 25-29 years/ 30-34 years/ 35-39 years/ 40-44 years/ 45-49 years/ 50-54 years/ 55-59 years/ 60-64 years/ 65-69 years/ 70-74 years/ 75 years and over)
3. Highest Education Level (Attending high school/ High school graduate/ Some college, no degree/ Associate's degree/ Bachelor's degree/ Master's degree/ Professional degree/ Doctoral degree)
4. Annual Income (Less than $15,000/ $15,000 to $24,999/ $25,000 to $34,999/ $35,000 to $49,999/ $50,000 to $74,999/ $75,000 to $99,999/ $100,000 to $149,999/ $150,000 to $199,999/ More than $200,000)
5. Occupation [Select all that apply] (Student/ Commercial company employee/ Self-employed/ Government employee/ Unemployed/ Business owner/ Other)

Section 3 – Factors affecting individual's intentions to use a sUAS for prescription medication deliveries

For the purposes of this study, sUAS is defined as a small unmanned aircraft system, commonly referred to as a drone, used for deliveries. Examples of such aircraft are shown below.

"Drone Delivery" by www.routexl.com is licensed under CC BY 2.0

"Drone Delivery" by www.routexl.com is licensed under CC BY 2.0

"Fast delivery post package for adv or others purpose use" by dirkdavidson1 is marked with CC0 1.0

1. PU1 I think that using a sUAS for prescription medication delivery would enable me to accomplish my prescription medication delivery needs more quickly.
2. PU2 I think that using sUAS for prescription medication delivery would make it easier for me to carry out my tasks.
3. PU3 Using a sUAS for prescription medication delivery will enhance my productivity.
4. PU4 I think using a sUAS for prescription medication delivery would be valuable to me.
5. PU5 Overall, I find using a sUAS for prescription medication delivery would be useful.
6. SN1 People who are important to me would think I should use a sUAS for prescription medication delivery.
7. SN2 People who influence me would think I should use a sUAS for prescription medication delivery.
8. SN3 People whose opinions I value will encourage me to use a sUAS for prescription medication delivery.

9. SN4 People who are important to me will support me using a sUAS for prescription medication delivery.
10. SN5 My individual values/beliefs morally support me using a sUAS for prescription medication delivery.
11. BI1 I would use a sUAS for my prescription medication delivery needs.
12. BI2 I will use a sUAS for prescription medication delivery in the future.
13. BI3 I plan to use a sUAS for prescription medication delivery at least every 90 days.
14. BI4 When choosing prescription medication delivery methods, use of a sUAS is my first choice.
15. BI5 I would recommend using a sUAS for prescription medication delivery to my relatives and friends.
16. ATU1 I think using a sUAS for prescription medication delivery is a good idea.
17. ATU2 In my opinion, it is desirable to use a sUAS for prescription medication delivery.
18. ATU3 Using a sUAS for prescription medication delivery is fun.
19. ATU4 Using a sUAS for prescription medication delivery makes my prescription medication delivery experience more interesting.
20. ATU5 I like the idea of using a sUAS for my prescription medication delivery needs.
21. PR1 Using a sUAS for prescription medication delivery is physically threatening to myself and/or others in society.
22. PR2 Using a sUAS for prescription medication delivery is physically threatening to other aircraft.
23. PR3 My sUAS may not perform prescription medication delivery well.
24. PR4 The costs of procuring, operating, and maintaining a sUAS for prescription medication delivery is concerning.
25. PR5 It would take me lots of time to learn how to use a sUAS for prescription medication delivery.
26. PR6 Security is a concern when using a sUAS for prescription medication delivery because other people may be able to intercept my information or affect the operation or delivery of the sUAS.
27. PR7 Legal liability is a concern when using a sUAS for prescription medication delivery.
28. PR8 The media and/or society influence my perceived risk level of using a sUAS for prescription medication delivery.
29. PR9 Others in society using a sUAS for prescription medication delivery will lead to a loss of privacy for me.
30. PR10 Using a sUAS for prescription medication delivery will not fit well with my self-image or self-concept.
31. TR1 Based on my perception of sUAS for prescription medication delivery, I believe it will function as intended.

32. TR2 Based on my perception of sUAS for prescription medication delivery, I believe it is predictable.
33. TR3 Based on my perception of sUAS for prescription medication delivery, I believe it is effective.
34. TR4 Based on my perception of sUAS for prescription medication delivery, I believe it is reliable.

Additional questions

1. I have used a sUAS for prescription medication delivery purposes.
2. I used a sUAS for prescription medication delivery purposes this year.
3. I have frequently used a sUAS for prescription medication delivery.
4. I have used a sUAS for prescription medication delivery more than once in the past two years.
5. When I needed prescription medication delivery tasks completed, I used a sUAS.
6. How do you currently obtain prescription medications?
7. What is your preferred delivery method for receiving prescription medications?

B2 Modified Data Collection Survey

Section 1 – Filter Questions

1. Are you a U.S. citizen, naturalized citizen, or have a green card?
2. Are you eighteen (18) years or older?
3. Do you currently live or previously lived in a rural community as defined by the U.S. Census Bureau (see definition below)?

   The Census Bureau identifies two types of urban areas:

   - *Urbanized Areas (UAs) of 50,000 or more people;*
   - *Urban Clusters (UCs) of at least 2,500 and less than 50,000 people.*

   "Rural" encompasses all population, housing, and territory not included within an urban area.

Section 2 – Demographics

1. Gender (Male/Female)
2. Age (18-24 years/ 25-29 years/ 30-34 years/ 35-39 years/ 40-44 years/ 45-49 years/ 50-54 years/ 55-59 years/ 60-64 years/ 65-69 years/ 70-74 years/ 75 years and over)
3. Highest Education Level (Attending high school/ High school graduate/ Some college, no degree/ Associate's degree/ Bachelor's degree/ Master's degree/ Professional degree/ Doctoral degree)
4. Annual Income (Less than $15,000/ $15,000 to $24,999/ $25,000 to $34,999/ $35,000 to $49,999/ $50,000 to $74,999/ $75,000 to $99,999/ $100,000 to $149,999/ $150,000 to $199,999/ More than $200,000)
5. Occupation [Select all that apply] (Student/ Commercial company employee/ Self-employed/ Government employee/ Unemployed/ Business owner/ Other)

Section 3 – Factors affecting individual's intentions to use a sUAS for prescription medication deliveries

For the purposes of this study, sUAS is defined as a small unmanned aircraft system, commonly referred to as a drone, used for deliveries. Examples of such aircraft are shown below.

"Drone Delivery" by www.routexl.com is licensed under CC BY 2.0

"Drone Delivery" by www.routexl.com is licensed under CC BY 2.0

"Fast delivery post package for adv or others purpose use" by dirkdavidson1 is marked with CC0 1.0

1. PU1 Using drones would enable me to acquire my prescriptions more quickly.
2. PU2 Using drones would make it easier for me to acquire my prescriptions.
3. PU3 Using drones would improve my quality of life.
4. PU4 Using drones would be valuable to me.
5. PU5 Using drones would better meet my needs for acquiring my prescriptions.

6. SN1 People who are important to me think I should use drones for prescription delivery.
7. SN2 People who are important to me expect me to use drones for prescription delivery.
8. SN3 People who are important to me encourage me to use drones for prescription delivery.
9. SN4 People who are important to me support me using drones for prescription delivery.
10. SN5 People who are important to me use drones for prescription delivery.

11. BI1 I intend to use drones for my current prescription deliveries.
12. BI2 I intend to use drones for my future prescription deliveries.
13. BI3 I intend to use drones for prescription deliveries at least every 90 days.
14. BI4 I intend to use drones as my first choice for prescription deliveries.
15. BI5 I intend to recommend using drones for prescription delivery to my friends and family.

16. ATU1 My attitude toward drones is that it is a good idea.
17. ATU2 My attitude toward drones is that it is desirable.
18. ATU3 My attitude toward drones is that it is fun.
19. ATU4 My attitude toward drones is that it is interesting.
20. ATU5 My attitude toward drones is positive.

21. PR1 The risk of drones includes physical harm to myself and/or others.
22. PR2 The risk of drones includes physical harm to other aircraft.
23. PR3 The risk of drones includes too high a cost.
24. PR4 The risk of drones includes unfavorable legal liabilities.
25. PR5 The risk of drones includes a loss of privacy.

26. TR1 I trust that drones will be reliable.
27. TR2 I trust that drones will be predictable.
28. TR3 I trust that drones will be secure.
29. TR4 I trust that drones will be dependable.
30. TR5 I trust that drones will be safe.

Appendix C

Tables

Table C1

Summary of Extant Literature

Author/Year	Topic	Type of Analysis
Claesson et al., 2016	Delivery of automated external defibrillators (AED) to rural patients via sUAS	Explorative study using Geographic Information Systems to identify suitable drone placement
Gardner, 2016	Delivery of medications and medical supplies via sUAS to Remote Area Medical outreach events in rural Appalachia	Pilot program
Kim et al., 2017	Cost-benefit analysis of sUAS-aided healthcare services and medication delivery to patients with chronic disease in rural areas	Explorative study to determine optimal drone delivery points
Lin et al., 2018	Discussion of current sUAS technology and regulatory considerations for possible medication delivery	Review of current regulations governing drone delivery
Truog et al., 2020	Effectiveness of sUAS in delivery of emergency medical supplies to existing medical clinics and hospitals	Comparative analysis of sUAS versus ground deliveries
Ghelichi et al., 2021	Conceptualized model for sUAS delivery of medical items to hard-to-access locations in both rural and suburban areas	Case study using simulated instances for optimized logistics
Tyerman, 2018	Delivery of AED following out-of-hospital cardiac arrest	Time studies measuring delivery times using various location points and multiple speeds
Velez et al., 2021	Delivery of critical medical supplies in emergencies via sUAS in urban areas	Case study testing sUAS deliveries in a defined logistic network model

Table C2

Summary of Sources Supporting VMUTES Constructs

Construct	Major Findings	References
Facilitating Conditions (FC)	FC indirectly influence ATU	Teo, Lee, & Chai (2008)
	FC are a significant predictor of PEOU	Teo (2012)
Perceived Ease of Use (PEOU)	PEOU has a significant effect on BI	Choi & Chung (2010); Pavlou (2003)
	PEOU has a significant effect on PU	Teo (2012)
Perceived Usefulness (PU)	PU is a predictor of attitude	Ha & Stoel (2009); Morosan (2014)
	PU has a significant effect on BI	Choi & Chung (2012); Park & Kim (2014); Teo (2012)
Subjective Norms (SN)	SN have a direct effect on attitude	Teo, Lee, & Chai (2008)
	SN have a significant effect on BI	Teo (2012)
	SN have a significant effect on PU	Teo (2012)
	SN are positively related to ATU	Lu, Huang & Lo (2010)
	SN influence intention and behavior	Ajzen (1991); Casper (2007)
Behavioral Intent (BI)	BI is influenced by ATU	Gong, Xu, & Yu (2004)
	BI is a predictor of AB	Mallya & Lakshimnarayanan (2017)
Attitude Toward Use (ATU)	ATU helps to determine BI	Lu, Huang & Lo (2010)
	ATU is affected by PU	Chang & Chang (2009)
Perceived Risk (PR)	PR has a direct effect on BI	Pavlou (2003)
	PR has a negative effect on BI	Teo (2012)
	PR may be accepted with high PU and PEOU	Kansal (2016)
Knowledge of Regulations (KR)	Outreach is important regarding guidance, regulations, and best practices	Terwilliger et al. (2017)
	Legislation governing sUAS operations are important to review for any restrictions based on privacy	FAA, AC-107-2 (2016)
	Legislation may restrict sUAS operations for security, noise, etc.	Elias (2016)

Construct	Major Findings	References
Actual Behavior/Use (AB)	AB is a predictor of BI	Mallya & Lakshimnarayanan (2017)
	AB is significantly affected by ATU	Ajzen (1991)

Table C3

Recommendations for Establishing Discriminant Validity in Literature

Reference	Recommendation	
	Fornell-Larcker	Cross-loadings
Barclay, Higgins, and Thompson (1995)	X	X
Chin (1998, 2010)	X	X
Fornell and Cha (1994)	X	
Gefen and Straub (2005)	X	X
Gefen, Straub, and Boudreau (2000)	X	X
Götz, Liehr-Gobbers, and Krafft (2010)	X	
Hair et al. (2011)	X	X
Hair et al. (2012a)	X	X
Hair et al. (2012b)	X	X
Hair et al. (2014)	X	X
Henseler et al. (2009)	X	X
Hulland (1999)	X	
Lee et al. (2011)	X	X
Peng and Lai (2012)	X	
Ringle et al. (2012)	X	X
Roldán and Sánchez-Franco (2012)	X	X
Sosik et al. (2009)	X	

Note. Table adapted from Henseler et al., 2015.

Table C4

Descriptive Statistics Scores of Pilot Study 1

Construct	Item Question	Mean (N=575)	SD	Skewness	Kurtosis
PU	PU1	5.402	1.170	-1.254	2.103
	PU2	5.353	1.300	-1.063	1.353
	PU3	5.311	1.326	-0.963	0.980
	PU4	5.405	1.288	-1.058	1.413
	PU5	5.405	1.318	-1.066	1.226
SN	SN1	5.226	1.332	-1.054	1.181
	SN2	5.296	1.335	-1.055	1.261
	SN3	5.176	1.321	-0.945	1.000
	SN4	5.384	1.272	-1.173	1.854
	SN5	5.363	1.246	-0.996	1.336
BI	BI1	5.403	1.277	-1.261	1.989
	BI2	5.365	1.346	-1.061	1.352
	BI3	5.125	1.410	-1.069	1.210
	BI4	5.205	1.443	-1.214	1.429
	BI5	5.186	1.315	-1.006	1.243
ATU	ATU1	5.449	1.268	-1.090	1.539
	ATU2	5.409	1.321	-1.211	1.707
	ATU3	5.170	1.369	-0.969	1.012
	ATU4	5.426	1.258	-1.154	1.943
	ATU5	5.419	1.315	-1.227	1.753
PR	PR1	4.854	1.603	-0.867	0.070
	PR2	5.007	1.585	-0.965	0.329
	PR3	5.057	1.489	-0.978	0.602
	PR4	5.176	1.398	-0.854	0.581
	PR5	5.024	1.516	-0.938	0.345
	PR6	5.216	1.362	-0.976	1.030
	PR7	5.205	1.388	-1.022	1.093
	PR8	5.002	1.443	-0.890	0.525
	PR9	4.969	1.425	-0.855	0.504
	PR10	4.908	1.555	-0.828	0.082
TR	TR1	5.365	1.147	-0.810	0.770
	TR2	5.332	1.153	-0.721	0.581
	TR3	5.424	1.160	-0.857	0.987
	TR4	5.317	1.182	-0.963	1.276

Note. PU = Perceived Usefulness; SN = Subjective Norms; BI = Behavioral Intent; ATU = Attitude Toward Use; PR = Perceived Risk; TR = Trust.

Table C5

Reliability Assessment for Pilot Study 1 CFA Model

Construct	Item Question	Factor Loading	CR (≥0.7)	Cronbach's Alpha (≥0.7)	AVE (≥0.5)
Perceived Usefulness	PU1	.748	.786	.857	.547
	PU2	.724			
	PU3	.733			
	PU4	.751			
	PU5	.741			
Subjective Norms	SN1	.758	.770	.849	.533
	SN2	.740			
	SN3	.779			
	SN4	.704			
	SN5	.664			
Behavioral Intent	BI1	.757	.770	.862	.557
	BI2	.785			
	BI3	.697			
	BI4	.743			
	BI5	.747			
Attitude Toward Use	ATU1	.731	.731	.822	.488
	ATU2	.722			
	ATU3	.531			
	ATU4	.706			
	ATU5	.778			
Perceived Risk	PR1	.736	.818	.907	.495
	PR2	.776			
	PR3	.654			
	PR4	.652			
	PR5	.761			
	PR6	.655			
	PR7	.655			
	PR8	.690			
	PR9	.702			
	PR10	.737			
Trust	TR1	.635	.703	.760	.447
	TR2	.592			
	TR3	.721			
	TR4	.717			

Table C6

HTMT2 Values for Pilot Study 1 CFA Model

	PU	SN	BI	ATU	PR	TR
PU						
SN	.983*					
BI	.937*	.973*				
ATU	.956*	.979*	.984*			
PR	.342	.440	.413	.377		
TR	.825	.814	.839	.887*	.386	

Note. *values do not establish discriminant validity.

Table C7

EFA Assumptions for Pilot Study 1 Dataset

Test	Value	Result
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	.969	Satisfactory
Bartlett's Test of Sphericity		
Approx. Chi-Square	11218.658	Satisfactory
df	561	
Sig.	0	

Table C8

Rotated Component Matrix from Pilot Study 1 EFA Analysis

	Component		
	1	2	3
PU1	0.713		
PU2	0.714		
PU3	0.721		
PU4	0.755		
PU5	0.732		
SN1	0.784		
SN2	0.741		
SN3	0.733		
SN4	0.690		
SN5	0.641		
BI1	0.757		
BI2	0.754		
BI3	0.693		
BI4	0.708		
ATU3	0.505		
PR1		0.758	
PR2		0.800	
PR3		0.698	
PR4		0.675	
PR5		0.731	
PR6		0.704	
PR7		0.677	
PR8		0.636	
PR9		0.731	
PR10		0.776	
TR2			0.633
BI5	0.690		
ATU1	0.702		
ATU2	0.682		
ATU4	0.667		
ATU5	0.738		
TR1			0.581
TR3			0.624

Note. PU = Perceived Usefulness; SN = Subjective Norms; BI = Behavioral Intent; ATU = Attitude Toward Use; PR = Perceived Risk; TR = Trust.