5-2020

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DETERMINANTS OF AVIATION STUDENTS' INTENTIONS TO USE VIRTUAL REALITY FOR FLIGHT TRAINING

By

Stephanie Gill Fussell

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

Embry-Riddle Aeronautical University
Daytona Beach, Florida
May 2020

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Stephanie Gill Fussell

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

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Immersive simulation technology has been incorporated into numerous training environments, including medicine, engineering, and marketing. The aviation industry, in particular, has a history of embracing technology to enhance training and has especially regulated the requirements of devices for flight training. Virtual reality (VR) is the newest technology being adapted for training purposes. Many educational institutions training providers are incorporating virtual environments (VE) and VR systems into curricula and training programs to expand educational opportunities, enhance learning, promote deep cognitive learning, and leverage the abilities of a generation of students who have adopted technology from an early age.

As VR is adopted for educational purposes, researchers are conducting experiments to learning with the VE occurs at an equal or greater level than in the real world. However, research surrounding students' perceptions of the technology and intentions to use it for training has been neglected. This is especially true in the realm of aviation and flight training. The goal of this research was to determine the factors that influence aviation students' intention to use VR for flight training. An extended Technology Acceptance Model (TAM) was developed that incorporates elements of the Theory of Planned Behavior (TPB); factors derived from relevant, validated extended

TAMs; and new factors that are theorized to impact use intention. These factors are related to aviation education, the use of VR technology in training environments, and using VR for flight training. The new model may explain flight students' acceptance of VR for flight training as well as their intent to use the technology.

A quantitative research method with a cross-sectional survey design was utilized. Descriptive statistical analysis, a confirmatory factor analysis (CFA), and a structural equation modeling (SEM) process were employed. Data were collected from aviation students enrolled in FAA-approved Part 141 pilot schools in early 2020 using a survey design. Results indicated a good model fit to answer the three research questions of the study. There were 14 hypotheses in the original model. Although one was removed, an additional relationship was discovered, validated, and added to the model. Nine of the hypotheses were supported. Eight of the nine predictor factors of the model were determined to directly or indirectly impact behavioral intention (BI). The original TAM factors had the strongest relationships. Relationships between factors particularly relevant to VR technology and aviation training were also supported.

The results of the study fill a gap in the research surrounding the use of VR for flight training and the influencing factors of behavioral intention. The model may also be modified for other educational and training environments as well as other forms of immersive simulation technology.

DEDICATION

This dissertation is dedicated to my family:

To the two loves of my life, Roy and Austin, who always quelled my stress and fears through every class, the preparation for the qualifying exam, and the dissertation phase. I would have been lost without you both behind me, reminding me that I could do this… I did it!

To my parents and my immediate family, who didn’t always understand why I was stressed or why I was excited but celebrated every milestone with me, knowing something big had happened. Thank you for your love.

To my extended family, especially my in-laws who propelled me on this journey by gifting me money to take the GRE. You gave me the courage to take that first step in 2016. Thank you for your support and encouragement.

To my cohort, my academic family. You made this journey hilarious. You cried with me, you complained with me, and in the end, you helped me get past it. We are the greatest cohort (Ward, 2019).

ACKNOWLEDGMENTS

This project could not have been completed without the support of many people. I would like to thank my Committee Members, Dr. David Cross, Dr. Chang-Geun Oh, and Dr. Robert Thomas, for their guidance and support during this process. I especially thank my Chair, Dr. Dothang Truong, for taking the time to always answer my questions and remind me that everything would turn out fine.

I would like to thank Dr. Mark Friend: You never once doubted me, and I have learned so much working with you. Thank you for always being a champion to my cause. I acknowledge the support of other faculty at ERAU who encouraged me during all these years, especially all of the faculty within the School of Graduate Studies. I joined you as a wide-eyed Master’s student, and I appreciate your mentorship and encouragement all these years. And Mr. Bill Kohlruss, who always insisted on coffee dates and kept me from taking myself too seriously; I appreciate you and your friendship.

And finally, to those whom I have worked with in the COE TTHP. I learned something from each and every one of you, and I always had a person to reach to for support. Working with you throughout my Master’s and Doctorate has shaped my future.

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CHAPTER I

INTRODUCTION

Technology is increasingly being used in education and training for a variety of fields and presents a wide range of options for educators (Suh & Prophet, 2018). The late 20th century saw a rise in popularity of video games and similar technologies prompting game developers to shift from the pure entertainment value of games into the educational domain (Sitzmann, 2011). These technologies can be leveraged in many ways, including mobile learning (m-learning) on smartphones, augmented reality (AR) by way of a tablet, and fully immersive experiences in simulated environments such as virtual reality (VR). There is anecdotal and empirical evidence that gaming and simulation technology can enhance knowledge, psychomotor skills, and motivation (Sitzmann, 2011).

Beaubien, Oster, and Spruill (2018) identify four affordances immersive simulation technology (e.g., AR, VR) bring to the learning environment: an immersive, realistic experience filled with sensory cues; interaction facilitated by voice and/or naturalistic gestures that reduce cognitive load; superimposed content onto the environment to enhance understanding (e.g., text, symbols, animations); and accessible information to reduce the reliance on memorization (e.g., checklists, schematics). However, attaining these affordances necessitates designing a safe, effective, and usable virtual environment (VE) wherein the user may attain goals in a motivating and cost-efficient environment (Eastgate, Wilson, & D’Cruz, 2015). As technology is incorporated into the classroom, educators and trainers must ensure learning outcomes are met while providing cognitive experiences for students associated with using immersive simulation technology.

This is especially relevant in aviation education. Researchers and educators have long advocated the use of flight training devices (FTDs) and other simulation technologies as high-fidelity, low-cost options for training in aviation (Macchiarella & Brady, 2006; Macchiarella, Brady, & Lyon, 2008; Macchiarella & Doherty, 2007). Immersive simulation technology provides aviation students the opportunity to iteratively train on procedures without the cost and time associated with flying in an aircraft. Additionally, students can acquire knowledge, skills, and attitudes training in a simulator that may be transferred to flying in the aircraft. The design of the immersive simulation technology and virtual learning environment is, therefore, an important consideration when incorporating technology into aviation education such as flight training. Benefits provided by training devices and other aviation simulators have been well researched and incorporated into flight training programs.

A review of the literature reveals that research surrounding student's attitude toward and intent to use technology for flight training has received little attention using objective measures. Researchers often collect subjective data regarding how students perceive a given technology will benefit flight training (Bürki-Cohen, Sparko, & Go, 2007; Koglbauer, 2016; Landman et al., 2018; Svensson, Angelborg-Thanderz, Borgvall, & Castor, 2013). However, the studied simulation technologies do not encompass VR technology as it has yet to be incorporated into the flight training environment.

This chapter will introduce the use of immersive simulation technology in aviation training programs. The theories that ground the research are presented, followed by a discussion on the gaps in the literature that drive the research. The purpose of the study is explained and research questions and hypotheses presented. The significance and contributions of the study will be discussed. Assumptions, limitations, and delimitations will be addressed. The definitions of terms and acronyms are provided at the end of the chapter.

Background

Virtual reality is a 3-dimensional (3D), digital environment generated to create a fully immersive, realistic environment (Jerald, 2016; Virtual Reality Society, 2017). This technology is being adopted in a variety of educational environments as a training device including maintenance and assembly operations (Yuviler-Gavish, Krupenia, & Gopher, 2013); construction and civil engineering (Sampaio, Ferreira, Rosário, & Martins, 2010); and surgery, autopsies, cardiac procedures, and other medical applications (Satava, 2013). Using VR in training impacts student knowledge retention and motivation while transforming the learning environment (Strategy Analytics, 2018). Aviation education, specifically flight training, is an environment that could benefit from this form of immersive training (Puiu, 2019).

Simulation technology in flight training environments. Flight training is regulated by the Federal Aviation Administration (FAA) and described under the Code of Federal Regulations (CFR). CFR Parts 141 and 61 describe in detail the requirements for creating training programs, issuing flight certificates, and general operating rules for civilian aviation training. The Part 141 and Part 61 training environments are distinguished by how training proceeds, the number of hours required to obtain flight certificates, and how the flight training school conducts operations. Due to the nature of the study, only Part 141 training programs and pilot schools will be discussed. Universities and colleges with flight training programs often follow more stringent guidelines, as mandated by the federal government, to be classified as a 14 CFR Part 141 pilot school. These flight programs are often created for career-minded pilots seeking a stable curriculum, continuity in training, and steady progression through ground school and flight training. Flight training standards at Part 141 schools follow strict guidelines for courses and curricula (Pilot Schools, 14 CFR §141, 2019). Approval is obtained from the FAA regarding the rooms that will be used for training purposes; descriptions of aircraft, simulators, and devices used for training; training syllabi of lessons, objectives, standards, etc.; and other stipulations. Additionally, there are recording procedures and facilities' requirements that must be approved and maintained.

The aviation industry has utilized simulation devices since the Link trainer was introduced for instrument training in the early 1930s. Historically, trainers have been concerned with fidelity, procedural similarity, and the dynamics of the training device as these and other factors may impact the transfer of training from the simulated device to an actual aircraft. Many Part 141 schools utilize qualified aviation training devices (ATDs) and flight training devices (FTDs) in addition to aircraft. These devices, generally grouped together as flight simulation training devices (FSTD) or more generically termed *simulators*, are governed under the 14 CFR Part 60, Flight Simulation Training Device Initial and Continuing Qualification and Use. This regulation defines the terms and Qualification Performance Standards for each type of training device, how each device may be used for training, and the types of records that must be maintained to use each device. Specific flight experience is mandated for flight training centers, including ground training in a classroom and the use of FSTDs (Pilot Schools, 14 CFR §141, 2019). The FAA publishes Advisory Circulars (AC) on compliance with regulations and standards such as AC 61-136B regarding approval of ATDs as well as use in training and experience (FAA, 2018), and the application, certification, and compliance of flight schools, published under AC 41-1B (FAA, 2019). Numerous researchers have demonstrated that ATDs, FTDs, and FFSs may be used to effectively and efficiently train pilots, a small selection of which is shown in Table 1. The training technologies are described in Chapter II.

Table 1

Transfer of Training Studies Related to Aviation Training

Topic	Training Technology	Chief Results	Reference
Effect of simulator motion on training	FFS, training aircraft	Generally positive transfer; small but significant effects from using motion	Bürki-Cohen & Go (2005); Bürki-Cohen et al. (2007)
Abnormal event training	FTD	Training in an FTD can improve procedural memory	Koglbauer (2016)
Abnormal event training	PC ATD, FTD, aerobatic aircraft	Training treatment in PC ATD or FTD resulted in better performance than those in the control group	Leland et al. (2009)
Training proficiency	FTD, training aircraft	The treatment group showed positive transfer for procedural training; achieved standards in fewer iterations in 53% of tasks	Macchiarella et al. (2006); Macchiarella et al. (2008)
Abnormal event training	PC ATD, aerobatic aircraft	Treatment group significantly exceeded the control group in 70% of the tasks	Rogers et al. (2009; 2010)
Training proficiency	PC ATD, FTD, training aircraft	FTDs and PCATDs are effective in teaching instrument tasks to private pilots and maintaining instrument flight skills	Taylor et al. (2004; 2005)

Note. ATD = Advanced Training Device. FFS = Full Flight Simulator. FTD = Flight Training Device. PC = Personal Computer. PCATD = Personal Computer Aviation Training Device. Adapted from "Research Recommendations from the Airplane Simulation Transfer Literature" by J. G. Neal, S. G. Fussell, and S. Hampton, 2020, in press, *Journal of Aviation/Aerospace Education & Research.*

Although the cost and time saving benefits of ATDs, FTDs, and FFSs have been demonstrated, the approved use of simulation technology in training is limited. Table 2 details the number of training hours allowed per training device at Part 141 flight schools, adapted from Hoffman (2017). ATDs and FTDs lack the full immersion of the large and expensive FFS. Less expensive immersive simulation technology with a smaller physical footprint (e.g., AR, VR) is being explored for training purposes in aviation maintenance, pilot certification and training, and unmanned aircraft systems (Macchiarella, Liu, Gangadharan, Vincenzi, & Majoros, 2005; Rigby, Macchiarella, & Mirot, 2017; Wang, Anne, & Ropp, 2016). Of note, innovative technology such as augmented and virtual reality devices are not included, nor are they addressed in the CFRs. The technology has yet to be accepted for training instruments.

Table 2

Simulation Allowance in Part 141 Flight Training

	Minimum required flight hours	BATD	AATD	FTD	FFS
		Maximum Credit for Minimum Requirements			
Private Pilot Certificate (PPC)	35 hours	5.25 hours	5.25 hours	7 hours	7 hours
Instrument Rating (IFR)	35 hours	8.75 hours	14 hours	14 hours	17.5 hours
Combined PPC & IFR	70 hours	17.5 hours	17.5 hours	17.5 hours	24.5 hours
Commercial Pilot Cert.	120 hours	n/a	24 hours	24 hours	36 hours
Flight Instructor Cert.	25 hours	n/a	1.25 hours	1.25 hours	2.5 hours
IFR Flight Instructor Cert.	15 hours	n/a	0.75 hours	0.75 hours	1.5 hours
Airline Transport Pilot Cert.	25 hours	n/a	6.25 hours	6.25 hours	12.5 hours

Note. All hours reflect requirements for flight training in an airplane. BATD = Basic Aviation Training Device. AATD = Advanced Aviation Training Device. FTD = Flight Training Device. FFS = Full Flight Simulator.

Virtual reality. As a fully-immersive environment, Jerald (2016) notes that the design of an “ideal VR system enables users to physically walk around objects and touch those objects as if they were real” (p. 9). VR applications have been adopted in a variety of industries such as architecture, medical training, military training, and widely in entertainment (Jerald, 2016). The field of education has been slower to adopt the technology, largely due to the financial commitment required to purchase the hardware, software, and other equipment associated with the technology. However, the enterprise and industrial VR markets are forecasted to increase to $68.6 million by 2023 (VIAR, Inc., 2019). As the technology expands and becomes more accessible, associated costs will decrease. VR in education and training provides the opportunity to leverage motor skills, human sensory capabilities, and scenario-based training to enhance deep cognitive learning in an engaging environment. Indeed, the ability to train and practice in a VE encourages active learning, intuitive decision making, and engagement with a task (Jerald, 2016). Learning can be expanded outside of the classroom, or in the case of aviation, the cockpit, to further training in the VE. VR also has the potential to enhance scenario-based training and allow students to practice risky skills or procedures (e.g., surgery for medical students or emergency procedures for flight students). Repeating tasks in the VE can positively impact cognition and memory, visual-spatial skills, psychomotor skills, and emotional responses (Jensen & Konradsen, 2018). VR technology has the potential to transform learning for a new generation of students. Table 3 highlights VR usage in training and in aviation research, which will be further detailed in Chapter II. Notably, little research has been done on the use of immersive simulation technology outside of typical FAA-approved devices for aviation training. This may be because the technology is still quite new, and training programs have yet to be developed outside of military ventures (Lewis & Livingston, 2018; Palla, Brent, & Sikorski, 2018; Sikorski, Palla, & Brent, 2017). Another reason may be that because the technology has not been incorporated into FAA-approved training curriculum, training facilities and aviation students have been slow to adopt VR for aviation training (Pilot Schools, 14 CFR §141, 2019).

Table 3

VR-related Usage and Research

Environment	Research Type	Context	Limitation of study	Reference
Aviation	System development	VR part-task trainer (PTT) development for cockpit familiarization	Analysis, design, and development of PTT for military pilots	Sikorski et al., 2017
Aviation education	Study	TAM for AR use in maintenance training	Original TAM constructs, AR not VR	Wang et al., 2016
Aviation	Study	VR PTT for checklist training	Usability and validation of PTT for military pilots; did not use TAM	Palla et al., 2018
Education	Study	VR training with augmented cues to enhance performance in the real world	Focus on training transfer using VR	Cooper et al., 2016
Education	Study	Memory awareness to assess VE fidelity in relation to the real world	Focus on memory and awareness	Mania et al., 2003
Education and Gaming	Study	Use of VR to increase K12 student academic achievement	Focus on academic achievement	Vogel et al., 2006
Education/ Training	Review	Review of studies of VR use in education and training	Literature review	Jensen & Konradsen, 2018
Maintenance	Study	Training on area layout using traditional and VR methods	Spatial training transfer of nuclear maintenance workers	Sebok et al., 2003
Maintenance	System development	Developing VR training systems for industrial training	System development	Yuviler-Gavish et al., 2013
Medicine	Study	VR training for minimally invasive surgery	Medical student population	Basdogan et al., 2007
Medicine	Review	Review of VR training for improving operating room performance	Literature review of medical studies	Seymour, 2008
Medicine and Gaming	Study	VR gaming for the rehabilitation of stroke survivors	Gamification, medical rehabilitation	Saposnik et al., 2010

Foundation Theories

Technology acceptance model. The perception of technologies by individuals may impact how they use them in different environments. Davis, Bagozzi, and Warshaw (1989) developed the technology acceptance model (TAM) “to explain the potential user’s behavioral intention to use a technological innovation” (King & He, 2006, p. 740). The TAM’s reliability and validity have been demonstrated in the information technology environment, and it has been extended and adapted to introduce new and novel constructs relevant to new environments. As the TAM has been extended with new factors and tested in a variety of fields, the reliability and validity of the model have been demonstrated, as has the adaptability of the model. In education, the TAM has been utilized to assess behavioral intent to use e-learning tools (Gong, Xu, & Yu, 2004; Park, 2009). The TAM has not been widely used to explain intention to use technology in an aviation environment, although the applications where it has been utilized are diverse (Lu, Chou, & Ling, 2009; Myers, 2019; Richardson, 2017). The use of the TAM for VR has received little attention as the technology is quite new, but researchers are starting to explore the technology in different contexts (Chang, Heo, Yeh, Han, & Li, 2018; Manis & Choi, 2018; Shen, Ho, Ly, & Kuo, 2018).

The intersection of VR, aviation training, and the TAM is virtually nonexistent outside of the work of Wang, Anne, and Ropp (2006). When the TAM has been used in the context of aviation or VR, the constructs investigated are not usually expressly created for aviation nor for innovative technology such as immersive simulation and VR. As these technologies become more ubiquitous in training environments, the constructs must be reconsidered through the lens of the virtual environment and, as this proposal demonstrates, the needs of the aviation industry.

Theory of planned behavior. Ajzen proposed the theory of planned behavior (TPB) in 1991 to study, predict, and explain human behavior with an emphasis on intent to perform anticipated behavior (Ajzen, 1991). The TPB has been used in the aviation environment to assess consumer behavior (Buaphiban & Truong, 2017; Lee, Wang, Hsu, & Jan, 2018; Pan & Truong, 2018) and in the learning environment to assess perceptions toward online learning (Cheon, Lee, Crooks, & Song, 2012; Chu & Chen, 2016). A review of the literature reveals that the TPB has not been used in the context of immersive simulation technology for education or training purposes nor in the aviation environment. The original model proposed by Ajzen (1991) may not be suitable for assessing intent to use immersive simulation because it is not designed for technology adoption but explains general behaviors (Chu & Chen, 2016). The underlying constructs may be adapted for intent to use specific technologies for aviation training, and constructs of the TPB may be adapted and incorporated into extended TAM models.

Statement of the Problem

The current and incoming generation of students has utilized technology more so than previous generations (Eckleberry-Hunt, Lick, & Hunt, 2018). In response, academic institutions are incorporating new technology to both expand educational opportunities and leverage the latent abilities of a generation of students who have used a variety of technologies from an early age. VR is being adopted in diverse training environments, and immersive aviation training programs are no exception. Research surrounding VR technology and its use in the aviation training environment is lacking, as evident by the lack of published literature (Jensen & Konradsen, 2018; Palla et al., 2018; Sikorski et al., 2017).

Although the TAM and other models have been used extensively in the realm of software, mobile device use, and even e-learning, immersive simulation technologies have received little attention (Manis & Choi, 2018; Shen et al., 2018). The factors that drive students to use immersive simulation technology in aviation training have been limited to AR in aviation maintenance (Wang et al., 2016). No prior research was found examining the factors that influence the acceptance and use of immersive simulation technology, specifically VR, for flight training. This is a gap in the literature of an environment that historically has utilized training technologies for many aspects of flight training. Cost and time saving benefits have been demonstrated facilitating the adoption of simulation technologies into training curricula (Macchiarella et al., 2008; Taylor et al., 1996, 1999; Taylor, Talleur, Phillips, Emanuel, & Hulin, 1998). However, aviation student perception of these technologies has been largely confined to subjective feedback (Bürki-Cohen et al., 2007; Koglbauer, 2016; Landman et al., 2018; Svensson et al., 2013).

Incorporating these factors directly related to aviation education, the use of VR technology for training, and VR in flight training into an extended TAM provides a more robust way of examining hypothesized factors that influence the acceptance and use of VR technology for training in an aviation environment. The TAM in its original form does not consider the immersive training qualities of VR technology (Davis, Bagozzi, & Warshaw, 1992; King & He, 2006; Manis & Choi, 2018). Additionally, the TAM does not consider factors that influence using technology in flight training nor constructs related to aviation in general (Lee, Kim, & Choi, 2018; Lu et al., 2009; Myers, 2019; Wang et al., 2016). Not only must a student consider the usefulness and usability of the proposed technology, but they may also have certain performance expectancies of how the technology will function, facilitate their training, and if technology will be enjoyable or worthwhile to use (Abdullah, Ward, & Ahmed, 2016; Esteban-Millat, Martínez-López, Pujol-Jover, Gázquez-Abad, & Alegret, 2018; Park, 2009). All these factors analyzed in an extended TAM may influence aviation students' attitude toward and intent to use VR for flight training.

Purpose Statement

The purpose of the research was to determine the factors influencing aviation students' intention to use VR for flight training. This was accomplished by creating an extended TAM based on the foundation theories presented by Davis et al. (1989). This model encompassed new factors that are unique for assessing VR technology in an aviation training environment. These factors included performance expectancy, perceived health risk in using VR for training, regulatory uncertainty surrounding the use of VR in flight training, and self-efficacy in terms of technology and flight training. Validated factors from the TAM and TPB model (i.e., perceived ease of use and usefulness, perceived behavioral control, and attitude toward use) were adapted to focus on aviation training utilizing VR technology. A survey design was utilized to collect data from aviation students enrolled at 34 Part 141 flight training schools in the United States to test and validate the survey instrument and model. This model may explain the flight students' acceptance of VR in a flight training environment as well as their intent to use the technology.

Significance of the Study

Theoretical applications. The main goal of the research was to contribute to the aviation training body of knowledge as well as expand how TAM and TPB may be applied to VR technology, aviation training, and the use of VR in aviation training. The model utilized established factors and relationships with a focus on VR for aviation training. These validated factors were extended beyond the scope they were founded upon (e.g., software and information technology). New factors and relationships were developed related to VR training technologies. The new constructs were selected to provide insight into why students choose to use VR for training as well as those constructs that deter them from adopting VR. Furthermore, the validated model may be applied to other training environments with proper revision to leverage the usage of VR technology in maintenance, medicine, commerce, etc.

Practical applications. This study focused on VR for flight training at a Part 141 flight school (e.g., procedural and maneuver training). Aviation training at a Part 141 flight school is a complex matter governed by federal regulations. As technology continues to develop and become more ubiquitous in a training environment, research must ensure that the technology delivers material efficiently and that learning objectives are met (Dalgarno & Lee, 2010; Hedberg & Alexander, 1994). VR technology is quickly gaining popularity as a training tool, yet researchers have not assessed how the technology can benefit training, especially for aviation students. Of importance is the students’ perspective of the technology: its use for flight training, the acceptance of the technology for training, and those factors that influence the decision to use the technology. The findings may enhance educators’ understanding of aviation student intentions toward VR technology for aviation training. Flight instructors and curriculum developers may also utilize this information as they work with students in a new, virtual environment to expand flight training options.

The shortage of qualified professional pilots, air traffic controllers, and aviation maintenance technicians is negatively impacting the aviation industry. Expanding training for these professions, utilizing VR, will allow training facilities to increase the efficiency and effectiveness of training for an increased number of students. The FAA may also apply the results when considering the expansion of flight training regulations to include VR and other technologies that provide training methodologies comparable to live-task environments.

Finally, the model may also benefit other researchers, industries that can incorporate VR training programs, and developers of VR software, hardware, and programs. The model expanded the TAM by incorporating factors from other models as well as factors directly related to VR technology and aviation, and thus customization is possible.

Research Questions and Hypotheses

The following research questions were explored:

- What factors influence aviation students' intentions to use VR technology for flight training?
- How do these factors impact students' intentions to use VR technology for flight training?
- To what extent do these factors influence aviation students' intentions to use VR technology for flight training?

The following hypotheses were investigated in the study using the new model:

H_1: Perceived ease of use positively influences perceived usefulness.

H_2: Perceived ease of use positively influences attitude toward use.

H_3: Perceived usefulness positively influences attitude toward use.

H_4: Performance expectancy positively influences perceived usefulness.

H_5: Performance expectancy positively influences attitude toward use.

H_6: Perceived enjoyment positively influences perceived usefulness.

H_7: Perceived enjoyment positively influences attitude toward use.

H_8: Perceived health risk negatively influences attitude toward use.

H_9: Regulatory uncertainty negatively influences attitude toward use.

H_{10}: Self-efficacy positively influences perceived ease of use.

H_{11}: Self-efficacy positively influences attitude toward use.

H_{12}: Perceived behavioral control positively influences perceived ease of use.

H_{13}: Perceived behavioral control positively influences behavioral intention.

H_{14}: Attitude toward use positively influences behavioral intention.

The model used to test the research questions and hypotheses may be viewed in Chapter II (Figure 5), which provides a thorough rationale and literature support for the proposed hypotheses.

Delimitations

A delimitation of the research was the focus on flight training in a Part 141 flight training environment in the United States. Part 141 flight schools are often housed within accredited colleges and universities (FAA, 2019); there are over 150 colleges and universities with aviation degree programs (Flightschoollist.com, 2019). Such a delimitation precludes flight students in a Part 61 or other training environment from participating in the study. These delimitations ensured that all participants have a standardized curriculum and similar flight training experience as dictated by CFR 14 and the FAA. Generalizability was ensured by recruiting students from 34 of Part 141 flight schools across the United States that are representative of the target population. Furthermore, the model and survey instrument can be adopted and revised for use in other populations. A VR system was presented for training on flight procedures and maneuvers (e.g., training to performance standards) to augment training in an FTD. The user dons a VR headset to view the virtual world in which the training takes place. Physical flight control instruments, such as yoke, switches, and throttle, are used to control flight operations within the VE. Tracking of the user's hands facilitates orientation within the VE so they are aware of the placement of their hands in relation to the flight control instruments. The training program may also use controls in the VE, such as virtual switches, for the user to interact with. This type of training offers a more immersive experience than training in an FTD alone. Figure 1 shows a user interacting with such a training program.

Figure 1. A student demonstrates the use of a part-task trainer supported by VR.

Limitations and Assumptions

VR technology is rapidly changing, as is the aviation training environment. Results captured indicated the student's intention at the time of the survey. The design and approach of the study, using the same survey instrument, can be used in the near future for a longitudinal study.

Only Part 141 flight students participated, and students who receive training at Part 61 or military establishments were not considered. The study may be expanded to other flight students and results compared. Only aviation students in the United States were allowed to participate, as Part 141 flight training is defined under an American regulation. Expanding the study to countries with similar flight training programs may provide interesting comparisons.

A survey was employed for data collection, completed online, and primarily distributed through email. The data was self-reported by the participants. The survey and model were created with factors and questions relevant to the research questions and hypotheses, worded as clearly as possible to obtain accurate information, and structured to ensure model fit.

It was assumed that the participants would answer the survey questions honestly and accurately. The survey was voluntary and anonymous, with the option to withdraw from the study at any time. Minimal personal data was collected and only reported in aggregate. Potential participants were informed of the study through official communication channels (e.g., an email from an educator on an academic server). Because the participants were enrolled in a Part 141 accredited college or university, it was assumed that participants could read and communicate in English, the language used in the survey instrument; that the participants were familiar with aviation terminology; and that the participants were familiar with immersive simulation technology typically used in flight training environments. The instrument's validity and reliability were assessed to ensure the quality of the data. Additionally, questions that have been previously developed and used in similar models were used and adapted to suit the factors of the model.

Another assumption was that VR technology will be incorporated into Part 141 flight training environments in the near future. It was assumed that this technology will be rapidly developed for flight training, integrated into training curricula, utilized by flight students on a regular basis, and provide comparable training to traditional ATDs, FTDs, and FFSs.

Chapter Summary

The goal of the study is to better understand the factors that influence aviation students' attitude toward and intention to use VR for flight training. This chapter presented the background of the study, including the use of VR and immersive simulation technologies used in education as well as aviation training programs. The problem being investigated, as well as the purpose and significance of the study, was described. Research questions, hypotheses, and the model designed to test these were defined. Finally, delimitations, limitations, and assumptions of the study were addressed. Chapter II reviews relevant literature related to the use of VR in education, training, and aviation; a brief history of simulation technology in aviation training; and the ground theories and theoretical framework upon which the study was based. Chapter III details the research methods for the study, including the approach, design, population and sample, instrument, data treatment, and ethical concerns.

Definitions of Terms

Advanced aviation training device	A training device that provides a training platform for procedural and operational performance tasks required for PPC, IFR, COM, ATP, and Certified Flight Instructor ground and flight training (FAA, 2018).
Aviation training device	A training device other than an FTD or FFS that may vary in fidelity and complexity in representing a category and class of aircraft operations and may include replica instruments, equipment, panels,

	controls, hardware, and software; the term encompasses AATD and BATD (FAA, 2018).
Attitude toward use	The degree to which a student has a favorable or unfavorable appraisal or evaluation of VR for flight training (Lemay, Morin, Bazelais, & Doleck 2018; Lu et al., 2009; Manis & Choi, 2018).
Augmented reality	A term applied to a variety of technologies that overlay alphanumeric, graphical, and/or symbolic information on the user's view of the actual world (Aukstakalnis, 2017).
Aviation student	A student actively enrolled in a Part 141 accredited college or university pilot school.
Basic aviation training device	A training device that may be used as a training platform for procedural and operational performance tasks required for PPC and IFR ground and flight training (FAA, 2018).
Behavioral intention	An indication of how hard a student is willing to try or how much effort they are planning to exert in order to use VR for flight training (Gong et al., 2004; Park, 2009; Shen et al., 2018).
Flight training device	A training device that replicates an aircraft cockpit in an open or closed environment, including all equipment and programs necessary to represent

	aircraft operations with the full range of capabilities (Pilot Schools, 14 CFR §141, 2019).
Full flight simulators	A training device that replicates a specific type, make, model, and series of aircraft with all equipment, programs, systems, and capabilities that would be found in the physical aircraft (Pilot Schools, 14 CFR §141, 2019).
Immersive simulation technology	Technology that endeavors to imitate the real world by creating a sense of immersion through digital means.
Part 141 training environment	Flight training programs that conduct training per the guidelines and minimum requirements defined in 14 CFR Part 141 (*Pilot Schools,* 14 CFR §141, 2019).
Perceived behavioral control	The extent to which an aviation student feels able to control using VR technology for flight training (Ajzen, 1991; Lu et al., 2008).
Perceived ease of use	The degree to which a student believes that using VR for flight training would be free of effort (Davis, 1989; Manis & Choi, 2018; Venkatesh & Davis, 1996).
Perceived enjoyment	The degree to which using VR for flight training is perceived to be enjoyable in its own right apart

	from any performance consequences that may be anticipated (Davis, Bagozzi, & Warshaw, 1992; Manis & Choi, 2018; Teo et al., 1999).
Performance expectancy	The degree to which a student believes that using VR for flight training will improve flight performance as compared to an FTD (Lewis, Fretwell, Ryan, & Parham 2013; Onaolapo & Oyewole, 2018).
Perceived health risk	The perception a student forms and revises based on the possible physical health risks of using VR for flight training (Lu et al., 2008; Moussaïd, 2013; Myer, 2019).
Perceived usefulness	The degree to which a student believes that using VR for flight training would enhance his or her performance (Davis, 1989; Manis & Choi, 2018; Venkatesh & Davis, 1996).
Regulatory uncertainty	The degree to which the lack of FAA regulations regarding the use of VR for flight training impacts attitude toward the technology (Folkinshteyn & Lennon, 2016; Yang, Liu, Li, & Yu, 2015).
Self-efficacy	Perception of one’s flight skills in the virtual and real-world environments (Davis, 1989; Gong et al.,

	2004; Lemay et al., 2018; Venkatesh & Davis, 1996).
Simulator	A generic term to describe any training device with digital, immersive technology characteristics.
Social cognitive theory	A psychological behavioral model that studies learning through observation in a social context (Bandura, 1991; Frey, 2018).
Technology Acceptance Model	A model used to study and explain behavioral intention to accept and use a given technology (Davis, 1989; King & He, 2006).
Theory of Planned Behavior	A psychological theory used to explain and predict human behavior through the lens of behavioral intention (Ajzen, 1991).
Virtual environment	The artificial, computer-generated environment which the user interacts with, designed to elicit cognitive and psychomotor behaviors and mimic complexities of the real world (Blade & Padgett, 2015; Hale, Stanney, & Badcock, 2015).
Virtual reality	A fully immersive, 3-dimensional, digital environment experienced through sensory stimuli that may be interacted with as if the environment were real (Jerald, 2016).

List of Acronyms

2D	2-Dimensional
3D	3-Dimensional
AATD	Advanced Aviation Training Device
AC	Advisory Circular
AGFI	Adjusted Goodness of Fit Index
AMOS	Analysis Moment of Structures
AR	Augmented Reality
ATC	Air Traffic Control
ATD	Aviation Training Device
ATP	Airline Transport Pilot Certificate
ATU	Attitude Toward Use
AVE	Average Variance Extracted
BATD	Basic Aviation Training Device
BI	Behavioral Intention
C-TAM/TPB	Combined TAM/TPB model
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CFII	Certificated Flight Instructor – Instrument
CFR	Code of Federal Regulations
COM	Commercial Pilot Certification
COTS	Commercial Off The Shelf
CR	Construct Reliability

df	Degrees of Freedom
DOT	Department of Transportation
EFA	Exploratory Factor Analysis
ERAU	Embry-Riddle Aeronautical University
FAA	Federal Aviation Administration
FFS	Full Flight Simulator
FOI	Fundamentals of Instruction
FSTD	Flight Simulation Training Devices
FTD	Flight Training Device
GETAMEL	General Extended Technology Acceptance Model for E-Learning
GFI	Goodness of Fit Index
HMD	Head-mounted display
HTMT	Heterotrait-monotrait Ratio of Correlations
IFR	Instrument Flight Rating
IPC	Instrument Proficiency Check
IRB	Institutional Review Board
MALE	Medium Altitude Long Endurance
MEI	Multi-Engine Instructor
MI	Modification Index
MLE	Maximum Likelihood Estimate
MOSES	Military Open Simulator Enterprise Software
MSV	Maximum Shared Variance

NFI	Normed Fit Index
PBC	Perceived Behavioral Control
PC	Personal Computer
PC ATD	Personal Computer Aviation Training Device
PEU	Perceived Ease of Use
PENJ	Perceived Enjoyment
PEXP	Performance Expectancy
PLS	Partial Least Squares
PPC	Private Pilot Certificate
PHR	Perceived Health Risk
PTT	Part Task Trainer
PU	Perceived Usefulness
R-ATP	Restricted Airline Transport Pilot Certificate
RMSEA	Root Mean Square Error of Approximation
RU	Regulatory Uncertainty
SBT	Scenario-Based Training
SCT	Social Cognitive Theory
SD	Standard Deviation
SE	Self-efficacy
SEM	Structural Equation Modeling
SME	Subject Matter Expert
SPSS	Statistical Package for the Social Sciences
TAM	Technology Acceptance Model

ToT	Transfer of Training
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
UAS	Unmanned Aerial/Aircraft System
UTAUT	Unified Theory of Acceptance and Use of Technology
VAT	Virtual Air Traffic
VE	Virtual Environment
VR	Virtual Reality
XR	Extended Reality

CHAPTER II

REVIEW OF THE RELEVANT LITERATURE

Chapter II is comprised of eight sections. A review of virtual reality (VR) and its use in training and education is presented. Then, an overview of simulator use in aviation training is presented, followed by the current state of immersive simulation technology in aviation training. Gaps in the research are then highlighted. Next, the ground theories of the study are discussed including the technology acceptance model (TAM), the theory of planned behavior (TPB), combined models, and extended versions of TAM and TPB. Gaps in the research of the ground theories are presented in the sixth section, justifying the need for the research and theoretical framework. The subsequent section describes the constructs of the model and justification for inclusion. Finally, the theoretical framework of the study and hypotheses are detailed.

Virtual Reality in Education and Training

VR has been utilized for a wide variety of purposes and has seen many periods of evolution. As a device often relegated to entertainment, the onus has been on researchers to demonstrate that the technology is an efficient and effective training device. However, research using the current form of the technology must be differentiated from older, less-immersive, or more cumbersome forms of immersive simulation technology. This section provides background information on VR, definitions of different types of immersive simulation technology, and studies related to using VR for educational and training purposes. Additionally, the benefits and drawbacks of using the device are discussed. The goal of this section is to demonstrate that although VR is a novel technology with many perceived benefits, research must be conducted to ensure the technology enhances education and training and does not deter from it. The research studies described also serve as a foundation for future research using the technology in education and training contexts.

Background information. The precursors of VR can be traced to the early 1900s when Albert Pratt patented a head-mounted pointing and firing device for firearms (Jerald, 2016). Pratt's invention was among the first devices to go beyond presenting and manipulating visual images in a dynamic format. The trend to augment the real world continued with Stanley G. Weinbaum's fiction work, *Pygmalion's Spectacles*, in 1935, when the protagonist learns to use a pair of glasses that replaces stimuli from the real world with artificial stimuli. Although a work of fiction, Weinbaum is among the first to write about perceiving a world through an augmented view (Jerald, 2016). During the 1950s and 1960s, the first head-mounted displays (HMDs) were introduced with features that are used in the equipment of the 21st century, such as 140 degrees horizontal and vertical field of view, stereo earphones, and discharge nozzles to create an artificial breeze. Morton Heilig's Sensorama device of the 1950s played an immersive film complete with stereoscopic views and stereo sounds for the viewer while also stimulating other senses through seat vibration, scents, and wind (Heilig, 1992). Engineers at Philco Corporation created the first working HMD with head tracking abilities in 1961, resulting in the first operating telepresence system (Jerald, 2016). Tom Furness and other researchers at Wright-Patterson Air Force Base were among the first to integrate visual systems into the helmets of pilots in 1965, the forerunners to the heads up displays that are widely used by military pilots.

Although many inventors conceived of and created innovative ways to explore the world in a “virtual” sense, Ivan Sutherland is credited with creating the first HMD with head tracking and computer-generated imagery in 1968 (Jerald, 2016; Oakes, 2007). Sutherland’s system, called the Sword of Damocles, featured a primitive user interface, limited realism and graphics, and stereoscopic images. The weight of the HMD necessitated the system to be suspended from the ceiling. Soon after, Dr. Frederick P. Brooks, Jr. began research in interactive graphics, forced feedback through haptic sensors, and other ways to promote the educational benefits of learning with immersive technology. Atari Research, led by Alan Kay and other computer scientists, was formed in 1982 to investigate human-computer interaction and design through the lens of entertainment. The work of Atari Research led to new technology designs that paved the way for commercial virtual systems. Jaron Lanier and Thomas Zimmerman, researchers from Atari Research, went on to form VPL Research and developed commercial gloves, HMDs, and software for exploring virtual environments (VEs). Lanier is credited with coining the term *virtual reality* during the mid-1980s. NASA also researched the technology and produced the first commercially viable HMD with head tracking ability, wide field of view, and audio capability. The device, called the Virtual Visual Environment Display, was available for purchase by the public in 1985 and ushered in a new industry of virtual technology devices (Jerald, 2016).

By the 1990s, the VR industry had expanded to entertainment companies, the military, and market research. The industry was predicted to reach $4 billion in 1998, yet the technology advancement peaked in 1996; many companies that had developed the technology in the early 1990s were out of business by 1998 (Jerald, 2016). Despite the setback, VR research continued into the 21st century at academic, corporate, military, and government research facilities. Human-centered design philosophies were incorporated into the development of the technology, and formal evaluations through user studies became the norm. Interestingly, HMDs of the 1990s had limited fields of view and lacked in the feeling of presence (Jerald, 2016). Devices of the early 2000s were given the wider field of view found in early HMDs, along with other abilities. By the 2010s, VR technology had once more gained traction not only in research related fields but in entertainment. A new era of VR, led by Palmer Luckey and John Carmack of Oculus VR and other developers, began.

Virtual reality technology overview. As of 2020, the term *virtual reality* refers to a computer-generated, 3-dimensional (3D) environment created to immerse the user in an interactive, sensory-driven world (Blade & Padgett, 2015). Jerald (2016) emphasizes that the VE should encourage the user to interact with surroundings as one would in the real world. To facilitate this exploration, users may explore the VE using headsets, controllers, and gloves; sensors defining a space or an omnidirectional treadmill; and other instruments. Audio, visual, and haptic information are utilized to stimulate the user's brain and senses to fully immerse the user in an illusion of reality (Virtual Reality Society, 2017).

VR is part of the *virtuality continuum* collectively known as XR (extended reality) that encompasses the different variations, compositions, and combinations of both real and virtual objects. Milgram and Kishino (1994) presented the virtuality continuum, shown in Figure 2, to distinguish between various simulation technologies based on immersion and classification. The continuum spans from reality – the physical, real world – to virtual reality – the completely digital, created world – and includes augmented reality (AR) and mixed reality (MR). *Reality* on the continuum refers to the real world. The term *augmented reality* refers to the integration of cues (e.g., graphics, text, symbols) onto the real world by aid of a device (Aukstakalnis, 2017). *Augmented virtuality* describes capturing real-world content for virtual viewing, such as immersive film. *Mixed reality* goes beyond AR so users interact with virtual objects placed in the real world in real-time and encompasses AR, augmented virtuality, and VR (Jerald, 2016). A key difference between the technologies is the level of immersion and presence provided in the VE.

Figure 2. The virtuality continuum, adapted from "A taxonomy of mixed reality visual displays" by Milgram and Kishino (1994).

Virtual reality use in education. Learning new, cognitive tasks can be difficult for students, requiring extra motivation and diverse learning strategies. The rise of popularity in computer games prompted teachers and developers to create educational games and capitalize on a technology that had been adopted by learners of all ages (Virvou, Katsionis, & Manos, 2005). Computer games have allowed students to learn through an engaging, fun, and stimulating system that may be designed to reward the learner as they progress through the program. Computer games have become ubiquitous in the learning environment, with many schools instituting a “Bring Your Own Technology” program. Indeed, the International Society for Technology Education has set standards and produced guidelines for facilitating learning through the use of appropriate technology by creating technology proficiency measures, curriculum guidelines, and incorporation of best practices (Cardoza & Tunks, 2017). Integrating technology into the learning process has allowed students to explore subject matter through a medium they are familiar with, promoting self-efficacy with the technology, the material, and the learning process (Gegenfurtner, Quesada-Pallarès, & Knogler, 2014).

Lindgren, Tscholl, Wang, and Johnson (2016) asserted that computer simulations are effective tools for teaching difficult topics, especially in STEM. The immersive properties of technology may be exploited to promote active learning with an interactive interface. Psotka (2013) posited that using VR in education can emphasize the student’s internal motivation and engagement with complex tasks. Further, immersion and presence in the VE can heighten the learning experience for deeper cognition. Researchers are exploring how using VR and related technologies in the classroom affects several variables, including learning, transfer of skills from the VE to the real world, and memory. Selected studies of VR use in education are presented in Table 4. Brief descriptions of relevant studies featuring truly immersive environments follow. This distinction is an important one, as several research studies from the early 2000s focused on PC-based programs as opposed to fully immersive, 3D simulations.

Table 4

Selected Studies of VR Use in Education

Training Technology	Environment / Context	Variables Studied	Chief Results	Reference
CAVE, VR HMD	University/ engineering education	Performance, platform, learning	CAVE and VR improved performance	Alhalabi, 2016
VR HMD, PC based training	University/ diagnostic and interviewing skills	Platform, effectiveness, usability, learning	No significant difference in learning effectiveness	Gutiérrez-Maldonado et al., 2015
PC simulator, VR HMD	University/ science lab	Platform, regime, presence, learning, satisfaction, cognitive workload	More presence but less learning in VR; VR may cause cognitive overload and distraction	Makransky et al., 2017
PC simulator, VR HMD	University/ spatial memory and awareness in VE	Platform, memory recall, presence	Treatment did not negatively affect recall, confidence, or awareness	Mania et al., 2003
PC simulator, VR HMD	High school/ marine biology education	Platform, learning, environmental attitude, presence	Treatment generally increased knowledge, inquisitiveness, and attitude	Markowitz et al., 2018
VR HMD, PC based slide show	University/ biology education	Platform, instructional effectiveness, learning efficacy, subjective measures	PC based training had higher test scores but lower motivation, interest, and engagement	Parong & Mayer, 2018
VR HMD, AR HMD	University/reading in a VE	Speed reading, recall, response time	Reading response times were 10% higher	Rau et al., 2018

An early study by Mania, Troscianko, Hawkes, and Chalmers (2003) investigated the perception of memory states for assessing simulation fidelity of scenes in both the VE and reality. A photorealistic VE was created to assess task performance-based approaches and evaluation of cognitive awareness states. HMDs with and without head tracking were used to view the VE and compared to a live task scenario designed to test spatial memory. Data were collected from 105 university student participants in a between-groups experimental design with subjective and objective measures. Spatial recollection was assessed by self-reported indications of awareness states, initial information recall, and retention a week later. Mental visualization of the scenario resulted in a higher proportion of correct answers when compared to other awareness states. Employing mnemonic strategies and word-based cueing also enabled participants to accurately retain information. A significant main effect of condition and the “remember” awareness state indicated that a high-fidelity simulation interface may not result in “visually induced memory awareness states” (Mania, Troscianko, Hawkes, & Chalmers, 2003, p. 17). Researching how tasks are achieved, rather than what was achieved, provided context relating the memory, recall, retention, presence, and awareness states in both the VE and a real-world counterpart.

Lindgren et al. (2016) studied the effects of learning about gravity and planetary motion in a middle school. Learning and attitudes were compared in a between-groups experiment using a computer simulation and an immersive, whole-body simulation that required interaction in a defined environment without the use of an HMD or another wearable device. The interactive simulation included the projection of images onto wall and floor surfaces and laser scanning to track user movement in the defined space. Learning engagement, knowledge, attitude, science self-efficacy, and presence were measured through objective and subjective measures. Results indicated that students who learned using whole-body activity in the immersive environment had significantly higher learning gains, higher engagement with the subject, and a more positive attitude toward science. Using active learning for complex and dynamic concepts, such as physics and planetary motion, and experiencing the concepts may positively impact learning and understanding.

Makransky, Terkildsen, and Mayer (2017) sought to investigate the repercussions of integrating immersive VR to virtual learning simulations in a university animal biology class. The researchers also examined if the principles of utilizing multimedia for learning generalized to immersive VR. An electroencephalogram collected cognitive processing data during the learning process. An experimental, cross-panel design with 52 university students utilized either a PC-based digital simulation or a VR HMD to learn about a complex topic, mammalian transient protein expression. The simulations featured a virtual laboratory with equipment wherein students cultured cells and practiced call transfection and protein expression techniques. Simulations included textual cues and were with or without narration. A knowledge test assessed conceptual and procedural knowledge, and a transfer test assessed the ability to apply learned information to new situations. Students reported higher presence in the VR learning environment; however, results indicated they learned less and had a significantly higher cognitive workload. Although the VR environment had motivating properties, the cognitive workload results may also indicate that students were overloaded, distracted, and had fewer opportunities to build learning outcomes.

Instructional effectiveness for teaching scientific knowledge was compared between immersive VR and a computer slideshow by Parong and Mayer (2018). Using an experimental design, 55 university students learned about human biology, and data were collected regarding interest, motivation, and learning. The students who learned the subject material using a computer slideshow performed significantly better on a knowledge test than students who learned in the VE. However, students in the computer group also reported lower interest and engagement with the material as well as lower motivation. The contrast between learning gains and engagement warrants further study. The researchers also explored the efficacy of adding *generative learning* strategies – “the process of taking incoming information and transforming it into usable information by engaging in appropriate selecting, organizing, and integrating” (Parong & Mayer, 2018, pp. 788-789) – into a VR lesson. In this between-groups experimental design, 57 university students viewed either a segmented VR lesson and summarized learning after each section or viewed an uninterrupted VR lesson. Students in the segmented lesson group performed significantly better than those who did not summarize concepts between lessons. Both groups reported similar interest, motivation, and engagement with the material. The higher performance of the segmented lesson group supports the cognitive theory of multimedia learning and validates that generative learning strategies can impact learning in a VE. Further, the authors posited that interest in a subject can be “primed with new and exciting technology” (Parong & Mayer, 2018, p. 785) and used as an effective tool for learning scientific concepts.

To summarize, the rise in popularity of immersive VR programs has led to adopting the technology for educational purposes. VEs are being constructed to facilitate interactive learning, enhance motivation and engagement, and explore material in a new way. Consideration of workload and distraction in the VE is imperative to assure the achievement of learning outcomes. Active learning through virtual technologies may positively affect the learning process and attitude toward learning complex concepts. Finally, the VE must be designed to promote learning strategies and knowledge acquisition and not as a sole means of eliciting interest.

Virtual reality use in training. As in education, VR technologies are being incorporated into training programs, especially of manual tasks in dynamic environments. The VE can be used to train workers and novices on complex scenarios in a safe environment, complete training in a controlled environment, and practice iterative procedures without impacting wear and tear of expansive machinery. The VE can also be used to instruct learners on how to identify safety hazards. Using VR technology for training purposes can reduce error rate and enhance the learning experience while increasing time-saving and decreasing costs (Smith & Salmon, 2017). The same cognitive and knowledge acquisition benefits described in the previous section regarding education also apply to training environments. Selected studies of VR use in training are presented in Table 5 followed by brief descriptions of relevant studies.

Table 5

Selected Studies of VR Use in Training

Training Technology	Environment / Context	Variables Studied	Chief Results	Reference
VR HMD and haptic gloves	Manual task training	Use of VR, use of augmented cueing, performance, time to complete the task	Treatment groups performed significantly faster than control; no difference between VR groups	Cooper et al., 2016
VR HMD	Manual task training	Task completion, training transfer	33% obtained psychomotor skills in VE, accomplished the task in the real world	Kahlert et al., 2015
VR HMD, CAVE, PC based	Factory / virtual touring	Training platform, cybersickness, learning, spatial memory	HMD group had the lowest knowledge acquisition, cybersickness resulted in decreased learning	Polcar & Horejsi, 2015
VR HMD	Visual scanning training	Fidelity, training effectiveness, performance, field of view	Field of view and realism significantly affect target detection in training; performance in VE may not measure mastery in the real world	Ragan et al., 2015
2D training methods; VR HMD	Industrial factory / mechanical assembly training	Time, error rate, performance, subjective measures	VR instruction preferred for complex assembly procedures; VR training provided no loss in time nor accuracy	Smith & Salmon, 2017

Sacks, Perlman, and Barak (2013) researched safety training in a virtual construction site. The between-groups experiment featured 66 participants who completed training in construction safety in either a traditional classroom environment or an immersive VR environment. Learning, safety knowledge, and recall in identifying and analyzing safety risks were tested before training, immediately following training, and after one month. Participants who trained with VR demonstrated significantly higher performance in the subjects of stone cladding work and cast-in-situ concrete work. However, there was no significant difference pertaining to general site safety. Training in VR was also more engaging, as participants' attention and concentration levels were higher than participants who received classroom training. Finally, results demonstrated that VR training was more effective over a period of time. These findings indicate that VR can be an efficient and effective tool to facilitate learning, engage learners, and positively impact knowledge retention, as opposed to traditional slide shows and lectures.

The Army and other military branches have researched using VEs for training novices on complex and potentially dangerous military operations and maneuvers. Maraj, Lackey, Badillo-Urquiola, Ogreten, and Maxwell (2015) researched the effectiveness of training soldiers on room-clearing tasks when compared to traditional training methods. Their research indicated that novice soldiers benefit from training in the VE as measured by training effectiveness ratios and correlations between self-reported stress states and perceived workload. The experimental design tested the training of 64 Reserve Officers' Training Corps cadets. Trainees using the VE experienced higher frustration, stress, and workload. This may have been due to limited prior experience with the technology, which impacted performance, or may have been attributed to a desire to perform well. The novelty of the technology may have impacted engagement with the training for the VE group. The researchers recommended that participants be exposed to the VE before training exercises and introduce a virtual instructor to aid the trainees and provide feedback during training.

Ragan et al. (2015) conducted an experiment to determine how varying field of view and visual complexity during training affected training effectiveness in a visual scanning task. The researchers used a simulated urban environment to train 45 university student participants on scanning techniques to identify threatening human targets (e.g., an avatar with a firearm). Adherence to a prescribed visual strategy was also measured. Three different fields of view and three levels of visual complexity were studied for nine experimental conditions; all participants completed an assessment in a high-fidelity, high visual-complexity VE. Results revealed that the field of view and visual complexity significantly impact target detection. A higher field of view will result in better performance, while higher visual complexity can decrease performance. Those participants who trained in a VE that matched the environment in which they were assessed adhered to the prescribed visual strategy better than those who trained in other conditions. The authors concluded that training in similar conditions to the live task environment, especially where visual complexity was concerned, may be a factor in effectively learning a task. Further, the researchers noted that successful performance in a training environment may not result in mastery of a technique as it translates to the real world.

The use of augmented cues in a VE was tested by Cooper et al. (2016). Participants were divided into three groups to learn how to change a tire: a real-world scenario, a VR scenario, and a VR scenario with augmented cues. The purpose of the experiment was to analyze how augmented cues in VR impact performance and user satisfaction in a virtual training environment. Performance and transfer of training to the real world were also studied. The between-groups design included a real-world assessment (i.e., changing a tire) after training. Time to complete the task was collected as an objective measure, and subjective measures were also collected. Those participants in the VR training groups had significantly faster performance times in the real-world assessment, although performance times between the groups were not significantly different. Participants who received augmented cues in VR training had fewer errors in the assessment than participants who received non-augmented VR training. Results indicated that virtual training on manual tasks can positively impact performance. Although changing a tire is not overly complex nor dangerous, the concepts tested indicated that using VR and augmented cues may be beneficial and translate across many industries and environments.

VR training has also been used to explore how different levels of immersive instruction translated to assembling a mechanism with 17 parts. Smith and Salmon (2017) used a between-groups experiment with 30 participants divided into three groups to receive training. One group studied with traditional video instruction, one group used written instructions supplemented by 2-dimensional photographs, and the third group received VR training. Data were collected on how long participants spent in training, how long they required to assemble the mechanism, and error rate (both resolved and unresolved errors) while assembling the mechanism. Participants were also surveyed on the preferred training method. There was no difference in time nor accuracy between the three groups when tested on assembly in the real world. Over 85% of the participants indicated that VR training with a 3D walkthrough and instructions were preferred, particularly when the assembly procedure was very involved or complex. The results further revealed that trainees can easily adapt to a VR training program despite previous experience with VR technology. The hands-on, visual, immersive experience of training in VR may have benefitted the trainees. Participants who preferred training in VR also reported the program was fun and engaging with the benefit of learning through an interactive experience.

In conclusion, training in dangerous or complex environments can be enhanced by incorporating VR and immersive simulation training scenarios. Researchers have demonstrated that learning in a VE can positively affect engagement with the content as well as retention over time. Additionally, training in a VE offers an interactive, hands-on experience with virtual objects as opposed to physical objects which may be damaged through wear and tear. Using VR training programs may reduce training time and cost while increasing performance. However, adequate performance of a task in the VE is not an indicator of the ability to perform a task in the real world; further research in how training transfers between the environments is required. Although VR training may transfer to the live task environment, it should not be relied upon; rather, it should be used as a tool to facilitate the learning and mastering of concepts. It must also be mentioned that inexperience with virtual technologies may negatively impact performance; thus, tutorials are recommended to increase user confidence and self-efficacy.

Benefits of using virtual reality in training and education. Although the benefits of using VR in training and education have been presented in the studies previously reviewed, an in-depth review is warranted. Identifying the pedagogical benefits of using VEs for training and education enables educators and institutions to objectively assess if VR is an appropriate tool to facilitate learning.

Dalgarno and Lee (2010) noted several theoretical and actual applications of using VEs for learning in their review of two decades worth of research. They also noted that VEs facilitate learning related to the development of spatial knowledge. The VE offers learners the chance to freely move, explore, manipulate objects, and develop spatial knowledge in environments that may otherwise be inaccessible. Interaction with objects in a VE can elicit a deeper understanding of the subject material and dynamic concepts. Further, direct manipulation of a virtual object may facilitate an internal frame of reference in students (Jang, Vitale, Jyung, & Black, 2017). This may be especially beneficial for learners who have low spatial ability. Lindgren et al. (2016) summarized that using immersive, interactive, whole-body simulations allow learners to merge "sensorimotor perceptions with augmented representations and digital scaffolds that make critical concepts salient" (p. 182) thereby facilitating new learning.

Dalgarno and Lee (201) posited that the immersive quality of a VE, wherein the learner can focus all their attention on the given task, may increase engagement. High-fidelity and realistic settings can increase the feeling of presence and immersion, thus impacting engagement with the environment. Embodiment and whole-body learning may allow learners to internalize a complex subject through active engagement as opposed to other learning methods (Lindgren et al., 2016). A meta-analysis by Merchant, Goetz, Cifuentes, Keeny-Kennicutt, and Davis (2014) suggested that games, simulations, and VEs can effectively improve learning outcome gains. The authors also noted that game-based learning environments were more effective than computer simulations or VEs. Obtaining knowledge in VR is facilitated by creating a VE contextually modeled on the environment on which the training or learning is to be applied (Dalgarno & Lee, 2010). Using 3D, immersive simulations provide visual and sensory realism similar to the real world. This consistency between environments may impact recall, retention, and application of both knowledge and skills.

Motivation is another key element when learning subjects that are complex and that require effort (Hussein & Nätterdal, 2015). Parong and Mayer (2018), Psotka (2013), and others have demonstrated that using VR can positively impact student motivation. Dalgarno and Lee (2010) echoed this statement, noting that personalization of learning and the ability to make choices in the VE to facilitate learning can impact intrinsic motivation to achieve goals.

Learning potentially dangerous or risky tasks or procedures learned in a simulated environment allows the learner to make mistakes without detrimental consequences. Maneuvers may be iteratively practiced until prescribed standards are met. For example, training on recovery procedures in an actual airplane may require flying in unsafe conditions and result in a fatal accident if recovery is not executed in a correct and timely manner. Training in a VE also allows for experiential learning of tasks that may be “impractical or impossible to undertake in the real world” (Dalgarno & Lee, 2010, p. 8).

In an immersive training environment, the learner will not fear the outcome of their performance level.

As with any technology, VR has an initial, upfront cost to acquire hardware, software, and resources required to integrate the technology into the learning or training environment. Effort is also required to train both the educators and the learners on how to use the technology. Programs must be created or purchased. Prices of VR and related technology have steadily decreased as the market has expanded to include systems that vary in features, and pricing reflects this trend (Viar Inc., 2018). Currently, VR systems are less expensive than FTDs and most ATDs. As a low-cost training solution, institutions will be able to purchase multiple VR systems, upgrade and adopt new hardware and software, and maintain systems at a fraction of the cost of FTD and ATD counterparts (Hussein & Nätterdal, 2015; Sikorski et al., 2017). Because VR systems also have a small physical footprint, multiple systems can be used in a small space, increasing the availability for training (Sikorski et al., 2017). More research is required to provide an in-depth cost-benefit analysis for using VR as opposed to other immersive training devices.

Potential drawbacks of using virtual reality in training and education. Before VR is implemented into a training environment, potential drawbacks must be considered and mitigated if possible. Several studies have demonstrated that VR can enhance skills acquisition, especially cognitive skills related to recall, retention, visualization, and psychomotor skills (Jensen & Konradsen, 2018). Outside of these skills, Jensen and Konradsen (2018) argued that VR may yield “no advantage when compared to less immersive technologies or traditional instruction” (p. 1515). Further, the technology may be counterproductive in some instances. Richards and Taylor (2015) noted that when comparing 2D and 3D platforms to present a theory or concept, “the complexity added by a 3D model will not improve understanding but may worsen it” (p. 166). Their results also indicated that learning may be lost if the representation of the environment and learning concepts are flawed. Makransky et al. (2017) also found that learning with VR may increase cognitive workload and distraction. The VE must be designed appropriately to elicit learning while appropriately representing the theories and concepts students are intended to learn.

Cyber sickness, or the physiological symptoms that may occur from prolonged exposure to a simulator, have been studied through the years and comparisons between technologies made (Jones, Kennedy, & Stanney, 2004; Polcar & Horejsi, 2015). These symptoms may include nausea, vertigo, dizziness, blurred vision or eyestrain, and decreased ability to concentrate. Those who are subject to motion sickness may have a more visceral reaction to using immersive simulation technology than others. Jones, Kennedy, and Stanney (2004) list five groupings of factors that may cause cybersickness: technical system factors (e.g., refresh rate, resolution, flicker); user characteristics (e.g., gender, age, mental rotation ability); duration in the environment; exposure schedule; and “kinematics” (e.g., how content effects interaction). Some of the technical issues have decreased with the advancement of technology, increased refresh rates, and increased field of view. However, the potential for cybersickness is an issue that must be considered as VR programs are developed and integrated into training regimes.

Simulator Use in Aviation Training

Aviation as an industry has a long history of using immersive simulation technology for training purposes. This section details the history of simulator use in aviation training. Relevant federal regulations that govern flight training and the use of simulation devices, as well as definitions thereof, are described. Finally, research utilizing simulation training devices are described, to provide a foundation on which researching the use of VR for flight training may be built. These studies also demonstrate how the introduction of each new technology is surrounded by rigorous research to ensure the simulator has adequate fidelity, offers positive transfer of training, and adds quantifiable value to the training regimen.

Background information. In 1907, four years after the Wright Brothers made their historic powered flight, the U.S. Army Signal Corps requested a training device that was simple in construction and operation, and would allow for proficient training within a reasonable time frame (Moroney & Lilienthal, 2009). Two entities answered the call: The Wright Brothers produced the *kiwi bird* in 1910, a device with rudimentary flight controls configured in an older Wright Flyer. The French manufacturer Antoinette created a training device made from a barrel with short wings and flight controls with multiple axes of motion. These two basic devices were utilized for training for over a decade.

The most notable historic flight simulator, and which modern devices can trace their origin to, is Edward A. Link’s trainer of the 1930s (Moroney & Lilienthal, 2009). The trainer featured three degrees of freedom (pitch, roll, and yaw), short wings and rudder that responded to control input, and realistic flight instruments. This last feature enabled pilots to train using only instruments in a safe environment. The design of the simulator was realistic and mimicked the real aircraft cockpit as closely as possible to create an analogous operational setting (Moroney & Lilienthal, 2009). Recognizing the value of the trainer, both the U.S. Army Air Corps and Navy purchased simulators in 1934, and the devices were used for several decades. The advent of World War II prompted the need for flight simulators that utilized computing technology to respond to dynamic input. After the war ended, military flight simulators were adapted for commercial aviation training. By 1949, the flight training time for airline pilots was reduced by half (Loesch & Waddell, 1979).

Flight simulators with diverse configurations and complexity were developed through the 1950s and beyond, representing many different airplane models. A shift in the simulator platform emerged in the early 1980s when Microsoft Flight Simulator was released featuring numerous makes and models of aircraft. The software was designed for flight training on a personal computer (PC) and quickly became the subject of transfer of training research. By the mid-1990s, the flight simulator industry had grown to over $5 billion in annual sales from commercial, military, and government entities. This growth continued well into the early 21st century (Moroney & Lilienthal, 2009). Advancements in technological ability and reduced costs contributed to the growth of the industry. Spearheaded by the military, researchers investigated the use of simulators to save time, resources, and costs associated with training.

Throughout the history of flight simulators, numerous devices were created and adopted by flight training centers. Trainers have historically believed that higher simulator fidelity (e.g., exact replication of the aircraft and flight characteristics) will lead to greater transfer of training from the device to the real airplane. Moroney and Lilienthal (2009) note that although this adherence to high-fidelity environments prevailed into training devices of the 21st century, researchers have debated and investigated the necessity of exact replication. Spannaus (1978) noted that students could not gain proper education through observation alone but through active participation. He cited three requirements for using simulators for education and training: “(1) they are based on a model of reality, (2) the objectives must be at the level of application, and (3) the participants must deal with the consequences of their decisions” (Moroney & Lilienthal, 2009, p. 21). Salas, Bowers, and Rhodenizer (1998) also argued against emphasizing fidelity and realism in favor of enhancing how complex skills are learned. Of note, Spannaus and others called for a realistic training setting but did not demand exact replication. Thus, the development, design, and use of flight simulators have varied. These devices are discussed in the following section.

Federal regulations and definitions. The Department of Transportation (DOT) and the Federal Aviation Administration (FAA) has detailed rules and regulations relevant to aviation in Title 14 of the Code of Federal Regulations (CFR), *Aeronautics and Space* (2019). 14 CFR has detailed aspects of aeronautics and space over five chapters. The FAA has served as the governing body that oversees all aspects of the U.S. aerospace system including regulation and approval of flight simulators for use at flight schools and training centers. Chapter 1, volumes 1-3, has information that pertains to flight schools and flight training requirements for certification. Relevant regulations are presented.

Pilot schools. Requirements for issuing pilot school certificates, such as those housed within colleges and universities, have been prescribed under 14 CFR 141, *Pilot Schools* (14 CFR §141, 2019). In 14 CFR 141, the DOT has described the requirements of the school's personnel, aircraft, and facilities. Training course and curriculum requirements are detailed, as are the operating rules, privileges and limitations of the school, and how records must be maintained. The chapter appendices detail the requirements of the different flight certifications, ratings, and courses thereof.

The DOT has also prescribed requirements for flight centers, or facilities with no real aircraft and only simulators, under 14 CFR 142, *Training Centers* (14 CFR §142, 2019). The CFR has details on the requirements and approval of training curriculum, personnel, training equipment, and the operating privileges and limitations of the training center. 14 CFR 61, *Certification: Pilots, Flight Instructors, and Ground Instructors* (14 CFR §61, 2019), has details regarding another avenue of instruction. Although Part 61 instruction has requirements for training and obtaining flight certificates and ratings, it does not have prescribed curricula, facility requirements, nor record keeping beyond logbook (lesson) requirements. Part 141 flight schools are distinguished from Part 61 establishments in several ways, shown in Table 6.

Table 6

Differences Between Part 141 and Part 61 Flight Training Institutions

Regulation	Potential Advantages	Potential Disadvantages
Part 141	Structured curriculum geared for career-minded pilots	Rigidity may not be advantageous for those not pursuing a piloting career
	Complete training in fewer hours, per school approval	The faster pace may be overwhelming
	Efficient progression through multiple certificates and ratings at one location	Financial, personal, and physical issues may disrupt training and progression through coursework
	Culture of high success rate	Choice of the instructor may not be available
		Travel may be required from the flight school to the airport
Part 61	Flexible training environment	Increased flight training hours for certain certificates and ratings
	Ability to choose a training location and instructor	Instructor choice may be limited, based on the size of the facility
		Training may progress slowly, depending on student and instructor availability

Flight simulation training devices. The FAA has qualified and described the use of flight simulation training devices (FSTDs) under 14 CFR 60, *Flight Simulation Training Device Initial and Continuing Qualification and Use* (14 CFR §60, 2019). This subchapter has prescribed rules regarding the initial and continuing qualification of FSTDs. Details on how FSTDs can be used for training, evaluation, and flight experience have been included. Qualification Performance Standards of different simulator types are outlined in the Part 60 appendices. Part 141 flight schools have often incorporated a variety of training devices into training programs.

Aviation training devices. The FAA General Aviation and Commercial Division has provided evaluation and approval of aviation training devices (ATDs) which may be used for flight training as permitted under Part 61, subsection 4(c) (*Certification: Pilots, Flight Instructors, and Ground Instructors*, 14 CFR §61, 2019). The FAA has provided further guidance on the approval and use of ATDs in Advisory Circular (AC) 61-136B

(FAA, 2018). Guidance on the use of ATDs includes flight training, logging of training, and the types of devices which may be used. ATDs are often divided into basic and advanced aviation training devices (BATDs and AATDs, respectively). The FAA has defined an *ATD* as “a training device, other than a full flight simulator (FFS) or flight training device (FTD), that has been evaluated, qualified, and approved by the Administrator as a basic or advanced ATD” that “includes a replica of aircraft instruments, equipment, panels, and controls in an open flight deck area or an enclosed aircraft cockpit” as well as hardware and software (FAA, 2018, p. A-1). An ATD may represent a category and class of aircraft. A BATD and AATD must meet or exceed the requirements expressed in appendices B and C of AC 61-136B (FAA, 2018). The *BATD* must also provide “an adequate training platform and design for both procedural and operational performance tasks specific to the ground and flight training requirements for Private Pilot Certificate and instrument rating” as well as “both procedural and operational performance tasks required for instrument experience and pilot time” (FAA, 2018, p. A1). An *AATD* must provide a training platform adequate for “both procedural and operational performance tasks specific to the ground and flight training requirements for Private Pilot Certificate, instrument rating, Commercial Pilot Certificate, and Airline Transport Pilot (ATP) Certificate, and Flight Instructor Certificate” as well as “procedural and operational performance tasks required for instrument experience, the instrument proficiency check (IPC), and pilot time” (FAA, 2018, p. A-1 – A-2).

The term *personal computer-based aviation training device* (PC ATD) was established in 1997 under AC 21-126 but was retired in 2008 when differences between BATDs and AATDs were distinguished. In the 21st century, the informal use of PC

ATD encompasses both BATDs and AATDs and refers to the use of PC-based simulators for training purposes. PC ATDs may utilize commercial software, such as Microsoft Flight Simulator, physical control inputs, and a commercially available monitor.

Flight training devices. The FAA has defined an FTD as:

> A replica of aircraft instruments, equipment, panels, and controls in an open flight deck area or an enclosed aircraft flight deck replica. It includes the equipment and computer programs necessary to represent aircraft (or set of aircraft) operations in ground and flight conditions having the full range of capabilities of the systems installed in the device as described in part 60 of this chapter and the qualification performance standard (QPS) for a specific FTD qualification level. (*Appendix F to Part 60—Definitions and Abbreviations for Flight Simulation Training Devices*, 14 CFR §60, 2019)

Guidance for the evaluation and qualification of FTDs has been prescribed in Appendix B of the Part 60 regulations (*Appendix B to Part 60—Qualification Performance Standards for Airplane Flight Training Devices*, 14 CFR §60, 2019). In Appendix B, the FAA has detailed the requirements of using an FTD for flight training, including experience, maintenance requirements, record keeping, and requirements related to equipment and personnel.

Full flight simulators. An FSS has been defined as:

> A replica of a specific type, make, model, or series aircraft. It includes the equipment and computer programs necessary to represent aircraft operations in ground and flight conditions, a visual system providing an out-of-the-flight deck view, a system that provides cues at least equivalent to those of a three-degree-of-

> freedom motion system, and has the full range of capabilities of the systems installed in the device as described in part 60 of this chapter and the QPS for a specific FFS qualification level. (*Appendix F to Part 60—Definitions and Abbreviations for Flight Simulation Training Devices*, 14 CFR §60, 2019)

Guidance for the evaluation and qualification of FTDs has been prescribed in Appendix A of the Part 60 regulations (*Appendix A to Part 60—Qualification Performance Standards for Airplane Full Flight Simulators*, 14 CFR §60, 2019). The FAA has included FFS maintenance requirements, record-keeping, how the device may be used for flight training and experience, requirements related to equipment and personnel, and other prescribed conditions in Appendix A.

Research utilizing aviation training devices. Flight simulators have been used extensively at many Part 141 flight schools to reduce the cost of training and mitigate wear and tear on real aircraft. As these devices have been developed and made available for purchase, researchers have investigated the benefits of using them for training. This section highlights the robust history of research of the efficiencies associated with immersive simulation technology. As these technologies have demonstrated their worth to train aviation students effectively with positive skill and training transfer to the real world, they have been incorporated into training hours associated with flight certification (see Table 2). However, apart from FFSs, these devices lack the full immersion associated with VR. VR is the logical next technology to conduct transfer of training research, yet the literature is lacking. Thus, Table 7 identifies selected studies of simulator use in aviation training that serve as foundational research surrounding the use of immersive simulation technology in aviation education. Brief descriptions of selected studies represent common applications of simulation devices in flight training follow.

Table 7

Selected Studies of Simulator Use in Aviation Training

Training Device	Context	Variables Studied	Chief Results	Reference
FFS	Effect of simulator motion on training	Control input, performance, motion condition	Small but significant effects of using motion	Bürki-Cohen & Go, 2005
FFS, airplane	Effect of simulator motion on training	Performance, training platform, training regime	Generally positive transfer	Bürki-Cohen et al., 2007
FTD	Abnormal event training	Performance, task time, the training platform	Training in an FTD can improve procedural memory	Koglbauer, 2016
PC ATD, FTD	Training proficiency	Training platform, performance, transfer type	Training platform and gaming experience led to near- and far-ToT	Korteling et al., 2017
PC ATD, FTD, aerobatic aircraft	Abnormal event training	Performance, response time, the training platform	Training treatment in PC ATD or FTD resulted in better performance than those in the control group	Leland et al., 2009
FTD, airplane	Training proficiency	Performance, training platform, training regime	The treatment group had positive transfer, achieved standards in significantly fewer iterations for 53% of tasks	Macchiarella et al., 2006
FTD, airplane	Training proficiency	Performance, training platform, training regime	The treatment group had positive transfer, achieved standards in fewer iterations for 33 of 34 tasks	Macchiarella et al., 2008
PC ATD, aerobatic aircraft	Abnormal event training	Performance, training platform, training regime	Treatment group significantly exceeded the control group in 70% tasks	Rogers et al., 2009, 2010
PC ATD, airplane	Training proficiency	Trials for task completion, performance, total time, the training platform	PCATD are effective and reduce the time needed for learning instrument tasks	Taylor et al., 1996, 1998, 1999
PC ATD, FTD, airplane	Training proficiency	Trials for task completion, performance, total time, the training platform	FTDs and PCATD are effective for teaching advanced instrument tasks and IPC	Taylor et al., 2004, 2005

Note. ATD = Advanced Training Device. FFS = Full Flight Simulator. FTD = Flight Training Device. IPC = Instrument Proficiency Check. PC = Personal Computer. PCATD = Personal Computer Aviation Training Device. ToT = Transfer of Training. Adapted from “Research Recommendations from the Airplane Simulation Transfer Literature” by J. G. Neal, S. G. Fussell, and S. Hampton, 2020, in press, *Journal of Aviation/Aerospace Education & Research.*

Studies related to aviation training devices. The extent to which a PC ATD can be used for training was studied by Taylor and colleagues for over a decade starting in 1996. The researchers published numerous articles demonstrating the use of PC ATDs for instrument flight skills and the effectiveness of using the devices to maintain instrument currency. Early studies by the researchers (Taylor et al., 1996, 1999; Taylor, Talleur, Phillips, Emanuel, & Hulin, 1998) used a PC ATD to develop instrument flight skills and measure the effectiveness and extent of skill transfer from the computer to the airplane. The transfer of training was compared between a control group and a treatment group. The control group was trained only in an airplane, while the treatment group received training first in a PC ATD before transitioning to an airplane. The researchers measured the number of trials to meet the training criterion in the airplane, time to complete lessons, and total course completion time. Results repeatedly demonstrated that PC ATDs were effective for training on instrument flight tasks. The authors also found that transfer savings were generally positive especially when new tasks were learned. Courses were completed in less time when a PC ATD was used, saving four hours of training time for a transfer effectiveness ratio of 0.15 – a savings of 1.5 flight hours per 10 PC ATD hours.

Taylor, Talleur, Rantanen, and Emmanuel’s 2004 study and subsequent publications (Taylor et al., 2004, 2005) were prompted by an FAA advisement that authorized PC ATD use for 10 of the 15 hours of flight training performed in an approved ground training device. The PC ATD was not authorized for Instrument Proficiency Checks (IPCs). In collaboration with the FAA, the authors compared the effectiveness of PC ATDs, FTDs, and an airplane for conducting an IPC. An experimental design was used to train and test the performance of 75 pilots in three groups (FTD, PC ATD, and airplane/control). Participants were given a baseline proficiency check (IPC 1) in their assigned devices/airplane, then a second proficiency check (IPC 2) in an airplane after a period of time. The proficiency checks contained a scenario in which pilots flew seven maneuvers required to maintain instrument currency. Flight performance variables were judged as pass or fail as measured by specific performance standards by the instructor; overall performance was also rated as pass or fail. No significant differences in performance were found among the three groups. Results also indicated that participants were likely to pass or fail the IPC 1 in an airplane as often as in the FTD or PC ATD. The results of the IPC 2 indicated that the device used in IPC 1 did not influence pass/fail rates in IPC 2 in an airplane. Thus, PC ATDs were determined to be just as effective for conducting an IPC.

Studies related to flight training devices. As the expense of FTDs has been reduced, more flight schools have purchased them for training, research, and development purposes (Macchiarella et al., 2008). The simulators are efficient training platforms with high-fidelity, realistic training scenarios, and the ability to cue the program to a specific point for iterative training.

Another benefit of using an FTD for training has been the ability to practice maneuvers in a low-risk environment with the additional advantage of resetting a simulation to iteratively perform procedures. Koglbauer (2016) leveraged these aspects of the FTD to evaluate procedural memory and pilot behavior for training on aircraft recovery procedures. Thirty-one pilots were divided between a training and control group to examine the effects of simulator training on recovery from unusual attitudes, overbanking, stalls, and spins. Pilots received written and oral briefings, a demonstration of correct recovery procedures in an aircraft, and practiced recovery procedures in an aircraft. The training group received subsequent recovery training practice in a simulator, while the control group practiced radio navigation. All participants received a post-test in a simulator that required the participant to recover from an unexpected event. Performance was measured by the instructors, and task completion time was recorded during the post-test. The results of the study indicated that the training group performed better than the control group with high-performance accuracy and shorter task completion time, demonstrating a positive effect in improving procedural memories. Positive training effects were also seen on pilot performance, and both groups reduced their task completion time between training and the post-test. The training group performed better during recovery than the control group but not at a level of statistical significance. Finally, the study revealed combining procedural and declarative training techniques with "the use of a simulator with sufficient psychological fidelity have a positive effect on pilots' acquisition and generalization of skills to recover from unusual attitudes in flight" (Koglbauer, 2016, p. 365).

Macchiarella and colleagues performed a series of transfer of training experiments at Embry-Riddle Aeronautical University (ERAU) (Macchiarella, Arban, & Doherty, 2006; Macchiarella & Doherty, 2007; Macchiarella et al., 2008). Ab initio student pilots —or, those at the beginning of their training— enrolled in the flight training program for 18 months and received either the standard curriculum or an experimental curriculum that included 60% training in an FTD and 40% training in an airplane. A transfer effectiveness ratio and multivariate analysis of variance analysis were used to calculate the time saved using an FTD for training. Results revealed that the experimental group, who received extra flight training in an FTD, required fewer iterations to achieve flight standards when compared to the control group. Eighteen of the 34 tasks were significantly different in iterations to achieve standards between the groups. Further, the experimental group demonstrated positive transfer for 33 of the 34 tested tasks. The additional FTD use in the experimental group realized a 29.24% cost savings. The results indicated that FTDs are an efficient, effective, and cost-saving platform for training ab initio pilots in procedural maneuvers.

Studies related to full flight simulators. Research involving an FFS has been used extensively to determine the effect motion has on training. Incorporating an FFS into training has often been used for type-rating in the specific aircraft for which the FFS is configured. The FAA and Volpe National Transportation System Center collaborated to investigate the effect of simulator motion on recurrent training for airline pilots. A series of studies revealed that motion does not improve the transfer of training for recurrent exercises and evaluation (Bürki-Cohen & Go, 2005). Flight precision measures were only minimally different between control and treatment groups. The results of motion on initial training of engine loss during an instrument approach confirmed a small but statistically significant difference alerting effect from motion (Bürki-Cohen & Go, 2005). However, it was noted that pilots with or without motion training were able to complete the tasks satisfactorily; the lack of motion training did not negatively affect the performance of the control group when tests were performed in a motion simulator. Bürki-Cohen, Sparko, and Go (2007) posit motion training in an FFS does not fully reflect motion experienced in the real world. They also state that “virtually no scientific evidence supports the notion that flight-simulator platform-motion bases contribute to transfer of training across a range of aircraft types, missions, maneuvers, and measures" (Bürki-Cohen et al., 2007, p. 7). Transfer of training from a simulator to an airplane did not require motion to be positive. Overall, the cost associated with motion training in an FFS may be higher than the outcome of the training.

In summary, the use of flight simulators for training has a century-long history. A wide variety of simulators have been used in aviation training. These devices have demonstrated the ability to reduce training time and costs while making more resources available for training. Training with PC ATDs has been effective for learning and practicing procedures and maneuvers, especially when related to instrument flight tasks. Studies indicated that using FTDs can enhance procedural memory and performance while decreasing costs associated with flight training. FFS have been used primarily to evaluate transfer of training when motion is introduced into the training environment; empirical evidence suggests that motion does not affect the transfer of training but that using an FFS provides effective training in general. Overall, training devices have been used efficiently and effectively to train pilots at all experience levels.

Immersive Simulation Technology in Aviation Training

A review of the extant literature revealed that VR is relatively unused in flight training programs. The exception is the use of VR programs for military pilots; even then, research is limited to the development, usability testing, and pilot tests of new systems (Lewis & Livingston, 2018; Palla et al., 2018; Sikorski et al., 2017). Despite this gap in the literature, there are instances where immersive simulation technology has been studied in other areas of aviation training, selected studies of which are featured in Table

8. These studies highlight the potential research opportunities for, and subsequent integration of, VR in aviation training. Brief descriptions of relevant studies follow.

Table 8

Selected Studies of Immersive Simulation Technology Use in Aviation Training

Device Type	Environment/ Context	Variables Studied or Considered	Chief Results	Reference
SBT in a virtual learning environment	Flight training/VE and SBT to enhance Certified Flight Instructor training	Training regime, performance on FAA FOI exam	Learning improved understanding and performance in four topic areas	Byrnes, 2017
PC ATD and FTD equivalents	High school/aerospace science course for space flight	Training platform, training regime	Performance of the treatment group higher than control; no difference in subjective measures	Ke & Carafano, 2016
PTN VR-enabled flight simulator	Military aviation / USAF pilot training	Physiology and cognitive mapping on COTS flight simulator technology; integration	13 of 20 pilots graduated in half the time of traditional training	Lewis & Livingston, 2018
Virtual ATC VAT development	University / ATC training	Transfer, fidelity, procedural similarity	N/A: Design and development of VAT	Macchiarella & Meigs, 2008
VR PTT development	Military aviation/cockpit and checklist training	Fidelity, acceptance, usability, validation	Pilots reported the VR PTT would easy to use	Palla et al., 2018
SBT using MALE UAS	University / UAS training	Mission completion, efficiency, performance	Realism and fidelity in SBT devices may enhance learning	Rigby et al., 2017
NASA DOME VE	Aerospace/astronaut preflight training in variable conditions	Starting orientation, ToT, performance, time, training condition	Treatment group performed tasks faster and with less simulator sickness during training	Stroud et al., 2005
TAM for AR use in maintenance training	University/aviation maintenance	Original TAM constructs	No negative attitudes towards development, use, and integration of AR in training	Wang et al., 2016

Macchiarella, Liu, Gangadharan, Vincenzi, and Majoros (2005) conducted an experiment to determine how using AR in aviation maintenance training impacts learning, recall, and long-term memory. The study included 96 undergraduate students who learned about removing an oil pump from an engine using one of four presentation methods: video instruction, interactive AR, AR, or paper-based instruction. The groups were compared and data collected regarding the amount of information recalled in an immediate posttest and retention after a week had passed. Results revealed that participants in the print- and video-based instruction groups had significantly greater loss of information as the two AR groups. Both groups who learned with AR technology showed no significant loss of information after one week; that is, they had higher levels of information retention than the paper- and video-instruction groups. Notably, the use of AR technology did not affect recall in immediate testing.

Immersive simulation technology has also been used in space flight simulation training. A mixed-methods approach was used by Ke and Carafano (2016) to investigate the effect simulation-based learning can have on a collaborative learning process. High school students in an earth space science class participated in a program to learn about basic aerospace science concepts and space flight. Ten participants were trained in an immersive simulator while another 10 participants received computer-based training. All participants received materials to study outside of the training and were tested on knowledge after the study was concluded. Objective data was recorded for knowledge and attitude as well as subjective data from research observation and video recordings. The researchers found that immersive, simulation-based, collaborative learning processes promoted student learning. Those students who received training in a simulator had better knowledge scores although it did not appear to impact attitude nor interest in STEM subjects. Despite the mixed results of the object data, qualitative analysis revealed that the use of simulation may have positively impacted students’ levels of task engagement. The authors indicated that future research is required to understand the use of immersive simulation in a collaborative learning environment.

The military has been exploring the use of low-cost, high-fidelity flight simulators using COTS hardware and software. Palla, Brent, and Sikorski (2018) created an immersive AC-130 virtual part-task trainer to the U. S. Air Force Special Operations Command. Students received checklist instruction with an intelligent, computer-generated guide in a VR cockpit. The researchers conducted a formative evaluation to measure the effectiveness of the training and solicited participation from subject matter experts (SMEs), pilots, and flight instructors. Participants reported that the trainer was easy to use and would benefit the training program by increasing both confidence and proficiency. The trainer needed to complete an evaluation stage to ensure the training requirements of the Air Force were met. Initial analysis indicated that the virtual part-task trainer will be a viable, low-cost, time-saving option for training Air Force AC-130 pilots.

Lewis and Livingston (2018) also created a testbed to study the incorporation of VR, cognitive mapping, and artificial intelligence technologies into a pilot training program called Pilot Training Next, using COTS hardware and software. Using these technologies, the researchers ushered student pilots through an accelerated training timeline with a goal to reduce training from 12 months to 6 months. Data collected on training effectiveness, return on investment, and other standards thus far have demonstrated that the Pilot Training Next program is an affordable option that can leverage VR and other technologies to enhance military pilot training.

Wang et al. (2016) applied the TAM to understand the factors that impact aviation students to use AR technology in maintenance training. The authors stated that AR was an efficient tool that can provide information in the user's field of view, thus enhancing how the information is received and assimilated. However, Wang et al. (2016) also noted user perception of the technology had not been studied. Using the TAM, the authors examined how the factors of perceived usefulness (PU), perceived ease of use (PEU), and attitude toward use (ATU) affected intention to use AR technology for aviation maintenance instructions during training. Data were collected from 41 undergraduate aviation students who first saw a demonstration of using AR during the fan removal process of an aircraft engine; participants were then given the chance to use the technology and finally completed a survey. Results indicated that PEU significantly impacted PU and ATU, that PU significantly impacted ATU and intention, and that ATU significantly impacted intention. Further, there were no indications of negative attitudes nor perceptions of using AR technology in aviation maintenance training, and overall, the results supported the incorporation of the technology into the training program.

Gaps in the Research of the Aviation and VR Studies

Academic institutions are employing immersive simulation technology to expand educational opportunities and take advantage of the technological capabilities of incoming students. A variety of educational and training domains have examined the benefits of using VR to elicit motivation and engagement from students, to enhance psychomotor and visual-spatial skills, and to create a safer training environment for iterative procedures or risky maneuvers. Although numerous studies have been discussed that highlight how immersive simulation technologies are effective and efficient tools for aviation education, they are often limited to the use of FAA-approved simulators. These studies do not address the potential benefits of using VR in aviation education nor consider how flight training can be improved upon through the use of VR. Specifically, no research was found that investigates the affordances of using VR for flight training, nor was there subjective or objective data related to using VR for flight training. This is a noticeable gap in the literature of a domain that has historically incorporated training technologies for many aspects of flight training.

Moreover, these studies did not investigate factors that influence aviation students to use a given technology. Wang et al. (2016) did study the perception of using a less-immersive technology (AR) with aviation maintenance students. However, the unique factors that influence the acceptance and use of immersive simulation technology, specifically VR, for flight training have not been explored. These factors and models that may be used to determine them will be explored in the following section.

Ground Theories of the Study

Chapter I and the previous sections of this chapter included an overview of immersive simulation technology in aviation training as well as VR technology use in education and training environments. The benefits and drawbacks of using VR for educational purposes were also described. Understanding how immersive simulation technology enhances the educational environment and learning processes provide a knowledge base for implementing the technology into training programs and curricula. However, the previous sections do not explain the decision-making processes that influence students’ behavioral intentions toward using VR in education contexts, let alone aviation education. A solid theoretical basis and validated methodology, models, and variables will allow for examining and understanding the context of aviation students' behavior. The TAM and TPB, along with extended models and modified variations, will be explored to fulfill the research purpose of identifying determinants of aviation students' intentions to use VR for flight training. In theory, because these models and variables have been previously tested and validated, the models will have factors applicable to the research purpose. The models have been prevalent in information technology as well as studies concerning less immersive technology and may, therefore, be adaptable for other domains and technologies including VR and education.

Technology acceptance model (TAM). Created by Davis (1989) to study the acceptance of information technology, the TAM is a derivative of studies in the 1970s that centered on how perceived usefulness (PU) and perceived ease of use (PEU) impacted system utilization. Davis also considered how performance and expectancy influenced system usage and concluded that user unwillingness to accept and use a system would inhibit performance. Endeavoring to counter the lack of unvalidated and subjective measures used to predict user acceptance of computers, Davis' (1989) research led him to the correlate PU and PEU with self-reported current usage of computers and self-predicted future use. Initial studies indicated that PU "had a significantly greater correlation with usage behavior" and that PEU "may actually be a causal antecedent to perceived usefulness, as opposed to a parallel, direct determinant of system usage" (Davis, 1989, p. 319). Although his research has a foundation in computers and information technology, it has since become a valid, robust model to determine the factors that impact user acceptance for a variety of technologies (King & He, 2006).

TAM Components. King and He (2016) noted that the TAM has become a widely used model in part due to its “understandability and simplicity” (p. 740). The applicability of the model has led to its use in a variety of domains for a variety of technologies. Davis’ (1989) original variables, PEU and PU, have been demonstrated to strongly correlate with user’s attitude toward using (ATU) a technology and behavioral intention (BI) to use a given technology. These four factors have formed the foundation of many studies investigating new technology. Davis’ original TAM is shown in Figure 3. *Perceived ease of use* is the degree to which the user perceives using the technology is free of effort, whereas *perceived usefulness* is the degree to which the user believes the technology will enhance performance (Davis, 1989); both have been shown to influence ATU and BI. *Attitude toward use* is the user’s feeling toward the technology (i.e., favorable or unfavorable), and *behavioral indentation* indicates the user’s level of desire to use the technology (Davis, 1989). Reviews of the TAM have demonstrated that the model may be used to measure intention and also point out that the model may not predict actual behavior (Abdullah & Ward, 2016; King & He, 2006; Turner, Kitchenham, Brereton, Charters, & Budgen, 2010).

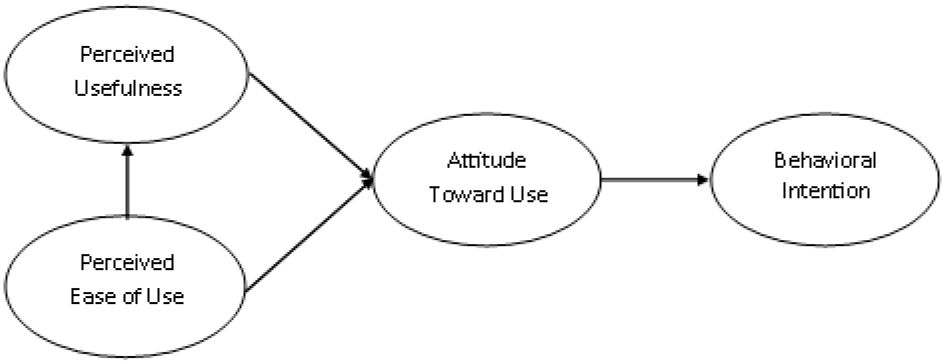


Figure 3. Original technology acceptance model. Adapted from “Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology” by Davis, 1989.

The TAM has been extended to include new factors beyond the original model. In his 1989 work, Davis described that PEU is supported by Bandura's (1982) research of self-efficacy (SE). In his development of the social cognitive theory (SCT), Bandura (1991) proposed that change in behavior could be attributed to self-regulation, of which there are three elements: the monitoring, judgment, and evaluation of one's behavior and subsequent effects. SE is a major component of self-regulation and defined as personal belief (confidence) in one's ability to accomplish a given behavior. This confidence "plays a central role in the exercise of personal agency" (Bandura, 1991, p. 1) and directly impacts a person's thoughts, actions, and motivation. The construct of SE has been adapted by researchers within both the TAM and TPB, as there are suspected relationships between SE and BI. Indeed, SE has been applied to technology use in numerous instances when researchers believe users will engage in a given behavior based upon confidence in personal capability.

TAM selected studies. Several studies have demonstrated that the TAM is a versatile, adaptable, and robust model. Table 9 features a selection of the studies that are relevant to the domains of education and training, aviation, and consumer use and highlight a variety of technologies. A brief description of the applicable studies follows.

Table 9

Selected TAM Studies and Factors

Model / Environment	Technology	Factors/Variables	Method	References
GETAMEL/ education	e-portfolio tools	PEU, PU, SE, enjoyment, SN, computer anxiety, experience, BI	Survey with CFA and SEM	Abdullah et al., 2016
GETAMEL/ education	e-learning tools	SN, experience, computer anxiety, enjoyment, BI, PEU, PU, technological innovation	Survey with CFA and SEM	Chang et al., 2017
Extended TAM/education	e-learning tools	Flow (motivation to adopt), PEU, PU, ATU, BI, AU	Survey with CFA and SEM; interviews	Esteban-Millat et al., 2018
Extended TAM/education	e-learning tools	Computer SE, PEU, PU, ATU, BI	Survey with CFA, PLS-SEM	Gong et al., 2004
Extended TAM/ social networking	VR device	Attitude, PEU, PU, PENJ, social interaction, strength of social ties, BI	Survey with CFA, SEM	Lee et al., 2018
Extended TAM/ medical education	Simulation-based learning	ATU, BI, PEU, PU SN, FCC, AU, SE fidelity	Survey with CFA and PLS-SEM; interviews	Lemay et al., 2018
Extended TAM/ airline service	Airport check-in kiosks	PEU, PU PBC, perceived risk, perceived service quality of kiosk, attitude, BI, need	Survey with CFA and SEM; interviews	Lu et al., 2009
Extended TAM/ consumer use	VR hardware	Age, past use, price willing to pay, curiosity, PEU, PU, PENJ, purchase intention, attitude toward purchasing VR, attitude toward using VR, BI	Survey with CFA and SEM	Manis & Choi, 2018
Extended TAM/ aviation	sUAS	PEU, PU, SN, ATU, FC, perceived risk, BI, knowledge of regulations, AU	Survey with CFA and SEM	Myers, 2019
Extended TAM/ education	e-learning tools	Attitude, PU, PEU, SE of e-learning, SN, system accessibility	Survey with SEM using LISREL, correlations, model fit	Park, 2009
TAM/ aviation education	AR technology	PEU, PU, ATU, BI	Survey with CFA, correlation, factor analysis	Wang et al., 2016

A 2004 study by Gong, Xu, and Yu investigated determinants of accepting information technology in education. Full-time teachers who were also students in a bachelor's degree program were surveyed using the TAM and an additional factor of computer SE to understand teacher’s attitudes toward a web-based learning system.

Responses from 280 participants indicated that the original relationships of the TAM held true and that computer SE was a substantial influence on the acceptance of the web-based learning system. The authors concluded that to facilitate the acceptance of information technology among teachers, they must perceive the technology to be useful but also easy to learn and use. The strong impact from computer SE indicated that personal confidence can influence acceptance of the technology. Training on technology may be a useful way to positively impact the attitude and use of a system by teachers.

User intention to use a technology was studied in an aviation domain by Lu, Chou, and Ling (2009). The technology in question was self-check-in services (e.g., kiosks) at an airport. The authors expanded the original TAM to include external stimuli (including employee demonstration, use by other passengers, and incentives), perceived behavioral control (PBC), perceived risk, perceived service quality of the kiosk, and need for service. Data analyzed from 337 airline passengers indicated that although PU and PEU impacted intention to use the kiosk, user attitude and the external stimuli were stronger indicators of BI. The study demonstrated that the TAM can be expanded and used in an aviation domain to understand consumer perception of a technology, the results of which can be used by management and airlines to instruct how they engage with consumers to adopt a new technology.

Huang, Liaw, and Lai (2016) explored learner acceptance to use immersive simulation technology in medical education using a modified TAM. The authors extended the model to include variables relevant to simulation technology: interaction, immersion, and imagination. Notably, the immersive simulation technology used in the study was not VR as has been defined in this document; the technology used by Huang et al. (2016) featured 3D projection on a screen viewed through 3D glasses. A total of 230 student participants learned about anatomy using the 3D projection aided by 2D computer-based training. Results indicated that the immersion and integration facilitated through simulation technology positively impacted PU and was a predictor of PEU. Their findings supported the work by Merchant et al. (2014) in that immersion and virtual technology can improve spatial cognition. The authors suggested that interaction was not found to be a predictor of PU as medical students may find working with cadavers to be a more interactive experience as opposed to simulation. The additional factors provided insight into how external variables affect attitude and BI.

The General Extended Technology Acceptance Model for E-learning (GETAMEL) was created by Abdullah and Ward (2016) and used by Chang, Hajiyev, and Su (2017) in the education domain. Abdullah and Ward (2016) developed the model from the TAM to determine factors that influence students’ intention to use an e-learning system. The model was validated by Abdullah, Ward, and Ahmed (2016) before its use by Chang et al. (2017), who used the model to examine the BI of 714 university students to use an e-learning system. The factors included the original TAM factors (i.e., PEU, PU, ATU, and BI) as well as external factors of computer anxiety, experience, enjoyment, SE, and subjective norm. The researchers found that the external factors were a valuable addition to the TAM while also validating the original relationships proposed by Davis (1989).

The TAM was used in a mixed-methods study by Lemay, Morin, Bazelais, and Doleck (2018) to understand student perceptions of simulation-based learning in a nursing program. In addition to the original TAM factors, the authors investigated how subjective norm, fidelity, SE, and facilitating conditions influenced attitude, BI, and actual use of the technology. Over 150 nursing students participated in the study. Participant responses upheld relationships presented in the original TAM. Relationships between theorized factors were also supported, namely that fidelity and subjective norms impacted PU and PEU and that SE impacted PEU – although SE did not impact PU. Results supported other studies in that although BI was related to actual use, it may not lead to the actual use of the technology due to a variety of reasons. The work of the authors supported the theory that an extended TAM can be used to understand student perception, ATU, BI, and actual use of a simulator in a rigorous academic program.

Lee, Kim, and Choi (2018) utilized an extended TAM to investigate user adoption of VR for social networking. The authors added VR-related factors to the original TAM (i.e., social interaction, perceived enjoyment, the strength of social ties) and surveyed 350 consumers. The authors found that the social interaction and strengths of social ties increased perceived enjoyment, which in turn significantly impacted intention to use VR. Indeed, results indicated that perceived enjoyment had a more significant effect in intention than PU, opening up the model for further research to explore the relationship between and among original TAM variables, variables related specifically to VR, and BI.

Manis and Choi (2018) extended the TAM to investigate VR hardware from a consumer domain. The TAM used in the study included factors specifically relevant to VR use and purchase intention. The additional factors were perceived enjoyment and antecedents to accepting VR hardware, specifically curiosity, price willing to pay for the technology, and purchase intention. Past use and age were also incorporated into the model. Data were collected from 283 consumers through a snowball sampling technique.

The study confirmed the TAM as a robust model adaptable to new technologies such as VR. Relationships of the original TAM were supported. Additionally, results revealed that PU was not significantly influenced by the factors of age, past use, nor price willing to pay. Perceived enjoyment was influenced by PEU and price willing to pay, which in turn impacted purchase intention. Overall, the authors identified several factors directly related to VR that may influence both intention to purchase and intention to use. These factors can be utilized by developers, marketers, and educators alike to understand how users perceive VR hardware.

Folkinshteyn and Lennon (2016) used the TAM framework to analyze acceptance processes toward developers and end-users of Bitcoin, a digital currency. Using an exploratory and qualitative approach, the authors considered the TAM factors of PEU and PU as well as factors associated with the perceived risk of using a technology. The authors considered regulatory uncertainty risk as an element of perceived risk for Bitcoin developers – but not for end-users – due to the fact that the early years of Bitcoin were surrounded by regulatory "best guesses" (p. 226). When Bitcoin was first developed, there was no regulatory guidance nor did any regulatory agency consider the currency within its purview. Additionally, developers initially feared that regulatory agencies may enact rules that would cripple the technology. The authors theorized that the regulatory uncertainty of the technology during its early years may impact development and use.

Finally, Wang et al. (2016) used the TAM to investigate perceptions of aviation students toward AR in maintenance training, as discussed in a previous section. Their study confirmed that the TAM may be used in an aviation education environment to investigate perceptions toward an immersive simulation technology such as AR. It is theorized that the factors used by Wang et al. (2016) could translate to a more immersive technology such as VR.

The highlighted studies featured several commonalities. First, the original TAM relationships presented by Davis (1989) were consistently confirmed in a variety of domains and a broad range of technology. Second, the authors all incorporated factors that were relevant to the unique environments and technologies within the context of the research purposes. These studies demonstrated the versatility, validity, and robustness of the TAM as an adaptable model suitable for research beyond the realm of information technology. The review of the relevant research also revealed that immersive simulation training technology, especially VR, has received limited investigation in an educational environment. Those studies that did feature similar technology lacked the true immersion that comes with VR. When VR was studied, it was in a consumer environment and not considered as a training tool. Finally, the domain of aviation education has received only limited consideration despite the wealth of technology used for training purposes. Despite the gaps in the research, the variety of studies validated the methodology of the study, including the use of a pretest, a pilot study, a survey with Likert response items, and analyses of descriptive statistics, CFA, and SEM. The theory that TAM is adaptable for the study is supported.

TAM effectiveness. A strength of the TAM is its ability to determine factors that influence a user to accept or reject a technology (Olushola & Abiola, 2017). The original model proposed by Davis (1989) has been repeatedly validated through research and meta-analyses as a robust, versatile model that applies to a wide variety of domains and technologies (King & He, 2006; Olushola & Abiola, 2017; Turner et al., 2010). Despite this, others have argued that the model may be better suited for individual use and perception as opposed to use at a large scale, and results should only be viewed as a general conclusion regarding factors that influence behavior (Ajibade, 2018). A limitation of the original TAM is that user environments, constraints, and social influences are not considered. Turner, Kitchenham, Brereton, Charters, and Budgen (2010) argued that although the results of TAM studies are often accepted as accurate usage and adoption predictors, the intention to use a technology is more often measured than the actual use of a technology. There is, therefore, a debate as to whether a TAM can predict actual usage or if it is restricted to intention to use. Further, Turner et al. (2010) posited that because PEU and PU are not accurate predictors of actual behavior, the model may be measuring perceived use as opposed to actual use. On the other hand, Yucel and Gulbahar's (2013) review of 50 studies concluded that Davis' (1989) original factors were the most effective at predicting BI. A meta-analysis by King and He (2006) supported this claim, stating the "influence of perceived usefulness on behavioral intention is profound" (p. 751) and that the context of the relationship of PEU and BI is important, especially in internet applications. Finally, the TAM has been deemed valid and reliable by numerous authors. In a meta-analysis of 88 studies, King and He (2006) found a consistently high average reliability (Cronbach's α) across constructs, the original factors to be above 0.8 with low variance. Turner et al. (2010) stated that the TAM consistently demonstrates high internal consistency. The TAM has been demonstrated as a reliable model to predict intention to use a technology.

Theory of planned behavior. Created by Ajzen (1991), the TPB is a derivative from the theory of reasoned action (TRA) to measure behavioral disposition. Ajzen felt that the TRA was limited in how it handled behaviors seen in those with no volitional control in a situation. To compensate for this limitation, Ajzen (1991) added the factor of perceived behavioral control (PBC) as a predictor of intention to the TRA to create the TPB. The goal of the model is to predict intention to perform a behavior, as opposed to the TAM's goal of predicting acceptance. The strength of the intention, Ajzen theorized, may indicate the likelihood of behavior or use occurrence. The model also identifies those factors or beliefs that influence a user's perception of the given behavior (Ajzen, 1991).

Ajzen (1991) purported that the TPB captures both behavioral and social principles which allow for understanding how behaviors in given contexts can be used to predict behavior. The TPB has been widely used in social sciences in part due to the ability to predict BI based on limited components (McEachan, Conner, Taylor, & Lawton, 2011; Rise, Sheeran, & Hukkelberg, 2010). The components, or direct predictors, are PBC, attitude, and social norms. These direct predictors impact BI which in turn influences actual behavior (McEachan et al., 2011). Further, the TPB may be used to introduce interventions when a change in behavior is required or recommended (Ajzen, 1991). Due to the ability to examine and predict behavior using these attitudinal components, the TPB is "one of the most influential models in predicting behavioural intentions and behaviours" (Olushola & Abiola, 2017, p. 78).

TPB components. The components of the TPB are both similar to the TAM components and differentiated due to the difference in the focus of the two models. The TPB investigates BI through the lens of the motivational aspects that encourage engagement with a given behavior (McEachan et al., 2011). *Intention* is determined by attitudinal variables. Like the TAM, the TPB uses an attitude construct that impacts the user's behavioral intention. Similar to PEU, *perceived behavioral control* is how easy the user believes it will be to use the given technology or behavior. It encompasses individual beliefs about the frequency of occurrence of enabling or inhibiting factors that influence behavior, impacted by the perceived power of those factors (McEachan et al., 2011). PBC is dependent upon opportunity, available resources, and user familiarity (Ajzen, 1991).

Other factors, such as subjective norms and facilitating conditions, are part of the TPB but were not incorporated into relevant studies or were not deemed significant influencers. Thus, only a brief description is given. *Subjective norms* include beliefs about perceived social pressures from important others to engage or not engage in the behavior (Rise et al., 2010). *Attitude* in the TPB is the overall evaluation of engaging in the behavior. Ajzen's (1991) original model and components are shown in Figure 4.

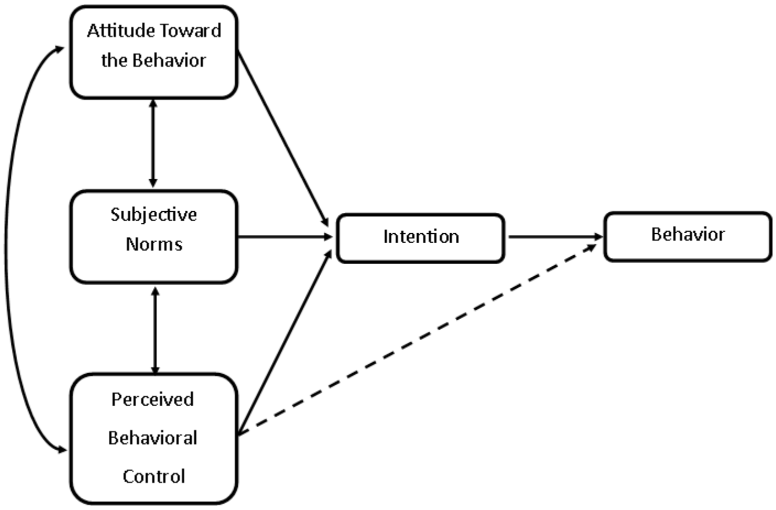


Figure 4. Components and relationships of the theory of planned behavior. Adapted from "The Theory of Planned Behavior" by Ajzen, 1991.

TPB selected studies. The TPB has been used in a variety of contexts. User behavior and intention may be accurately predicted so long as PBC and intention are compatible (Armitage & Conner, 2001). Table 10 highlights selected studies relevant to the research, and descriptions of the most relevant follow.

Table 10

Selected TPB Studies and Factors

Model / Environment	Technology	Factors/Variables	Method	References
Extended TPB/ entertainment	Online gaming	Flow experience, attitude, SN, PBC, AU, PENJ	Survey with CFA, PLS-SEM	Alzahrani et al. 2017
TPB/ consumer aviation	Travel on low-cost carriers	Attitude, SN, PBC buying intention, behavior	Survey with CFA, SEM	Buaphiban & Truong, 2017
Extended TPB/	e-learning adoption	Attitude, SN, PBC, social identity, social bond, intention, behavior	Survey with CFA, PLS-SEM	Chu & Chen, 2016
Extended TPB/ airline service	Pre-flight safety videos	Perception of pre-flight safety communication, attitude, PBC, SN intention	EFA; survey with CFA, SEM	Lee et al., 2018
Extended TPB/ consumer aviation	Travel on low-cost carriers	Attitude, SN, PBC, price, access, service quality, frequency, uncertainty avoidance, tech self-efficacy, intention	Survey with CFA, SEM	Pan & Truong, 2018

The impact of social influences on individual e-learning adoption was examined using the TPB by Chu and Chen (2016). Chu and Chen (2016) postulated that social pressures from a group can impact how an individual engages in a given behavior. In the study, the authors focused on the adoption of e-learning technology by extending the original TPB to include the factors of social identity and social bonds. Data from 201 university students were analyzed. Results confirmed that social influences of identity and bonding can moderate the effects of subjective norms on intention. The original TPB factors and relationships were also upheld, demonstrating how the TPB can be used in an educational domain to predict engagement in a behavior.

Alzahrani, Mahmud, Ramayah, Alfarraj, and Alalwan (2017) used an expanded TPB to explore factors that influence college students to play online games. The original TPB was extended to incorporate hypothesized variables related to playing games online, including social interaction, human-computer interaction, flow experience, and perceived enjoyment. Over 1,580 students were surveyed to model determinants of actual use (playing) of online games. Perceived enjoyment, a variable relevant to many interactive technologies, had the strongest impact on actual use. The other factors of the study also influenced actual use. The results confirm that the TPB may be used to predict usage behaviors when gaming technology is considered, and demonstrated that the model can be extended to explore behavior and engagement in an immersive environment.

The attitudes of air passengers that impact buying intention and actual purchase of low-cost carrier airline tickets were explored by Buaphiban and Truong (2017). A model based on the original TPB was used, and 791 air passengers in Thailand were surveyed to understand how the theorized factors impacted actual buying behavior. Results indicated that the original TPB relationships are reliable and valid factors to predict the actual behavior of buying airline tickets. PBC did not influence buying intention; however, it did positively influence actual buying behavior, revealing a new area of research. Although the variables were modified for the consumer aviation domain, additional factors that may influence buying behaviors were not considered.

Lee, Wang, Hsu, and Jan (2018) used the TPB to understand passenger perception toward pre-flight safety briefing videos. The original TPB was expanded to include indirect communication factors. By surveying 630 frequent air-traveling passengers, the authors concluded that perceptions toward pre-flight safety briefing videos were influenced by three main sub-dimensions of regulation and safety equipment, instructions for equipment, and general information. It was concluded that although the perception of communication from the videos positively and significantly influenced attitudes and PBC and therefore intention to watch the video, the perception of the video's communication effectiveness does not impact intention. The study demonstrated how the TPB can be expanded to understand the behaviors of consumers in an aviation domain toward a given technology and give insight as to how safety stakeholders can better relay information.

An extended TPB was used in a consumer aviation context to examine factors that influence passenger intention to use low-cost carrier airlines in China by Pan and Truong (2018). The model used the original TPB factors as well as others related to psychology, service, and culture. Results from 596 passengers indicated that access, uncertainty avoidance, price, service quality, and technology self-efficacy were significant influencers along with attitude and subjective norms. However, PBC and frequency of use did not significantly impact intention. The study demonstrated the adaption of the TPB for both a consumer and an aviation environment to investigate how attitude affects behaviors and intention.

In summary, the described studies identify several commonalities. First, the original TPB relationships presented by Ajzen (1991) were repeatedly supported in a variety of domains and technologies. Second, each research study integrated factors that were relevant to the unique environments and applicable technologies within the context of the research. Results consistently demonstrated the validity and robustness of the TPB as a versatile model suitable for research beyond social contexts to predict engagement in a behavior. A review of the relevant research revealed that, although the TPB has been used in both aviation and educational domains, immersive simulation technologies have not been analyzed using a TPB model. Additionally, the context of studies in the aviation domain is limited to consumer perception as opposed to training. The TPB has been reliably used in education environments, but the technologies studied do not feature the immersive qualities of VR. Although there are gaps, the studies validated that methodology is supported through the use of a pretest, pilot study, a survey instrument with a survey with Likert response items, descriptive statistical analysis, CFA, and SEM. The theory that the TPB is adaptable for the study is supported.

TPB effectiveness. The TPB has been utilized to investigate factors that influence behavior and predict actual behavior in a wide variety of contexts. There is documented support that the TPB can predict behavior reliably and that the addition of external variables can further enhance the predictive qualities of the model (Olushola & Abiola, 2017). The TPB has demonstrated its ability to predict intention with a 40-49% variance and explain behavior with a 26-36% variance (McEachan et al., 2011). Rise, Sheeran, and Hukkelberg (2010) postulated that this variance in discrepancy may detract from the assumption that the theory can sufficiently encompass all theoretical determinants of intention, and thus the addition of external, predictor variables can augment the predictive capability and validity of the model.

Other limitations of the TPB have been noted. Ajzen (1991) specified that measures of PBC and intention must be compatible with the given behavior to ensure accurate predictions. Sutton (1998) also noted that because prediction may have limited value based on the context and setting of the research, the model may be better served to explain the behavior to develop interventions if a behavioral change is needed. It has also been argued that because individual behavior is both complex and variable, the TPB may be better suited to understand the motives and perceptions of an individual rather than a group (Ajzen, 1991). Despite these limitations, the TPB offers an adaptable framework that considers a variety of attitudinal and social factors that may accurately predict engagement in a given behavior.

TAM extensions and combinations. The TAM and TPB models have been successfully merged to leverage the strengths of both models and offset limitations (Mathieson, 1991). In this way, researchers may identify the influence of social norms and predictive factors using TPB constructs while investigating technology acceptance, a strength of the TAM. As previously described, both models are versatile and adaptable to investigate different domains and technologies/given behaviors and to which new variables may be added. Venkatesh, Morris, Davis, and Davis (2003) merged several models, including the TAM and TPB, to explore user acceptance as well as actual use and created the Unified Theory of Acceptance and Use of Technology (UTAUT) and its predecessor the UTAUT2. However, the model was developed for information technology and has not been adopted as widely in other domains.

Extended and combined models selected studies. Table 11 highlights relevant research and the factors or variables that were measured. By examining the variables across different domains and technologies, the viability of the variables in the model may be considered. Following the table are descriptions of selected studies.

Table 11

Selected Combined Model Studies and Factors

Model / Environment	Technology	Factors/Variables	Method	References
TAM, health belief model/ health	Internet for health care	PHR, PU, ATU, health consciousness, health-related internet use, internet use for health information seeking, internet use for communication	Survey with PLS-SEM	Ahadzadeh et al., 2015
C-TAM, TPB/ education	Mobile learning	Attitude, SN, PBC, external beliefs, intention	Survey with CFA, SEM	Cheon et al., 2012
C-TAM, TPB/ education	e-learning tools	PU, PEU, ATU, BI, system usage, SN, SE, compatibility, perceived resources, sharing	Survey with CFA, PLS-SEM	Cheung & Vogel, 2013
UTAUT/ education	Tech. in general	PEXP, effort expectancy, social influence, FC, hedonic motivation, habit, intention, AU	Survey with CFA, PLS-SEM	Lewis et al., 2013
C-TAM/, TPB/ entertainment	Virtual worlds	PENJ, attitude, SE, SN, PEU, PU interpersonal influence, PBC, intention	Survey with CFA and SEM	Mäntymäki et al., 2014
UTAUT/ education	Mobile learning	PEXP, effort expectancy, FC	Survey with correlation and regression analysis	Onaolapo & Oyewole, 2018
UTAUT/ education	VR technology	PEXP, effort expectancy, social influence, FC, BI, Kolb's learning constructs	Survey with CFA and SEM	Shen et al., 2018

An extended TPB, with factors of the TAM, was used in an educational environment to investigate college students’ perceptions of using mobile learning (Cheon, Lee, Crooks, & Song, 2012). The authors sought to understand how beliefs influence the intention to adopt mobile devices for use in college coursework. Original factors and relationships of the TPB were expanded to include external beliefs that were categorized as attitudinal, normative, and control beliefs. Attitudinal beliefs were PEU and PU, taken from the TAM as variables that impact the TPB’s attitude construct. The results indicated that a TPB, augmented by external factors including PEU and PU, can explain student acceptance of a technology for educational purposes and provide insights for the integration of technology to ensure user acceptance.

Cheung and Vogel (2013) used a combined TAM and TPB model to predict student acceptance toward Google Applications for collaborative learning. The model used the original TAM variables, behavior-related variables, and subjective norm variables from the TPB, and additional variables to predict actual system usage. Data were collected from 136 university students. The original TAM variables were found to significantly influence the adoption of the technology for collaborative learning. Subjective norms significantly moderated the relationship between ATU and BI as did the ability to share information. The integration of the models allowed the researchers to better understand the factors that led to user adoption of the collaborative learning tool as well as the social context that facilitates adoption and use.

The UTAUT2 was used by Lewis, Fretwell, Ryan, and Parham (2013) to study how educators accept and use technology in higher education. The model included factors that predicted conditions for BI and actual use including hedonic motivation, performance expectancy, social influence, effort expectancy, habit, BI, and actual use; facilitating conditions was removed due to low loading and validity values. Participants were full-time university faculty who taught in a traditional environment (e.g., a face-to-face classroom); 46 educators participated in the study. Results indicated that social influence, effort expectancy, performance expectancy, and habit were important antecedents in determining how faculty used technology in the classroom. Understanding the context of how and why educators utilize technology in the classroom can instruct educators and administrators alike to ensure technology is appropriately integrated into the classroom.

Factors of perceived health risk (PHR) were investigated by Ahadzadeh, Pahlevan, Sharif, Ong, and Khong (2015) through the lens of using the Internet for health-related information seeking. The authors used a TAM combined with the health belief model to understand how PHR as well as health consciousness influenced Internet usage and considered mediating effects of PU and ATU. The authors found that PHR positively influenced using the Internet for health-related purposes. In the context of the study, PHR was related to the motivation individuals felt to change or adopt healthier behaviors; this is in contrast to the present study which suggests perceived risks regarding health may deter ATU.

The UTAUT was used by Onaolao and Oyewole (2018) to study how factors related to mobile learning influenced the use of smartphones by postgraduate students. The predictive model focused on the variables of performance expectancy, effort expectance, and facilitating conditions as new and innovative variables for the model. The data of 186 students were analyzed, and results revealed that the variables significantly and positively influenced students to use smartphones for mobile learning. Of the factors, performance expectancy was the strongest predictor of usage. The research provided insight on how specific factors influence smartphone usage for learning and how the UTAUT may be used in an educational setting.

Behavioral intention to use VR in a learning environment was correlated with learning modes (Shen, Ho, Ly, & Kuo, 2018). University students were shown a video of how VR could be utilized in a learning environment before data was collected via a survey. In total, responses from 376 students were analyzed. The variables of the model came from UTAUT and also included four modes of learning for a total of eight variables to predict BI. The four UTAUT variables were found to positively and significantly impact the intention to use VR for learning. Only one learning mode had a positive and significant effect on BI. The research demonstrated how UTAUT can be used in an education domain to understand BI toward an immersive technology such as VR. The additional learning mode variables further provided insight into how to encourage students to use VR in learning as well as how to develop VR programs for learning.

To summarize, the selected studies of extended and combined models offer important findings related to the research. First, the studies support the theoretical foundation upon which the model is based, namely that a combined TAM and TPB model with variables unique to aviation education and immersive simulation technology (i.e., VR) may be used to answer the research questions. Second, many of the studies incorporated variables that not only considered BI but predicted actual use of the given technology. Third, relationships between and among variables from different modes were validated. Finally, the UTAUT and combined TAM-TPB models may be used in a variety of domains with diverse technologies.

Gaps in the Research of the Ground Theories

The TAM and similar models have been used extensively in several domains, ranging from software in information technology to m-learning in education. As shown in the previous section, numerous studies have demonstrated that the TAM is a versatile and adaptable model that may be combined with other models such as the TPB.

The factors of PEU and PU have been validated numerous times as significantly influencing ATU as well as BI. The incorporation of new factors into the model further demonstrated that the TAM is suitable for examining many contexts and technologies. Studies using the TPB are also highlighted to demonstrate the validity of the model's factors. Factors from the TPB and UTAUT have also been successfully integrated into the TAM to create combined models, as in the present study. The extant research and models reflect various realms in which the ground theories of the model have been applied.

However, the aviation environment and VR technology have been largely overlooked, demonstrating a gap in the research. Limited studies have been conducted in the aviation domain, let alone aviation education. Only one study was found that utilized a TAM to examine immersive technology use in an aviation training environment, yet Wang et al. (2016) did not expand the model for aviation nor immersive technology. Further, the study investigated AR as opposed to VR; although both are examples of immersive technology, AR imposes textual, symbolic, and/or graphical information onto the physical world in real-time, whereas VR is a complete replacement of the physical world (Aukstakalnis, 2017). Given the immersive qualities unique to VR, it is evident that the original TAM factors may not be sufficient to fully explain user attitude toward and intention to use VR, necessitating an expansion to the original model. Other studies that utilized a TAM, a TAM derivative, or a TPB in an aviation domain did so from the point of consumers (Lu et al., 2009; Myers, 2019; Pan & Truong, 2018) as opposed to students. Those studies that focused on technology in an educational environment primarily examined e-learning tools, which are less immersive than VR and simulation. No research was found that specifically examines the factors that influence the acceptance and use of immersive simulation technology, specifically VR, for educational purposes, let alone aviation education.

Although several researchers have used combined TAM/TPB models to explore user perception and BI of different technologies in a variety of domains, fewer have used the relatively new UTAUT. The model utilizes factors from the original TAM and TPB models as well as those found in extended and combined models. Indeed, four of the 10 constructs were taken from studies that utilized TAM or TPB as a theoretical foundation but incorporated new and innovative measures to examine acceptance and/or predict behavior. Expanding upon newer constructs that have been previously validated by combined models demonstrates the versatility of the TAM, the TPB, and combinations thereof. Previously validated, combined models also strengthen the theoretical foundation of the model, as elements from multiple models and theories are incorporated. These studies provided a foundation for more understanding of how students accept and use immersive technology for training.

Constructs for the Theoretical Model

The model for the study was an extended TAM that incorporated constructs from TPB and previously validated extensions of TAM and UTAUT. The new constructs directly related to aviation, training, and VR. The constructs may be adapted to other aviation technologies or for VR use in other domains. In this section, the constructs are explained and justification provided as to how the model fills a gap in both aviation training and VR technology. Ten constructs are used in the model, derived from relevant and related research. They are attitude toward use (ATU), behavioral intention (BI), perceived behavioral control (PBC), perceived ease of use (PEU), perceived enjoyment (PENJ), performance expectancy (PEXP), perceived health risk (PHR), perceived usefulness (PU), self-efficacy (SE), and regulatory uncertainty (RU). Table 12 details the relevant research used to derive the factors (constructs) for the model as well as major findings for each factor.

Table 12

Sources and Major Findings for the Model Constructs

Factor	Technology; Domain	Major Findings	References
Attitude toward use (ATU)	e-learning; education	ATU influences BI ATU is influenced by PU and PEU	Cheung & Vogel, 2013; Esteban-Millat et al.; 2018; Lemay et al., 2018; Park, 2009
	VR hardware; consumer use	ATU is impacted by PEU, PENJ, and PU	Manis & Choi, 2018
Behavioral intention (BI)	e-learning, education	BI is influenced by ATU and SE	Cheung & Vogel, 2013; Park, 2009
	VR; education	BI is influenced by PEXP	Shen et al., 2018
	Check-in kiosks; airline service	BI is positively influenced by PBC	Lu et al., 2009
Perceived behavioral control (PBC)	Check-in kiosks; airline service	PBC positively influences PEU and BI	Lu et al., 2009
	Information technology; commercial business	PBC is a strong determinant of PEU	Venkatesh, 2000
Perceived ease of use (PEU)	e-learning, education	PEU influences PU, ATU	Cheung & Vogel, 2013
	e-learning; education	PEU influences ATU	Esteban-Millat et al., 2018; Park, 2009
	e-learning; education	PEU impacts PU	Gong et al., 2004
	Check-in kiosks; airline service	PEU impacts PU	Lu et al., 2008
	VR hardware; consumer use	PEU impacts PU	Manis & Choi, 2018
Perceived enjoyment (PENJ)	e-learning tools; education	PENJ significantly influences PEU and PU	Abdullah & Ward, 2016; Chang et al., 2017
	VR; education	PENJ strongly influences perceived learning using VR	Makransky & Lilleholt, 2018
	VR hardware; consumer use	PENJ positively influences PU and ATU	Manis & Choi, 2018
Perceived health risk (PHR)	Internet; health care	PHR impacts PU, ATU, and use	Ahadzadeh et al., 2015
	sUAS; aviation	PR negatively impacts ATU	Myers, 2019
Perceived usefulness (PU)	e-learning, education	PU influences ATU	Cheung & Vogel, 2013; Esteban-Millat et al., 2018
	e-learning; education	PU is influenced by PEU	Gong et al., 2004
	Check-in kiosks; airline service	PU is influenced by PEU	Lu et al., 2008
PU Continued	VR hardware; consumer use	PU is influenced by PEU	Manis & Choi, 2018

Table 12 Continued

Factor	Technology; Domain	Major Findings	References
PU Continued	e-learning tools; education	PU is influenced by PEU and PENJ	Abdullah & Ward, 2016; Chang et al., 2017
Performance expectancy (PEXP)	Tech. in general; education	PEXP had a significant impact on use	Lewis et al., 2013
	Mobile learning; education	PEXP was the strongest predictor of use	Onaolapo & Oyewole, 2018
	VR; education	PEXP had a significant impact on use	Shen et al., 2018
Regulatory uncertainty (RU)	Bitcoin digital currency; consumer and developer use	RU may impact ATU and BI	Folkinshteyn & Lennon, 2016
	Mobile payment; consumer use	Perceived RU partially impacts perceived risk factors, negatively impacting intention	Yang et al., 2015
Self-efficacy (SE)	e-learning tools; education	SE impacts PU	Abdullah & Ward, 2016
	e-learning, education	SE impacts BI	Cheung & Vogel, 2013
	e-learning; education	Computer SE positively effects PEU and BI	Gong et al., 2004
	Simulation-based learning; education	SE impacts PEU; SE does not impact PU	Lemay et al., 2018
	e-learning; education	SE positively influences PEU, PU, and BI; SE does not influence ATU	Park, 2009
	Learning systems; education	Computer SE directly influences PEU	Venkatesh & Davis, 1996

These 10 constructs have been utilized in multiple studies in various domains, including education, training, and information technology and systems. However, technologies related to virtual environments and the aviation environment have been neglected. Further, the overlap of aviation training and immersive simulation revealed only one study using the original TAM (Wang et al., 2016). The factors that motivate an aviation student to accept and use the immersive simulation technology for training have remained unexamined. The model incorporated validated constructs and introduces new constructs that may be adapted for other studies related to aviation technology or VR technology. The operational definitions for each construct are provided in Table 13. Survey questions were created for each construct with Likert response items ranging from

1 (strongly disagree) to 5 (strongly agree). The survey instrument with all questions related to each construct can be found in Appendix B.

Table 13

Operational Definitions of the Model Constructs

Factor	Definition	Variable Type	Reference
Attitude toward use	The degree to which a student has a favorable or unfavorable appraisal or evaluation of VR for flight training.	Endogenous	Esteban-Millat et al., 2018; Gong et al., 2004; Lee et al., 2018; Manis & Choi, 2018; Park 2009
Behavioral intention	An indication of how hard a student is willing to try or how much effort they are planning to exert in order to use VR for flight training.	Endogenous	Esteban-Millat et al., 2018; Gong et al., 2004; Lee et al., 2018; Manis & Choi, 2018; Makransky & Lilleholt, 2018; Shen et al. 2018
Perceived behavioral control	The extent to which an aviation student feels able to control using VR technology for flight training.	Exogenous	Chang et al., 2018; Pan & Truong, 2018
Perceived ease of use	The degree to which a student believes that using VR for flight training would be free of effort.	Endogenous	Esteban-Millat et al., 2018; Gong et al., 2004; Lee et al., 2018; Makransky & Lilleholt, 2018; Manis & Choi 2018, Park, 2009; Richardson, 2017
Perceived enjoyment	The degree to which using VR for flight training is perceived to be enjoyable in its own right apart from any performance consequences that may be anticipated.	Exogenous	Chang et al., 2018; Lee et al., 2018; Makransky & Lilleholt, 2018; Manis & Choi, 2018
Performance expectancy	The degree to which a student believes that using VR for flight training will improve flight performance as compared to an FTD.	Exogenous	Onaolapo & Oyewole, 2018; Shen et al., 2017
Perceived health risk	The perception a student forms and revises based on the possible physical health risks of using VR for flight training.	Exogenous	Ahadzadeh et al., 2015; Myers, 2019
Perceived usefulness	The degree to which a student believes that using VR for flight training would enhance his or her performance.	Endogenous	Esteban-Millat et al., 2018; Gong et al., 2004; Lee et al., 2018; Manis & Choi, 2018; Makransky & Lilleholt, 2018; Park, 2009; Richardson, 2017
Regulatory uncertainty	The degree to which the lack of FAA regulations regarding the use of VR for flight training impacts attitude toward the technology.	Exogenous	Folkinshteyn & Lennon, 2016; Yang et al., 2015
Self-efficacy	Perception of one’s flight skills in the virtual and real-world environments.	Exogenous	Chang et al., 2018; Gong et al., 2004; Pan & Truong, 2018

Theoretical Framework and Hypotheses

The TAM has been used to explain a user's behavioral intention to use a given technology (King & He, 2006), while the TPB has been used to explain and predict behavioral intention (Ajzen, 1991). The review of relevant literature was used to inform the conceptual framework of the model for the study, including hypothesized relationships between variables. A theoretical framework for aviation student's intention to use VR for flight training was based on the preceding literature review. Aviation student's behavioral intention to use VR for flight training was chosen as the outcome variable. The framework's predictor variables were derived from the TAM and TPB. The exogenous variables included PBC, PENJ, PEXP, PHR, RU, and SE. The endogenous variables included ATU, PEU, PU, and BI.

All hypotheses were derived from previously validated relationships utilizing TAM, TPB, or an extension or combination thereof, although the factors have been combined in a new way for the aviation environment and VR technology. The theoretical framework highlights the relationships between the predictor variables and intention as opposed to actual behavior. Figure 6 shows the constructs and theorized relationships between them; of note, interrelationships are currently unknown. The model also did not include other factors that may influence behavioral intention. As the scope of the study was limited, the factor and path selections in the model were realistically restricted and only include relevant factors derived from the literature review. Relationships were primarily direct between the outcome and predictor variables. The following relationships are graphically depicted in Figure 5 and subsequently described.

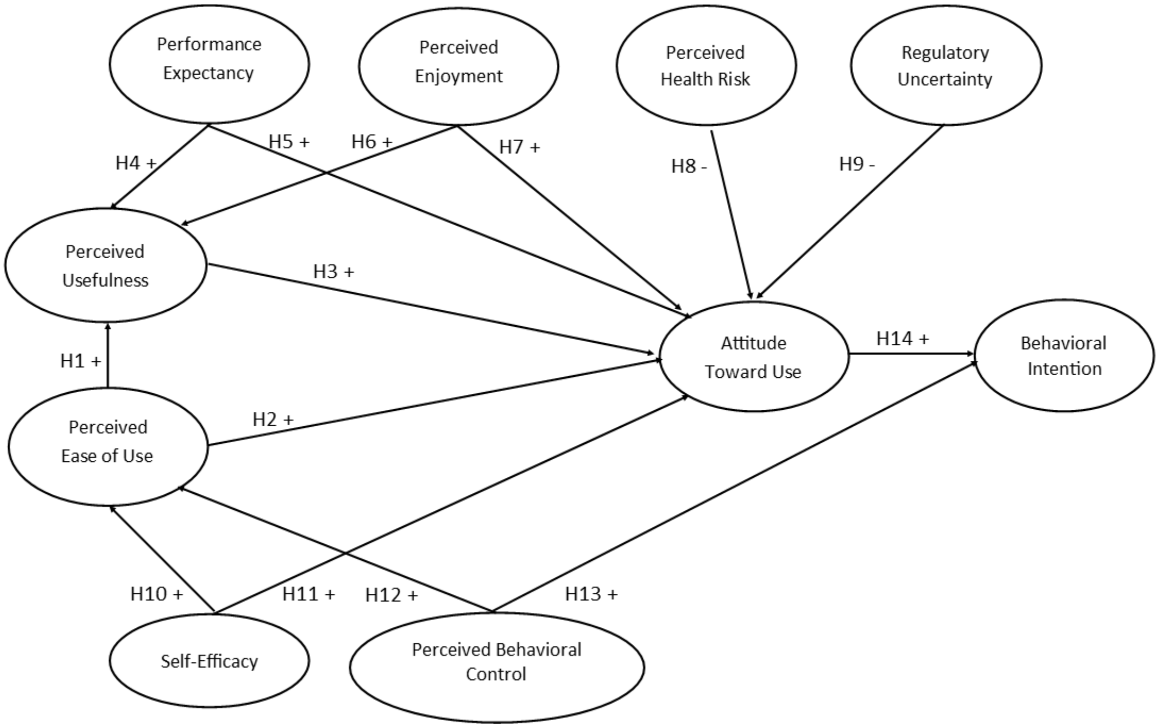


Figure 5. Research theoretical framework and hypotheses.

The review of the relevant literature for the study was used to develop the conceptual framework of the model, including the theorized relationships between the constructs. The hypotheses for the study included four new hypotheses derived from previous studies: PEXP was shown to strongly impact use (Lewis et al., 2013; Onaolapo & Oyewole, 2018; Shen et al., 2018); however, the construct of ATU and therefore relationships between ATU and PEXP were not explored. The construct of RU has not been used extensively as a TAM construct, nor has it been used in the domains of aviation and education. The negative relationship between RU and ATU was theorized and unique to the model. Although the theorized relationships were derived from previous, validated studies, the relationships have not been tested nor validated for using VR for flight training. Therefore, 14 hypotheses were formed to investigate the research questions.

The relationship between perceived ease of use and perceived usefulness stems from Davis (1989). It was expected that an increase in perceived ease of use will increase the ease of using VR technology for flight training, thus increasing performance. This concept has been validated in numerous other studies across a variety of domains and technologies, as demonstrated by Gong et al. (2004), Lu et al. (2008), Manis and Choi (2018), and others. As a necessary part of the TAM, H1 was hypothesized:

H1: Perceived ease of use positively influences perceived usefulness.

Perceived ease of use was also hypothesized to positively and directly influence attitude toward use. A user may expect that using VR for flight training will not require extraneous effort and no more so than other immersive technology used in flight training (e.g., an FTD or ATD). If the technology is easily mastered, the user will be more inclined to use it. Davis (1989) first demonstrated this relationship in the original TAM, and it has been subsequently validated by Cheung and Vogel (2018), Lemay et al. (2018), Manis and Choi (2018), and others. The relationship was hypothesized in H2 as:

H2: Perceived ease of use positively influences attitude toward use.

The third hypothesis supports a relationship validated in Davis' (1989) original TAM and subsequent studies using the TAM and its variants, such as by Cheung and Vogel (2018) and Esteban-Millat et al. (2018). Using VR technology for flight training offers benefits that may enhance flight training and may not be found in other technologies, thereby positively impacting attitude toward using the technology. The hypothesized relationship was:

H3: Perceived usefulness positively influences attitude toward use.

A relatively new construct, performance expectancy was used by Lewis et al. (2013), Onaolapo and Oyewole (2018), and Shen et al. (2018) in the UTAUT, a variant of the TAM. Performance expectancy relates to the belief that VR technology will improve flight performance as compared to an FTD. Previously, performance expectancy has been associated with the constructs of behavioral intent and actual use in the UTAUT model. The hypothesized relationship between performance expectancy and perceived usefulness is a new relationship incorporated into the model. It was theorized that as the user's belief that using VR technology for flight training will improve flight performance as compared to an FTD, so too will the user's belief that VR is a useful tool to enhance performance. Both constructs measure the performance value of the technology. Thus, a new relationship was hypothesized:

H4: Performance expectancy positively influences perceived usefulness.

The fifth hypothesis depicts a relationship between performance expectancy and attitude toward use. As the user's expectancy increases in a favorable manner, it was theorized that attitude to use VR for flight training will also increase. The UTAUT does not utilize the attitude toward use construct but proposes direct relationships between variables and behavioral intent thereby affecting actual use behavior. The construct has therefore been adopted from the UTAUT model and placed within the model of the study and a new relationship supported. The H5 hypothesis was:

H5: Performance expectancy positively influences attitude toward use.

Perceived enjoyment is another relatively new construct incorporated by Abdullah and Ward (2016) in the General Extended Technology Acceptance Model for E-Learning (GETAMEL). Enjoyment is an intrinsic motivation and, in this context, describes the extent to which the user will appreciate the experience of a technology in its own right, regardless of performance expectations or results (Abdullah & Ward, 2016). Learners who believe that using a given technology is enjoyable are also more likely to believe that the technology is useful and positively affects learning. The positive relationship between perceived enjoyment and perceived usefulness has been supported by Abdullah and Ward (2016) as well as Chang et al. (2017). The hypothesized relationship was:

H6: Perceived enjoyment positively influences perceived usefulness.

Manis and Choi (2018) are among the only researchers to examine the relationship between perceived enjoyment and attitude toward using VR technology. They found that consumer perception of enjoyment was a key belief variable impacting motivation to use VR hardware, thereby influencing behavioral intent. Individual enjoyment of VR for flight training may affect an aviation student's attitude to use VR in training. The hypothesis was:

H7: Perceived enjoyment positively influences attitude toward use.

An increased perception of health risk of using VR for flight training may negatively impact acceptance and attitude toward using the technology. In the VE, users may experience health concerns due to simulator sickness. Those who have little to no experience with VR may also be less inclined to use the technology for flight training than those with experience. Perceived risk has been used in the aviation environment in association with sUAS (Clothier, Greer, Greer, & Mehta, 20015; Myers, 2019) and airline check-in kiosks (Lu et al., 2009). Lu et al. (2009) found that perceived risk negatively influences behavioral intent, while Myers (2019) found perceived risk negatively impacts attitude toward use. Perceived health risk has not been examined for aviation, education, nor VR technology. Building upon these relationships, H8 was:

H8: Perceived health risk negatively influences attitude toward use.

The uncertainty caused by the lack of regulations regarding the use of VR for flight training may also impact attitude toward using the technology. Because VR is not currently approved for flight training, aviation students may be hesitant to use the technology. Moreover, the FAA is notoriously slow to adopt new regulations and is often deemed reactive as opposed to proactive regarding updating or creating regulations especially when technology is concerned. Aviation students' attitude toward using VR for flight training may, therefore, be negatively impacted by regulatory uncertainty. Although this construct has been discussed in the theoretical capacity by Folkinshteyn and Lennon (2016) and Hong, Nam, and Kim (2019) and used in an extended TAM by Yang, Liu, Li, and Yu (2015), it has not been widely used. The construct and relationship are unique to the model and was formed as:

H9: Regulatory uncertainty negatively influences attitude toward use.

Self-efficacy is a user's individual judgment of how well a course of action can be executed in a prospective situation. Participant perception of VR technology self-efficacy and flight performance self-efficacy were measured. The aviation students' belief in their flight abilities, as well as their confidence in using VR technology, may positively influence their belief that using VR for flight training will be easy. This construct has been validated by Gong et al. (2004), Lemay et al. (2018), Park (2009), and Venkatesh and Davis (1996). Thus, the hypothesis was:

H10: Self-efficacy positively influences perceived ease of use.

Aviation student’s flight and VR self-efficacy may also influence attitude toward using VR technology for flight training. Those students who are confident in their flight abilities and/or their ability to use VR technology may be more favorably inclined toward using VR. Those students with less confidence in their abilities may have an unfavorable evaluation of using VR for flight training. This, in turn, will impact behavioral intention. Notably, this relationship has had mixed results in the TAM. Gong et al. (2004) found that SE positively affects behavioral intent; however, they did not examine the relationship between computer self-efficacy and attitude toward using web-based learning systems. Park (2009) found that although self-efficacy positively influenced behavioral intent to use e-learning, there was not a statistically significant relationship between e-learning attitude and self-efficacy. The relationship was hypothesized as:

H11: Self-efficacy positively influences attitude toward use.

The next hypothesis analyzed perceived behavioral control, a construct from the TPB. Perceived behavioral control refers to the perceptions formed about the ease or difficulty of using VR for flight training. Those aviation students who perceive they have resources available to them may believe that VR will be easy to use for flight training. This relationship was validated in extended models by Lu et al. (2009) and Venkatesh (2000). H12 was, therefore, formed as:

H12: Perceived behavioral control positively influences perceived ease of use.

As a component of Ajzen’s (1991) original TPB model, perceived behavior was theorized to have a direct relationship with behavioral intent. The construct has a strong influence on behavioral intention as it considers available cognitive and situational resources required to perform a behavior (Ajzen, 1991; Lu et al., 2009). Aviation students who believe they have the opportunity to successfully use VR for flight training may have a greater amount of perceived behavioral control. The relationship has not been widely investigated beyond Lu et al. (2009). The hypothesis was:

H13: Perceived behavioral control positively influences behavioral intention.

The final hypothesis has been validated by numerous researchers, including Cheung and Vogel (2018), Esteban-Millat et al. (2018), Lemay et al. (2018), and Park (2009). It was hypothesized that attitude toward using VR for flight training will directly and positively influence the behavioral intention to use VR for flight training. Thus, H14 was identified:

H14: Attitude toward use positively influences behavioral intention.

Chapter Summary

This chapter described the relevant literature related to the technology and domain of the study, including simulator use in aviation training, a review of virtual reality and its use in training and education, and the current state of immersive simulation technology in aviation training. A review of the literature revealed that although immersive simulation technology is an effective and efficient tool for aviation training, the published research has not yet thoroughly explored VR in aviation education. Additionally, the potential benefits of using VR in aviation education outweigh the risks, as VR can enhance the acquisition of psychomotor skills, visual-spatial skills, cognition, and memory.

The ground theories of the study were discussed including the TAM, TPB, combined models, and extended versions of TAM and TPB. The studies reviewed included a variety of educational contexts, technologies, and behavior in different domains. Although VR technology was considered, it was limited to either a consumer or a science-related domain as opposed to aviation education. When the domain of aviation was studied, it was from the point of view of a consumer as opposed to a student. Thus, there are substantial gaps in understanding the factors that influence aviation students' intentions to use VR technology for flight training. These gaps in the research were presented, justifying the need for the research.

Finally, the theoretical framework was established, and justification for each construct was provided. Research related to defining the constructs, creating items to measure each construct, and relationships among constructs were presented. Each construct was adjusted to reflect the research questions related to using VR for flight training. Although new relationships between constructs were created, the majority were supported by related studies and previously validated models and questions.

Chapter III will describe the research design and methodology of the study as well as data collection, treatment, and analysis.

CHAPTER III

METHODOLOGY

This chapter describes the research methods for the study, including the approach, design, population and sample, instrument, data treatment, and ethical concerns. Explicit details will allow others to replicate the study, increasing the reliability and validity of the constructs, model, and survey instrument.

Research Method Selection

This study utilized a quantitative research method with a deductive, non-experimental survey design. Quantitative data analysis employed a Structural Equation Modeling (SEM) method. Deductive reasoning was an appropriate research path as the study was developed from validated models (TAM and TPB), had pre-defined hypotheses to test, resulted in empirical data, and followed a path from the general to the specific (Babbie, 2013).

The research design was non-experimental as variables were not manipulated, causation was not determined, and participants were not randomly assigned (Vogt, Gardener, & Haeffele, 2012). Participant intention and attitude were being considered and analyzed through a survey; causal relationships were not identified nor was it appropriate to manipulate the variables in the present study. A cross-sectional design was used for the research. This design observes a sample of the target population at a single point in time as opposed to over a period of time (Vogt et al., 2012). Cross-sectional studies collect data once without the manipulation of the environment. Different population groups may be compared when demographic data is collected (e.g., age, flight hours, previous VR usage).

Vogt et al. (2012) describe surveys as the most common research design used in social and behavioral sciences thus making it an appropriate design. Surveys allow data to be obtained directly from participants, and it is assumed to be reliable and truthful. Additionally, surveys allow for the collection of a large amount of data in a systematic method through structured questions. As the goal of the study was to understand factors influencing student's attitude toward and intention to use VR for flight training, a survey design provided subjective data directly from aviation students. Responses were anonymous, and minimal personal data were collected beyond demographics to report in aggregate. It was reasonable to assume that participants provided reliable, quality responses. Data quality is also important for SEM; anonymity allows participants to respond openly and honestly. The survey may also be sent to only the target population and the results generalized to the group rather than an individual.

Population/Sample

Population and sampling frame. The target population for the study was aviation students enrolled in an FAA-approved Part 141 pilot school at an accredited college or university in the U. S. The population can change regularly as students join and leave flight training programs for various reasons (e.g., health, disinterest, leaving the institution, finances). As such, it is difficult to define the parameters of the population as a whole.

Using a sampling frame, or a list of components from which a probability sample may be drawn, was, therefore, required to restrict how the sample was selected and make data collection a manageable process. The sampling frame for the study was refined to FAA-approved Part 141 pilot schools, invited, accredited colleges and universities, allowing for a sampling pool of several thousand students. The colleges and universities invited to participate included 39 colleges and universities from across the United States. Appendix C details information about these institutions. Participants had to be enrolled in the institution's Part 141 pilot training program and have begun flight training. All participants had to be at least 18 years of age. American citizenship was not a requirement for participation, as many accredited college and university flight training programs train international students using Part 141 standards. The approximate size of the sampling frame was 7,982 aviation students. The total number of flight students was collected from the invited institutions to ensure participants were representative of the population and increase the generalizability of the results.

Sample size. Computing sample size for a study using SEM depends upon the number of observed and latent (unobserved) variables in the model, probability, statistical power, and anticipated effect size (Soper, 2019; Westland, 2010). SEM analyses are more sensitive to sample size than other multivariate analyses, and a small sample size may impact validity testing of the model resulting in poor model fit (Byrne, 2010; Hair et al., 2010). A sufficient sample size also ensures inferences may be made about the target population (Vogt, Vogt, Gardner, & Haeffele, 2014). A sample size that is too small may result in inaccurate or inappropriate conclusions regarding the population as well as inaccurate estimate analyses in SEM (Kline, 2016; Westland, 2010).

Kline (2016) states four factors that affect sample size requirements. The first factor to consider is the number of parameters used in the model, as more complex models require more estimates and therefore larger samples. Second, the type of data (e.g., continuous, normally distributed, linear data) and the types of analyses used may impact sample size as well as the ability to use certain estimation methods. Third, low reliability scores may need higher sample sizes to "offset the potential distorting effects of measurement error" (Kline, 2016, p. 15). Reliability may be impacted by type and amount of variables as well as the amount of missing data. Finally, factor analyses generally require large sample sizes to explain unequal proportions of variance. Westland (2010) notes that a "practical viewpoint" when determining sample size considers if it is (a) *a priori*, as in what sample size is sufficient to meet the researcher's belief regarding the minimum effect which should be detected; (b) *ex posteriori*, or the sample size needed to detect the minimum effect actually found in the existing test; or (c) *sequential test optimal-stopping*, wherein sample size is incremented until deemed sufficient (p. 482).

Having established that a large sample is required for SEM, the minimum sample size must be defined. Although Iacobucci (2010) proposes that smaller sample sizes may be used when variables are reliable, effects are strong, and the model simple, she also notes that simplifying load on a factor in a less complex model may result in bias. Thus, a sample size between 100 and 150 for simple models with three or more indicators per factor may suffice. Kline (2016) suggests a minimum sample size should be 20 participants per parameter but that a sample size of 200 may be too small for a complex model or when missing data is apparent. Further, Kline states that a sample size of fewer than 100 is untenable except for very simple models and that studies may be underpowered if the sample size is fewer than 200 participants. Hair et al. (2010) note that increasing sample size may produce too high of a power level for the statistical test, thus increasing statistically significant findings. This could be detrimental if almost every effect is deemed statistically significant. Smaller effect sizes need larger sample sizes to achieve the desired power level, and an increase of sample size may be used to increase power. Larger sample sizes of 200 or more will be less impacted by normality issues of the data. Hair et al. (2010) provide the following guidelines to estimate sample size, described in Table 14.

Table 14

Suggested Minimum Sample Sizes Based on Model Complexity

Minimum Sample Size	Number of Constructs	Model Notes
100	1 – 5	Each construct has 3+ items (observed variables) and high item communalities of 0.6 or greater
150	1 – 7	Modest item communalities of 0.5 and no underidentified constructs
300	1 – 7	Low items communalities of 0.45 or less and/or multiple underidentified constructs
500	7 +	Some items may have lower communalities and/or fewer than three measured items

Note. Adapted from Hair et al. (2010, p. 574).

A more appropriate method to calculate sample size requires a formula designed for SEM studies. Westland (2010) provides a minimum sample size formula, shown in Equation 1. This formula has been used in other SEM studies to calculate the minimum sample size (Myers, 2019; Pan & Truong, 2018).

$$n = \frac{1}{2H}(A\left(\frac{\pi}{6} - B + D\right) + H$$

$$+\sqrt{(A\left(\frac{\pi}{6}\right) - B + H)^2 + 4AH(\frac{\pi}{6} + \sqrt{A} + 2AB - C - 2D))} \qquad (1)$$

Where:

$$A = 1 - \rho^2$$

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

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

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

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

Thus, calculating an appropriate sample size is not straightforward but may be calculated based on the number of latent variables and observed variables in the model. Soper (2019) created an online SEM sample size calculator using Westland's equation. The user sets the parameters of the study and chooses effect size, power level, and probability level and defines the number of latent and observed variables. The model for the study has 10 latent variables and 34 observed variables. Soper's a-priori sample size calculator determined a minimum sample size of 475 for an anticipated effect size of 0.2, the desired power level of 0.8, and a probability level of 0.05.

Sampling strategy. Proportional quota sampling, a form of non-probability sampling, was used for the study. Privitera (2017) defines this form of sampling as "a type of quota sampling used when the proportions of certain characteristics in a target population are known" (p. 139). This technique is appropriate when participants can be chosen to proportionately represent the sample and the population. Institutions will be categorized proportionately by the number of students in the aviation training program.

The target population was divided into an accessible population, or strata, consisting of accredited colleges and universities at FAA-approved Part 141 pilot schools. Students were contacted by aviation faculty within the university to join in the study and self-selected to participate. Completed surveys that met eligibility requirements for the study (e.g., the respondent is a student of 18 years or older enrolled in an FAA-approved Part 141 pilot school) were used in the analysis. A proportionate number of responses from each university were analyzed based on either enrollment size. Further, this approach allows for sampling to meet proportionate demographics from each institution. In this way, a given demographic was not over-represented in the sample. Random sampling was inappropriate for the study as direct access to the aviation students enrolled in each invited institution was not provided.

Data Collection Process

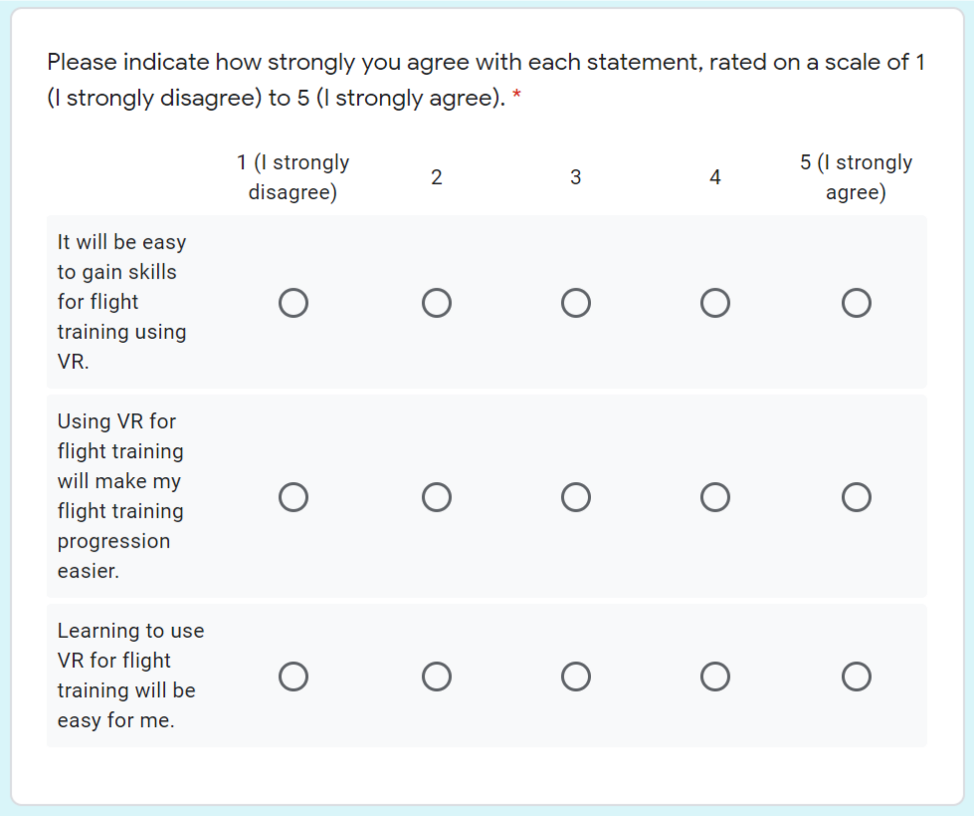
Design and procedures. The study used a non-experimental, cross-sectional survey design followed by quantitative data analysis using an SEM approach. A cross-section survey design allowed the investigation of a population at a specific point in time. Results from surveys may be quantitative, qualitative, or a combination thereof (Vogt et al., 2012). The study survey employed Likert response items which were coded for quantitative analysis. Vogt et al. (2012) note that the Likert format has many positive features, including the summation of responses for individual questions for an overall assessment and the ability to easily code answers. An SEM approach to analyze the data followed. The TAM and TPB, as well as extensions and combinations of the models, have been utilized for several decades to examine user attitude toward and intention to use various technologies. The ubiquity of the TAM and TPB created widespread research on user acceptance of and intent to use many technologies. Because the study expanded the TAM for different technologies and different domains, a survey allowed the integration of questions from previously-validated surveys as well as questions customized for VR and flight training.

There are six stages of SEM, as described by Hair et al. (2010): define each construct, develop the overall measurement model, design the study, assess the validity of the measurement model, create and specify the structural model, and assess the validity of the structural model. These stages are incorporated in six steps of the model: develop the survey instrument, gain Institutional Review Board (IRB) approval, perform a pilot study, revise the survey instrument, collect data through a large-scale survey, and finally analyze the data.

The first step of the study was to define each construct and develop the survey instrument based on previous studies and with input from flight training and immersive simulation technology experts. Hair et al. (2010) identify two common approaches of using scales from prior research and developing new scales to measure a construct. Factors of the model were derived from foundation theories of TAM and TPB. Relationships of the factors were hypothesized from extant literature to create the research framework. Constructs were operationalized and measurement scale items and scale type determined.

The path diagram was created with indicator variables assigned to latent constructs. Indicator variables were designed to empirically support the validity of the constructs, ultimately in the form of survey questions and response items. The survey was designed using foundation theories from previous studies as a guide, as described in

Chapter I and in the review of the relevant literature. A structured questionnaire was designed using previously validated questions as well as questions customized for aviation, flight training, and VR technology (see Appendix B). The process of using questions from previous, related studies and adapted for the context of the study strengthened the validity of the questions and saved time. Questions were precise, short, and clear with non-biased and non-negative responses ranked using a Likert response item format. The ordering of the questions was grouped by construct, enabling participants to easily follow the content logically and consistently. Within each construct grouping, indicator variables were shuffled for individual participants to counteract potential issues with ordering effect. Figure 6 depicts a construct and Likert response indicator variables in Google Forms. Demographic data was collected, although all answers were anonymous.



Please indicate how strongly you agree with each statement, rated on a scale of 1 (I strongly disagree) to 5 (I strongly agree). *

	1 (I strongly disagree)	2	3	4	5 (I strongly agree)
It will be easy to gain skills for flight training using VR.	○	○	○	○	○
Using VR for flight training will make my flight training progression easier.	○	○	○	○	○
Learning to use VR for flight training will be easy for me.	○	○	○	○	○

Figure 6. A construct and indicator variables in the study survey.

The survey instrument was reviewed by a panel of subject matter experts (SMEs) to ensure the face validity of the items and constructs. The SMEs had familiarity with flight training, the learning environment of an aviation institution, and immersive simulation technology such as FTDs and VR. These experts evaluated the wording, structure, and order of the questions as well as responses and scale of the items. Survey questions were modified as required.

The second step was gaining approval from the ERAU IRB. This was an important consideration as the study required human participation.

The third step was to conduct a pilot study to test the reliability and validity of the survey instrument; a sample of 40 participants was deemed an appropriate sample size.

This step allowed for the review and modification of questions as appropriate before mass distribution. A confirmatory factor analysis (CFA) was used to test the relationship of the indicator variables to the constructs as well as the relationships between the constructs. Cronbach's alpha was used to test the reliability of the survey items and the constructs. Factor loadings, or the representation of regression weights in the model, were assessed. Items with non-significant *p*-values were assessed with methodical removal from the model based on model fit and literature support, with comparison to the original model. Model fit was evaluated per Byrne (2010) and Hair et al. (2010). A post-hoc or model specification process was used if a good model fit was not obtained. Should all values meet the specified requirements, the model was deemed fit.

Following the pilot study, in step four, the survey instrument and protocol was revised based on the results. A large-scale survey was then conducted to collect data in step five. The survey instrument was disseminated through an online platform, Google Forms. The consent form was available through the platform with an agreement question (Yes/No). Each question and response item was force-choice. Questions were written clearly and concisely and organized by factor. Points of contact from each invited institution sent an email to aviation students at their respective institutions with an explanation of the study and a hyperlink to the survey instrument. Aviation students received an initial invitation to participate in early January 2020 and a reminder email in late March 2020. Verbiage for the consent form, email invitation sent to participants, and associated items can be found in Appendix A.

Step six occurred upon completion of data collection. Data analysis consisted of descriptive statistical analysis, CFA, and full structural model testing. This data analysis is appropriate when investigating the relationship between latent constructs (Westland, 2010).

Demographic data were used to examine the sample profile to evaluate representativeness. Descriptive statistics were used to determine the maximum, minimum, mean, and standard deviation of the data as appropriate. Missing values and outliers were assessed followed by assumption testing. SEM may be used to analyze the multiple and interrelated dependence relationships, explain the relationships, account the measurement error of estimation, and examine unobserved conceptual relationships (Hair et al., 2010). CFA and structural modeling was an appropriate technique, as the study incorporated untested factors and may be used to test the theoretical framework.

Apparatus and materials. The extended TAM survey was accessed through an online survey instrument, Google Forms, and distributed via email. The instrument included a short introduction on the purpose of the study, procedures of the survey, and a consent form. A video was incorporated to ensure all participants had a baseline understanding of VR technology as a mechanism for flight training. The first set of questions determined participant eligibility to participate in the study. The second set of questions collected demographic information and contained items for examining factors of the model.

Sources of the data. A non-experimental, cross-sectional survey design was used and data collected from the survey were quantitative. Survey administration may occur through self-administration, face-to-face interviews, or telephone communication (Babbie, 2013). Self-administered surveys may be further categorized as mailed, on-site, or online surveys (Fink, 2006). Babbie (2013) describes the online survey as “an increasingly popular method of survey research” and “one of the most far-reaching developments of the late twentieth century” (p. 282). The design employed an online, self-administered survey, hosted on the internet and distributed via email. An online survey is advantageous due to the ease of distribution and global reach, ability to “opt-out” at any time, ability to provide links and descriptions for unfamiliar terms, and automatic collection and aggregation of data (Fink, 2006). However, Fink (2006) points out that online surveys are dependent upon reliable internet connection and the ability of the respondent to access the survey through an internet browser.

FAA-approved Part 141 pilot schools housed within U.S. accredited colleges and universities were invited to participate in the study. Representatives from each school were contacted via email with an invitation to participate, details on the methodology of the study, IRB application and approval documents once obtained, and the survey instrument, if required. Each representative was provided with an email and link to the survey instrument which was sent to each aviation student in the respective program. The email included an introduction, a survey link with the survey instrument, and contact information of the researcher; verbiage of the email may be found in Appendix A. The survey link included an informed consent form and screening questions, a short video demonstrating VR for flight training, demographic questions, and the survey instrument. No personal or identifying information was collected. Data collection began early January 2020 and ended in late March 2020.

Ethical Consideration

Vogt et al. (2012) state that in comparison to data collection using observation and experimentation, ethical concerns in survey research are “relatively minor” (p. 241) as the design requires less intervention, contact, and interaction. Informed consent and avoidance of harm may be easily built in to survey research, especially when the survey instrument and procedures are highly structured. Five aspects of ethical consideration were considered for this study.

1. Voluntary consent: A written statement regarding the purpose of the research was provided at the beginning of the survey instrument. Participants were required to read an informed consent form embedded in the survey instrument and acknowledge agreement before moving forward with the study. Participants were free to participate or leave the study at any time.
2. Protection from harm: In general, the potential for harm to the participant is limited in a survey design but is an important consideration. As the nature of the study was to examine attitude and behavioral intention toward using VR for flight training, and thus pertains to participant beliefs, values, and opinions, sensitivity must be used when designing the survey instrument. Questions were worded concisely, using non-negative and non-biased language, and no question was worded in such a way to cause discomfort in the participant. Additionally, the design of the study limits the potential of physical, psychological, and reputational harm to the participant.
3. Privacy: Ensuring anonymity or confidentiality is a priority when conducting survey research. Although aviation students received an email from a faculty member within their institution, access to this list was not

provided by the participating institution. Personal identifiers were not collected, and only limited demographic information deemed relevant to the study was asked of the participant. Thus, there was no way to confirm or deny if a student from a particular institution participated in the study. Demographic information was not directly linked to any individual at any time during the data collection process. Any direct correspondence was kept confidential and destroyed at the end of the study. The survey instrument was administered online. Passwords were needed to access any data collected during the study.

4. IRB: Student participation in research studies requires IRB approval. The ERAU IRB process was followed to ensure participant rights and welfare are protected at all times during the research. No harm of any kind (i.e., economic, legal, physical, psychological, social) was anticipated for this research. The IRB application, supporting documents, survey instrument, and informed consent documents may be found in Appendix A and Appendix B. There were no special actions required of the participants beyond watching a short video on VR technology for flight training and completing the survey online. IRB training was required to perform research with human participants at ERAU. The distribution of the survey commenced only after IRB approval was received.
5. Integrity of the study: Results were reported as fairly and accurately as possible. Both positive and negative results were presented, and potential researcher bias was avoided. Falsifying of results, data, authorship, and

conclusions was avoided. The data contains no identifying information and was saved locally and not shared with others.

Measurement Instrument

An online survey was used to collect the data to answer the research questions. The first section of the instrument included the purpose of the study, a consent form, a short video of VR use in flight training, and screening questions. These questions used yes-no questions to confirm the eligibility of the participants. Participants must answer "yes" to all questions to be eligible to participate.

The second section contained 11 questions to collect demographic data. Demographics included: age, gender, race, international affiliation as applicable, institution, flight hours and certification, experience using a flight training device, VR experience, gaming experience, and school standing.

Likert response items to measure the latent constructs (factors) that may influence aviation students' intentions to use VR technology for flight training as well as attitude and behavioral intention factors immediately followed the demographic portion of the survey. Hair et al. (2010) recommend using at least three items to measure each construct. To measure the 10 constructs of the model, 34 measurement items (questions) were modified from previous studies to reflect flight training using VR technology and thus the context of the study. The construct, definition, measurement items, and related sources are described. Likert response formats were used for each measurement item.

Attitude toward use. The degree to which a student has a favorable or unfavorable appraisal or evaluation of VR for flight training (Esteban-Millat et al., 2018; Gong et al., 2004; Lee et al., 2018; Manis & Choi, 2018; Park, 2009).

- Using VR for flight training is a good idea.
- Using VR for flight training is a wise idea.
- I feel positively toward using VR for flight training.

Behavioral intention. An indication of how hard a student is willing to try or how much effort they are planning to exert in order to use VR for flight training (Esteban-Millat et al., 2018; Gong et al., 2004; Lee et al., 2018; Makransky & Lilleholt, 2018; Manis & Choi, 2018; Shen et al., 2017, 2018).

- If made available, I am willing to use VR for flight training.
- If made available, I intend to use VR for flight training.
- If made available, I intend to use every flight training lesson provided through VR.

Perceived behavioral control. The extent to which an aviation student feels able to control using VR technology for flight training (Chang et al., 2018; Pan, 2017).

- I could use VR technology for flight training if no one was around to tell me what to do (e.g., a flight instructor or an assistant).
- I could use VR technology for flight training if I had only the manuals for reference.
- I could use VR technology for flight training if I had only a virtual instructor guiding me.
- I could use VR technology for flight training if I could call someone for help if I got stuck.

- I could use VR technology for flight training if I had used similar systems (e.g., an advanced aviation training device, a flight training device) previously.

Perceived ease of use. The degree to which a student believes that using VR for flight training would be free of effort (Esteban-Millat et al., 2018; Gong et al., 2004; Lee et al., 2018; Makransky & Lilleholt, 2018; Manis & Choi, 2018; Park, 2009; Richardson 2017).

- Learning to use VR for flight training will be easy for me.
- It will be easy to gain skills for flight training using VR.
- Using VR for flight training will make my flight training progression easier.

Perceived enjoyment. The degree to which using VR for flight training is perceived to be enjoyable in its own right apart from any performance consequences that may be anticipated (Chang et al., 2018; Lee et al., 2018; Makransky & Lilleholt, 2018; Manis & Choi, 2018).

- Using VR for flight training would be enjoyable.
- Using VR for flight training would be exciting.
- I enjoy using immersive simulation technology such as VR.
- I have fun using immersive simulation technology such as VR.

Perceived health risk. The perception a student forms and revises based on the possible health risks of using VR for flight training (Ahadzadeh et al., 2015; Myers, 2019).

- Using VR for flight training may negatively affect my physical health.

- Using VR for flight training is safer for me physically than using a flight training device.
- Using VR for flight training is safer for me physically than using an actual aircraft.

Perceived usefulness. The degree to which a student believes that using VR for flight training would enhance his or her performance (Esteban-Millat et al., 2018; Gong et al., 2004; Lee et al., 2018; Makransky & Lilleholt, 2018; Manis & Choi, 2018; Park, 2009).

- Flight training using VR will be useful for flying in the real world.
- Using VR would enhance flight training.
- Using VR would improve my performance in flight training.
- Using VR would make flight training more effective.

Performance expectancy. The degree to which a student believes that using VR for flight training will improve flight performance as compared to an FTD (Onaolapo & Oyewole, 2018; Shen et al., 2017, 2018).

- Using VR for flight training is more productive than using a flight training device.
- Using VR for flight training will improve my flying skills more efficiently than using a flight training device.
- By expending the same effort as in a flight training device, using VR for flight training will improve the progression of my training.

Regulatory uncertainty. The degree to which the lack of FAA regulations regarding the use of VR for flight training impacts attitude toward the technology (Folkinshteyn & Lennon, 2016; Yang et al., 2015).

- I am hesitant to use VR for flight training because there are no FAA regulations regarding its use.
- I am uncertain if the FAA will approve VR for flight training purposes.
- Recording flight training hours in a logbook is a concern when using VR for flight training.

Self-efficacy. Perception of one's flight skills in the virtual and real-world environments (Chang et al., 2018; Gong et al., 2004; Pan, 2017).

- I feel confident in my ability to use VR for flight training.
- I feel confident that my flight skills will make flying in VR easy.
- I feel confident in my flight skills in the real-world environment.

The survey contained 49 questions in total: 4 screening questions, 11 demographic questions, and 34 questions to observable items to measure the latent variables. The survey instrument can be found in Appendix B.

Constructs. There were 10 constructs and 34 indicator variables, highlighted in Table 15. These constructs and the indicator variables associated with them have been taken from the literature and adapted for the study.

Table 15

Sources for Constructs

Construct	Number of Indicators	References
Attitude toward use	3	Gong et al., 2004; Manis & Choi, 2018; Park, 2009; Pan, 2017
Behavioral intention	3	Gong et al., 2004; Maransky & Lilleholt, 2018; Park, 2009
Perceived behavioral control	3	Park, 2009; Manis & Choi, 2018; Maransky & Lilleholt, 2018
Perceived ease of use	3	Park, 2009; Gong et al., 2004; Manis & Choi, 2018
Perceived enjoyment	4	Manis & Choi, 2018; Maransky & Lilleholt, 2018
Perceived health risk	3	Ahadzadeh et al., 2015; Myers, 2019
Perceived usefulness	4	Gong et al., 2004; Maransky & Lilleholt, 2018; Park, 2009; Shen et al., 2018
Performance expectancy	3	Gong et al., 2004; Manis & Choi, 2018; Maransky & Lilleholt, 2018; Park, 2009; Shen et al., 2018
Regulatory uncertainty	3	Folkinshteyn & Lennon, 2016; Yang et al., 2015
Self-efficacy	5	Deng et al., 2004; Park, 2009; Yuan et al., 2017

The review of the relevant literature for the study, as described in Chapter II, was used to develop the conceptual framework of the model and the theorized relationships between the constructs. All 10 constructs were derived from the literature review and deemed appropriate for the selected domain (aviation education), technology (VR), and purpose (flight training). Of the 14 hypothesized relationships, four hypotheses were brand new between the constructs and supported by the literature. Ten hypothesized relationships between constructs have been tested in previous studies; however, the relationships have not been tested nor validated for using VR for flight training. Therefore, 14 hypotheses investigated the research questions using 10 constructs. Table 13 highlights the definition of each construct and includes relevant studies that incorporated the construct into the research model, thereby justifying the constructs as well as the relationships.

Variables and scales. The research was conducted using a deductive, non-experimental survey design with quantitative data. The constructs were assessed using three to five indicator variables, detailed in Tables 16 and 17, with responses gauged on a 5-point Likert response format ranging from 1 (strongly disagree) to 5 (strongly agree). A Likert response format has ordinal, numeric response options for a survey item (question) as opposed to a distinct measurement (Carifio & Perla, 2007). Although Likert response formats are often called “scales,” the data collected is not a continuous measurement and thus the term is erroneous (Carifio & Perla, 2007). Likert first developed the response format in 1932 to analyze scale data in interval values measuring a single variable within a larger construct. Ordinal data implies that although the order of the variables matter, the difference between them does not.

Due to the nature of ordinal variables, data analysis is typically completed using nonparametric tests. However, nonparametric tests are limited, lacking the power and complexity demonstrated by parametric tests (Wadgave & Khairnar, 2016). Additionally, nonparametric tests often report descriptive statistics (e.g., mean, standard deviation) which may be unclear and inappropriate for reporting Likert responses (Jamieson, 2004; Sullivan & Artino, 2013). Parametric testing, on the other hand, provides robust statistical analysis without the assumptions associated with nonparametric tests (Norman, 2010; Wadgave & Khairnar, 2016). Carifio and Perla (2007; 2008) argue that Likert responses may be analyzed as interval data, wherein the variables have meaningful distance between them, as when the response format uses a range of numbers (e.g., 1 for strongly disagree through 5 for strongly agree). Knapp (1990) supports this idea, stating that although the response format is not a true interval scale, the differences between the response categories may be treated as equal.

Norman (2010) notes that parametric statistical analyses, including factor analysis and SEM, require interval data that has normally distributed means. Although a single response may qualify as ordinal data, the summation of responses across several items lends the qualities of interval data (Norman, 2010). Gaito (1980) notes that a number in a data set does not recognize itself to be ordinal nor interval, nor does the computer program analyzing it. Indeed, the statistical software used to analyze SEM, SPSS Amos, does not distinguish between ordinal and interval data; the program simply analyzes the data with parametric testing. Pan and Truong (2018) utilized a structured questionnaire with Likert response items to analyze factors that influence passengers' intention to use low-cost carriers using an extended TPB model. CFA and SEM were utilized for data analysis to test relationships between the latent variables, following the processes put forth by Byrne (2010) and Hair et al. (2010). Likert response items, presented in a questionnaire, were employed by Hunt and Truong (2019) to measure passenger preference in trans-Atlantic transportation carrier options. Along with CFA and SEM, exploratory factor analysis and decision tree analysis were used to investigate relationships between latent variables. Additionally, analyzing Likert response data with CFA and SEM has been utilized by Myers (2019); Richardson, Troung, and Choi (2019); and many others. Norman (2010) summarizes that Likert response data may be considered interval data and used in parametric tests as supported by "empirical literature dating back nearly 80 years" (p. 631).

Data Analysis Approach

Demographic data and non-response bias analysis. Demographic information of the target population is extremely limited, and the privacy of aviation students enrolled in FAA-approved Part 141 programs is protected by the institutions. Before beginning the study, limited demographic data of aviation students enrolled in the flight training programs of the invited institutions was requested. This information was requested to ensure proportionate representation among the institutions and to ensure no demographic group was over- or under-represented. A participant profile of the population is presented in Table C1. Demographic results were compared to this profile to ensure the sample represents the population. Due to the sensitivity of this information, limited data are presented in Table C1.

Non-response bias analysis. Response bias may be defined as "the effect of nonresponses on survey estimates" (Creswell, 2014, p. 162). Bias may occur if the responses of non-respondents would have substantially changed the overall results of a study. For the study, non-respondents were quantified as those participants who answered less than 50% of the Likert response questions or those who gave straight line responses to the questions. A Chi-square test was used to detect bias in demographics between the respondent and non-respondent groups. Participant responses were compared between those who completed the survey soon after receiving the invitation and those who completed the survey after a reminder email after a specific period. Demographic variables compared included gender, age, institution, flight hours and certification, VR experience, gaming experience, and school standing. Probability significance was set at $p < .05$, and values greater were deemed insignificant.

Descriptive analysis. Because students from multiple institutions are the accessible sample for the study, demographics collected via the survey instrument included: age, gender, race, international affiliation as applicable, institution, flight hours and certification, experience using a flight training device, VR experience, gaming experience, and school standing. These data were reported for each demographic variable graphically, as appropriate, and in table form, and may include mean, standard deviation, Kurtosis and skew, median, mode, and other quantitative data.

Missing values. All data were reviewed in SPSS for missing values. This step is critical before performing a CFA to ensure the model is not unspecified, nonrandom, and that no more of 10% of the data is missing (Hair et al., 2010). The pattern of the missing data for a given variable was considered missing completely at random if it does not depend upon another variable in the dataset nor the values of the variable itself. The pattern was considered missing at random if the missing data for a variable is related to a different variable but not its own values. Missing data may be remedied through four methods as described by Hair et al. (2010). A complete case approach, or *listwise deletion*, may be used to eliminate all data from a participant. This method is a traditional method in SEM but may increase the likelihood of non-convergence if factor loadings are low (less than 0.6) and sample sizes are small (less than 25). The all-available approach, or *pairwise deletion*, uses all non-missing data. Pairwise deletion has become more popular as more data may be analyzed and may be used in sample sizes in excess of 250, when factor loadings are high (greater than 0.6), and when less than 10% of data among measured variables are missing. Imputation techniques (e.g., mean substitution, case substitution, regression imputation) may be used to substitute values into the missing cases. A model-based approach, such as a maximum likelihood estimation of missing values, may be used. The pattern and amount of missing data were assessed and the appropriate remedy chosen.

Outliers. Outliers are cases of data that are substantially different from other values in the dataset. Byrne (2010) and Kline (2016) distinguish between a univariate outlier (an extreme score of a single variable) and a multivariate outlier (extreme scores on multiple variables). The squared Mahalanobis distance of each case was computed to detect multivariate outliers in AMOS. All values greater than 100 were examined to determine if they should be kept, removed, or transformed (Kline, 2016). Extreme scores were converted to a value equal to the next most extreme score. Models with and without the outliers were compared to aid the decision.

Assumption testing. The normality of the data was assessed in SPSS and AMOS. Byrne (2010) states that testing the normality of the data is of critical importance to ensure the assumption of multivariate normality is not violated. Further, multivariate kurtotic data may be problematic for SEM analyses. In this situation, the distribution of observed variables has tails and peaks differing in character from the multivariate normal distribution. Histograms were examined in SPSS as well as descriptive statistical analysis, including Kolmogorov-Smirnov and Shapiro-Wilk tests, as appropriate. Multivariate positive kurtosis exhibited distributions of peaks and heavy tails. Multivariate negative kurtosis exhibited a flatter distribution with light tails. Kurtosis values analyzed in AMOS below three were preferred, but less than five were acceptable (Byrne, 2010). These values, in particular, were scrutinized as kurtosis may indicate an issue with covariance structures and impact the SEM analyses. Data with high levels of kurtosis were transformed in SPSS and both models (transformed vs. original data) ran in AMOS for comparison. Data may be transformed through linear transformation, an estimation method, or a bootstrapping method.

Another assumption of SEM is that the scale used to measure constructs yields continuous data (Byrne, 2010). This assumption was met through the use of Likert response items with numeric response options for each survey item.

Confirmatory factor analysis and structural equation modeling. An SEM methodology was used for data analysis based on the works of methods of Byrne (2010) and Hair et al. (2010) and the research of Lee et al. (2018), Myers (2019), Manis and Choi (2018), Wang et al. (2016), and others. The SEM process utilized a path diagram of the constructs followed by a CFA of the variables and relationships in SPSS AMOS. The CFA was appropriate as the study used latent variable structures from known theories (i.e., TAM and TPB) as well as extant literature related to aviation, flight training, and VR. Reliability and validity tests were performed after the CFA. Finally, the full structural model analysis was performed with applicable evaluation and post hoc analysis. The model fit was evaluated during both CFA and SEM.

A CFA was used to test the relationship of the indicator variables to the constructs as well as the relationships between the constructs. Cronbach's alpha was used to test the reliability of the survey items and the constructs. Factor loadings, or the representation of regression weights in the model, were assessed. Hair et al. (2010) state that factor loadings are ideally greater than 0.7, but those above 0.5 may also be acceptable; low factor loadings may be of concern as they are associated with non-significant *p*-values and low critical ratio values below 1.96 (Kline, 2016). Those items with non-significant *p*-values were assessed with methodical removal from the model based on model fit and literature support, with comparison to the original model. Model fit was evaluated per Byrne (2010) and Hair et al. (2010). The Comparative Fit Index (CFI) minimum value was 0.93 and compared the fit of a target model to the fit of an independent model. Goodness of Fit (GFI) and Adjusted GFI (AGFI) report variance explained by the estimated population covariance; these values should be greater than or equal to 0.90. The Normed Fit Index (NFI) indicated the incremental measure of fit of the model and would ideally be greater than or equal to 0.90. The CMIN/df (minimum discrepancy over degrees of freedom) should be less than or equal to 3. Finally, the Root Mean Square Error of Approximation (RMSEA) was a parsimony adjusted index and should be less than 0.06.

A post-hoc or model respecification process was to be used if a good model fit was not obtained. During the post-hoc process, areas of misfit within the model were identified. Byrne (2010) describes two key factors that impact the decision to perform respecification. It must first be decided if the estimation of the targeted parameter was substantively meaningful and if the respecification process would lead to an over-fitted model. The latter case could result in representing weak effects that are not replicable, significant inflation of standard errors, and over-influence of primary model parameters. Item questions with poor factor loadings (less than 0.7) were reviewed and either deleted or reworded. Modification indices were reviewed for high values that may indicate relationships between error terms or a cross-loading situation between items and factors. Error terms were correlated with high modification index values. Changes were made individually and the model was reexamined and compared in an iterative process.

Should all values meet the specified requirements, the model was deemed fit. The last step is to interpret the results of hypothesis testing and determine any new relationships identified within the model.

Reliability assessment method. The reliability of the instrument refers to the consistency of scores from the items (survey questions) and responses across the constructs as well as the stability of the instrument over time (Creswell, 2014). A construct may be considered reliable if repeated techniques yield the same results. Ten constructs were investigated and each was measured by 3-5 items in survey form to ensure the construct was reliably assessed. Questions were simply written in clear and concise language and ordered by construct to increase reliability (Babbie, 2016). Constructs and survey questions were based on established items from the published literature. The survey instrument was reviewed by SMEs and went through a pilot study to ensure the survey questions were relevant and measured the intended constructs.

Modification indices were consulted for large values, indicating relationships between error terms and suggested regressions between an item and a factor (cross-loading). Reliability was assessed for a model with a good model fit. Composite reliability was used to measure the extent to which measured variables represented the construct it should measure (Hair et al., 2010). The sum of each construct's standardized factor loadings was squared and divided by the squared value of the standardized factor loadings plus the sum of the error variances, as shown in Equation 2.

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

Ideal values were greater than 0.7 (Hair et al., 2010). Cronbach's alpha was used as an alternative way to evaluate construct reliability. This widely-used analysis evaluates the consistency of a scale with higher values indicating greater reliability and lower values indicating less reliability or that the variables do not adequately measure the construct (Groves et al., 2009; Hair et al., 2010). A Cronbach's alpha value of 0.7 was the lower limit of acceptability, and those items with values below 0.7 were revised or removed (Hair et al., 2010) during the pilot study and reassessed for the full structural model. When a change to the path diagram of the structural model was required, items were changed individually and analyses redone as supported by the literature (Byrne, 2010).

Validity assessment method. The validity of an instrument refers to the ability to obtain useful and meaningful conclusions from scores, thus ensuring the items measure the intended construct (Creswell, 2014). Construct validity is applicable to survey research designs and refers to the relationships of the constructs of the model and the degree to which variables are related, as proposed in the model (Babbie, 2016). The CFA process, and ultimately the full SEM process, relies on the testing and confirming of relationships. Thus, construct validity was tested using a pilot survey followed by the study.

Convergent validity is the degree to which two measures of a construct are related (Byrne, 2010). Factor loadings were assessed and the average variance extracted (AVE) computed using CFA output. Shown in Equation 3, AVE is the division of the summed square of standardized factor loadings by the number of items.

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

Factor loadings greater than 0.7 were considered to have good convergent validity (Byrne, 2010). These values were then squared to determine AVE with acceptable values below 0.5. Additionally, discriminant validity, or the extent to which constructs are distinct from one another (Fornell & Larcker, 1981), was evaluated by comparison of the maximum shared variance (MSV) to AVE of each construct. Discriminant validity was met if the AVE of one factor was greater than the MSV of corresponding factors.

If discriminant validity was not met, the heterotrait-monotrait ratio of correlations (HTMT; Henseler, Ringle, & Sarstedt, 2015) was used to determine if discriminant validity was met. This method uses the ratio of between-trait correlations to within-trait correlations. The ratio is an estimate of the true correlation between constructs, and a correlation value close to 1 means there is a lack of discriminant validity between the constructs. A good indicator value is less than 0.85, but less than 0.90 is considered acceptable (Henseler et al., 2015; Kline, 2016). SPSS and Excel may be used to calculate HTMT. Equation 4 shows a simplified HTMT formula.

$$\frac{A}{\sqrt{BC}} \tag{4}$$

A = Average of all pairwise correlations between items of the first construct and items of the second construct (average heterotrait-heteromethod correlations)

B = Average of all pairwise correlations between items of the first construct (average monotrait-heteromethod correlations)

C = Average of all pairwise correlations between items of the second construct (average monotrait-heteromethod correlations)

If acceptable values were indicated using either the Fornell-Larcker or HTMT approaches, the discriminant validity was rated acceptable.

Structural equation modeling. Following the CFA process and the testing of reliability and validity, a full structural model was created. This is the final step of SEM and details relationships between constructs based on the theoretical framework. The SEM process began with creating the CFA path diagram. In the path diagram, covariance is defined between constructs. Hypothesis arrows were added with a point toward endogenous latent variables. Residual items of “1” were added to all endogenous variables. The model diagram was created when an acceptable model fit, convergent and discriminant validity, and construct reliability were attained (Byrne, 2010; Hair et al., 2010). The full structural model was then tested using a process similar to a CFA.

First, standardized regression weights were examined to determine the positive and negative relationships and strength of the relationships. Observed and unobserved variables were checked and verified using the variable summary output. The next step was to verify the model fit, reliability, and validity. Although it was expected that a CFA with acceptable model fit would yield an acceptable full structural model, the same model fit indices were used to verify this. Values of CFI, GFI, AGFI, NFI, CMIN/df, and RMSEA of the full structural model were assessed using previously stated criteria for the

CFA. Having ensured all values met the minimal acceptable values, the model was deemed fit. If values did not meet minimal accepted values, adjustments were made using a post-hoc or model respecification process. In this step, the values of the modification indices were examined for cross-loading issues between items and factors or covariance issues between error terms. Modification index values between factors were reviewed for new, undefined relationships. For any new relationships identified, the relevant literature was reviewed for support.

Hypothesis testing. Values from AMOS output were reviewed to test the hypotheses of the study. The critical ratio t-values should be above 1.96 with p values below 0.05 to indicate support for a hypothesis. Standardized regression weights were compared between constructs to identify the strongest and weakest correlations of the model. All hypotheses were examined to identify which hypotheses were supported. The process overall was the most appropriate analysis to answer the research questions. Using an SEM approach demonstrated how well observed data fit in the model structure as well as the strength of the relationships.

Chapter Summary

This section presented a research methodology to meet the research questions of a study to better understand those factors that influence aviation students' attitude toward and intention to use VR for flight training. The approach, design, population and sample, instrument, data treatment, and ethical concerns of the study were discussed.

CHAPTER IV

RESULTS

This chapter reports significant findings in nine sections, including results of the pilot study, survey responses and sample, demographics, descriptive statistics, confirmatory factor analysis (CFA), structural model assessment (SEM), encompassing hypothesis testing and addressing the research questions, and chapter summary.

Pilot Study

A pilot study was conducted using Google Forms. The survey was sent to students enrolled in the Embry-Riddle Aeronautical University (ERAU) Aeronautical Science degree program during the winter break between the Fall 2019 and Spring 2020 semesters. The survey was prepared in Google Forms and disseminated to the students via email by the ERAU Flight Training Department. A sample size of 42 students participated in the pilot study, which was considered an acceptable size (Hertzog, 2008; Hill, 1998). The data was then prepared, a CFA model created and run, and analyses completed. Assessment in AMOS revealed that the initial CFA model was underidentified. Through iterative removal and testing, it was determined that the indicator variables of PHR were affecting the model, and regression weights were added to PHR1 and PHR2. The indicator variable PEXP2 was also given a regression weight that lent to better model specification. Table 16 details the analysis results with values below the minimum accepted value highlighted.

Table 16

Factor Loading and Reliability Assessment of Pilot Study

Construct	Item Question	Factor Loading (≥ 0.5)	CR (≥ 0.7)	Cronbach's Alpha (≥ 0.7)	AVE (≥ 0.5)
ATU	ATU1	0.97	0.97	0.98	0.94
	ATU2	0.97			
	ATU3	0.97			
BI	BI1	0.93	0.82	0.89	0.75
	BI2	0.90			
	BI3	0.76			
PBC	PBC1	0.64	0.78	0.85	0.55
	PBC2	0.85			
	PBC3	0.76			
	PBC4	0.82			
	PBC5	0.59			
PENJ	PENJ1	0.78	0.90	0.93	0.76
	PENJ2	0.71			
	PENJ3	0.97			
	PENJ 4	0.97			
PEU	PEU1	0.66	0.83	0.87	0.70
	PEU2	0.89			
	PEU3	0.94			
PEXP	PEXP1	0.80	0.87	0.86	0.72
	PEXP2	0.96			
	PEXP3	0.82			
PHR	PHR2	4.63	**-3.81**	**0.50**	**0.36**
	PHR3	**0.07**			
PU	PU1	0.92	0.95	0.96	0.85
	PU2	0.96			
	PU3	0.89			
	PU4	0.92			
RU	RU1	0.99	0.71	0.76	0.52
	RU2	0.55			
	RU3	0.53			
SE	SE1	0.89	0.89	0.90	0.77
	SE2	0.93			
	SE3	0.80			

Note. ATU = Attitude Toward Use. BI = Behavioral Intention. PBC = Perceived Behavioral Control. PEU = Perceived Ease of Use. PENJ = Perceived Enjoyment. PEXP = Performance Expectancy. PHR = Perceived Health Risk. PU = Perceived Usefulness. RU = Regulatory Uncertainty. SE = Self Efficacy.

Model fit was not achieved for the CFA due to the low sample size. Upon review of the modification indices, there was a large, suggested covariance between error terms

10 and 11, associated with items PENJ1 and PENJ2, respectively. A covariance arrow was added to the model between these items. No other modification indices indicated a covariance.

The factor PHR had the lowest Cronbach's alpha of 0.40. The analysis indicated that removing PHR1 from the model would increase the value to 0.50. An issue was noted with the construct, in that initial analysis resulted in no AMOS output related to the factor. By removing item PHR1 from the model, analyses could continue. SMEs were consulted on how to reword PHR1 as well as align the wording of PHR1, PHR2, and PHR3 to an updated definition of PHR. After consultation with SMEs and the literature, the operational definition was redefined, and the indicator items restructured to focus on physical health risks. Changes are described, with italics to highlight changes. The original definition of the construct was "The perception a student forms and revises based on the possible health risks of using VR for flight training." This was changed to "The perception a student forms and revises based on the possible *physical* health risks of using VR for flight training." PHR1 was added back to the model but wording changed for the final survey instrument from "Using VR for flight training may negatively affect my physical health" to "Using VR for flight training *will have a bad effect on my physical health*." PHR2 was changed from "Using VR for flight training is safer for me physically than using a flight training device" to "Using VR for flight training is safer for *my physical health* than using a flight training device." Likewise, PHR3 was reworded from the original "Using VR for flight training is safer for me physically than using an actual aircraft" to "Using VR for flight training is safer for *my physical health* than using an actual aircraft."

Factor RU had low construct reliability (CR) of 0.67, possibly due to the low but acceptable values of items RU2 and RU3. However, the factor had an acceptable Cronbach's alpha of 0.76 and AVE of 0.65; thus, no changes were made. The reliability of the instrument, survey constructs, and items were deemed acceptable to move forward with the large-scale survey.

Survey Responses and Sample

Data was collected for the study using the mass distribution of a Google Form to students enrolled in 33 Part 141 flight schools across the United States. The email invitation was distributed by points of contact at each institution on January 17, 2020, with a follow up (reminder) email distributed on February 14, 2020. Approximately 7,928 students were contacted to achieve a minimum of 475 valid responses. Responses from participants who did not meet all of the requirements to complete the survey or who did not complete the survey in its entirety were removed from the data set. A total of 704 responses were completed in the time frame, of which 607 were valid cases. It was determined that each school would be proportionately represented. A review of the response rates revealed that a minimum response rate of 6% was needed. This was based on school size and the actual response rate of smaller institutions to ensure an adequate number of responses per school were utilized. Seven schools had zero responses from students. Eleven schools had response rates 5% or below, and these cases were removed from the data set. After cleaning the data in SPSS, 489 cases were available for analysis. Because the minimum sample size was met, another form of sampling was unnecessary. Table C1 highlights the number of students who participated from each institution. Three screening requirements had to be met to be eligible to participate in the survey. The first requirement was that the student is enrolled in a flight training program at a college or university, to ensure only students in FAA-approved Part 141 flight schools participated; 28 participants answered “no” and were removed. The second requirement was that the student had begun flight training in an aircraft. This question was deemed an important aspect as several of the factors and indicator items were formed with the assumption that the student had familiarity with flying in an aircraft and had access to FSTDs; 76 cases were removed as the participant responded “no.” Finally, the student had to be over 18 as is required by the ERAU IRB; 15 students responded as younger than 18 and were removed. Table 17 summarizes the amount and rationale of case deletions during the data screening and cleaning process.

Table 17

Summary of Case Deletion

Rationale	Number of Cases
Respondents answered “disagree” to the informed consent screening question	5
Respondents answered “no” to an eligibility screening question	97
Institution participation was less than 4%	118
The participant had straight-line or missing answers	0

Demographics

The demographics analyzed in the study were used to compare different population groups within the sample and ensure proportionate representation from each institution. Demographic information included age, gender, race, international affiliation as applicable, institution, flight hours and certification, experience using a flight training device, VR experience, gaming experience, and school standing. Table 18 highlights the basic demographic attributes of the aviation students.

Table 18

Basic Demographic Attributes of Participants

Attribute	Subgroup Categories	Frequency (*N* = 489)	Percentage
Gender	Female	67	13.7
	Male	420	85.9
	Other/Prefer not to say	2	0.4
Race	African-American	16	3.3
	Asian	28	5.7
	Caucasian	373	76.3
	Latino or Hispanic	32	6.5
	Native American	5	1.0
	Other (please specify)	7	1.4
	Prefer not to say	6	1.2
	Two or More	20	4.1
	Unknown	2	.4
International student status	Yes	35	7.2
	No	454	92.8
If international student, general region of origin	Africa	2	.4
	Asia	23	4.7
	Europe	2	.4
	North America	91	18.6
	South America	6	1.2
Current education status: Undergraduate	Freshman	104	21.3
	Sophomore	121	24.7
	Junior	119	24.3
	Senior	102	20.9
	Graduated but continuing flight lessons or another certificate on campus	4	0.8
Current education status: Graduate	First year	7	1.4
	Second year	7	1.4
	Third year	5	1.0
	Fourth year	2	.4
	Fifth year or beyond	5	1.0
	Other/Did not specify	12	2.4
Highest level of flight certification received	ATP	1	.2
	CFI/CFII/MEI	26	5.3
	Commercial pilot	42	8.6
	Multi-engine	8	1.6
	Private pilot	170	34.8
	Private pilot, instrument flight rating	103	21.1
	Student pilot	139	28.4

Table 18 Continued

Attribute	Subgroup Categories	Frequency (*N* = 489)	Percentage
Experience with VR	I have never used VR	149	30.5
	I have used VR a couple of times but am not a frequent user	297	60.7
	I use VR a few times a week	35	7.2
	I use VR daily	8	1.6
Experience with computer or video gaming	I have some gaming experience	130	26.6
	I play computer/video games less than once a week	139	28.4
	I play computer/video games a few times per week, but not daily	125	25.6
	I play computer/video games daily	95	19.4

Due to the nature of student privacy, demographic information for each institution was not readily provided. There were also no databases with demographic information available for comparison. However, the majority of the institutions were willing to provide gender distribution (male/female) for students enrolled in their flight program. The average distribution of males to females in the sampling framework was 85% - 15%, respectively. In reviewing the study results, two participants opted to answer as other: “attack helicopter” was re-categorized as “prefer not to say,” and the participant who responded as “People can’t change their genetic code. I’m a man” was re-categorized as “male.” The answers for these two participants were reviewed to ensure they did not give straight-line or “Christmas tree” responses. The distribution of the sample was 85.89% male (*n* = 420), 13.70% female (*n* = 67), and 0.41% prefer not to say (*n* = 2). According to the FAA, as of December 31, 2018, there are an estimated 46,463 active women airmen, or approximately 7% of the civil airmen population (FAA, 2020). Of these, 22,266 women were student pilots or approximately 13%. Women In Aviation (n.d.) published a conversion rate from student pilot status to certificated pilot for the years 1991 through 2010 indicating that in 2010, the gender distribution of student pilots was

88% male, 12% female. Of note, a “student pilot” does not mean a student enrolled in a Part 141 flight school; rather, a student pilot is a pilot in training. Although further demographics are not available for comparison, the gender breakdown is the only reliable and readily-available source of demographic data on which to compare.

Participants ranged in age from 18 to 51 (*M* = 21. 74, *SD* = 4.78). Flight hours in an aircraft ranged from 1 hour to 3,000 hours (*M* = 139.12, *SD* = 180.01). Hours logged in an FTD ranged from 0 hours to 1,000 hours (*M* = 26.22, *SD* = 51.40). The participants ranged in highest level of flight certification from student pilot (*n* = 139, 28.4%) to ATP (*n* = 1, 0.2%). Participant education also varied. Although the majority identified as a student in a four-year degree program (i.e., freshman or sophomore, *n* = 446), many also responded with information on other degrees they had previously earned. The majority of participants identified as Caucasian (*n* = 373, 76.3%). Participants also identified as Latino or Hispanic (*n* = 32, 6.5%), Asian (*n* = 28, 5.7%), African-American (*n* = 16, 3.3%), or Native American (*n* = 5, 1.0%). Thirty-five participants (7.2%) self-identified as international students.

Students from 22 American institutions participated. These institutions are part of six of the nine FAA regions, which divide the country into nine central operations. Regions represented included the Central, Eastern, Great Lakes, Northwest Mountain, Southern, and Southwestern Regions. The Alaskan, New England, and Western Pacific Regions were not represented in the study. Table C1 details which institutions are associated with each region.

The final two questions asked about participant experience with VR and gaming. The majority of participants responded that although they had used VR a couple of times, they were not frequent users (*n* = 297, 60.7%). The next highest category was no VR experience (*n* = 149, 30.5%). Thirty-five participants (7.2%) identified as using VR a few times a week, while eight (1.6%) responded they used VR daily. The computer/video game experience was high. Most participants stated they play computer/video games a few times per week but not daily (*n* = 139, 28.4%), while 125 participants (25.6%) play games daily. Many identified as having some gaming experience (*n* = 130, 26.6%), and 95 participants (19.4%) stated they play computer/video games less than once a week.

Descriptive Statistics

Descriptive statistics of data of the 10 constructs were run in SPSS, shown in Table 19. Five-point Likert response items were used to answer the survey items, ranging from “strongly disagree” or “no confidence” (1) to “strongly agree” or “total confidence” (5). Because the survey items were designed to be grouped by factor, the summation of the factor is listed as “all” in the table.

Table 19

Descriptive Statistics Results of the Constructs

Construct	Item Question	Mean (*N* = 489)	SD	Skewness	Kurtosis
ATU	All	4.08	1.01	-1.04	0.40
	ATU1	4.08	1.05	-1.07	0.43
	ATU2	4.02	1.06	-0.92	0.04
	ATU3	4.13	1.04	-1.14	0.57
BI	All	3.71	1.10	-0.74	-0.20
	BI1	4.19	1.11	-1.42	1.24
	BI2	3.89	1.26	-0.94	-0.21
	BI3	3.05	1.37	0.04	-1.19
PBC	All	3.52	0.94	-0.20	-0.45
	PBC1	3.62	1.28	-0.13	-1.07
	PBC2	3.37	1.21	-0.23	-0.92

Table 19 Continued

Construct	Item Question	Mean (*N* = 489)	SD	Skewness	Kurtosis
PBC Continued	PBC3	3.36	1.30	-0.32	-1.00
	PBC4	3.79	1.12	-0.78	-0.08
	PBC5	3.81	1.06	-0.68	-0.16
PEU	All	3.61	0.97	-0.43	-0.18
	PEU1	3.77	1.08	-0.65	-0.19
	PEU2	3.52	1.12	-0.36	-0.50
	PEU3	3.56	1.12	-0.35	-0.57
PENJ	All	4.17	0.99	-1.32	1.23
	PENJ1	4.15	1.05	-1.28	1.04
	PENJ2	4.18	1.07	-1.40	1.42
	PENJ3	4.16	1.08	-1.23	0.74
	PENJ4	4.19	1.06	-1.33	1.15
PHR	All	2.53	0.86	0.63	1.00
	PHR1	1.98	1.10	1.09	0.55
	PHR2	2.51	2.00	0.32	-0.31
	PHR3	3.12	1.23	-0.15	-1.3
PU	All	3.62	1.03	-0.50	-0.17
	PU1	3.54	1.16	-0.48	-0.51
	PU2	3.81	1.08	-0.70	-0.16
	PU3	3.54	1.12	-0.40	-0.46
	PU4	3.60	1.10	-0.46	-0.39
PEXP	All	3.26	1.05	-0.14	-0.44
	PEXP1	3.07	1.16	0.06	-0.64
	PEXP2	3.18	1.18	-0.01	-0.75
	PEXP3	3.53	1.13	-0.41	-0.57
RU	All	3.32	0.99	-0.15	-0.57
	RU1	3.03	1.38	-0.04	-1.27
	RU2	3.46	1.11	-0.42	-0.45
	RU3	3.46	1.25	-0.41	-0.82
SE	All	3.95	0.84	-0.80	0.54
	SE1	3.72	1.11	-0.60	-0.35
	SE2	3.84	1.05	-0.77	0.00
	SE3	4.28	0.90	-1.35	1.55

The average mean and standard deviation (SD) were computed to assess the effect of the constructs on using VR for flight training. Many participants responded as neutral of higher for 9 of the 10 factors, which were all negatively skewed. The factor of PHR was below neutral (*M* = 2.53, SD = 0.86) with a positive skew. The factors detailed in Table 19 will be discussed in rank order from the highest mean to lowest mean.

PENJ has the highest all-item average of the factors (*M* = 4.17, SD = 0.99). Participants generally had a favorable opinion of VR as an enjoyable technology for flight training in its own right, rating the items as "agree" on average for all of the items.

ATU had an all-item average of 4.08 (SD = 1.01). This indicates that participants were generally favorable in their appraisal of using VR for flight training with all item responses clustered around the "agree" option.

SE also had all items generally rated as "agree," although the first item measuring the factor (SE1) was slightly below agree on average. The item mean for the factor was 3.95 (SD = 0.84), indicating that participants had a high perception of their flight skills in the virtual and real-world environments.

BI had an all-item average of 3.71 (SD = 1.10), which is evident in the range of individual item means of 3.05 (BI3, SD = 1.37) to 4.19 (BI1, SD = 1.11). This score is higher than neutral, but not as close to "agree" indicating that, although participants are willing to use VR for flight training if it is available, they may not be willing to use it at every opportunity instead of favoring other resources.

PU had an all-item average of 3.62 (SD = 1.03) which is greater than "neutral" but less than "agree." The item averages also clustered around this number. This indicates that many participants believe that using VR for flight training will enhance performance.

PEU's all-item average was similar to PU at 3.61 (SD = 0.97). The results reveal that, on average, participants are between "neutral" and "agree" in their belief that using VR for flight training will be free of effort. Item averages of the factor were similar in value.

PBC was measured in terms of confidence rather than agreement ranking. The all-item average was 3.52 (SD = 0.94), and item averages ranged from 3.36 (PBC3, SD = 1.30) to 3.81 (PBC5, SD = 1.06). These results imply that participants are generally confident in their ability to use VR for flight training regardless of if resources are made available (e.g., an instructor, a manual, previous knowledge of similar technology).

RU had an almost “neutral” all-item average (*M* = 3.32, SD = 0.99) with similar averages across the items. The results of this factor reveal that participants are mostly neutral to the fact that VR is not currently an approved training device for flight training, and are perhaps slightly hesitant to use it.

PEXP had the lowest above-“neutral” all-item average (*M* = 3.26, SD = 1.05). The item averages ranged from 3.07 (PEXP1, SD = 1.16) to 3.53 (PEXP3, SD = 1.13). As the factor assessed the degree to which participants believed that using VR for flight training will improve flight performance, the results indicate that participants are slightly in agreement, but generally neutral toward, this belief.

Finally, PHR had the only all-item average below “neutral” (*M* = 2.53, SD = 0.86) and the only positively skewed distribution. The item averages ranged from 1.98 (PHR1, SD = 1.10) to 3.12 (PHR3, SD = 1.23). PHR refers to the belief that using VR for flight training may impact physical health. In general, participants did not believe that using VR would have a bad effect on physical health (PHR1), did not agree that using VR for flight training was safer for physical health than using an FTD (PHR2, *M* = 2.51, SD = 2.00), but were neutral in the belief that using VR was safer for physical health than using an actual aircraft (PHR3).

Non-response bias testing. Bias was assessed to determine if the responses of non-respondents would have considerably changed the overall results of a study. Non-respondents were quantified as participants who answer less than 50% of the Likert response questions or those who gave straight line responses to the questions. None of the participants fit these criteria. Non-response was also assessed between students who received the initial study invitation and a reminder invitation. Initial invitations were sent between January 17, 2020, and February 14, 2020, based on the availability of the point of contact. Participation through the first three weeks was high, as 279 participants (57.1%) responded before a reminder invitation was initiated. After February 14, an additional 210 participants responded (42.9%). A Chi-square test was used to identify bias in demographics between the respondent and non-respondent groups. Participant responses were compared between those who completed the survey soon after receiving the invitation and those who completed the survey after a reminder email was sent. Given the range of participant ages (18 to 51, M = 21. 74, SD = 4.78), the significance of the age category was not deemed a critical issue. Participants represent students of all walks of life: traditional and non-traditional, undergraduates and recent graduates finishing hours before moving on. Gender, education level, and flight level were believed to have the most impact on responses, all of which were insignificant. Table 20 shows the results of the Chi-square tests with the probability significance set at $p < .05$. A Chi-square test for independence was used to assess if the gender distribution of the sample was comparable to that of the sampling framework. The expected distribution was 85% male and 15% female; the observed distribution was 85.89% male, 13.70%

female, and 0.41% prefer not to say. The test revealed the gender categories occurred with the specified probabilities, $p = 0.44$; thus, the distribution was acceptable.

Table 20

Chi-square Tests Comparing Respondents and Non-respondents

Demographic	Chi-square (X^2)	df	Probability (p)	Significant (Yes / No)
Gender	4.29	2	0.12	No
Age	39.77	27	0.05	Yes
Education level	23.06	21	0.34	No
Flight level	8.24	6	0.22	No
Flight hours	186.56	201	0.76	No
Flight hours in FTD	123.86	107	0.13	No
VR experience	1.23	3	0.74	No
Computer/gaming experience	1.58	3	0.66	No

Note. p is significant at $p \leq .05$.

Confirmatory Factor Analysis

The CFA included assessing the results of the study for normality, missing data, outliers, model fit follow by respecification as appropriate, reliability, and validity.

Normality. Hair et al. (2010) note that the assumption of normality of the data must be met to complete a CFA. Normality was checked in SPSS as previously described and also in AMOS. Byrne (2010) notes that for a CFA, a kurtosis value of less than 3.0 is acceptable, although a value less than 5.0 may also be deemed acceptable to assess normality. All values in the dataset, including outliers, had a kurtosis value below 2.0 for the original model and subsequent iterations; the normality assumption was met.

Missing data. No data was missing from the dataset after data was cleaned. CFA models cannot be analyzed if data is missing, thus, it was imperative to address missing data in SPSS before the CFA modeling began in AMOS. No steps were taken.

Outliers. Mahalanobis D-square values were examined in the CFA output to determine if outliers were present with those values greater than 100 representing extreme outliers. Five observations were identified; however, the decision was made to iteratively test the model covariance and regression weight values before addressing outliers following the process of Hair et al. (2010). After an acceptable model fit was attained, the model was again iteratively tested and compared as each outlier above 100 was removed. Model fit, reliability, and validity values increased with each iteration, and the cases were permanently removed from the dataset.

Model fit and respecification. Hair et al. (2010) note that in sample sizes greater than 400, the goodness of fit measures may become more sensitive and suggest a poor fit. Particularly, the Goodness of Fit Index (GFI) and the Adjusted Goodness of Fit Index (AGFI) may be affected and should be considered secondary indicators, greater than or equal to 0.90. The Maximum Likelihood Estimate (MLE) may be utilized to assess model fit as it provides valid, stable results when the assumption for normality is met (Hair et al., 2010). The original model had a slightly low model fit; thus, the decision was made to iteratively run post hoc analyses to respecify the model. This process entailed systematically reviewing the Modification Indices in the CFA output and making adjustments to the model; reviewing outliers and removing them; and assessing the reliability and validity of the model. Covariance between error terms was reviewed as were regression weights between items and factors which may suggest cross-loading. A systematic process resulted in the addition of a cross-loading arrow between PU and PHR1 and double-ended covariance arrows between E12 and E13, E14 and E15, and E28 and E29.

Reliability and validity. Before outliers were removed, the first specified CFA model was examined for convergent validity. The criteria to determine convergent validity included factor loading values of 0.5 at a minimum but 0.7 preferred, construct reliability of greater than or equal to 0.5 and Cronbach's alpha value of greater than or equal to 0.7, and average variance extracted (AVE) value of greater than or equal to 0.5. Table 21 shows the values assessed to determine the convergent validity of the first specified CFA model, and values below the acceptable minimum value are highlighted. The constructs of ATU, BI, PENJ, PEU, PEXP, and PU indicate high levels of all criteria. Other constructs had mixed values: PBC had low but acceptable factor loading and AVE values, RU had a low AVE, while SE had mixed factor loading values (e.g., SE3) and a low AVE. Although PHR had acceptable factor loadings, all other values were low.

Table 21

Convergent Validity Assessment of First Specified CFA Model

Construct	Item	Factor Loading (≥ 0.7, min 0.5)	Construct Reliability (≥ 0.7)	Cronbach's alpha (≥ 0.7)	AVE (≥ 0.5)
Attitude Toward Use	ATU1	0.97	0.96	0.96	0.90
	ATU2	0.95			
	ATU3	0.93			
Behavioral Intention	BI1	0.89	0.80	0.85	0.69
	BI2	0.92			
	BI3	0.67			
Perceived Behavioral Control	PBC1	0.72	0.79	0.84	0.52
	PBC2	0.71			
	PBC3	0.69			
	PBC4	0.76			
	PBC5	0.72			
Perceived Enjoyment	PENJ1	0.92	0.94	0.95	0.81
	PENJ2	0.93			
	PENJ3	0.88			
	PENJ4	0.88			
Perceived Ease of Use	PEU1	0.73	0.83	0.85	0.66
	PEU2	0.86			
	PEU3	0.85			
Perceived Health Risk	PHR1	0.73	**0.62**	**0.57**	**0.47**
	PHR2	0.77			
	PHR3	0.52			
Perceived Usefulness	PU1	0.86	0.93	0.94	0.81
	PU2	0.91			
	PU3	0.92			
	PU4	0.91			
Performance Expectancy	PEXP1	0.83	0.85	0.90	0.72
	PEXP2	0.83			
	PEXP3	0.89			
Regulatory Uncertainty	RU1	0.71	**0.63**	0.71	**0.47**
	RU2	0.65			
	RU3	0.69			
Self-efficacy	SE1	0.90	0.76	0.76	0.51
	SE2	0.75			
	SE3	**0.42**			

To test discriminant validity, the Fornell-Larcker method was used (Fornell & Larcker, 1981; Hair et al., 2010). This method compares the AVE values to the correlation estimates of two constructs, shown in Table 22. Bolded numbers indicate that the MSV was slightly higher than the AVE of one or both of the constructs in question.

Table 22

Discriminant Validity Assessment of First Specified CFA Model

	BI	PBC	PENJ	PEU	PEXP	PHR	PU	RU	SE
ATU	**0.75**	**0.26**	0.61	0.65	0.49	0.11	0.62	0.02	**0.53**
BI		0.31	0.68	0.73	0.54	0.15	0.63	0.02	0.49
PBC			0.31	0.40	0.29	0.15	0.40	0.01	0.51
PENJ				0.59	0.50	0.12	0.56	0.03	**0.53**
PEU					0.66	0.25	**0.78**	0.03	**0.68**
PEXP						0.45	0.71	0.03	**0.55**
PHR							0.32	0.01	0.18
PU								0.02	**0.64**
RU									0.03

Because discriminant validity was not met using the Fornell-Larcker method, a second discriminant validity test was deemed necessary. The heterotrait-monotrait ratio of correlations (HTMT, Henseler et al., 2015) is a ratio of between-trait correlations to within-trait correlations. Values less than 0.85 were preferred, but values of 0.90 or less were considered acceptable (Henseler et al., 2015). The results are shown in Table 23. As all values were 0.90 or less, discriminant validity was deemed acceptable.

Table 23

HTMT Assessment of First Specified CFA Model

Correlation	HTMT Ratio	Correlation	HTMT Ratio
ATU <--> PEU	0.81	PEXP <--> PU	0.80
ATU <--> PENJ	0.77	PEXP <--> SE	0.62
ATU <--> PEXP	0.85	PEXP <--> PBC	0.50
ATU <--> PHR	0.20	PHR <--> RU	0.20
ATU <--> RU	-0.14	PHR <--> PU	0.43
ATU <--> PU	0.78	PHR <--> PBC	0.31
ATU <--> SE	0.70	RU <--> PU	-0.15
ATU <--> PBC	0.51	RU <--> SE	-0.05
PEU <--> PENJ	0.77	RU <--> PBC	0.09
PEU <--> PEXP	0.74	PU <--> SE	0.74
PEU <--> PHR	0.34	PU <--> PBC	0.63
PEU <--> RU	-0.16	SE <--> PBC	0.71
PEU <--> PU	0.87	PHR <--> SE	0.25
PEU <--> SE	0.80	ATU <--> BI	0.88
PEU <--> PBC	0.64	BI <--> PEU	0.90
PEXP <--> PENJ	0.85	BI <--> PENJ	0.82
PENJ<--> PHR	0.28	BI <--> PEXP	0.75
PENJ <--> RU	-0.26	BI <--> PHR	0.52
PENJ <--> PU	0.89	BI <--> RU	-0.16
PENJ <--> SE	0.74	BI <--> PU	0.83
PENJ <--> PBC	0.54	BI <--> SE	0.68
PEXP <--> PHR	0.59	BI <--> PBC	0.57
PEXP <--> RU	-0.17		

Figure 7 shows the first specified CFA model with regression weights. The first specified CFA model had mixed results in terms of model fit, factor loadings, covariances, cross-loadings, AVE and convergent validity, discriminant validity, and construct reliability and Cronbach's alpha values. The model was evaluated, and it was determined that the PHR factor and the item SE3 may need to be removed to improve the model. The literature was reviewed to confirm the process (Hair et al., 2010). The iterative process included first removing PHR items and repeating the respecification process to evaluate model fit, reliability, and validity. By the end of the process, the PHR factor, the three PHR indicator items, and SE3 were removed which also removed the covariance arrow between E28 and E29 and the arrow between PU and PHR1. A review of the CFA output of normality revealed no change in kurtosis (e.g., all remained under 2.0) and no change in outliers. The final specified model is shown in Figure 8. Table 24 features the new model fit indices. The Chi-square value of the final specified model was 804.63 (df = 369, p =0.000).

Table 24

Model Fit Indices of the CFA Final Model

Model Fit Index	Acceptance Value	Original Model	First Specified Model	Final Specified Model
CFI	≥ 0.93	0.93	0.96	0.97
GFI	≥ 0.90	0.85	0.89	0.90
AGFI	≥ 0.90	0.82	0.86	0.87
NFI	≥ 0.90	0.91	0.93	0.94
CMIN/df	≤ 3.00	2.87	2.12	2.18
RMSEA	≤ 0.06	0.06	0.05	0.05
N		489	484	484

Note. Large sample sizes make these values more sensitive and may indicate poor model fit.

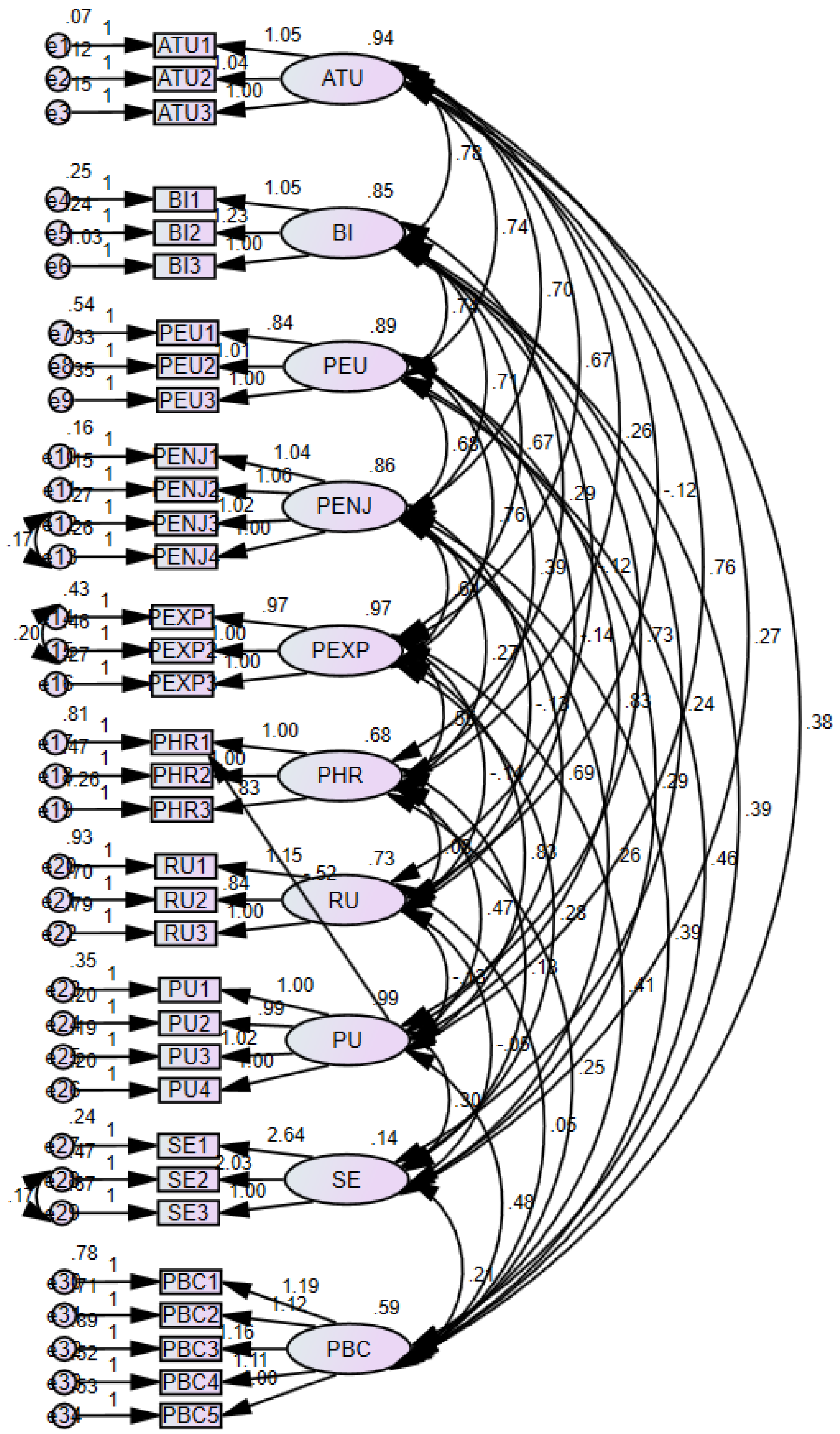


Figure 7. The first specified CFA model.

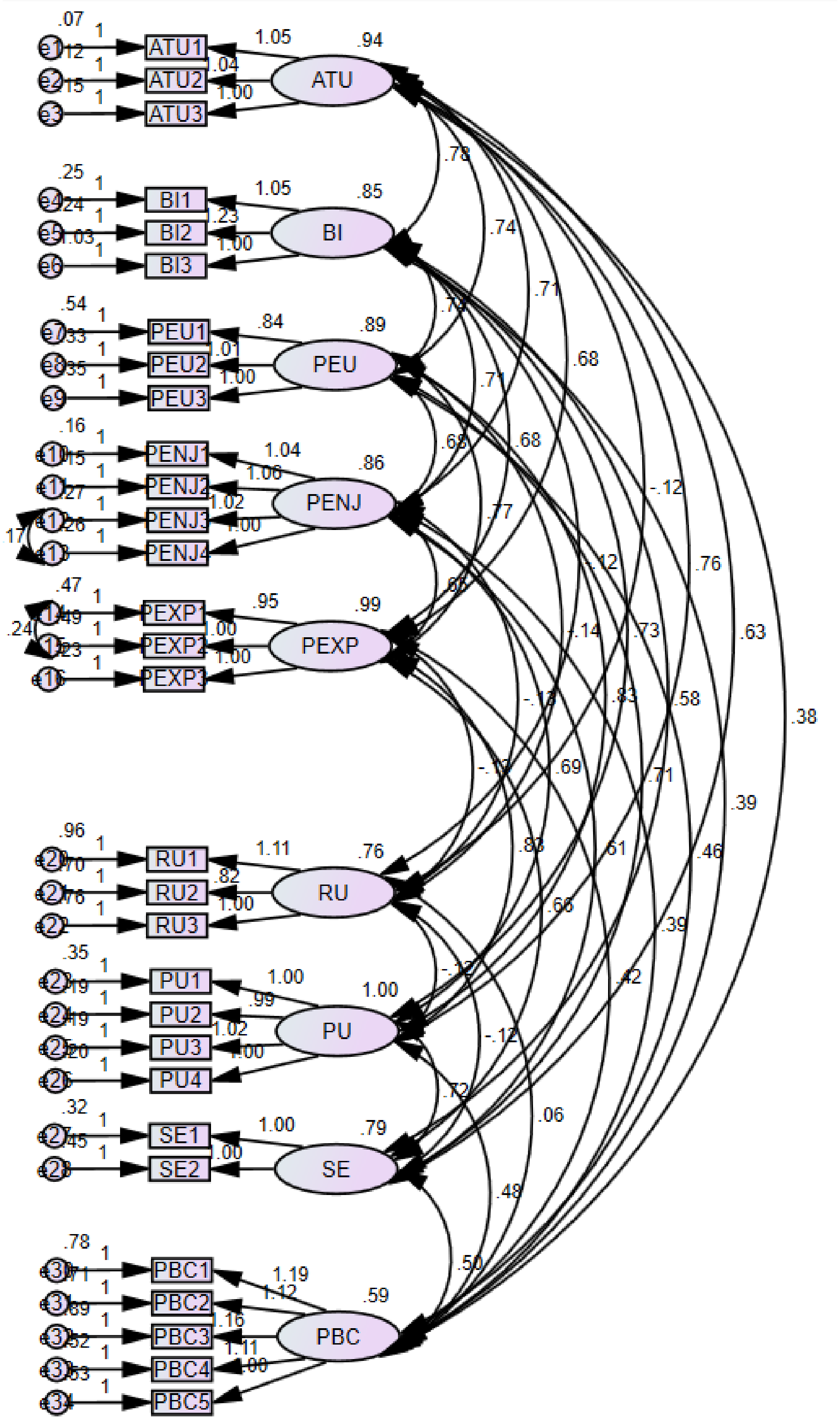


Figure 8. The final specified CFA model.

The reliability and validity of the first specified model had mixed values across the constructs and model fit indices. The deletion of PHR, PHR items, and SE3 impacted the reliability and validity of the model, as detailed in Table 25. In general, the reliability and validity values of the model remained the same or increased with the removal of the items and the PHR factor. Factor RU has the lowest AVE, 0.47, and a low CR of 0.63; however, removing RU2 decreased the values further. Adding a regression weight to RU2 also made no difference, so it was removed. Discriminant validity comparing AVE and MSV values again were assessed using the Fornell and Larcker method (Hair et al., 2010).

Table 25

Convergent Validity Assessment of Final Specified CFA Model

Construct	Item	Factor Loading (≥ 0.7, min 0.5)	Construct Reliability (≥ 0.7)	Cronbach's alpha (≥ 0.7)	AVE (≥ 0.5)
Attitude Toward Use	ATU1	0.97	0.96	0.96	0.90
	ATU2	0.95			
	ATU3	0.93			
Behavioral Intention	BI1	0.89	0.80	0.85	0.69
	BI2	0.92			
	BI3	0.67			
Perceived Behavioral Control	PBC1	0.72	0.79	0.84	0.52
	PBC2	0.71			
	PBC3	0.69			
	PBC4	0.76			
	PBC5	0.72			
Perceived Enjoyment	PENJ1	0.92	0.94	0.95	0.81
	PENJ2	0.93			
	PENJ3	0.88			
	PENJ4	0.88			
Perceived Ease of Use	PEU1	0.73	0.83	0.85	0.66
	PEU2	0.86			
	PEU3	0.85			
Perceived Usefulness	PU1	0.86	0.93	0.94	0.81
	PU2	0.91			
	PU3	0.92			
	PU4	0.91			
Performance Expectancy	PEXP1	0.81	0.84	0.90	0.71
	PEXP2	0.82			
	PEXP3	0.90			
Regulatory Uncertainty	RU1	0.70	**0.63**	0.71	**0.47**
	RU2	0.65			
	RU3	0.71			
Self-efficacy	SE1	0.84	0.78	0.80	0.68
	SE2	0.80			

Results of the final specified CFA model are shown in Table 26, with minimal changes between the first and final models; generally, discriminant validity improved yet was not acceptable. Bolded values indicate that the MSV was slightly higher than the AVE of one or both of the constructs in question. Items from the PHR factor and SE3 were removed. During the respecification process and discriminant validity assessment, items PEU1 and BI3 indicated unacceptable discriminant validity values. These items were individually removed from the model and MSV values compared to AVE. As discriminant validity did not improve, the items were reinstated in the model, and the HTMT method was once again utilized. Table 27 details the discriminant validity values. All were deemed acceptable at 0.90 or less.

Table 26

Discriminant Validity Assessment of Final Specified CFA Model

	BI	PBC	PENJ	PEU	PEXP	PHR	PU	RU	SE
ATU	0.75	0.26	0.61	0.65	0.49	0.11	0.62	0.02	0.68
BI		0.31	0.68	**0.73**	0.54	0.15	0.63	0.02	0.50
PBC			0.31	0.40	0.30	0.15	0.40	0.01	**0.53**
PENJ				0.59	0.49	0.12	0.55	0.03	0.55
PEU					0.66	0.25	**0.78**	0.03	**0.70**
PEXP						0.45	**0.70**	0.02	0.56
PHR							0.32	0.01	0.18
PU								0.02	0.65
RU									0.02

Note. Bolded items indicate values greater 0.1 of a given AVE; italicized items indicate values within 0.1 of a given AVE.

Table 27

HTMT Assessment of Final Specified CFA Model

Correlation	HTMT Ratio	Correlation	HTMT Ratio
ATU <--> PEU	0.81	PEXP <--> PU	0.80
ATU <--> PENJ	0.77	PEXP <--> SE	0.70
ATU <--> PEXP	0.85	PEXP <--> PBC	0.50
ATU <--> RU	-0.14	RU <--> PU	-0.15
ATU <--> PU	0.78	RU <--> SE	-0.13
ATU <--> SE	0.73	RU <--> PBC	0.09
ATU <--> PBC	0.51	PU <--> SE	0.83
PEU <--> PENJ	0.77	PU <--> PBC	0.63
PEU <--> PEXP	0.74	SE <--> PBC	0.72
PEU <--> RU	-0.16	ATU <--> BI	0.88
PEU <--> PU	0.87	BI <--> PEU	0.90
PEU <--> SE	0.86	BI <--> PENJ	0.82
PEU <--> PBC	0.64	BI <--> PEXP	0.75
PENJ <--> RU	-0.26	BI <--> RU	-0.16
PENJ <--> PU	0.89	BI <--> PU	0.83
PENJ <--> SE	0.74	BI <--> SE	0.73
PENJ <--> PBC	0.54	BI <--> PBC	0.57
PEXP <--> RU	-0.17		

Structural Model Assessment

Model construction, model fit, and respecification. The final CFA model, represented in Figure 8, was transformed into an SEM model, depicted in Figure 9. Covariance arrows between exogenous variables, one-way arrows were added to represent hypotheses, and residuals were added to endogenous factors.

Upon reviewing the standardized regression weights in the AMOS output, the relationship between SE and PEU indicated a potentially high value of 1.10. Jöreskog (1999) notes that a “common misunderstanding is that the coefficients in the completely standardized solution must be smaller than one in magnitude, and if they are not, something must be wrong” (p. 1). The author states that correlated factors have factor loadings that are regression coefficients rather than correlations. As such, they may be greater than one. However, Gaskin (2015) notes that a high standardized regression weight can indicate a Heywood Case. A review of the model revealed that both SE1 and SE2 had fixed regression weights of 1. Iterative removal and comparison of the model fit and standardized regression weights resulted in the removal of the regression weight from SE1. A constraint of 1 was also added to the path between SE and PEU; however, this did not allow for hypothesis testing of the relationship. The standardized regression weight was reduced to 1.09 and deemed acceptable, and there were no other issues in the standardized regression weight values.

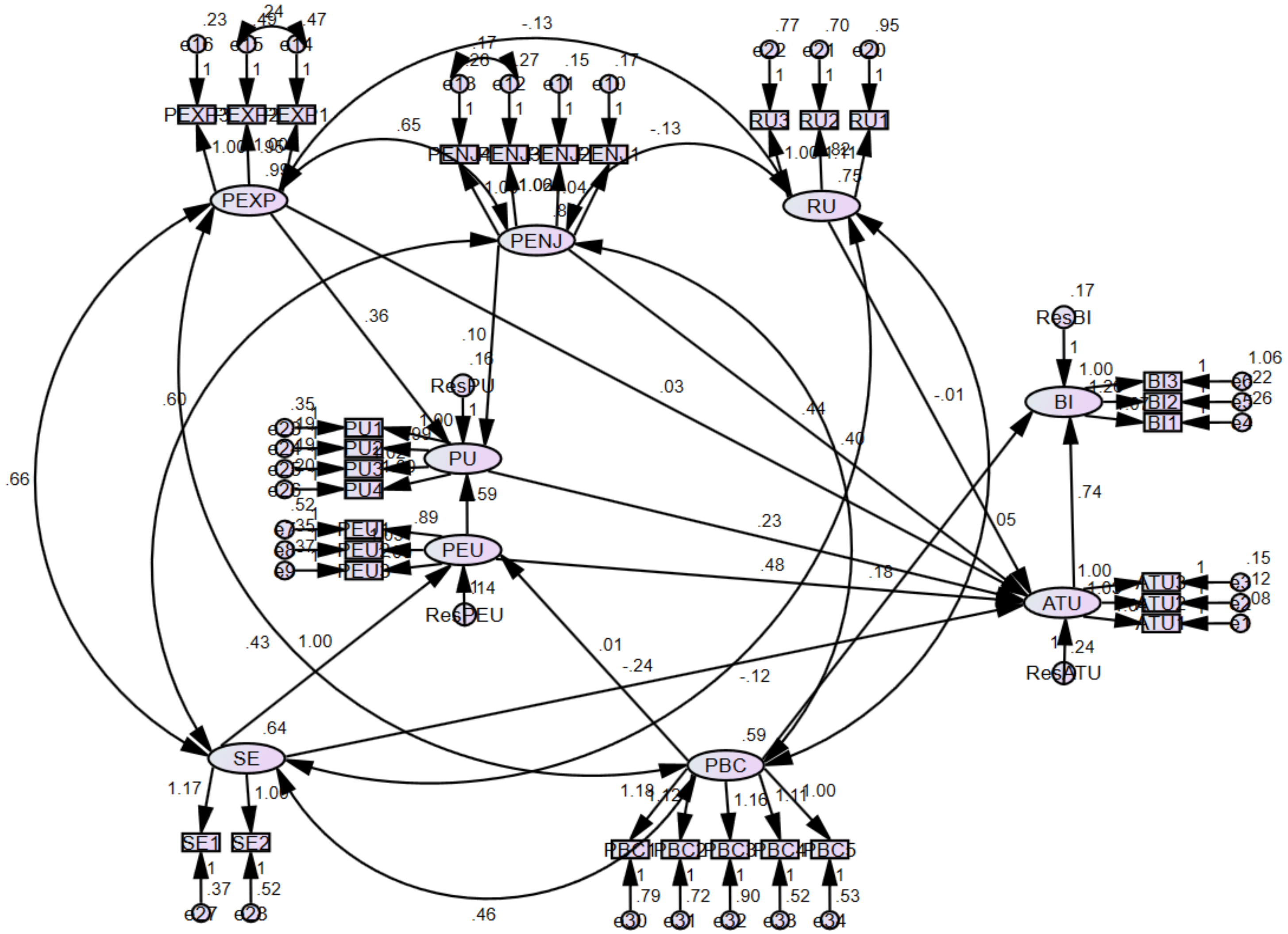


Figure 9. The SEM with standardized regression weights.

SEM hypothesis testing. The removal of construct PHR meant it was unnecessary to hypothesis 8, perceived health risk negatively influences attitude toward use. Hypothesis testing results are described in Table 28.

Table 28

Hypothesis Testing of First Structural Model

Hypothesis / Relationship	SRW	*t*-value	*p*-value	Result
H_1: PEU positively influences PU.	0.60	8.92	***	Supported
H_2: PEU positively influences ATU.	0.55	3.62	***	Supported
H_3: PU positively influences ATU.	0.22	2.65	0.008	Supported
H_4: PEXP positively influences PU.	0.34	6.28	***	Supported
H_5: PEXP positively influences ATU.	0.02	0.27	0.78	Not supported
H_6: PENJ positively influences PU.	0.08	1.71	0.087	Not supported
H_7: PENJ positively influences ATU.	0.44	7.96	***	Supported
H_9: RU negatively influences ATU.	0.00	0.11	0.913	Not supported
H_{10}: SE positively influences PEU.	1.41	12.09	***	Supported
H_{11}: SE positively influences ATU.	-0.36	-1.83	0.067	Not supported
H_{12}: PBC positively influences PEU.	-0.24	-2.62	0.009	Not supported
H_{13}: PBC positively influences BI.	0.18	4.24	***	Supported
H_{14}: ATU influences BI.	0.75	14.70	***	Supported

Note. *** indicates significance at $p < 0.001$. The critical ratio t-values should be above 1.96 with *p* values below 0.05 to indicate support for a hypothesis. SRW = Standardized regression weight.

Hypothesis 1 (H_1) is supported, indicating that PEU positively influences PU. The hypothesis has a statistically significant value ($p < 0.001$) and a *t*-value greater than 1.96. This result means that if PEU increases by 1.0, PU will increase by 0.60.

Hypothesis 2 (H_2) is supported, indicating that PEU is a positive influence on ATU at a statistically significant level ($p < 0.001$). The *t*-value is greater than 1.96, implying that as PEU increases by 1.0 so too will ATU increase by 0.55.

Hypothesis 3 (H_3) is supported, indicating that a change to PU will positively impact ATU. The relationship is significant ($p= 0.008$) and as PU changes by 1.0, the high *t*-value means that ATU will change by 0.22.

Hypothesis 4 (H_4) is supported at the statistically significant level ($p < 0.001$) with a *t*-value greater than 1.96. This indicates that as PEXP increases by 1.0, PU will also increase by 0.34.

Hypothesis 5 (H_5) is not supported, as the *p*-value was less than 0.05 ($p = 0.78$). The results indicate there is insufficient evidence to conclude that PEXP has a positive influence on ATU. The *t*-value was also less than 1.96, further indicating the lack of support.

Hypothesis 6 (H_6) is not supported, as indicated by the non-significant *p*-value ($p = 0.087$) and *t*-value below 1.96. The results indicate there is insufficient evidence to conclude that PENJ has a positive influence on PU.

Hypothesis 7 (H_7) is supported, indicating that PENJ has a positive influence on ATU. The relationship was significant ($p < 0.001$) with a *t*-value greater than 1.96. As PENJ increases by 1.0, ATU will also increase by 0.44.

Hypothesis 9 (H_9) is not supported, there is insufficient evidence to conclude that RU has a negative influence on ATU. The relationship was insignificant ($p = 0.913$) with a low *t*-value.

Hypothesis 10 (H_{10}) is supported with a significance of $p < 0.001$, indicating that SE positively influences PEU. The high *t*-value supports the relationship. As SE increases by 1.0, PEU will increase by 1.41.

Hypothesis 11 (H_{11}) is not supported, indicating there is insufficient evidence to conclude that SE has a positive influence on ATU ($p = 0.067$), which is reinforced by a *t*-value of less than 1.96. The standardized regression weight was negative (-0.36), further confirming the lack of support.

Hypothesis 12 (H_{12}) is not supported, indicating there is insufficient evidence to conclude that PBS has a positive influence on PEU. In fact, the standardized regression weight was negative (-0.24), indicating the opposite effect. The negative relationship was significant at $p = 0.009$ with a low *t*-value, implying a change of 1.0 for PBC will cause a decrease of 0.24 to PEU. This is an interesting finding and adds to the body of literature.

Hypothesis 13 (H_{13}) is supported, indicating that PBC positively impacts BI. The relationship is significant ($p < 0.001$) and further supported by a *t*-value greater than 1.96. As PBC increases by 1.0, BI will also increase by 0.18.

Hypothesis 14 (H_{14}) is supported, indicating that ATU is a positive influence on BI. The significance level ($p < 0.001$) and high *t*-value support this conclusion. As ATU increases by 1.0, BI will increase by 0.75.

New relationships identified and SEM testing. Modification indices were reviewed for regression weights between factors that indicate a potential, new relationship. Before being added to the model, the literature must be reviewed to support the inclusion of such a relationship because CFA and SEM are theory-driven approaches (Hair et al., 2010).

Only one possible new relationship was identified for review and potential inclusion in the model: PENJ -> BI (MI = 13.43). Lee et al. (2018) utilized PENJ in a TAM to measure the adoption of VR devices as a social connectivity device. The construct was identified as “an important factor statistically affecting all the basic components of TAM” (Lee et al., 2018, p. 7) including PU, PEU, an attitude construct, and intention to use a VR device. Manis and Choi (2018) also used PENJ in their virtual reality hardware acceptance model. They found that hypothesized relationships between PENJ and ATU of VR hardware, PENJ and attitude toward purchasing VR hardware, and PENJ and purchase intention were supported ($p < 0.001$). Given the support in the literature, the relationship was included and tested in the final, modified SEM. Results indicated sufficient evidence to conclude that PENJ has a positive influence on BI.

Modified SEM model fit. Adding the PENJ-BI relationship resulted in a new SEM, shown in Figure 10, and improved model fit values, detailed in Table 29. The relationship is H_{15}: Perceived enjoyment positively influences behavioral intention.

Table 29

Model Fit Indices of the First SE and Modified SE Models

Model Fit Index	Acceptance Value	First SEM	Modified SEM
CFI	≥ 0.93	0.96	0.96
GFI	≥ 0.90	0.88	0.89
AGFI	≥ 0.90	0.86	0.86
NFI	≥ 0.90	0.93	0.94
CMIN/df	≤ 3.00	2.40	2.28
RMSEA	≤ 0.06	0.05	0.05
N		484	484

Note. Large sample sizes make these values more sensitive and may indicate poor model fit.

Modified SEM model hypothesis testing. Hypotheses were again tested using the same process used to test the first SEM. Table 30 summarizes the hypothesis testing results. Hypothesis 15 (H15) is supported, indicating that PENJ positively influences BI. The hypothesis has a statistically significant value ($p < 0.001$) and a t-value greater than 1.96. This result means that if PENJ increases by 1.0, BI will increase by 0.34.

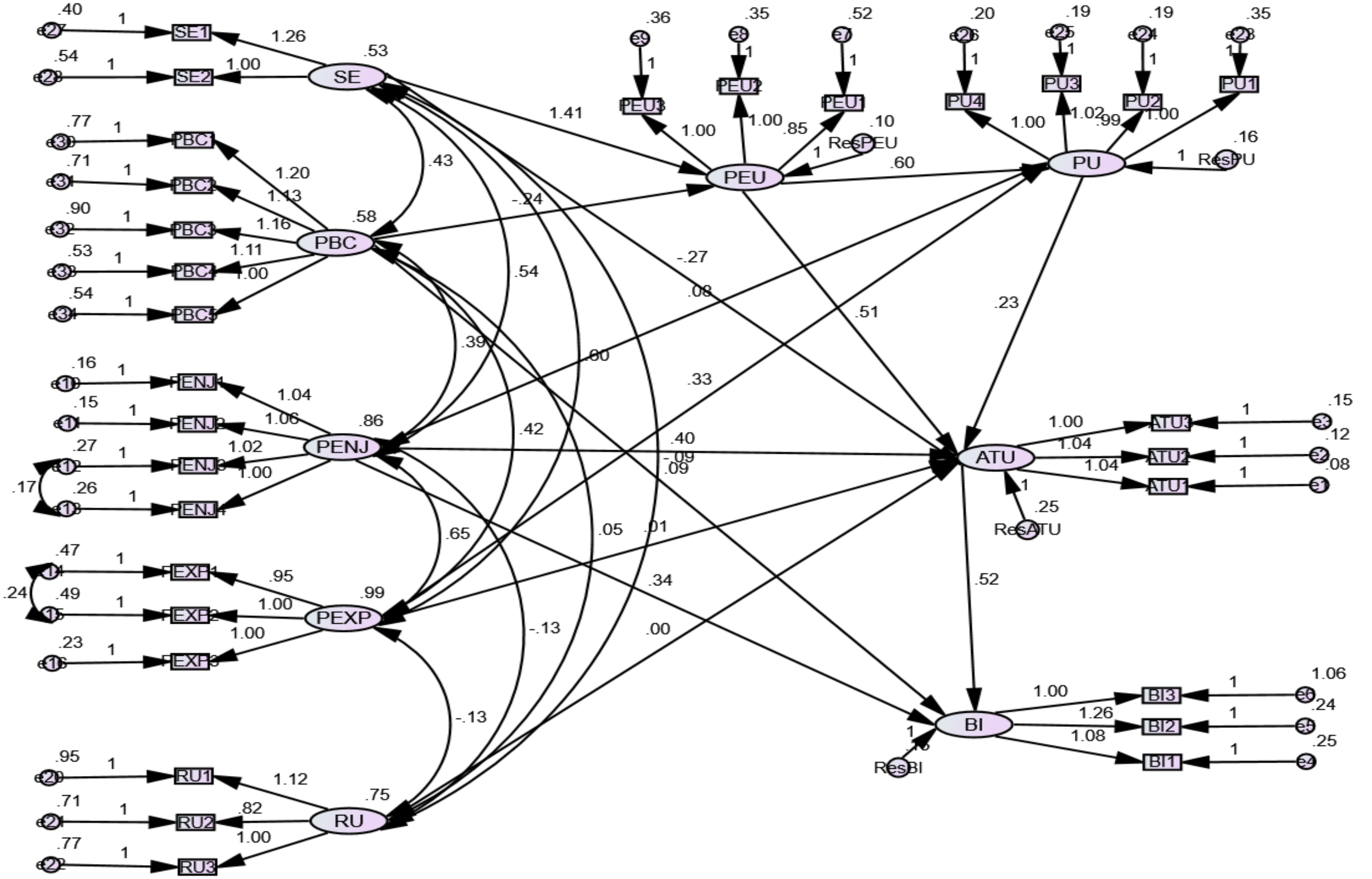


Figure 10. *The Modified SEM with standardized regression weights.*

Table 30

Hypothesis Testing of Modified Structural Model

Hypothesis / Relationship	SRW	t-value	*p*-value	Result
H_1: PEU positively influences PU.	0.60	8.90	***	Supported
H_2: PEU positively influences ATU.	0.51	3.35	***	Supported
H_3: PU positively influences ATU.	0.23	2.67	0.008	Supported
H_4: PEXP positively influences PU.	0.34	6.26	***	Supported
H_5: PEXP positively influences ATU.	0.01	0.08	0.940	Not supported
H_6: PENJ positively influences PU.	0.08	1.69	0.095	Not supported
H_7: PENJ positively influences ATU.	0.40	7.15	***	Supported
H_9: RU negatively influences ATU.	0.00	0.13	.900	Not supported
H_{10}: SE positively influences PEU.	1.41	12.16	***	Supported
H_{11}: SE positively influences ATU.	-0.27	-1.39	0.165	Not supported
H_{12}: PBC positively influences PEU.	-0.24	-2.67	0.008	Not supported
H_{13}: PBC positively influences BI.	0.09	2.29	0.022	Supported
H_{14}: ATU influences BI.	0.52	10.41	***	Supported
$H_{15:}$ PENJ positively influences BI.	0.34	6.87	***	New hypothesis, Supported

Note. *** indicates significance at $p < 0.001$. The critical ratio t-values should be above 1.96 with *p* values below 0.05 to indicate support for a hypothesis. SRW = Standardized regression weight.

As discussed, the addition of the relationship between PENJ and BI improved the model fit of the modified SEM. The new relationship did not impact the support or lack of support of the other 13 hypotheses previously tested. Standardized regression weights of the first SEM and modified SEM were compared, highlighted in Table 31. Four values decreased, four values increased, and six did not change.

Table 31

Standardized Regression Weight Comparison of the First and Modified SE Models

Hypothesis / Relationship	First SEM	Modified SEM	Change
H_1: PEU positively influences PU.	0.57	0.57	-
H_2: PEU positively influences ATU.	0.53	0.50	-0.04
H_3: PU positively influences ATU.	0.23	0.23	-
H_4: PEXP positively influences PU.	0.34	0.33	-
H_5: PEXP positively influences ATU.	0.02	0.01	-0.01
H_6: PENJ positively influences PU.	0.08	0.08	-
H_7: PENJ positively influences ATU.	0.42	0.38	-0.04
H_9: RU negatively influences ATU.	0.003	0.004	-
H_{10}: SE positively influences PEU.	1.09	1.09	-
H_{11}: SE positively influences ATU.	-0.27	-0.20	0.07
H_{12}: PBC positively influences PEU.	-0.20	-0.20	-
H_{13}: PBC positively influences BI.	0.80	0.08	-0.72
H_{14}: ATU influences BI.	0.15	0.56	0.41
H_{15}: PENJ positively influences BI.		0.35	0.35

Chapter Summary

Chapter IV presented the statistical and analytical results of the study to determine those factors that influence aviation students' attitude toward and intention to use VR for flight training. A pilot study was conducted, and the survey subsequently revised through the rewording of the PHR indicator items. The minimum number of responses (475) was surpassed using Google Forms with an initial sample size of 706 and a final sample size of 484. Descriptive statistics were used to characterize the responses of the participants. The only demographic that may be used to gauge adequate representation, gender, was representative of the gender distribution of the sampling framework as well as the ratio of male/female student pilots of the U.S.A.

The CFA process was used to assess the measurement model. The original model had mixed results in terms of model fit, factor loadings, covariances, cross-loadings, AVE and convergent validity, discriminant validity, and construct reliability and Cronbach's alpha values. Iterative testing of the model resulted in the removal of PHR, its items, and item SE3. Because discriminant validity was unsatisfactory, HTMT ratios were used as an alternative method to assess discriminant validly, and the analysis was successful. The final specified CFA model had good model fit, no cross-loadings, and no covariances between factors.

A full structural model process was completed and fit compared to the CFA model fit. Although the standardized regression weights between SE and PEU indicated a potentially high value of 1.10, removing an extraneous regression weight on item SE1 caused the standardized regression weight to decrease to an acceptable 1.09. Model specification was not required due to a good model fit. One new relationship between PENJ and BI was discovered and tested. The final SEM had 14 hypotheses, nine of which were supported at a statistically significant level ($p < 0.05$ or 0.001). Five hypotheses were not supported. The final model also had the best model fit in comparison to other iterations. All nine of the final constructs were important, relevant components to determine factors that influence aviation students' intentions to use VR technology for flight training. Six factors had a direct, positive influence on ATU, BI, or both. In Chapter V, the results of the study will be discussed, incorporating literature that helped frame the research and theoretical foundation. Conclusions will be drawn and recommendations for future research provided.

CHAPTER V

DISCUSSION, CONCLUSIONS, AND RECOMMENDATIONS

This study assessed factors that influence aviation students' attitude toward and intention to use virtual reality (VR) for flight training. Chapter IV reported significant findings of the study which included demographic information of participants, descriptive statistics, confirmatory factor analysis (CFA), and structural model assessment (SEM), and concluded with hypothesis testing and addressing the research questions. Chapter V discusses the results of the model, presents conclusions, and offers recommendations for future research.

The model utilized in the study was supported by the literature surrounding aviation, training, and VR; using immersive simulation technology for training in general and specifically for flight training; the ground theories of the technology acceptance model (TAM) and theory of planned behavior (TPB); and validated extensions of TAM, TPB, and combinations thereof. Ten constructs were used in the model, which were derived from the literature review and chosen for their adaptability to other aviation technologies, aviation training, or VR use in other environments. They are attitude toward use (ATU), behavioral intention (BI), perceived behavioral control (PBC), perceived ease of use (PEU), perceived enjoyment (PENJ), performance expectancy (PEXP), perceived health risk (PHR), perceived usefulness (PU), self-efficacy (SE), and regulatory uncertainty (RU). Data was collected through a survey created in Google forms and disseminated to aviation students enrolled in Part 141 flight schools at 34 institutions across the U.S. Upon analyzing the data using descriptive statistical analysis, CFA, and SEM processes, results indicated that the factor PHR, its three associated items, and an item relating to SE (SE3) should be removed to improve model fit. During the SEM process, one additional relationship between PENJ and BI was revealed, validated, and added to the model.

Discussion

Characteristics of the participants. Demographic information was collected from the participants and compared to population characteristics when appropriate. The sampling framework included approximately 7,982 actively-flying students enrolled in 34 FAA-approved Part 141 flight schools in colleges and universities across the United States. Data was collected from 704 participants (9%) at 22 institutions (65%). The institutions were from six of the nine FAA regional areas. The final sample size of viable data was 484 (6% of the sampling framework). Participants aged in range from 18 to 51 and represented flight students of varying levels of educational status and flight certification. Although all participants had begun flight training, their experience was quite varied, ranging from new student pilots (1 hr.) to advanced certification (i.e., airline transport pilot) and hours (3,000 hrs.). Most participants reported an education level within a traditional four-year degree program (e.g., freshman through senior), although several participants reported advanced degrees or multiple degrees/certification levels. While racial identity and international status information was requested, it was not used in the context of the study, as race distribution information of the target population was not available.

Gender information was collected to ensure representation, as gender is the only demographic of which published information is available. The distribution of the sample was approximately 86% male, 14% female, and 0.4% who did not say. This distribution aligns with data reported by the FAA (2020) and Women In Aviation (n.d.).

Participants reported their VR and gaming experience. In general, participants were not frequent users of VR, although the majority had some experience with the technology. Only a small percentage (9%) reported frequent or even daily use of VR. Despite the overall limited familiarity of VR, over half of the participants reported they played computer or video games frequently (i.e., a few times a week or daily). In general, about half of American adults play video games on a computer, game console, TV, or portable device (Duggan, 2015). The characteristics of the sample align well with general, known characteristics of the target population.

Model modifications and results. The original CFA model required modifications to improve the model fit as well as reliability and validity. Changes were made systematically and model fit values compared to ensure a change did not negatively affect the model and in support of the literature. Although a covariance between PU and PHR1 was noted, removal of the PHR factor negated this. An item from SE was also removed.

The PHR factor was removed due to low factor loading of one item (PHR3), low construct reliability, low Cronbach’s alpha, and low average variance extracted (AVE). Items of the factor were removed one at a time and model fit compared before the factor was removed altogether. The factor has been used to understand how PHR can influence Internet use for health-related information seeking (Ahadzadeh, Pahlevan Sharif, Ong, & Khong, 2015). Ahadzadeh et al. (2015) related PHR to the motivation individuals felt to change or adopt healthier behaviors as opposed to impacting ATU. Perceived risk was used in the aviation environment – specifically, sUAS (Clothier et al., 20015; Myers, 2019) and airline check-in kiosks (Lu et al., 2009). Although Lu et al. (2009) found perceived risk negatively influences BI and Myers (2019) found perceived risk negatively impacts ATU, Myers removed the construct from his model due to cross-loading and covariance issues. The factor PHR was defined as the perception a student forms and revises based on the possible physical health risks of using VR for flight training. It was hypothesized that perceptions of health risks associated with using VR for flight training may negatively impact acceptance and ATU. Because VR is not widely used by the participants, participants may have little firsthand knowledge of health risks associated with VR (e.g., simulation sickness) or they may not have concerns about health risks associated with VR. Aviation students enrolled in Part 141 flight schools have access to a variety of flight simulation training devices (FSTD), as shown in Table C1. Participants of the study reported on average that they had logged 26 hours in a flight training device (FTD) during their training and may, therefore, be comfortable using advanced, immersive simulation technology for their flight training. The factor was removed from the model.

An item from SE was removed from the model. SE was defined as the perception of one’s flight skills in the virtual and real-world environments. The measurable item SE3 was “I feel confident in my flight skills in the real-world environment.” This item had the highest average, lowest standard deviation, and the highest skew and kurtosis values of the factor, as noted in Table 19. It also had an unacceptable factor loading which affected the construct reliability, Cronbach’s alpha, and AVE of the factor. Removing the item improved these reliability values of the factor as well as the model fit.

Discriminant validity was tested using the Fornell-Larcker (1981) approach as well as by assessing the heterotrait-monotrait ratio of correlations (HTMT; Henseler et al., 2015). Testing discriminant validity is an important aspect of the CFA and SEM process as it is used to assess the intercorrelations of variables and ensure adequate difference among them. Indistinct factors can call discriminant validity into question (Kline, 2016). Hair et al. (2010) note that factor loadings between 0.60 and 0.80 can negatively impact the Fornell-Larcker (1981) approach to assessing AVE. Thus, the HTMT approach was also utilized to ensure discriminant validity criteria were met. This approach was also utilized by Myers (2019).

Nine predictor variables and one outcome variable were incorporated into the model, all of which were derived from relevant research using the TAM and TPB. Exogenous variables included PBC, PNEJ, PEXP, PHR, RU, and SE. The endogenous variables included ATU, PEU, PU, and BI (the outcome variable). The results of the structural model indicated the highest model fit values of all the previous iterations.

Discussion of the research questions. Three research questions were explored, each of which is addressed below. A detailed discussion of the individual hypotheses follows in the next subsection.

RQ1. The first research question was “What factors influence aviation students’ intentions to use VR technology for flight training?” The original CFA model identified 10 latent constructs, derived from the literature. Of these, eight were used in the final SEM as direct or indirect influencers of BI. The positive and negative strength of each between-factor relationship was described in Table 34.

The factor of PEU had the strongest indirect and direct positive influence on ATU and a strong, positive, indirect impact on BI. The relationship is part of the original TAM (Davis et al., 1989) and is supported by the literature. As expected from the literature, ATU also strongly influenced BI. The other factors that influence ATU and BI, directly and indirectly, are PU, PENJ, and PBC.

Of interest, SE was an indirect, positive influencer of BI through PEU, yet had a negative, direct impact on ATU. RU was also hypothesized to negatively impact ATU directly and BI indirectly; however, the relationship between RU and ATU was negligible and not significant. PEXP did not impact ATU directly, as hypothesized.

RQ2. Research question two asked, “How do these factors impact students’ intentions to use VR technology for flight training?” Hypothesis testing revealed that PEU and PU have a direct, positive impact on ATU and indirect, positive influence on BI. The factor of PENJ directly, positively impacts both ATU and BI. SE was shown to directly, negatively impact ATU, yet the relationship was statistically insignificant. Understanding which factors influence students to use VR for flight training, and which factors undermine efforts to use VR, can allow stakeholders (e.g., flight instructors, developers, designers) to target how VR is implemented into flight training. Table 32 shows the positive and negative rank-ordered strength of each between-factor relationship.

Table 32

Rank-ordered Strength of Between-factor Relationships

Hypothesis / Relationship	Positive Rank-Ordered Strength	Negative Rank-Ordered Strength
H10: SE positively influences PEU.	1.09	-
H1: PEU positively influences PU.	0.57	-
H14: ATU influences BI.	0.56	-
H2: PEU positively influences ATU.	0.5	-
H7: PENJ positively influences ATU.	0.38	-
H15: PENJ positively influences BI.	0.35	-
H4: PEXP positively influences PU.	0.33	-
H3: PU positively influences ATU.	0.23	-
H6: PENJ positively influences PU.	0.08	-
H13: PBC positively influences BI.	0.08	-
H5: PEXP positively influences ATU.	0.01	-
H9: RU negatively influences ATU.	0.004	-
H11: SE positively influences ATU.	-	-0.2
H12: PBC positively influences PEU.	-	-0.2

RQ3. The final research question was "To what extent do these factors influence aviation students' intentions to use VR technology for flight training?" The model fit of the final, modified SEM was good with all indices indicating acceptable value or greater. Table 23 detailed these indices which were used as the main confirmation of how well the model described the factors which influence aviation students' intentions to use VR technology for flight training. One hypothesis (H8) was removed due to the deletion of PHR. A new relationship between PENJ and BI (H15) was discovered and supported. The removal of H8 and the addition of H15 resulted in the support of nine out of 14 hypotheses (64%). The addition of the new relationship indicates that, although the original model was fit and, therefore, adequately answers the research question, it was slightly lacking in depicting all pertinent relationships.

Discussion of the hypotheses. Fourteen hypotheses were investigated using the model, the majority of which were derived from previously validated TAM, TPB, or extensions/combinations thereof relationships. An additional hypothesis (H15) was added based and supported by the literature, while one (H8) was removed. The chosen factors and relationships focused on intention as opposed to actual behavior. Four new hypotheses were supported by the literature and were carefully examined to determine the extent to which the relationships were supported in the study.

Hypothesis 1: Perceived ease of use positively influences perceived usefulness. The results indicate there is sufficient evidence to conclude PEU influences PU, which is supported by the literature. Davis (1989) first proposed and validated the relationship between PEU and PU. Gong et al. (2004), Lu et al. (2008), Manis and Choi (2018), and others have subsequently validated the relationship in numerous other studies across a variety of domains and technologies. The results indicate that there is a strong, positive relationship between the constructs. As the user’s belief that using VR for flight training will be free of effort increases, it influences their belief that VR for flight training will enhance his or her performance. Currently, the use of VR for flight training is theoretical, as the technology has not been developed for this purpose. However, the results of the relationship indicate that program developers, instructors, and other stakeholders should prioritize ensuring the flight students understand how to use the technology as an easy and beneficial alternative for flight training, thus positively impacting the belief that VR is a useful technology to enhance training.

Hypothesis 2: Perceived ease of use positively influences attitude toward use. The results indicate there is sufficient evidence to conclude PEU influences ATU, which is supported by the literature. Another key component of the TAM, Davis' (1989) relationship has been validated by numerous researchers including Cheung and Vogel (2018), Lemay et al. (2018), and Manis and Choi (2018). The relationship was strong and positive. If the user does not expect that using VR for flight training will require extraneous effort, no more so than other immersive technology used in flight training (e.g., an FTD or ATD), they may also expect that VR is easily learned and mastered. In turn, the user will be more inclined to use VR for flight training. Again, this suggests that emphasis be placed on training students on using the technology so that it is easy to incorporate into training which in turn will positively influence student attitude.

Hypothesis 3: Perceived usefulness positively influences attitude toward use. The results indicate there is sufficient evidence to conclude PU influences ATU, which is supported by the literature. As an original TAM relationship, Cheung and Vogel (2018), Esteban-Millat et al. (2018), and others have demonstrated the validity of this relationship. The factors are strongly, positively related in the current study, as was hypothesized. This indicates that attitude toward using VR for flight training will be positively impacted as the student believes that the technology offers benefits that may enhance flight training and may not be found in other technologies. Instructors, developers, and others should highlight the performance benefits of using VR for flight training in direct comparison to FTDs and even other training devices.

Hypothesis 4: Performance expectancy positively influences perceived usefulness. The results indicate there is sufficient evidence to conclude PEXP influences PU, which is supported by the literature. Lewis et al. (2013), Onaolapo and Oyewole (2018), and Shen et al. (2018) included PEXP in the UTAUT, and the construct has been positively associated with the constructs of behavioral intent and actual use. However, the construct has not received wide use outside these parameters. The new relationship between PEXP and PEU was a new hypothesis for the model and both constructs relate to the performance value of VR for flight training, especially as compared to an FTD. It was theorized that as the user's belief that using VR technology for flight training will improve flight performance, so too will their belief that VR is a beneficial tool to enhance performance. The strong, positive relationship between the constructs supports the theory and adds to the body of knowledge surrounding using VR in educational contexts and, more specifically, for flight training purposes. Instructors and developers can capitalize on this finding by introducing students to VR for flight training, explaining the differences between VR and FTDs, demonstrating how VR can improve flight training, and facilitating dedicated training in VR.

Hypothesis 5: Performance expectancy positively influences attitude toward use. The results indicate there is insufficient evidence to conclude PEXP influences ATU. Although PEXP has seen some use in the UTAUT, ATU was not utilized in favor of BI as an influencer of actual use behavior. The relationship was, therefore, new to the model but supported in a theoretical capacity as ATU impacts BI. The relationship was positive but not supported. This hypothesis is based on the belief that VR will improve flight performance, as compared to using an FTD, which will naturally impact the user's attitude toward using the technology. It was theorized that attitude toward using VR for flight training will increase as the user's expectancy in performance favorably increases. Participants were asked to consider VR for flight training as more productive than an FTD, as an efficient way to improve flying skills as compared to an FTD, and as a resource that would require the same amount of effort as an FTD to enhance training. However, the participants indicated infrequent use of VR in general, let alone for educational purposes. Moreover, VR is not currently used for flight training purposes. Participants had to consider the technology and its use in flight training from a purely theoretical perspective. Unsurprisingly, the hypothesis was not supported, as participants have little to base their responses on. This relationship warrants further investigation in the future as VR is more readily available for personal and educational use, which will impact aviation students' attitudes toward VR.

Hypothesis 6: Perceived enjoyment positively influences perceived usefulness. The results indicate there is insufficient evidence to conclude PENJ influences PU. Another relatively new construct, PENJ was developed by Abdullah and Ward (2016) for the GETAMEL and subsequently used by Chang et al. (2017) as a key factor to describe the extent to which the user will appreciate the experience of a technology in its own right; the researchers found PENJ to positively impact ATU. This is an important consideration as learners who believe that using a given technology is enjoyable are also more likely to believe that the technology is useful. As an intrinsic motivation, enjoyment can positively affect learning regardless of performance expectations or results. The hypothesized relationship was not supported. Again, participants reported some experience with VR, and those who have experience with the technology are infrequent users. It is difficult to judge a technology as enjoyable in its own right when the experience is limited. If VR is introduced to the aviation training environment, it may behoove stakeholders to encourage users to use the technology in their personal time to gain familiarity with using it for non-training purposes. Further investigation is warranted after VR becomes readily available for flight training.

Hypothesis 7: Perceived enjoyment positively influences attitude toward use. The results indicate there is sufficient evidence to conclude PENJ influences ATU, which is supported by the literature. As a newer construct for the TAM, PENJ has not been validated as an influencer of ATU beyond the study of Manis and Choi (2018). Enjoyment impacted consumer motivation to use VR and ultimately BI, which may also translate to the learning environment: As the student uses VR for flight training and enjoys the learning process, their attitude will be positively impacted as well. Studies have demonstrated that enjoyment can enhance the learning environment, which also impacts engagement and motivation. The relationship between enjoyment and attitude supports these studies. The confirmed relationship between the factors also adds to the body of knowledge surrounding PENJ as an important TAM factor. Instructors and VR developers can capitalize on the enjoyment provided by VR to enhance learning and keep students engaged as they progress through their training regimen. As VR receives more research, it will be interesting to see how the factor develops and is utilized in extended TAMs.

Hypothesis 8: Perceived health risk negatively influences attitude toward use. Although PHR was removed from the model, thereby negating the hypothesis testing, it is still important to understand how the construct can impact attitude and BI. The construct of PHR has been theorized but not widely investigated; others have investigated perceived risk in the aviation environment in association with sUAS (Clothier, Greer, Greer, & Mehta, 20015; Myers, 2019) and airline check-in kiosks (Lu et al., 2009), but not health concerns that may be associated with aviation, education, and VR technology. The new, negative relationship between PHR and ATU is not strongly supported in the literature. The negative relationship indicates that as a student's concern for their physical health increases, their attitude toward using VR for flight training will decrease. As previously discussed, participants had little experience with VR. They may not consider the potential side effects of using the technology (e.g., simulation sickness). Alternatively, they may not consider potential health risks to be an issue due to familiarity with FTDs. The relationship warrants further investigation as VR comes available for flight training.

Hypothesis 9: Regulatory uncertainty negatively influences attitude toward use. The results indicate there is insufficient evidence to conclude RU influences ATU. At the time of data collection, VR was not in use for flight training nor are there high-fidelity, realistic programs available to implement into flight training courses. This lack of regulations, and uncertainty surrounding when and if VR may be approved for flight training, can directly, negatively impact students’ attitude toward using the technology. Logically, this makes sense. If the technology is not approved (but others are), where is the incentive to use the technology outside of personal enjoyment? Hours spent in the VE will not be logged as training hours, and it is questionable as to when the FAA will approve VR for flight training. The study does not confirm the unique relationship between RU and ATU, which has not been widely used beyond Yang et al. (2015) in an extended TAM except in the theoretical capacity. The relationship between the factors was negligible and not statistically significant. The lack of a relationship may be because participants are not experienced with the technology, nor is it even an option for use in a training capacity. There may be no consideration of the regulatory concerns given the inability to use VR for flight training. As regulations change to include VR as a flight training device, the relationship should be reconsidered. More research is warranted to determine if the uncertainty caused by the lack of regulations impacts attitude or not.

Hypothesis 10: Self-efficacy positively influences perceived ease of use. The results indicate there is sufficient evidence to conclude SE influences PEU, which is supported by the literature. The results indicate a strong correlation between the factors, given the high critical ratio and standardized regression weight. The SE construct was introduced to the TAM by Venkatesh and Davis (1996) and subsequently validated in other studies by Gong et al. (2004), Lemay et al. (2018), and Park (2009). In the context of the present research, SE refers to a user's individual judgment of how well a course of action can be executed in a prospective situation. It was determined that the SE construct be measured in terms of flying skills and performance in the virtual and real-world environments. Students who are confident in their flight skills and technological abilities may believe more strongly that using VR technology will be easy. A strong, positive relationship was revealed. As VR becomes available, instructors can encourage their aviation students to practice flight skills in the VE often to hone procedural skills. These skills may then transfer to the actual aircraft, which will further impact the aviation student's flight skills but also their ability to use immersive simulation technology.

Hypothesis 11: Self-efficacy positively influences attitude toward use. The results indicate there is insufficient evidence to conclude SE influences ATU. Although SE has been utilized in extended TAMs, its relationship with ATU has not had strong support; however, Gong et al. (2004) and Park (2009) found that SE positively impacts

BI, which in turn is impacted by ATU in the current model. Individual confidence in flight abilities and/or their ability to use VR technology may impact attitude toward using VR and therefore BI. The hypothesized relationship was not supported. The relationship between SE and ATU had mixed results in the literature; thus, this finding adds to the discussion of how SE may be incorporated into a TAM. Although the construct has been used in other environments and with other technologies, it has not been used in an aviation context nor when VR is being assessed. The negative impact on ATU prompts further exploration. The operational definition of SE was the "perception of one's flight skills in the virtual and real-world environments." The relationship may have been impacted, in part, due to the removal of item SE3, "I feel confident in my flight skills in the real-world environment," which had a low factor loading and negatively impacted the reliability and validity of the construct. Given that virtual environments (VE) are not currently used in flight training, it is probable that participants are unsure of how their flight skills will translate to the VE. Indeed, the participants would have been forced to consider the items related to this construct from a theoretical capacity.

Furthermore, participants varied in age (18 to 51), educational status, and flight experience (1 to 3,000 hrs). Given that the construct related to the perception of one's flight skills in the virtual and real-world environments, it is unsurprising that the construct was sensitive to the experience of the participants. Comparing results between age and flight experience groups could lead to interesting observations. Regardless, stakeholders must consider the confidence of the users before implementing a new training device into the curriculum. Users who are not confident in their abilities may approach the environment with doubt and negatively impact their training experience.

Users with more experience may be more confident in the ability to use VR for flight training. Additional research stratified by flight experience may provide additional insight into how the construct can be utilized in an extended TAM, further adding to the body of knowledge.

Hypothesis 12: Perceived behavioral control positively influences perceived ease of use. The results indicate there is insufficient evidence to conclude PBC influences PEU. A construct from the TPB, PBC is related to the perception a student forms about being about to control the use of VR technology for flight training. This was measured by confidence to use VR based on knowledge/use of similar technologies, use of an instructional manual, and access to aid (e.g., an instructor or lab technician). Perceiving they have access to sufficient resources as they use VR for flight training may impact the perception that using the technology is easy. The relationship, validated by Lu et al. (2009) and Venkatesh (2000), was not supported in the current study. In fact, the relationship between the two factors was negative and statistically significant. PBC was measured using five items, each of which asked participants to respond in terms of confidence (i.e., 1 was “no confidence” and 5 was “total confidence”). All items for the construct were generally above neutral and “confident,” with item averages of 3.36 to 3.81, as detailed in Table 19. The construct overall was rated slightly above neutral as well. Because aviation students have low experience with VR, they have little knowledge on which to base their ability to utilize the technology. This relationship, or lack thereof, is important for instructors and developers to acknowledge as they consider utilizing VR for training purposes. For flight training, this relationship may indicate that aviation students will not adopt the technology until they understand how it works, how it will benefit their training, and believe it to be a useful resource. The discovery of the negative relationship warrants further investigation, as it may be a new relationship related to VR technology specifically.

Hypothesis 13: Perceived behavioral control positively influences behavioral intention. The results indicate there is sufficient evidence to conclude PBC influences BI, which is supported by the literature. Ajzen (1991) proposed that PBC has a strong, positive influence on BI as the relationship considers available cognitive and situational resources required to perform the behavior. If a student believes they have the resources and opportunity to successfully use VR in their flight training, BI may be directly impacted. As students have more confidence in their ability to control using VR technology for flight training, they will be more willing to exert effort to use the technology. Results indicate that the aviation students who are confident in their abilities – despite having VR low experience – may be more willing to exert effort to utilize a new, immersive, innovative technology to enhance their flight training. This is an important consideration that may be capitalized on by encouraging aviation students to gain familiarity with VR and making resources available during flight training.

Hypothesis 14: Attitude toward use positively influences behavioral intention. The results indicate there is sufficient evidence to conclude ATU influences BI, which is supported by the literature. The high critical ratio between the factors also indicated a strong correlation. The final component of Davis' (1989) original TAM, this relationship has received support from numerous researchers (Cheung & Vogel, 2018; Esteban-Millat et al., 2018; Lemay et al., 2018; Park, 2009). Students with a positive ATU of VR for flight training will logically be more favorably inclined to exert effort to use the technology. Moreover, the relationship has implications that positive attitudes influence choice. The attitudes of aviation students may be influenced through familiarity with the technology and adoption of VR for personal and training purposes. The relationship was strongly supported, as expected from the literature.

New hypothesis: Hypothesis 15: Perceived enjoyment positively influences behavioral intention. This relationship was identified while analyzing the SEM. The results indicate there is sufficient evidence to conclude PENJ influences BI, which is supported by the literature. PENJ has been utilized in TAMs to measure the adoption and purchase of VR devices and hardware. Lee et al. (2018) incorporated PENJ as a way to measure user intention to adopt VR for social connectivity purposes. The authors noted that the construct was a crucial component of the model and impacted the other TAM factors directly and indirectly. Manis and Choi (2018) also used the construct in their model, designed specifically for VR hardware acceptance in a consumer context. The authors found PENJ influenced attitude toward using and purchasing VR as well as purchase intention. The discovery of the relationship and the subsequent support further the validation of PENJ as an important factor in understanding user attitude toward and intention to use VR.

Conclusions

The purpose of this research was to determine factors that influence aviation students’ attitude toward and intention to use VR for flight training. The model used is the first of its kind to investigate VR technology in the context of aviation training. Further, the model is unique in that it encompasses new factors that assess VR technology in an aviation training environment. The model fit indices indicated that the model was adequate in identifying those factors that influence aviation students' attitude toward and intention to use VR for flight training and the extent thereof. The study also fills a gap in the literature surrounding VR for training and education in general, using an extended TAM in an aviation context, and using VR for flight training.

An additional relationship was discovered within the model, and the hypothesis testing of the 15 hypotheses contributes to the body of knowledge surrounding extended TAMs, especially to assess user acceptance of VR. PENJ was found to directly, positively impact PBC. Given the factor has been used successfully in other TAMs designed for evaluating attitude toward and actual behavioral use of VR; it is evident that this factor is an important component in understanding the user perspective of VR in different environments. Two other factors associated with VR use, PEXP and PENJ, had hypothesized unsupported relationships. These factors rely on experience with VR technology to inform the opinion of the user. In the present study, participants were asked to consider VR for use in flight training; however, the participants had low experience with VR overall. The lack of experience likely impacted the answers of the participants; future investigation, with a sample of participants who have experience with VR, may yield different results.

The factors of PHR, RU, and SE warrant further investigation in an aviation educational environment and for VR technology. The factor PHR was removed from the model, and neither RU nor SE was found to influence ATU. Participants reported a lack of experience with VR, and currently, VR is not utilized in flight training curriculum. Further, no regulations are guiding how the technology can be used for flight training. The combination of these factors leads to the conclusion that participants had little knowledge and experience on which to form an opinion on observable items related to these factors.

Additionally, the relationship between PBC and PEU in the context of VR for flight training needs further investigation. The success of the study indicates that the model could, theoretically, be used to assess student's attitude toward and intention to use VR in different aviation educational contexts as well as other dynamic learning environments. Further research and refinement could make the model a useful tool for flight instructors, educators, VR developers, curriculum designers, and other stakeholders in the aviation industry and beyond.

Theoretical implications. The results contribute to the literature in numerous ways. First, the study contributes to the body of knowledge surrounding aviation training. The model validated that established factors of the TAM and TPB may be extended and applied to VR technology, aviation training, and the use of VR in aviation training. These factors went beyond the scope of the ground theories to provide insight on factors that influence or deter students from adopting VR for training purposes. The validated model may be further adapted and applied to other immersive simulation technology as well as other training/education environments.

Second, the model further validated the use of PEXP and PENJ as factors that may be utilized to assess attitude toward and intention to used VR technology. The factors were also validated for use in the aviation education domain. The TAM and TPB have been adapted and validated for examining many contexts and technologies, yet the aviation environment and VR technology has received little research. The aviation training environment and the use of VR technology for educational or training purposes have been largely overlooked. Studies that have explored the aviation domain or VR technology often do so from a consumer perspective. When studies do assess the use of technology, it is often less immersive than VR (e.g., augmented reality [AR], mobile devices). Thus, the study fills a gap related to using an extended TAM to provide a more comprehensive understanding of aviation students' intention to use VR in an aviation environment for flight training.

Third, although the factors of PEXP and PENJ have been validated for the context of the present study, these factors warrant further investigation. PEXP was theorized to positively impact ATU, based on the literature surrounding these factors. As previously noted, PEXP has been used in UTAUT models as a predictor of actual use behavior as opposed to attitude. Similarly, the relationship between PENJ and PU was supported in the literature in research where, presumably, users had access to and experience with the technology in question. This was not the case in the present study, as those participants with VR experience also reported infrequent use with the technology. Thus, the hypotheses were not supported. As flight students gain experience with VR and have the chance to use the technology for flight training purposes, their answers will shift from a theoretical perspective to an opinion based on experience. This will likely impact the results of the relationship in a future study.

Fourth, the negative relationship between PBC and PEU is a discovery that is not supported by the theorized relationship. However, the relationship between these factors has not been investigated through the lens of using VR for flight training. The new relationship between PENJ and BI is novel and unique for the body of literature and implies that the intrinsic enjoyment associated with using immersive simulation technology may cause aviation students to expend effort to utilize VR. The unsupported hypotheses also add value to researchers wishing to utilize a TAM to understand how users accept VR for training purposes. Further investigation is needed.

Fifth, the study demonstrates that the model is a useful tool to understand how students perceive VR for training. The model may be used in other educational or training environments where VR is being considered as a training instrument. The model need not be only used for aviation contexts nor for VR technology. The factors are relevant to other immersive simulation technologies (e.g., AR, mixed reality [MR], mobile e-learning devices). Moreover, the factors are pertinent to students in other dynamic training environments (e.g., medicine, construction, manufacturing) and learning environments (e.g., science subjects, remote learning, engineering education). With proper revision, the survey instrument and model may be validated or extended for use in a variety of research contexts, populations, and technologies.

Finally, the study fills several gaps in the related literature. Although researchers have demonstrated that immersive simulation technologies such as FTDs and AATDs are effective for aviation training, the effectiveness and efficiency associated with VR have yet to be extensively studied for aviation training purposes. How flight training may be improved upon by using VR has not been widely considered, an obvious gap in a domain with a long history of adopting immersive simulation technology. Further, few studies considered why aviation students adopt a given technology; thus, factors that impact the acceptance and use of immersive simulation technology, specifically VR, have not been explored. Important findings related to these issues have been presented.

Practical implications. The study focused on VR for flight training at Part 141 flight schools. Steps were taken to ensure the results of the study were generalizable, reliable, and valid. The results of the study have practical implications for several parties.

First, the results provide insight into the student perspective, an important component that is often overlooked. VR can benefit training, especially for aviation students, but how the technology is introduced and incorporated into flight training may impact student attitude, acceptance, and intent to use it. Participants responded as having low experience with VR, which undoubtedly impacted their perspective of using the technology for flight training. For example, the construct PHR was removed from the model, and RU had a negligible relationship with ATU; these factors may not be of importance to aviation students at this time, but that stance may change as VR becomes more available and the technology is incorporated into the curriculum and federal regulations. Results also indicate that PEXP and PEU impact PU; this perspective is insightful as it implies that students will be more willing to use VR for flight training if it is easy to use, will improve flight training, and will enhance flight performance. Students must already prioritize their resources (e.g., time, finances) as they pursue a career in aviation. If the student does not perceive that VR will be beneficial for training, they will likely choose to use other devices.

Second, the findings can provide educators with a better understanding of aviation student intentions toward VR technology for aviation training. Currently, students do not have ready access to VR for educational use, let alone flight training. User familiarity with the technology, and therefore confidence in using it, may be initially low. Although

PEXP did not influence ATU, the factors of PEU, PU, and PENJ were found to influence ATU directly. Instructors and curriculum developers, as well as other stakeholders, can use this knowledge to design programs to educate students on how to use VR, the benefits of using VR for flight training, and encourage them to use VR for personal use to increase familiarity with and enjoyment of the technology. Flight instructors and curriculum developers may also utilize this information as they work with students in a new, virtual environment to expand flight training options.

Third, the FAA, industry, and other stakeholders can address the factors that influence aviation students to use VR for training. There is a shortage of qualified professional pilots, air traffic controllers, and aviation maintenance technicians which is negatively impacting the aviation industry. Using VR can expand training opportunities for these professions to increase efficiency, effectiveness, and training resources. As research into using VR for flight training continues, the FAA may use the findings of the study as they incorporate VR and other immersive simulation technologies into flight training regulations, curriculum, etc.

Finally, this model may be adapted for use by other researchers. The survey instrument and methodology may provide insight into students' attitudes toward and intention to use VR for training or educational purposes in other domains. The verbiage of the survey instrument could be adapted for other immersive simulation technologies, such as AR, MR, or simulators used in part-task training. Developers of VR software, hardware, and programs may also adapt the survey instrument for consumers or other users, as the factors apply to VR technology outside of the training or education environment. Specifically, the factors of PENJ, PEXP, SE, and PBC require more investigation in the realm of immersive simulation technologies.

Limitations of the study. This study has three main limitations. Although these limitations constrain the results of the study, the findings are no less diminished.

First, the representation of the results may be limited. The study was designed to capture the perceptions of students receiving flight training at Part 141 pilot schools. Every effort was made to ensure representation of the sample, however, few demographics could be utilized for comparison. The distribution of gender was the only reliable demographic characteristic that was readily available from the institutions as well as the FAA. This is due to the institutions ensuring the privacy of their students, but also because the FAA purposefully does not collect this type of data. The sampling framework also did not include student pilots at Part 61 or military establishments and, therefore, should not be generalized to those populations nor students in other environments. Additionally, students enrolled in Part 141 pilot schools make up a small portion of the educated population, and results cannot be generalized to other training environments that may utilize VR for training in dynamic environments. However, the design and approach of the study are such that replication is possible for other populations.

Second, data were collected using a cross-sectional survey design over two months in 2020. As of the writing of this paper, VR has not been utilized for flight training. Indeed, the participants reported low experience with VR, and those with experience and potential access were infrequent users of the technology. Participants responded to the survey subjectively and in a theoretical capacity, having not utilized VR for flight training. The institutions invited to participate in the study vary in terms of program size, location, and resource availability (see Appendix C). Although all students are receiving Part 141 training as regulated by the FAA, the experiences of the students may vary among schools based on resource availability (e.g., aircraft, FTDs, AATDs, instructors). The findings should not be generalized beyond the time period. However, the study may be easily replicated for a longitudinal study, especially if VR is incorporated into flight training. Such replication would validate the model as well as verify the findings presented here.

A third limitation is the factors used in the model. The scope of the study limited the factors to those relevant to VR/immersive simulation and aviation training. Other factors that may be relevant, but were not incorporated into the model, may provide more context. The survey instrument also focused on VR for flight training. Other immersive simulation technologies and environments were not considered. However, the survey was designed that it could be customized for use in other training and educational environments and with other immersive simulation technologies.

Recommendations for Future Research

There are six recommendations to guide future research of factors that influence aviation students' intentions to use VR technology for flight training or other immersive simulation training technologies.

First, the factors of the model should be reviewed and revised as appropriate. The factor of PHR should be reexamined, as it was removed from the model. Users may be unaware of the physical health risks associated with VR, as they are not very experienced with using the technology. It is suggested that the operational demonstration of the construct be reviewed once the technology is more accessible for training purposes. Comparison of results of the present study and a study in which participants have used VR and are aware of potential health risks may yield considerations that impact the use of VR in flight training. The construct of RU had negligible results in the model. Results related to the factor may change as the FAA reviews and incorporates the technology into regulations. Results may also vary as institutions introduce VR into a flight training curriculum as a supplemental technology or an alternative to FSTDs, as the technology and programs are developed. The construct SE should be reviewed for future inclusion in the model. Specifically, SE3 would need to be rewritten to enhance the reliability and validity of the construct. Additional research into how SE is affected by flight experience and VR experience is also suggested. Finally, more research surrounding how PBC, PEXP, and PENJ influence ATU and BI in aviation environments, and accepting VR technology for training purposes, is recommended. These factors have limited use in the context of the study, and further research will validate their importance as determinants of ATU and BI in an extended TAM.

Second, more research with clearly defined demographic parameters may allow for better representation as well as generalization. A replication study with similar demographic questions could be the beginning of such a parameter if it is not readily available from the participating institutions or other sources.

Third, additional research using the raw data of the study is recommended. Institutions with less than 6% participation rate were not analyzed in the present study. Results can be compared between institutions in similar geographic areas, FAA regions, or of enrollment size. Demographic characteristics could be compared as well, such as age, flight experience, educational level, and VR/gaming experience.

Fourth, a longitudinal study is recommended as VR comes available for flight training and after incorporation into the regulations. Although a firm foundation of using VR for flight training has been presented, it is from a theoretical standpoint. Conducting the study once VR is used for flight training may yield interesting results for comparison. The same methodology is advised for such a study.

Fifth, stakeholders, including Part 141 pilot schools, curriculum designers, VR developers, teachers and instructors, the FAA, and others, should use these results to their benefit. Understanding why users accept a given technology is an important component of a successful launch of technology into an environment. The results provide information that can be incorporated into introducing VR into the flight training environment, training students on how to use VR, and providing an atmosphere in which the students feel like the technology is fun and beneficial. In turn, these efforts can motivate the students to use the technology regularly and outside of their training curriculum. Although VR is less expensive than other FSTDs, it still requires the investment of resources, such as time, money, facility space, and staff support.

Sixth, other researchers using or considering using VR for training in other environments should utilize the model and study approach. Replication can validate the model and survey instrument, but also allow for comparison between training environments and populations. It is also recommended that researchers using or considering using other immersive simulation technologies (e.g., AR, MR) for training in other environments use the model and study approach. This would allow for more understanding of how these factors explain user behavior with similar but less immersive technologies.

Summary

The factors that influence aviation students' intention to use VR for flight training were investigated and the results discussed. An extended TAM, incorporating factors derived from the review of the relevant research, was utilized. The chosen factors were related to aviation education, the use of VR technology in training environments, and using VR for flight training. The results indicated a good model fit to answer the three research questions of the study. Of the 14 hypotheses, one hypothesis was removed, a new relationship was discovered, and nine hypotheses in total were supported. BI was directly or indirectly impacted by eight predictor factors. The results of the study fill a gap in the research surrounding the use of VR for flight training, and the model may be adapted for other educational/training environments as well as other forms of immersive simulation technology. Further research is recommended to validate the model and understand the relationships between the factors.

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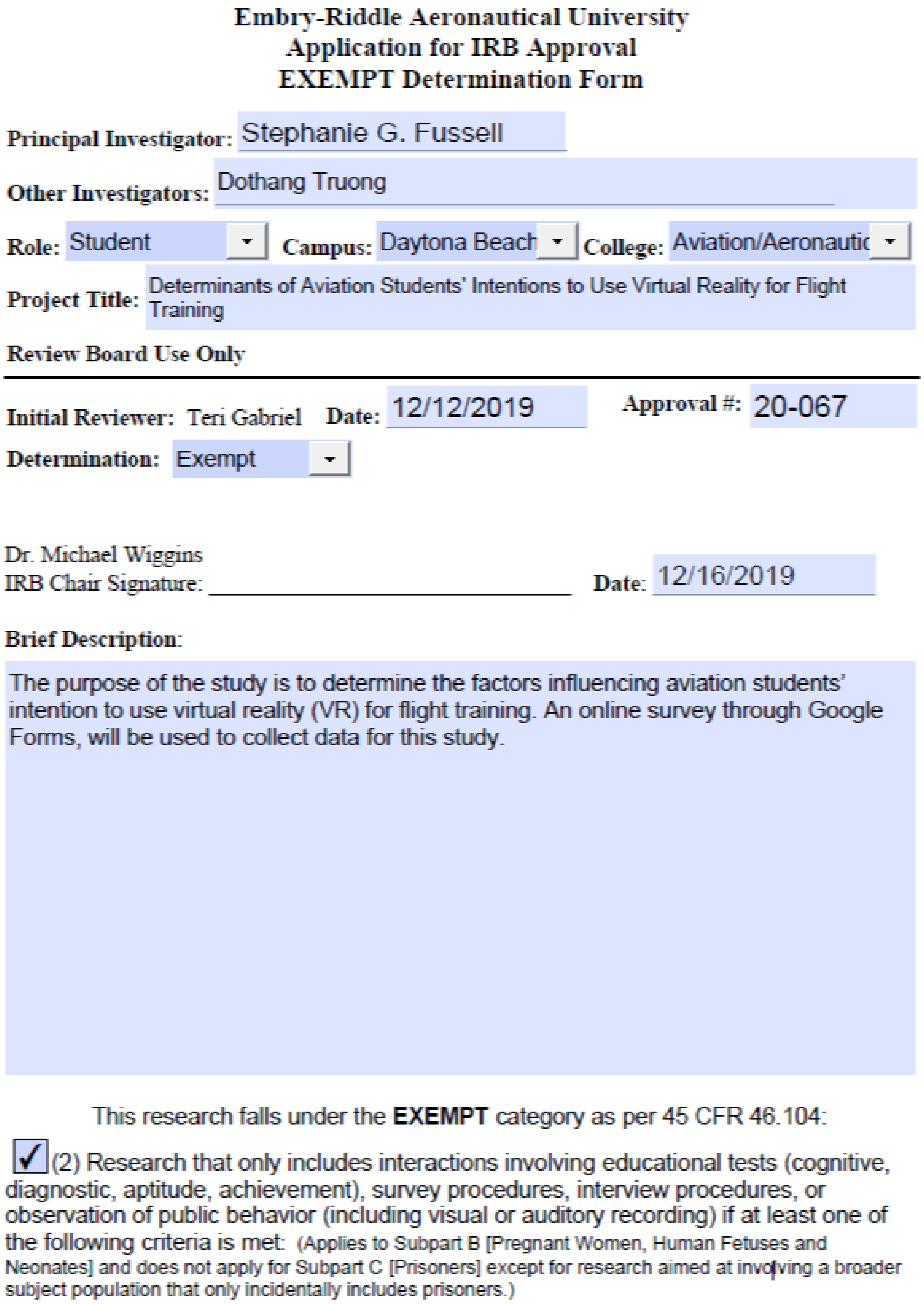
APPENDIX A

Permission to Conduct Research



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

Principal Investigator: Stephanie G. Fussell

Other Investigators: Dothang Truong

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

Project Title: Determinants of Aviation Students' Intentions to Use Virtual Reality for Flight Training

Review Board Use Only

Initial Reviewer: Teri Gabriel **Date:** 12/12/2019 **Approval #:** 20-067

Determination: Exempt

Dr. Michael Wiggins
IRB Chair Signature: ______________________ **Date:** 12/16/2019

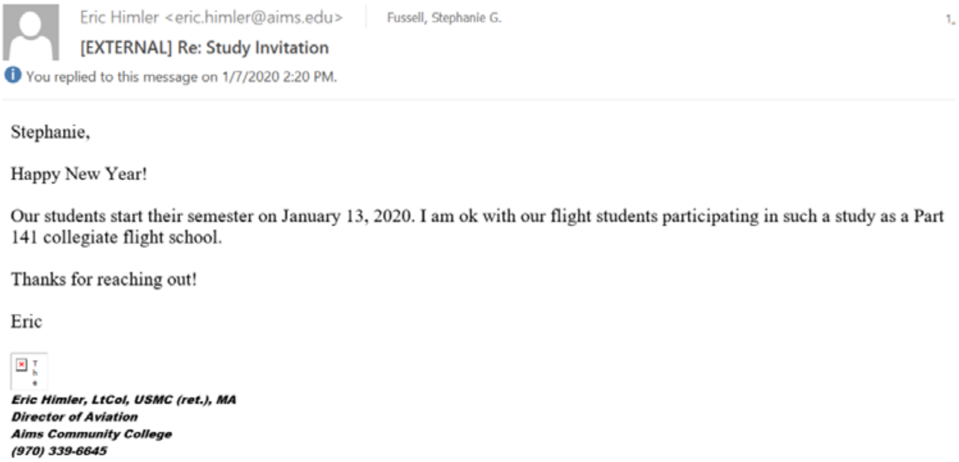
Brief Description:

The purpose of the study is to determine the factors influencing aviation students' intention to use virtual reality (VR) for flight training. An online survey through Google Forms, will be used to collect data for this study.

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.)

Aims Community College



Eric Himler <eric.himler@aims.edu> | Fussell, Stephanie G.

[EXTERNAL] Re: Study Invitation

You replied to this message on 1/7/2020 2:20 PM.

Stephanie,

Happy New Year!

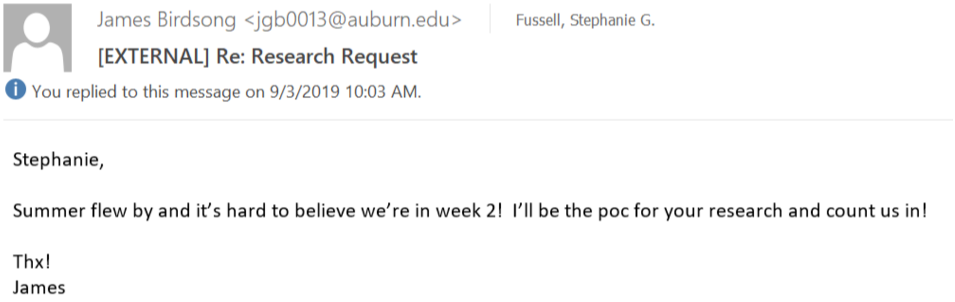
Our students start their semester on January 13, 2020. I am ok with our flight students participating in such a study as a Part 141 collegiate flight school.

Thanks for reaching out!

Eric

Eric Himler, LtCol, USMC (ret.), MA
Director of Aviation
Aims Community College
(970) 339-6645

Auburn University



James Birdsong <jgb0013@auburn.edu> | Fussell, Stephanie G.

[EXTERNAL] Re: Research Request

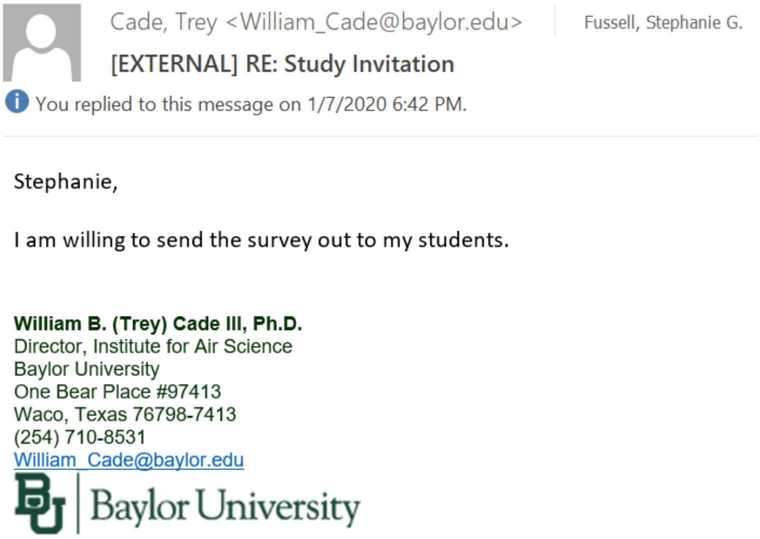
You replied to this message on 9/3/2019 10:03 AM.

Stephanie,

Summer flew by and it's hard to believe we're in week 2! I'll be the poc for your research and count us in!

Thx!
James

Baylor University



Cade, Trey <William_Cade@baylor.edu> | Fussell, Stephanie G.

[EXTERNAL] RE: Study Invitation

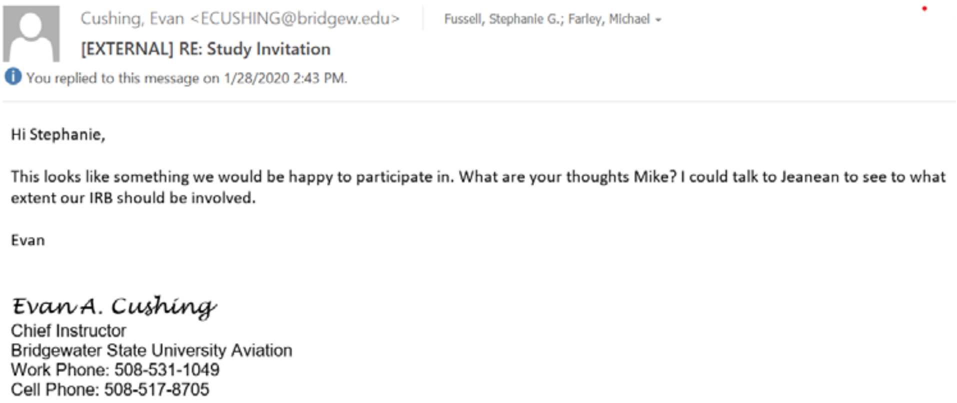
You replied to this message on 1/7/2020 6:42 PM.

Stephanie,

I am willing to send the survey out to my students.

William B. (Trey) Cade III, Ph.D.
Director, Institute for Air Science
Baylor University
One Bear Place #97413
Waco, Texas 76798-7413
(254) 710-8531
William_Cade@baylor.edu

Bridgewater State University



Cushing, Evan <ECUSHING@bridgew.edu> Fussell, Stephanie G.; Farley, Michael

[EXTERNAL] RE: Study Invitation

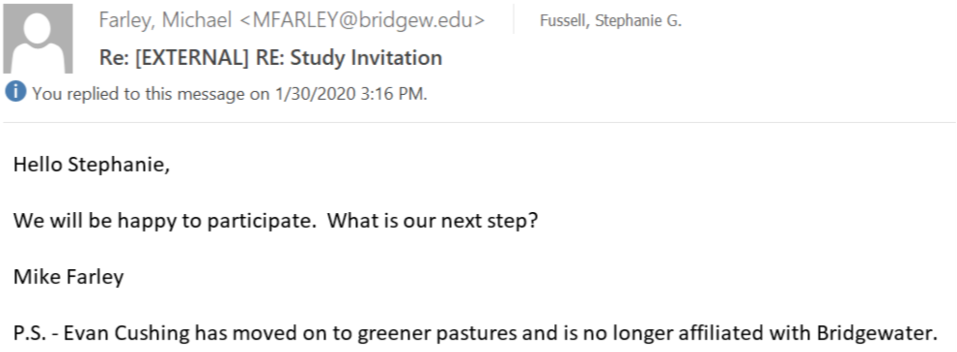
You replied to this message on 1/28/2020 2:43 PM.

Hi Stephanie,

This looks like something we would be happy to participate in. What are your thoughts Mike? I could talk to Jeanean to see to what extent our IRB should be involved.

Evan

Evan A. Cushing
Chief Instructor
Bridgewater State University Aviation
Work Phone: 508-531-1049
Cell Phone: 508-517-8705



Farley, Michael <MFARLEY@bridgew.edu> Fussell, Stephanie G.

Re: [EXTERNAL] RE: Study Invitation

You replied to this message on 1/30/2020 3:16 PM.

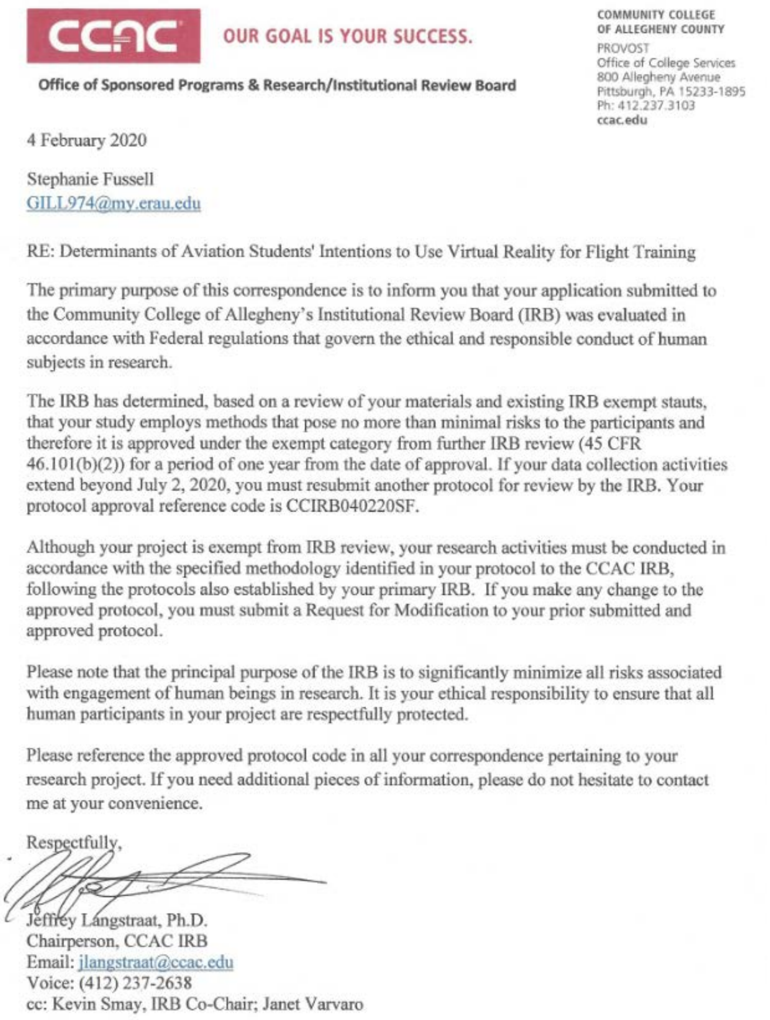
Hello Stephanie,

We will be happy to participate. What is our next step?

Mike Farley

P.S. - Evan Cushing has moved on to greener pastures and is no longer affiliated with Bridgewater.

Community College of Allegheny County



CCAC OUR GOAL IS YOUR SUCCESS.
Office of Sponsored Programs & Research/Institutional Review Board

COMMUNITY COLLEGE
OF ALLEGHENY COUNTY
PROVOST
Office of College Services
800 Allegheny Avenue
Pittsburgh, PA 15233-1895
Ph: 412.237.3103
ccac.edu

4 February 2020

Stephanie Fussell
GILL974@my.erau.edu

RE: Determinants of Aviation Students' Intentions to Use Virtual Reality for Flight Training

The primary purpose of this correspondence is to inform you that your application submitted to the Community College of Allegheny's Institutional Review Board (IRB) was evaluated in accordance with Federal regulations that govern the ethical and responsible conduct of human subjects in research.

The IRB has determined, based on a review of your materials and existing IRB exempt stauts, that your study employs methods that pose no more than minimal risks to the participants and therefore it is approved under the exempt category from further IRB review (45 CFR 46.101(b)(2)) for a period of one year from the date of approval. If your data collection activities extend beyond July 2, 2020, you must resubmit another protocol for review by the IRB. Your protocol approval reference code is CCIRB040220SF.

Although your project is exempt from IRB review, your research activities must be conducted in accordance with the specified methodology identified in your protocol to the CCAC IRB, following the protocols also established by your primary IRB. If you make any change to the approved protocol, you must submit a Request for Modification to your prior submitted and approved protocol.

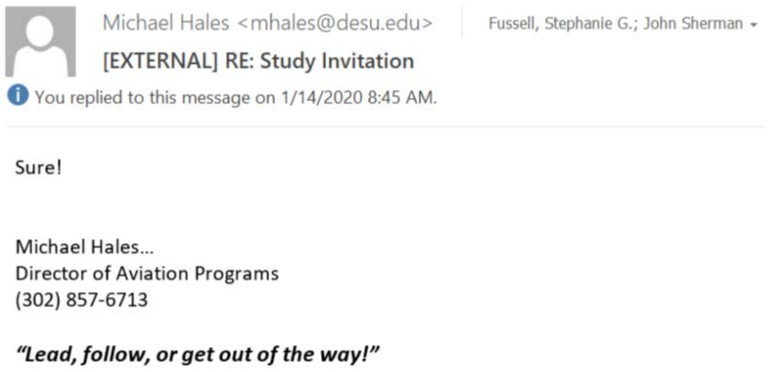
Please note that the principal purpose of the IRB is to significantly minimize all risks associated with engagement of human beings in research. It is your ethical responsibility to ensure that all human participants in your project are respectfully protected.

Please reference the approved protocol code in all your correspondence pertaining to your research project. If you need additional pieces of information, please do not hesitate to contact me at your convenience.

Respectfully,

Jeffrey Langstraat, Ph.D.
Chairperson, CCAC IRB
Email: jlangstraat@ccac.edu
Voice: (412) 237-2638
cc: Kevin Smay, IRB Co-Chair; Janet Varvaro

Delaware State University



Michael Hales <mhales@desu.edu>   Fussell, Stephanie G.; John Sherman

[EXTERNAL] RE: Study Invitation

You replied to this message on 1/14/2020 8:45 AM.

Sure!

Michael Hales…
Director of Aviation Programs
(302) 857-6713

"Lead, follow, or get out of the way!"

Delta State University

Joe Saia <jsaia@deltastate.edu> Fussell, Stephanie G.

[EXTERNAL] RE: [EXT]: Study Invitation

You replied to this message on 1/7/2020 2:56 PM.

Stephanie,

I will be more than happy to assist you in any way I can.

I would also like to encourage you to look at our Master's program. I am currently looking for a coordinator of our MCA Masters of Commercial Aviation program. The candidate can be ABD or PHD. I look forward to receiving your information for your research.

Warm regards,

Joe Saia
Chairman Commercial Aviation

Eastern Michigan University

Jerard Delaney <jdelane4@emich.edu>

[EXTERNAL] Re: Study Invitation

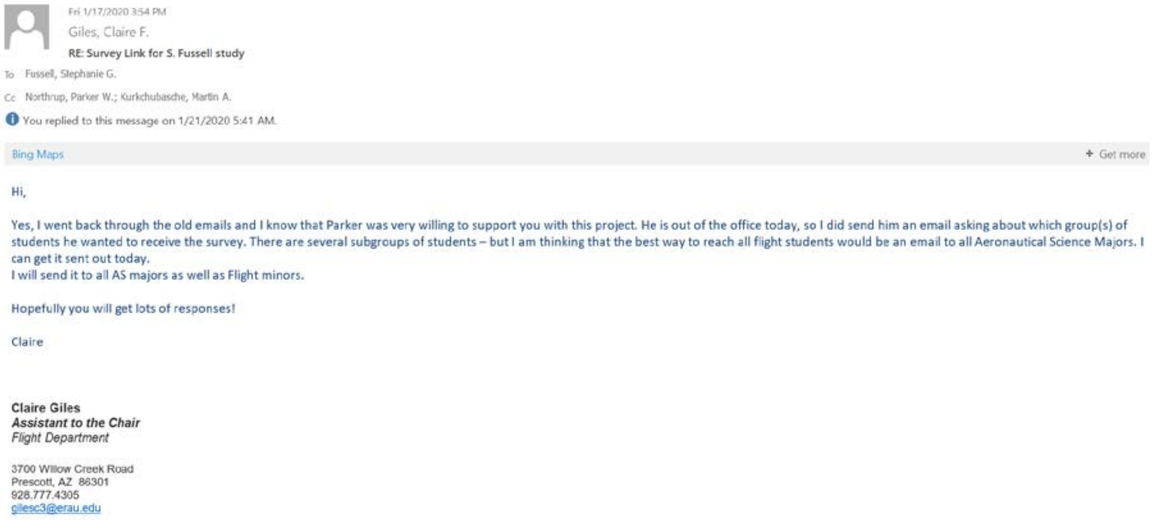
You replied to this message on 1/8/2020 10:51 AM.

Yes, we would participate.

Jerard E. Delaney II, Ph.D.
Program Coordinator, Aviation
Eastern Michigan University

(734) 487-4691
jdelane4@emich.edu

Embry-Riddle Aeronautical University – Prescott



Fri 1/17/2020 3:54 PM
Giles, Claire F.
RE: Survey Link for S. Fussell study
To Fussell, Stephanie G.
Cc Northrup, Parker W.; Kurkchubasche, Martin A.
You replied to this message on 1/21/2020 5:41 AM.

Hi,

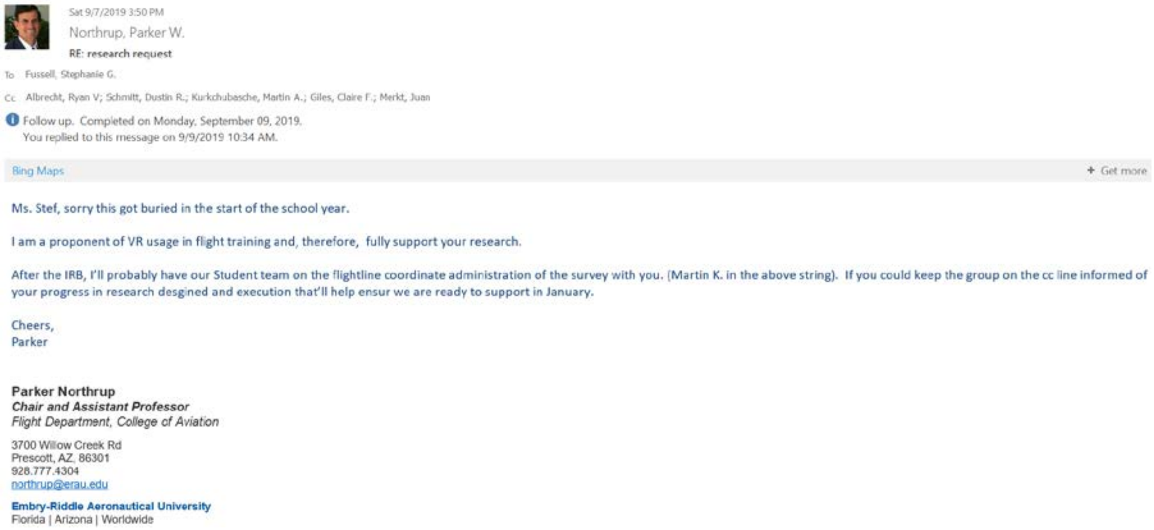
Yes, I went back through the old emails and I know that Parker was very willing to support you with this project. He is out of the office today, so I did send him an email asking about which group(s) of students he wanted to receive the survey. There are several subgroups of students – but I am thinking that the best way to reach all flight students would be an email to all Aeronautical Science Majors. I can get it sent out today.
I will send it to all AS majors as well as Flight minors.

Hopefully you will get lots of responses!

Claire

Claire Giles
Assistant to the Chair
Flight Department

3700 Willow Creek Road
Prescott, AZ 86301
928.777.4305
gilesc3@erau.edu



Sat 9/7/2019 3:50 PM

Northrup, Parker W.

RE: research request

To Fussell, Stephanie G.

Cc Albrecht, Ryan V; Schmitt, Dustin R.; Kurkchubasche, Martin A.; Giles, Claire F.; Merkt, Juan

Follow up. Completed on Monday, September 09, 2019.
You replied to this message on 9/9/2019 10:34 AM.

Ms. Stef, sorry this got buried in the start of the school year.

I am a proponent of VR usage in flight training and, therefore, fully support your research.

After the IRB, I'll probably have our Student team on the flightline coordinate administration of the survey with you. (Martin K. in the above string). If you could keep the group on the cc line informed of your progress in research desgined and execution that'll help ensur we are ready to support in January.

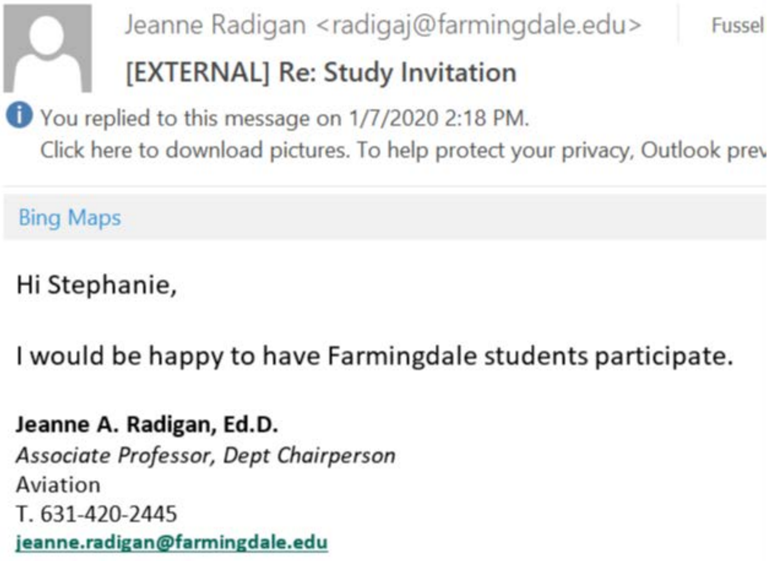
Cheers,
Parker

Parker Northrup
Chair and Assistant Professor
Flight Department, College of Aviation

3700 Willow Creek Rd
Prescott, AZ, 86301
928.777.4304
northrup@erau.edu

Embry-Riddle Aeronautical University
Florida | Arizona | Worldwide

Farmingdale State College



Jeanne Radigan <radigaj@farmingdale.edu>

[EXTERNAL] Re: Study Invitation

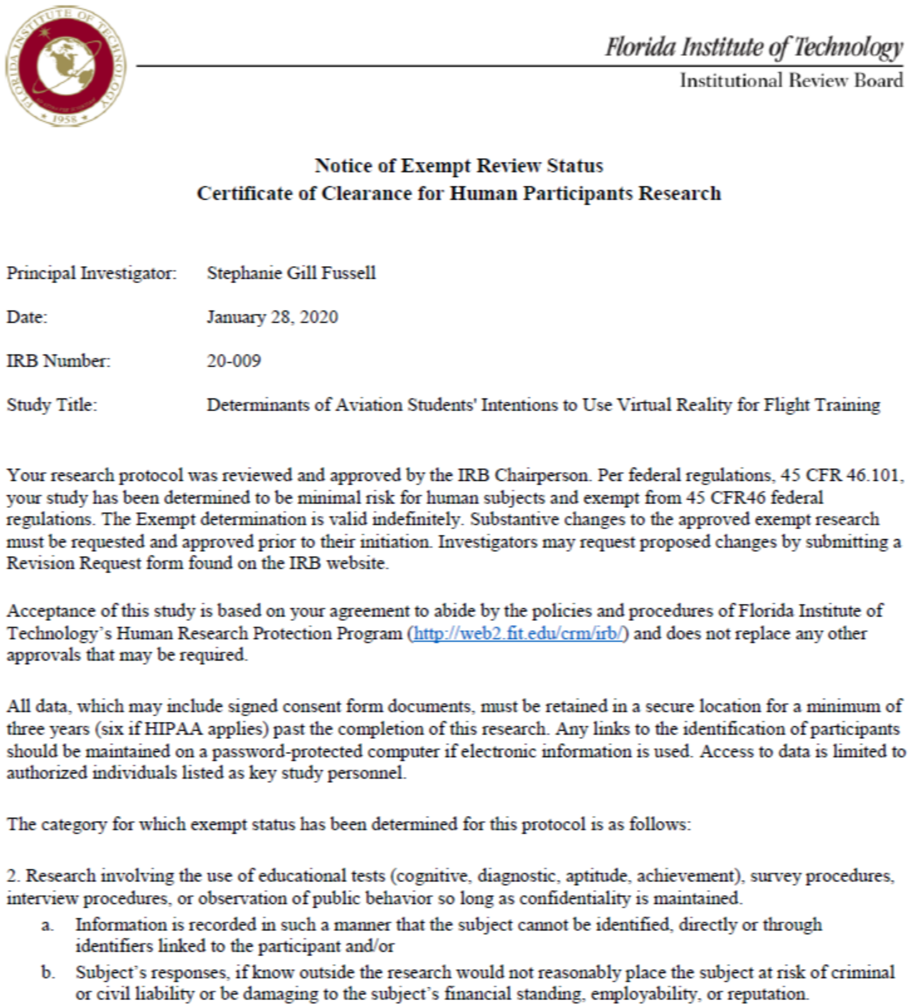
You replied to this message on 1/7/2020 2:18 PM.
Click here to download pictures. To help protect your privacy, Outlook prev

Hi Stephanie,

I would be happy to have Farmingdale students participate.

Jeanne A. Radigan, Ed.D.
Associate Professor, Dept Chairperson
Aviation
T. 631-420-2445
jeanne.radigan@farmingdale.edu

Florida Institute of Technology



Florida Institute of Technology
Institutional Review Board

Notice of Exempt Review Status
Certificate of Clearance for Human Participants Research

Principal Investigator:	Stephanie Gill Fussell
Date:	January 28, 2020
IRB Number:	20-009
Study Title:	Determinants of Aviation Students' Intentions to Use Virtual Reality for Flight Training

Your research protocol was reviewed and approved by the IRB Chairperson. Per federal regulations, 45 CFR 46.101, your study has been determined to be minimal risk for human subjects and exempt from 45 CFR46 federal regulations. The Exempt determination is valid indefinitely. Substantive changes to the approved exempt research must be requested and approved prior to their initiation. Investigators may request proposed changes by submitting a Revision Request form found on the IRB website.

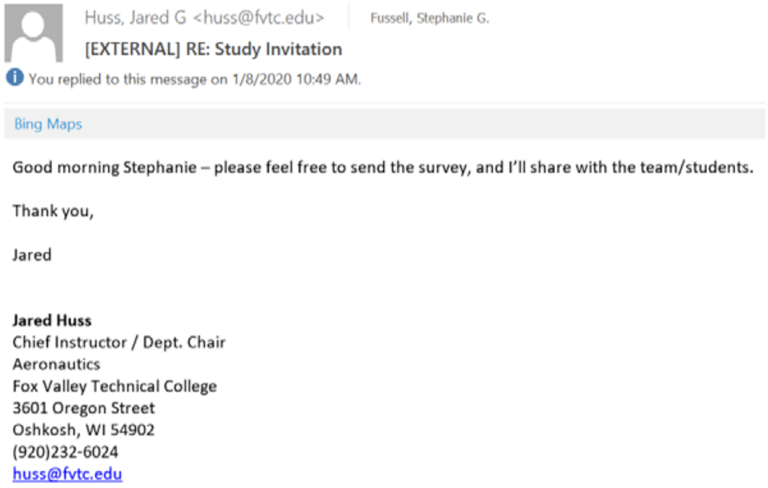
Acceptance of this study is based on your agreement to abide by the policies and procedures of Florida Institute of Technology's Human Research Protection Program (http://web2.fit.edu/crm/irb/) and does not replace any other approvals that may be required.

All data, which may include signed consent form documents, must be retained in a secure location for a minimum of three years (six if HIPAA applies) past the completion of this research. Any links to the identification of participants should be maintained on a password-protected computer if electronic information is used. Access to data is limited to authorized individuals listed as key study personnel.

The category for which exempt status has been determined for this protocol is as follows:

2. Research involving the use of educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior so long as confidentiality is maintained.
    a. Information is recorded in such a manner that the subject cannot be identified, directly or through identifiers linked to the participant and/or
    b. Subject's responses, if know outside the research would not reasonably place the subject at risk of criminal or civil liability or be damaging to the subject's financial standing, employability, or reputation.

Fox Valley Technical College



Huss, Jared G <huss@fvtc.edu> | Fussell, Stephanie G.

[EXTERNAL] RE: Study Invitation

You replied to this message on 1/8/2020 10:49 AM.

Good morning Stephanie – please feel free to send the survey, and I'll share with the team/students.

Thank you,

Jared

Jared Huss
Chief Instructor / Dept. Chair
Aeronautics
Fox Valley Technical College
3601 Oregon Street
Oshkosh, WI 54902
(920)232-6024
huss@fvtc.edu

Gateway Technical College

Patchel, Gregory <patchelg@gtc.edu> Fussell, Stephanie G.

[EXTERNAL] Re: Study Invitation

You replied to this message on 1/28/2020 3:15 PM.
Click here to download pictures. To help protect your privacy, Outlook prevented automatic download of some pictures in this message.

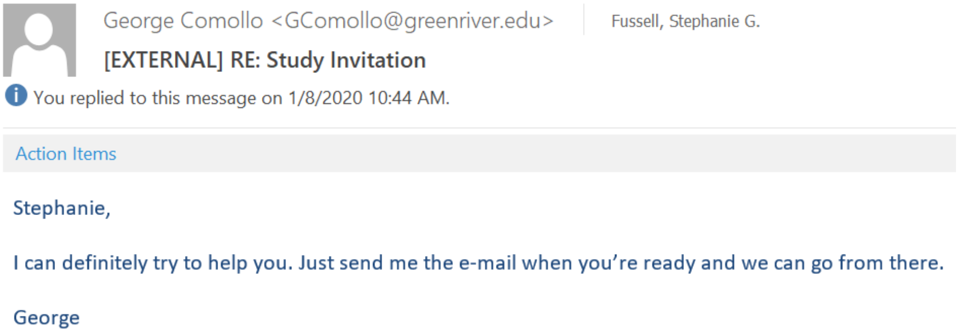
Stephanie,

I would be happy to participate.
I actually engaged in a short discussion about this topic during a Redbird seminar I attended a year ago.

Respectfully yours,

Gregory Patchel
Director and Chief Instructor Pilot - Aeronautics/Flight Training
Horizon Center
Phone: 262-564-3934
My Signature Strengths: Strategic, Achiever, Context, Relator, Analytical

Green River College



George Comollo <GComollo@greenriver.edu> Fussell, Stephanie G.

[EXTERNAL] RE: Study Invitation

You replied to this message on 1/8/2020 10:44 AM.

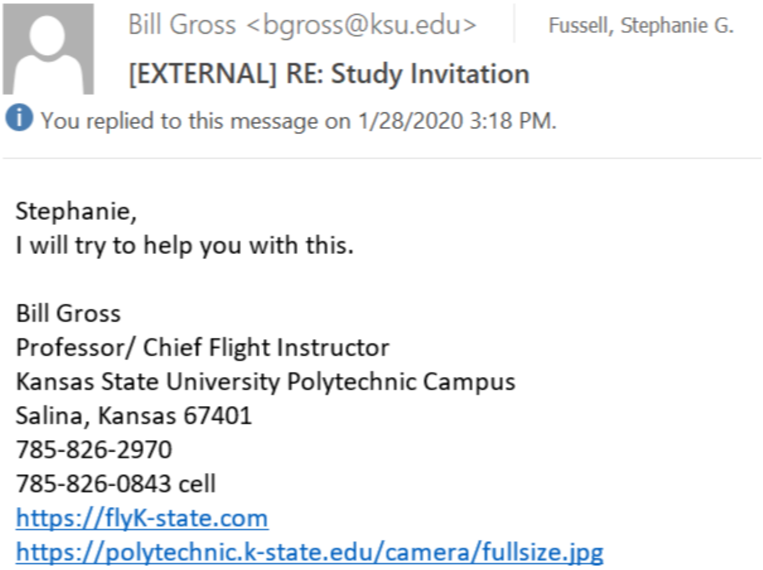
Action Items

Stephanie,

I can definitely try to help you. Just send me the e-mail when you're ready and we can go from there.

George

Kansas State University Polytechnic Campus



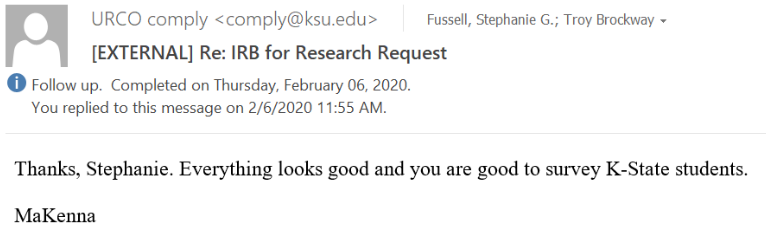
Bill Gross <bgross@ksu.edu> Fussell, Stephanie G.

[EXTERNAL] RE: Study Invitation

You replied to this message on 1/28/2020 3:18 PM.

Stephanie,
I will try to help you with this.

Bill Gross
Professor/ Chief Flight Instructor
Kansas State University Polytechnic Campus
Salina, Kansas 67401
785-826-2970
785-826-0843 cell
https://flyK-state.com
https://polytechnic.k-state.edu/camera/fullsize.jpg



URCO comply <comply@ksu.edu> | Fussell, Stephanie G.; Troy Brockway

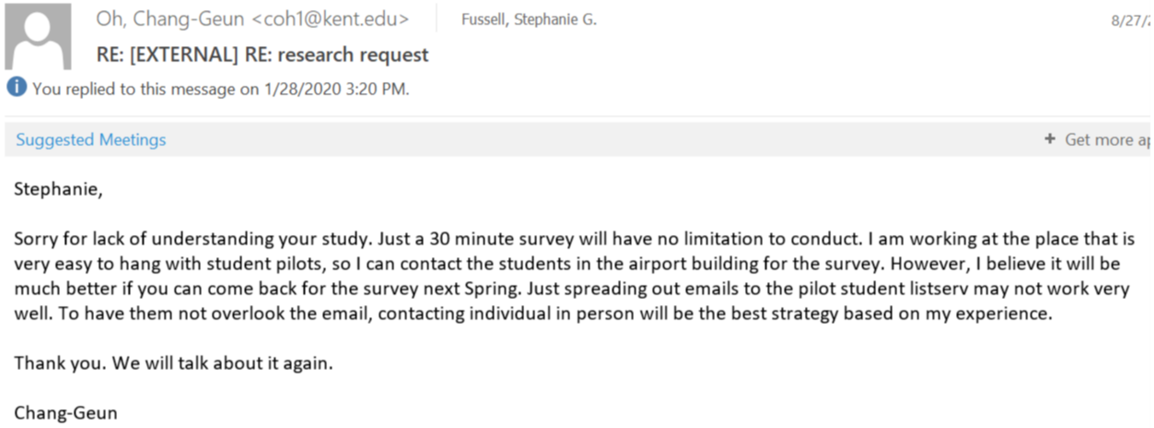
[EXTERNAL] Re: IRB for Research Request

Follow up. Completed on Thursday, February 06, 2020.
You replied to this message on 2/6/2020 11:55 AM.

Thanks, Stephanie. Everything looks good and you are good to survey K-State students.

MaKenna

Kent State University



Oh, Chang-Geun <coh1@kent.edu> | Fussell, Stephanie G. 8/27/

RE: [EXTERNAL] RE: research request

You replied to this message on 1/28/2020 3:20 PM.

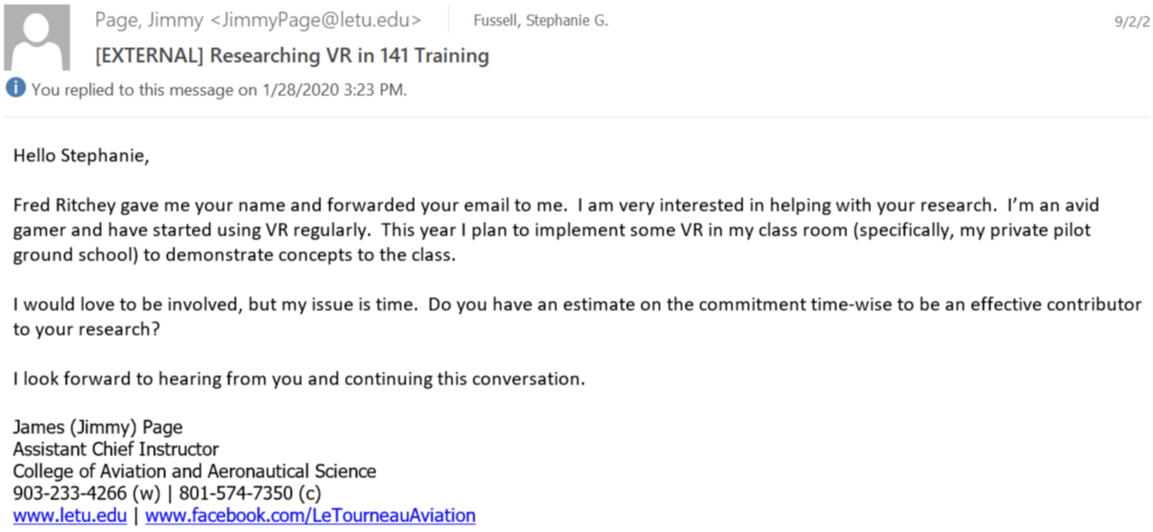
Stephanie,

Sorry for lack of understanding your study. Just a 30 minute survey will have no limitation to conduct. I am working at the place that is very easy to hang with student pilots, so I can contact the students in the airport building for the survey. However, I believe it will be much better if you can come back for the survey next Spring. Just spreading out emails to the pilot student listserv may not work very well. To have them not overlook the email, contacting individual in person will be the best strategy based on my experience.

Thank you. We will talk about it again.

Chang-Geun

LeTourneau University



Page, Jimmy <JimmyPage@letu.edu> | Fussell, Stephanie G. 9/2/2

[EXTERNAL] Researching VR in 141 Training

You replied to this message on 1/28/2020 3:23 PM.

Hello Stephanie,

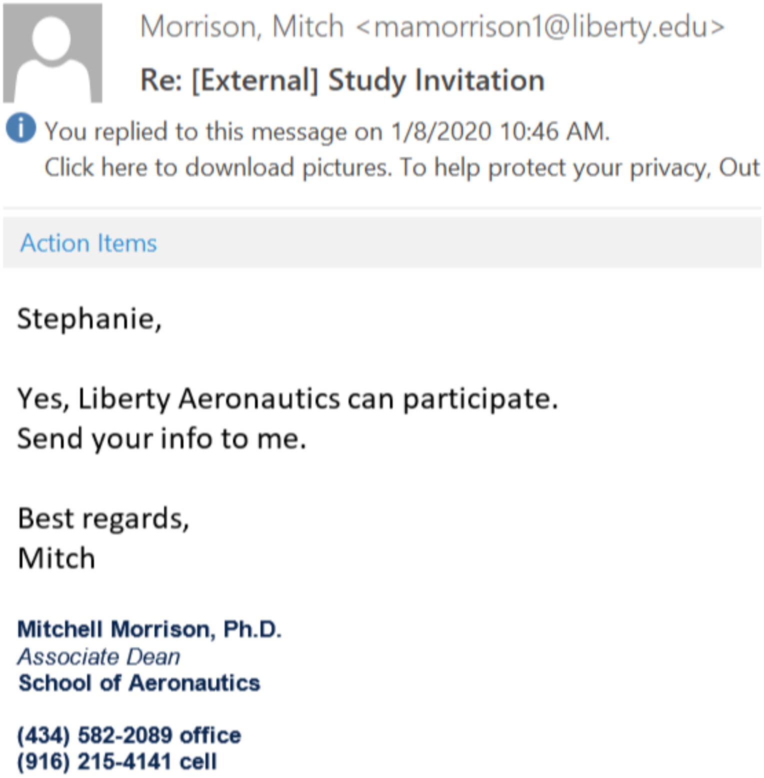
Fred Ritchey gave me your name and forwarded your email to me. I am very interested in helping with your research. I'm an avid gamer and have started using VR regularly. This year I plan to implement some VR in my class room (specifically, my private pilot ground school) to demonstrate concepts to the class.

I would love to be involved, but my issue is time. Do you have an estimate on the commitment time-wise to be an effective contributor to your research?

I look forward to hearing from you and continuing this conversation.

James (Jimmy) Page
Assistant Chief Instructor
College of Aviation and Aeronautical Science
903-233-4266 (w) | 801-574-7350 (c)
www.letu.edu | www.facebook.com/LeTourneauAviation

Liberty University



Morrison, Mitch <mamorrison1@liberty.edu>

Re: [External] Study Invitation

You replied to this message on 1/8/2020 10:46 AM.
Click here to download pictures. To help protect your privacy, Out

Stephanie,

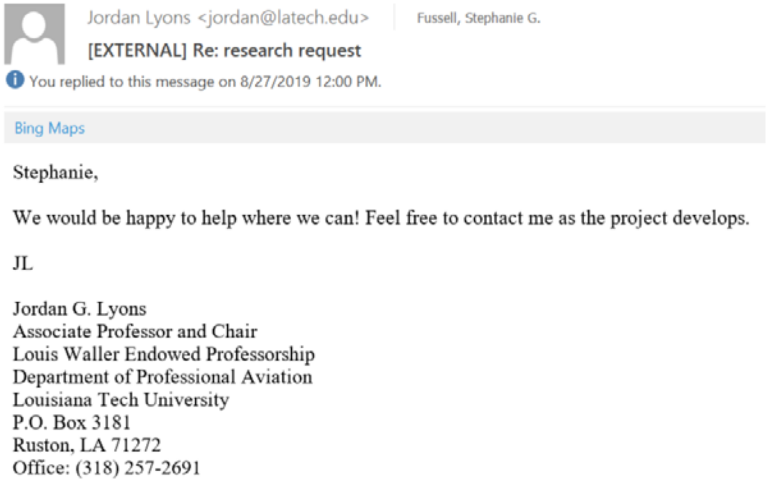
Yes, Liberty Aeronautics can participate.
Send your info to me.

Best regards,
Mitch

Mitchell Morrison, Ph.D.
Associate Dean
School of Aeronautics

(434) 582-2089 office
(916) 215-4141 cell

Louisiana Tech University



Jordan Lyons <jordan@latech.edu> | Fussell, Stephanie G.

[EXTERNAL] Re: research request

You replied to this message on 8/27/2019 12:00 PM.

Stephanie,

We would be happy to help where we can! Feel free to contact me as the project develops.

JL

Jordan G. Lyons
Associate Professor and Chair
Louis Waller Endowed Professorship
Department of Professional Aviation
Louisiana Tech University
P.O. Box 3181
Ruston, LA 71272
Office: (318) 257-2691

Marywood University

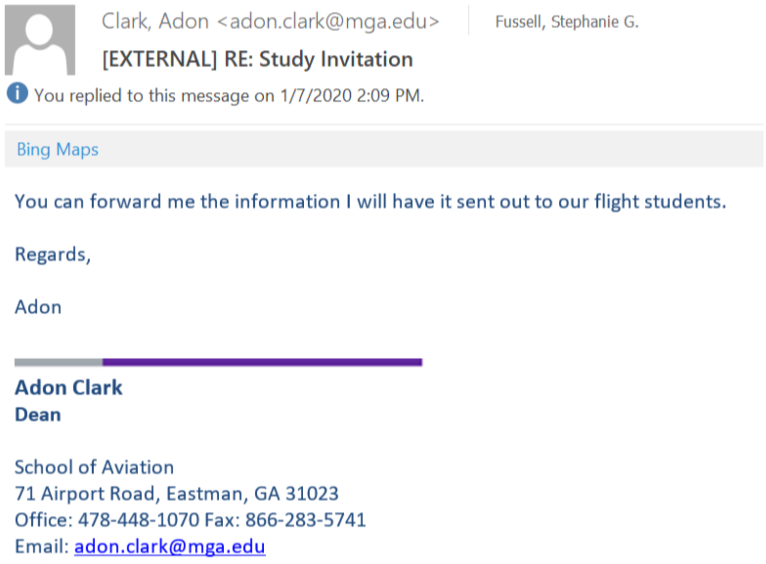
Capt Joseph McDonald <jmcdonald@maryu.marywood.edu> | Fussell, Stephanie G. | 1/7/2020

[EXTERNAL] Re: Study Invitation

You replied to this message on 1/8/2020 10:59 AM.

I will work with your study
Please be advised, my last name is McDonald, I am a retired American Airlines Captain, 38 years of service if that makes any difference to your study
Joe

Middle Georgia State University



[EXTERNAL] RE: Study Invitation

You replied to this message on 1/7/2020 2:09 PM.

You can forward me the information I will have it sent out to our flight students.

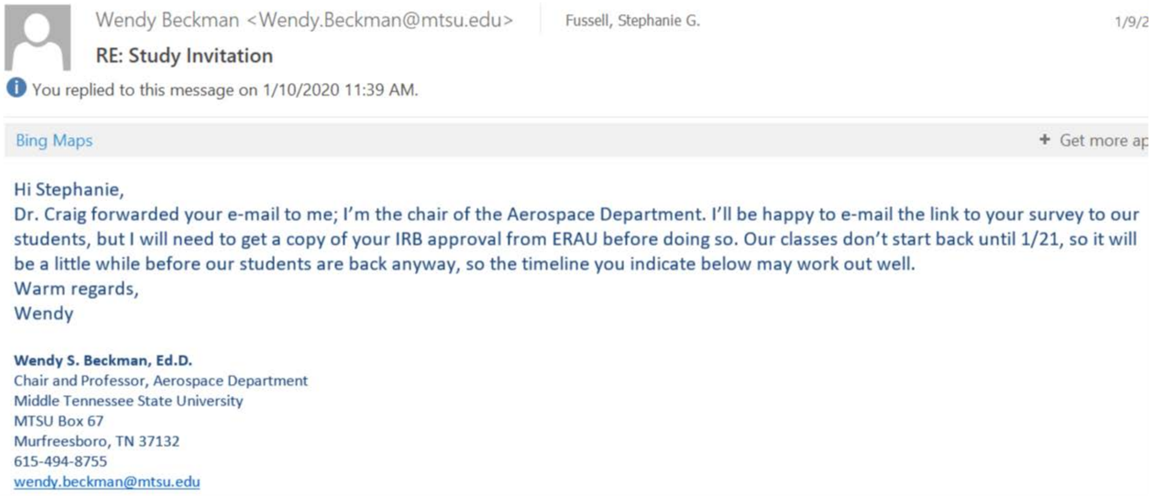
Regards,

Adon

Adon Clark
Dean

School of Aviation
71 Airport Road, Eastman, GA 31023
Office: 478-448-1070 Fax: 866-283-5741
Email: adon.clark@mga.edu

Middle Tennessee State University



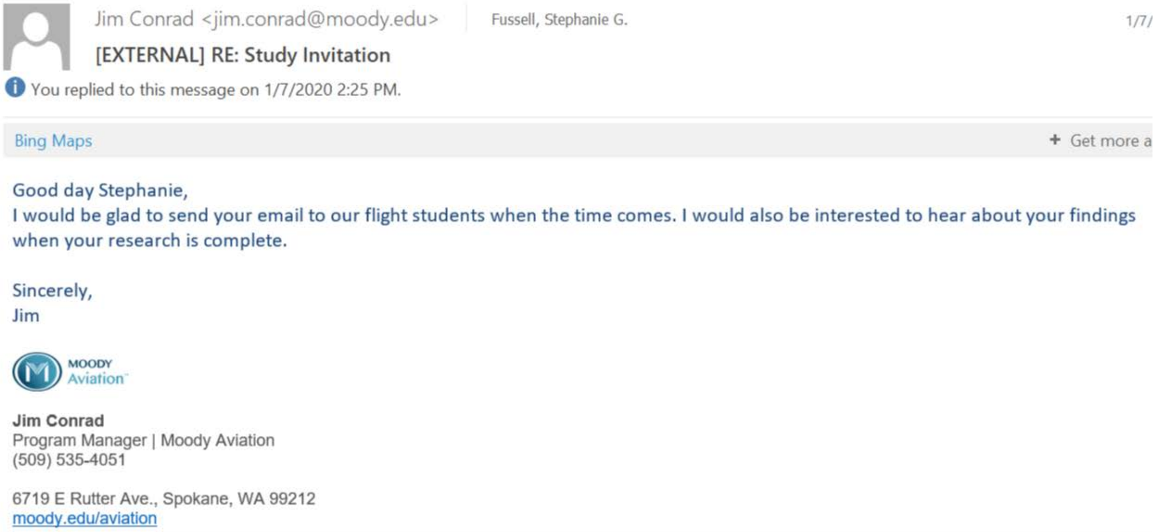
RE: Study Invitation

You replied to this message on 1/10/2020 11:39 AM.

Hi Stephanie,
Dr. Craig forwarded your e-mail to me; I'm the chair of the Aerospace Department. I'll be happy to e-mail the link to your survey to our students, but I will need to get a copy of your IRB approval from ERAU before doing so. Our classes don't start back until 1/21, so it will be a little while before our students are back anyway, so the timeline you indicate below may work out well.
Warm regards,
Wendy

Wendy S. Beckman, Ed.D.
Chair and Professor, Aerospace Department
Middle Tennessee State University
MTSU Box 67
Murfreesboro, TN 37132
615-494-8755
wendy.beckman@mtsu.edu

Moody Bible Institute



Jim Conrad <jim.conrad@moody.edu> | Fussell, Stephanie G. 1/7/

[EXTERNAL] RE: Study Invitation

You replied to this message on 1/7/2020 2:25 PM.

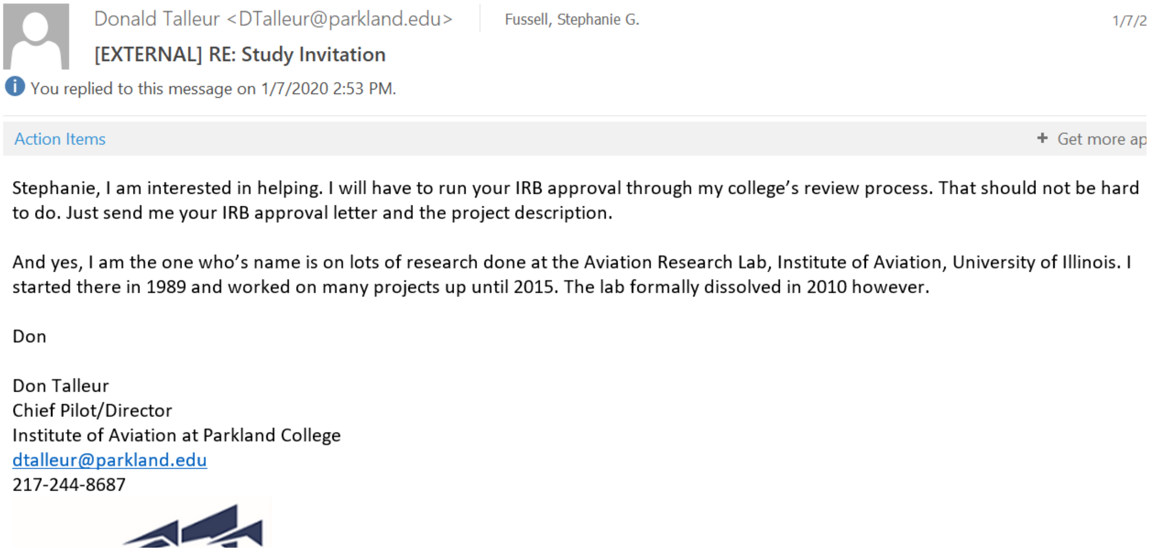
Good day Stephanie,
I would be glad to send your email to our flight students when the time comes. I would also be interested to hear about your findings when your research is complete.

Sincerely,
Jim

Jim Conrad
Program Manager | Moody Aviation
(509) 535-4051

6719 E Rutter Ave., Spokane, WA 99212
moody.edu/aviation

Parkland College



Donald Talleur <DTalleur@parkland.edu> | Fussell, Stephanie G. 1/7/2

[EXTERNAL] RE: Study Invitation

You replied to this message on 1/7/2020 2:53 PM.

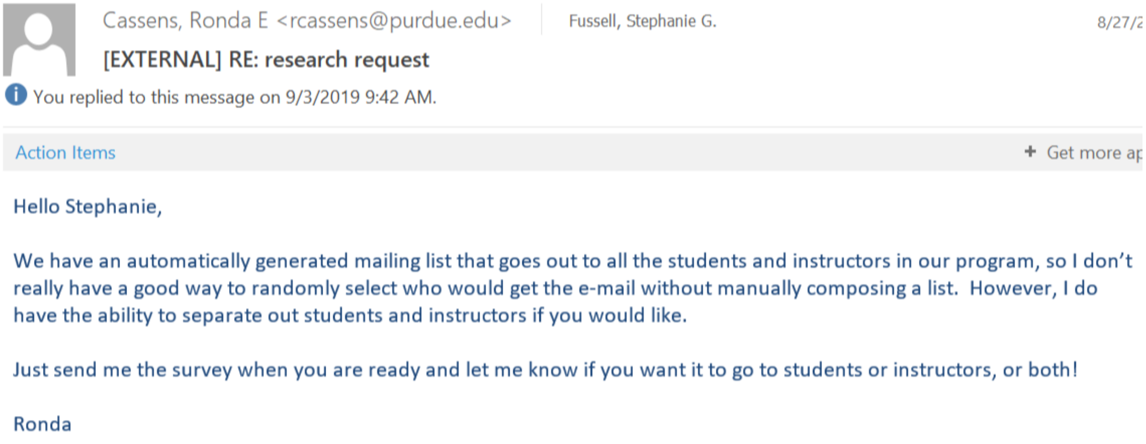
Stephanie, I am interested in helping. I will have to run your IRB approval through my college's review process. That should not be hard to do. Just send me your IRB approval letter and the project description.

And yes, I am the one who's name is on lots of research done at the Aviation Research Lab, Institute of Aviation, University of Illinois. I started there in 1989 and worked on many projects up until 2015. The lab formally dissolved in 2010 however.

Don

Don Talleur
Chief Pilot/Director
Institute of Aviation at Parkland College
dtalleur@parkland.edu
217-244-8687

Purdue University


Cassens, Ronda E <rcassens@purdue.edu> | Fussell, Stephanie G. 8/27/2

[EXTERNAL] RE: research request

You replied to this message on 9/3/2019 9:42 AM.

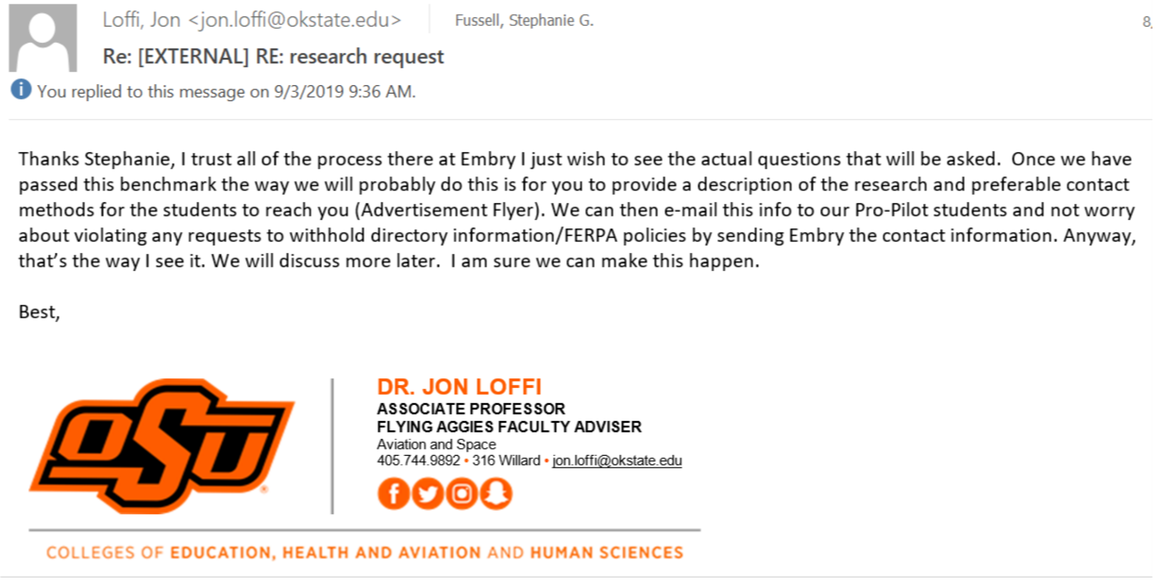
Hello Stephanie,

We have an automatically generated mailing list that goes out to all the students and instructors in our program, so I don't really have a good way to randomly select who would get the e-mail without manually composing a list. However, I do have the ability to separate out students and instructors if you would like.

Just send me the survey when you are ready and let me know if you want it to go to students or instructors, or both!

Ronda

Oklahoma State University


Loffi, Jon <jon.loffi@okstate.edu> | Fussell, Stephanie G. 8,

Re: [EXTERNAL] RE: research request

You replied to this message on 9/3/2019 9:36 AM.

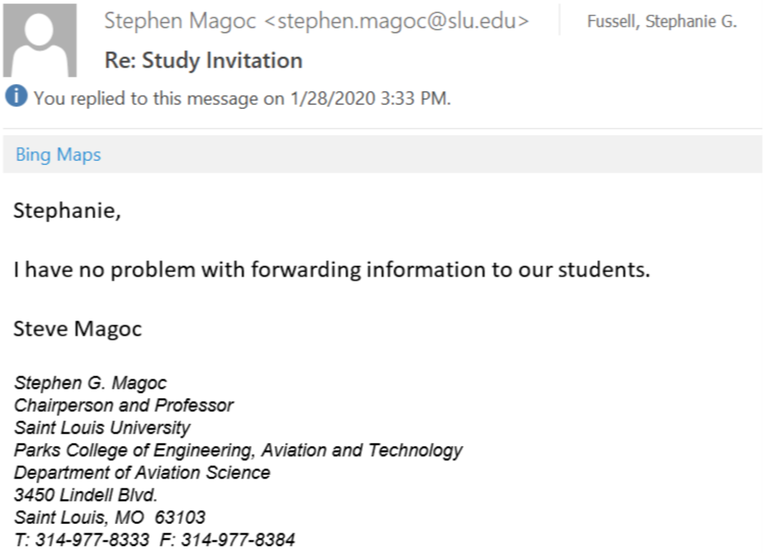
Thanks Stephanie, I trust all of the process there at Embry I just wish to see the actual questions that will be asked. Once we have passed this benchmark the way we will probably do this is for you to provide a description of the research and preferable contact methods for the students to reach you (Advertisement Flyer). We can then e-mail this info to our Pro-Pilot students and not worry about violating any requests to withhold directory information/FERPA policies by sending Embry the contact information. Anyway, that's the way I see it. We will discuss more later. I am sure we can make this happen.

Best,

DR. JON LOFFI
ASSOCIATE PROFESSOR
FLYING AGGIES FACULTY ADVISER
Aviation and Space
405.744.9892 • 316 Willard • jon.loffi@okstate.edu

COLLEGES OF EDUCATION, HEALTH AND AVIATION AND HUMAN SCIENCES

Saint Louis University



Stephen Magoc <stephen.magoc@slu.edu>

Fussell, Stephanie G.

Re: Study Invitation

You replied to this message on 1/28/2020 3:33 PM.

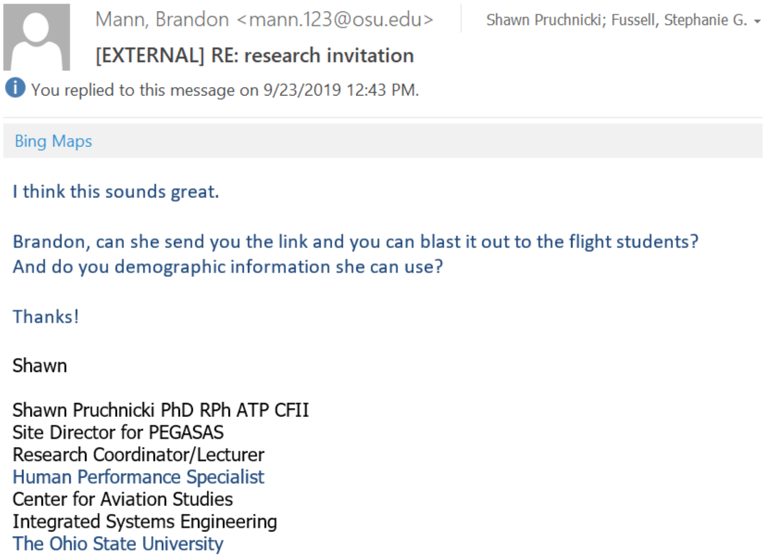
Stephanie,

I have no problem with forwarding information to our students.

Steve Magoc

Stephen G. Magoc
Chairperson and Professor
Saint Louis University
Parks College of Engineering, Aviation and Technology
Department of Aviation Science
3450 Lindell Blvd.
Saint Louis, MO 63103
T: 314-977-8333 F: 314-977-8384

The Ohio State University



Mann, Brandon <mann.123@osu.edu>

Shawn Pruchnicki; Fussell, Stephanie G.

[EXTERNAL] RE: research invitation

You replied to this message on 9/23/2019 12:43 PM.

I think this sounds great.

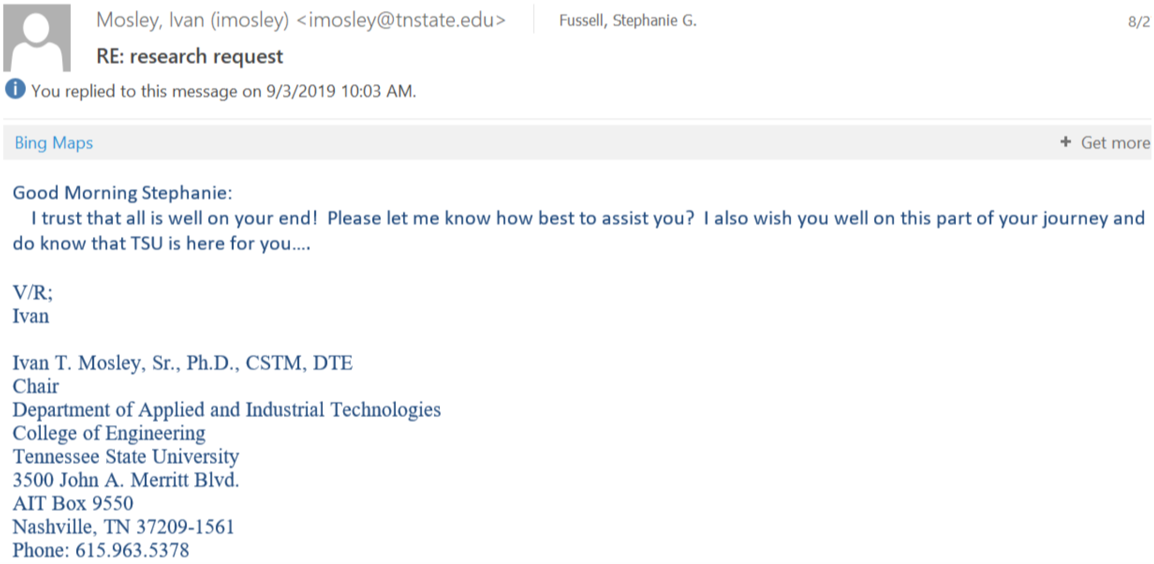
Brandon, can she send you the link and you can blast it out to the flight students?
And do you demographic information she can use?

Thanks!

Shawn

Shawn Pruchnicki PhD RPh ATP CFII
Site Director for PEGASAS
Research Coordinator/Lecturer
Human Performance Specialist
Center for Aviation Studies
Integrated Systems Engineering
The Ohio State University

Tennessee State University



Mosley, Ivan (imosley) <imosley@tnstate.edu> Fussell, Stephanie G. 8/2

RE: research request

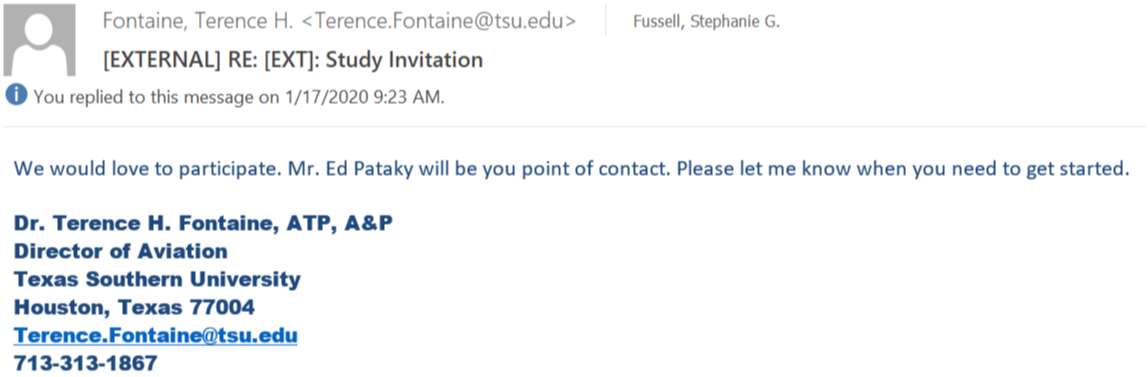
You replied to this message on 9/3/2019 10:03 AM.

Good Morning Stephanie:
I trust that all is well on your end! Please let me know how best to assist you? I also wish you well on this part of your journey and do know that TSU is here for you....

V/R;
Ivan

Ivan T. Mosley, Sr., Ph.D., CSTM, DTE
Chair
Department of Applied and Industrial Technologies
College of Engineering
Tennessee State University
3500 John A. Merritt Blvd.
AIT Box 9550
Nashville, TN 37209-1561
Phone: 615.963.5378

Texas Southern University



Fontaine, Terence H. <Terence.Fontaine@tsu.edu> Fussell, Stephanie G.

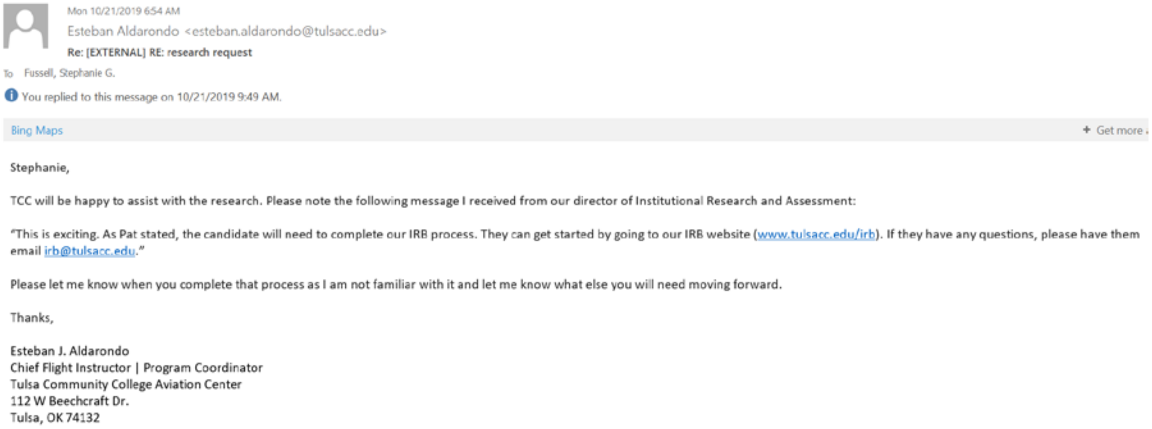
[EXTERNAL] RE: [EXT]: Study Invitation

You replied to this message on 1/17/2020 9:23 AM.

We would love to participate. Mr. Ed Pataky will be you point of contact. Please let me know when you need to get started.

Dr. Terence H. Fontaine, ATP, A&P
Director of Aviation
Texas Southern University
Houston, Texas 77004
Terence.Fontaine@tsu.edu
713-313-1867

Tulsa Community College



Mon 10/21/2019 6:54 AM
Esteban Aldarondo <esteban.aldarondo@tulsacc.edu>
Re: [EXTERNAL] RE: research request
To Fussell, Stephanie G.

You replied to this message on 10/21/2019 9:49 AM.

Stephanie,

TCC will be happy to assist with the research. Please note the following message I received from our director of Institutional Research and Assessment:

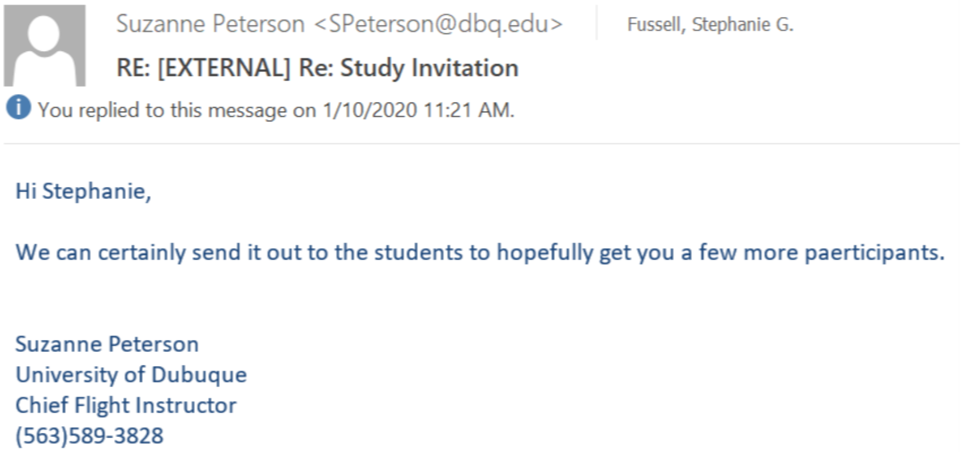
"This is exciting. As Pat stated, the candidate will need to complete our IRB process. They can get started by going to our IRB website (www.tulsacc.edu/irb). If they have any questions, please have them email irb@tulsacc.edu."

Please let me know when you complete that process as I am not familiar with it and let me know what else you will need moving forward.

Thanks,

Esteban J. Aldarondo
Chief Flight Instructor | Program Coordinator
Tulsa Community College Aviation Center
112 W Beechcraft Dr.
Tulsa, OK 74132

University of Dubuque



Suzanne Peterson <SPeterson@dbq.edu> Fussell, Stephanie G.

RE: [EXTERNAL] Re: Study Invitation

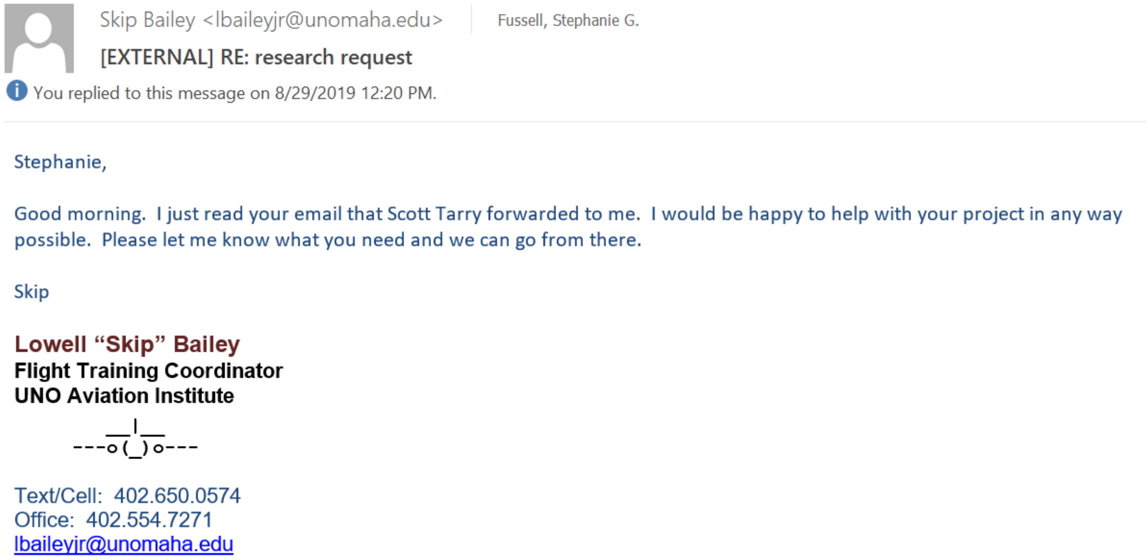
You replied to this message on 1/10/2020 11:21 AM.

Hi Stephanie,

We can certainly send it out to the students to hopefully get you a few more paerticipants.

Suzanne Peterson
University of Dubuque
Chief Flight Instructor
(563)589-3828

University of Nebraska – Omaha



Skip Bailey <lbaileyjr@unomaha.edu> Fussell, Stephanie G.

[EXTERNAL] RE: research request

You replied to this message on 8/29/2019 12:20 PM.

Stephanie,

Good morning. I just read your email that Scott Tarry forwarded to me. I would be happy to help with your project in any way possible. Please let me know what you need and we can go from there.

Skip

Lowell "Skip" Bailey
Flight Training Coordinator
UNO Aviation Institute

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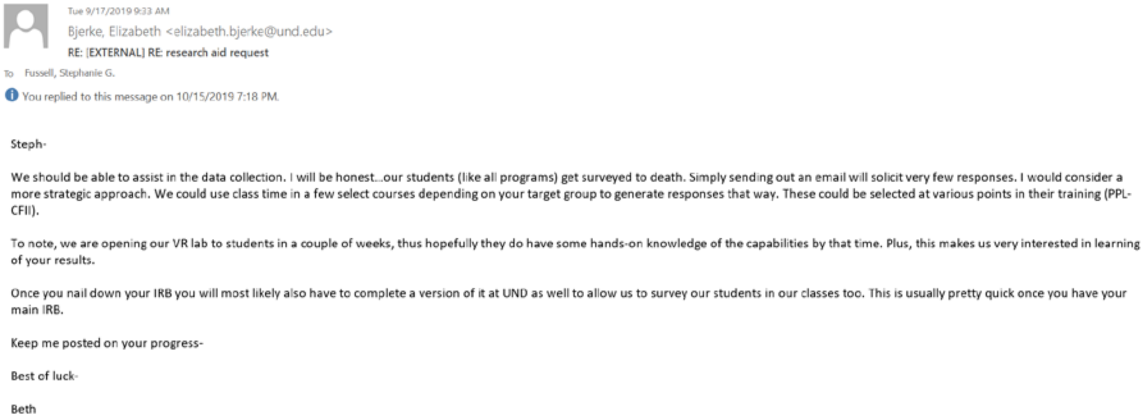
Text/Cell: 402.650.0574
Office: 402.554.7271
lbaileyjr@unomaha.edu

University of North Dakota



Tue 9/17/2019 9:33 AM
Bjerke, Elizabeth <elizabeth.bjerke@und.edu>
RE: [EXTERNAL] RE: research aid request
To Fussell, Stephanie G.

You replied to this message on 10/15/2019 7:18 PM.

Steph-

We should be able to assist in the data collection. I will be honest…our students (like all programs) get surveyed to death. Simply sending out an email will solicit very few responses. I would consider a more strategic approach. We could use class time in a few select courses depending on your target group to generate responses that way. These could be selected at various points in their training (PPL-CFII).

To note, we are opening our VR lab to students in a couple of weeks, thus hopefully they do have some hands-on knowledge of the capabilities by that time. Plus, this makes us very interested in learning of your results.

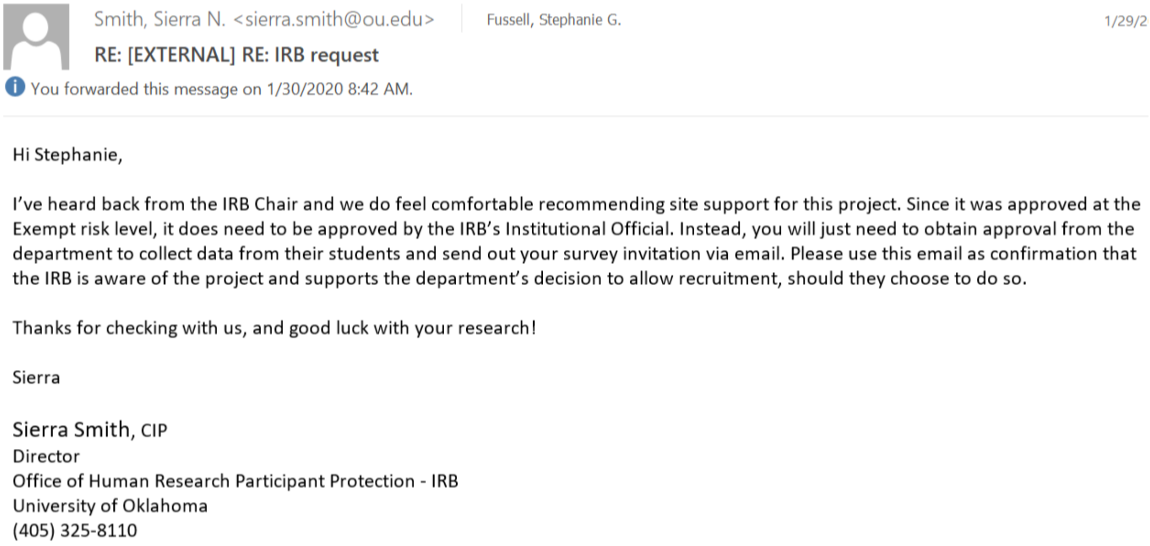
Once you nail down your IRB you will most likely also have to complete a version of it at UND as well to allow us to survey our students in our classes too. This is usually pretty quick once you have your main IRB.

Keep me posted on your progress-

Best of luck-

Beth

University of Oklahoma



Smith, Sierra N. <sierra.smith@ou.edu> | Fussell, Stephanie G. 1/29/2

RE: [EXTERNAL] RE: IRB request

You forwarded this message on 1/30/2020 8:42 AM.

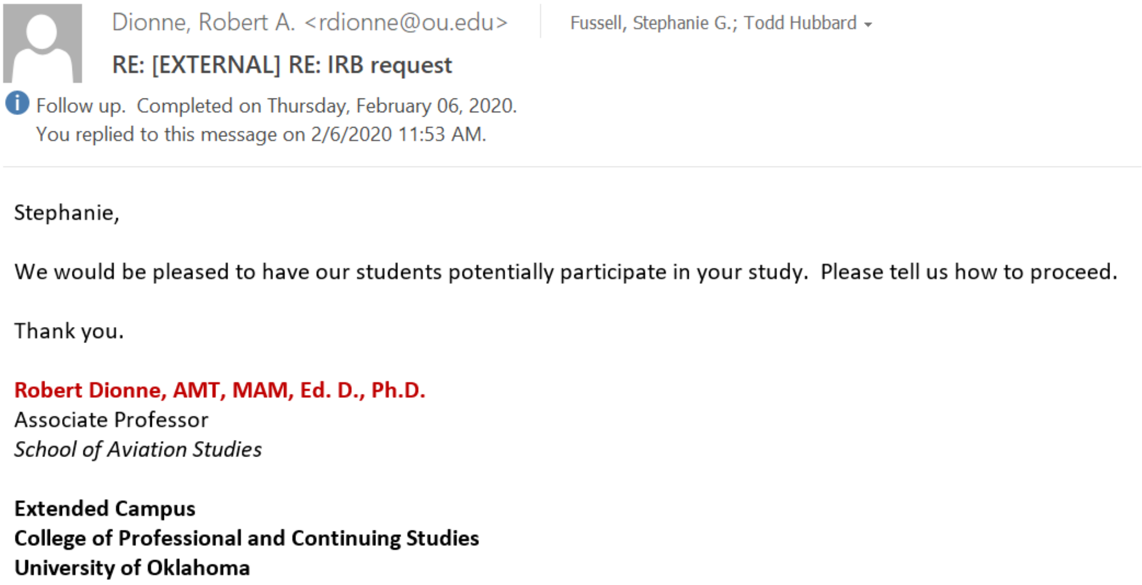
Hi Stephanie,

I've heard back from the IRB Chair and we do feel comfortable recommending site support for this project. Since it was approved at the Exempt risk level, it does need to be approved by the IRB's Institutional Official. Instead, you will just need to obtain approval from the department to collect data from their students and send out your survey invitation via email. Please use this email as confirmation that the IRB is aware of the project and supports the department's decision to allow recruitment, should they choose to do so.

Thanks for checking with us, and good luck with your research!

Sierra

Sierra Smith, CIP
Director
Office of Human Research Participant Protection - IRB
University of Oklahoma
(405) 325-8110



Dionne, Robert A. <rdionne@ou.edu> | Fussell, Stephanie G.; Todd Hubbard

RE: [EXTERNAL] RE: IRB request

Follow up. Completed on Thursday, February 06, 2020.
You replied to this message on 2/6/2020 11:53 AM.

Stephanie,

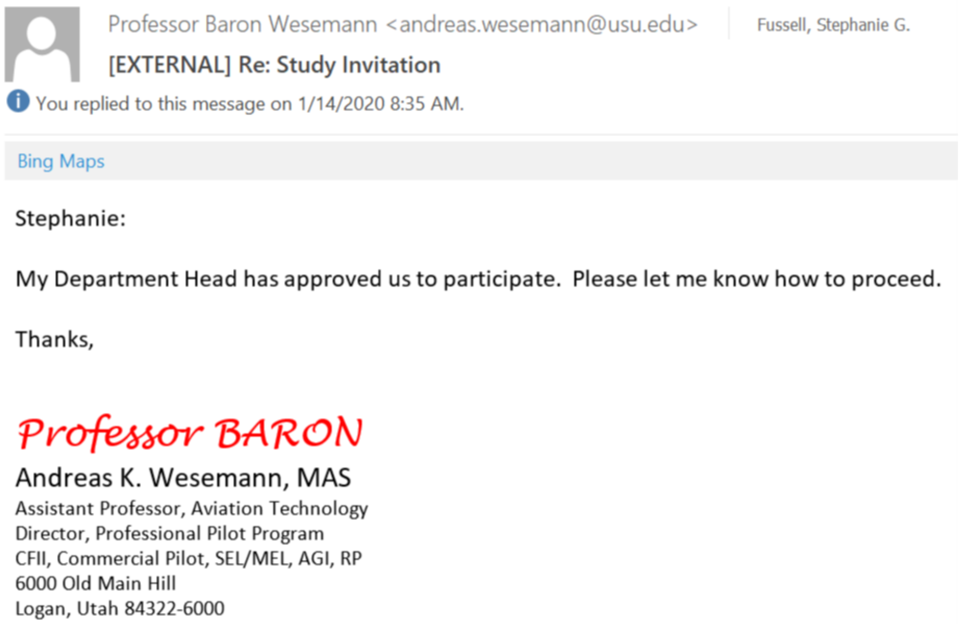
We would be pleased to have our students potentially participate in your study. Please tell us how to proceed.

Thank you.

Robert Dionne, AMT, MAM, Ed. D., Ph.D.
Associate Professor
School of Aviation Studies

Extended Campus
College of Professional and Continuing Studies
University of Oklahoma

Utah State University



Professor Baron Wesemann <andreas.wesemann@usu.edu> | Fussell, Stephanie G.

[EXTERNAL] Re: Study Invitation

You replied to this message on 1/14/2020 8:35 AM.

Bing Maps

Stephanie:

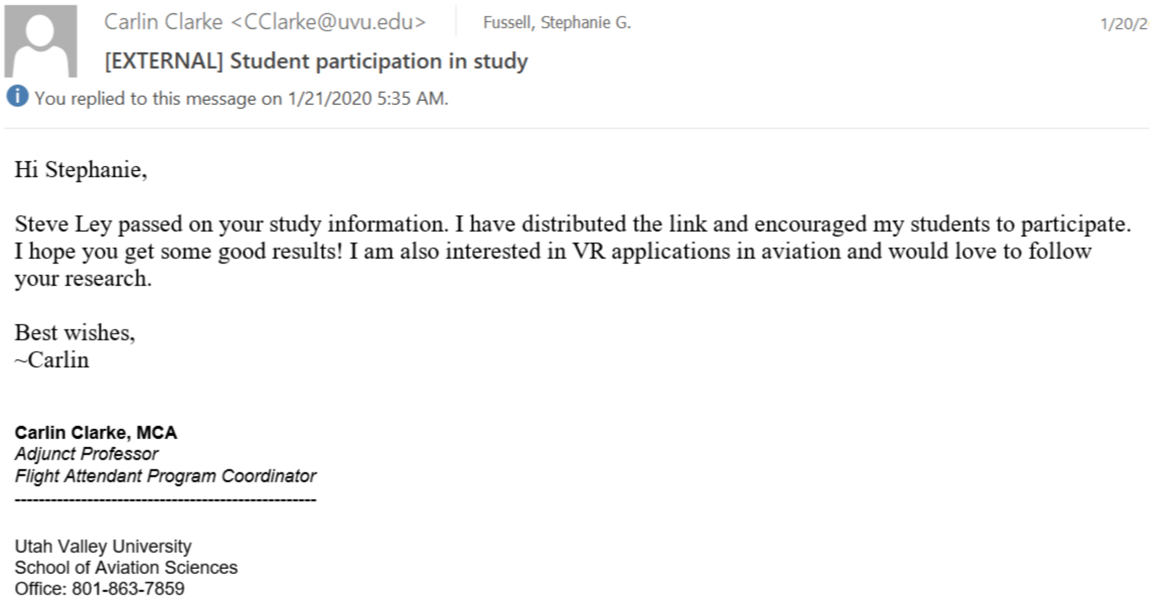
My Department Head has approved us to participate. Please let me know how to proceed.

Thanks,

Professor BARON

Andreas K. Wesemann, MAS
Assistant Professor, Aviation Technology
Director, Professional Pilot Program
CFII, Commercial Pilot, SEL/MEL, AGI, RP
6000 Old Main Hill
Logan, Utah 84322-6000

Utah Valley University School of Aviation Sciences



Carlin Clarke <CClarke@uvu.edu> | Fussell, Stephanie G. 1/20/2

[EXTERNAL] Student participation in study

You replied to this message on 1/21/2020 5:35 AM.

Hi Stephanie,

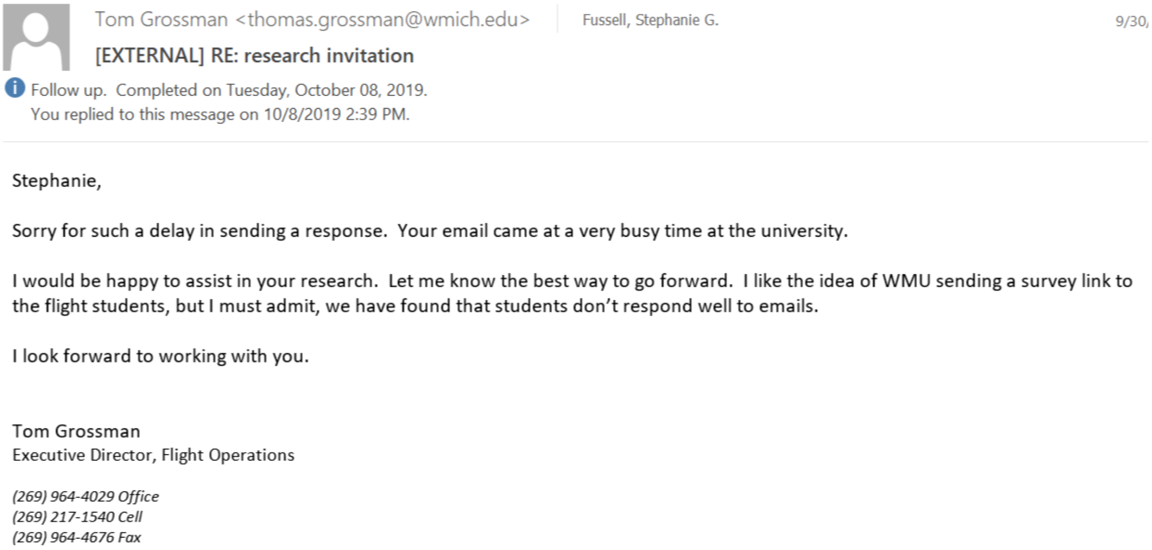
Steve Ley passed on your study information. I have distributed the link and encouraged my students to participate. I hope you get some good results! I am also interested in VR applications in aviation and would love to follow your research.

Best wishes,
~Carlin

Carlin Clarke, MCA
Adjunct Professor
Flight Attendant Program Coordinator

Utah Valley University
School of Aviation Sciences
Office: 801-863-7859

Western Michigan University



Tom Grossman <thomas.grossman@wmich.edu>　Fussell, Stephanie G.　9/30,

[EXTERNAL] RE: research invitation

Follow up. Completed on Tuesday, October 08, 2019.
You replied to this message on 10/8/2019 2:39 PM.

Stephanie,

Sorry for such a delay in sending a response. Your email came at a very busy time at the university.

I would be happy to assist in your research. Let me know the best way to go forward. I like the idea of WMU sending a survey link to the flight students, but I must admit, we have found that students don't respond well to emails.

I look forward to working with you.

Tom Grossman
Executive Director, Flight Operations

(269) 964-4029 Office
(269) 217-1540 Cell
(269) 964-4676 Fax

APPENDIX B

Data Collection Device

Screening questions

1. Are you enrolled in a flight training program at a college or university?
2. Have you begun flight training in an aircraft?
3. Are you over the age of 18?
4. Do you agree to the informed consent provided?

Demographics

1 What gender do you identify as?

- Female
- Male
- Other (blank to fill in)
- Prefer not to say

2 What is your age?

- (fill in the blank)

3 Please specify your race.

- Caucasian
- African-American
- Latino or Hispanic
- Asian
- Native American
- Native Hawaiian or Pacific Islander
- Two or More
- Other (please specify)
- Unknown
- Prefer not to say

4 Are you an international student?

  - (y/n)

4a If you are an international student, what general region are you from?

- North America
- South America
- Europe

- Asia
- Africa
- Australia

5 Which school do you attend?

- (list of schools, when finalized)

6 What is your current education status?

- Undergraduate student. Indicate year below.
    - Freshman
    - Sophomore
    - Junior
    - Senior
- Graduate student. Indicate year below.
    - First year
    - Second year
    - Third year
    - Fourth year
    - Fifth year or beyond
    - Other. Specify: ______________________

7 What is the highest level of flight certification you have received?

- Student pilot
- Private pilot
- Private pilot, instrument flight rating
- Multi-engine
- Commercial pilot
- CFI/CFII/MEI
- ATP

8 How many flight hours do you have?

- (fill in the blank)

9 How many flight hours in a flight training device do you have?

- (fill in the blank)

10 How much experience with VR do you have?

- I have never used VR
- I have used VR a couple of times but am not a frequent user

- I use VR a few times a week
- I use VR daily

11 How much experience with computer or video gaming do you have?

- I have some gaming experience
- I play computer/video games less than once a week
- I play computer/video games a few times per week, but not daily
- I play computer/video games daily

Please indicate how strongly you agree with each statement, rated on a scale of 1 (I strongly disagree) to 5 (I strongly agree)

1. Using VR for flight training is a good idea.
2. Using VR for flight training is a wise idea.
3. I feel positively toward using VR for flight training.
4. If made available, I am willing to use VR for flight training.
5. If made available, I intend to use VR for flight training.
6. If made available, I intend to use every flight training lesson provided through VR.
7. Learning to use VR for flight training will be easy for me.
8. It will be easy to gain skills for flight training using VR.
9. Using VR for flight training will make my flight training progression easier.
10. Using VR for flight training would be enjoyable.
11. Using VR for flight training would be exciting.
12. I enjoy using immersive simulation technology such as VR.
13. I have fun using immersive simulation technology such as VR.
14. Using VR for flight training is more productive than using a flight training device.
15. Using VR for flight training will improve my flying skills more efficiently than using a flight training device.
16. By expending the same effort as in a flight training device, using VR for flight training will improve the progression of my training.
17. Using VR for flight training will have a bad effect on my physical health.
18. Using VR for flight training is safer for my physical health than using a flight training device.
19. Using VR for flight training is safer for my physical health than using an actual aircraft.
20. I am hesitant to use VR for flight training because there are no FAA regulations regarding its use.
21. I am uncertain if the FAA will approve VR for flight training purposes.
22. Recording flight training hours in a logbook is a concern when using VR for flight training.
23. Flight training using VR will be useful for flying in the real world.
24. Using VR would enhance flight training.
25. Using VR would improve my performance in flight training.

26. Using VR would make flight training more effective.
27. I feel confident in my ability to use VR for flight training.
28. I feel confident that my flight skills will make flying in VR easy.
29. I feel confident in my flight skills in the real-world environment.

Please rate your confidence in your ability to use VR technology for flight training on a scale from 1 (no confidence) to 5 (total confidence), if VR is made available:

30. I could use VR technology for flight training if no one was around to tell me what to do (e.g., a flight instructor or an assistant).
31. I could use VR technology for flight training if I had only the manuals for reference.
32. I could use VR technology for flight training if I had only a virtual instructor guiding me.
33. I could use VR technology for flight training if I could call someone for help if I got stuck.
34. I could use VR technology for flight training if I had used similar systems (e.g., an advanced aviation training device, a flight training device) previously.

APPENDIX C

Institutions Invited to Participate in the Study

Table C1

Institutions Invited to Participate in the Study – Participation after Data Cleaning

Institution	Region	Approx. Program Size	Gender: Male / Female %	# of Participants	% of Participation
Aims Community College	Colorado, ANM	60	90% / 10%	5	8%
Auburn University	Alabama, ASO	339	85% / 15%	33	10%
Eastern Michigan University	Michigan, AGL	~100		10	10%
Embry-Riddle Aero.Uni. – Daytona Beach	Florida, ASO	1,636		47	8%
Farmingdale State College	New York, AEA	74	87% / 16%	8	11%
Fox Valley Technical College	Wisconsin, AGL	61	92% / 8%	13	21%
Green River College	Washington, ANM	102	81% / 19%	13	13%
Kansas State University Polytechnic Campus	Kansas, ACE			51	
Kent State University	Ohio, AGL	258	88% / 12%	23	9%
LeTourneau University	Texas, ASW	~100		27	27%
Liberty University	Virginia, AEA	511	88% / 12%	36	7%
Louisiana Tech University	Louisiana, ASO	123	76% / 24%	24	20%
Moody Bible Institute	Washington, ANM	25	76% / 24%	4	16%
Parkland College	Illinois, AGL	68	84% / 16%	10	15%
Purdue University	Indiana, AGL	287	84% / 16%	27	9%
Saint Louis University	Missouri, ACE	120	88% / 12%	15	13%

Table C1 Continued

Institution	Region	Approx. Program Size	Gender: Male / Female %	# of Participants	% of Participation
The Ohio State University	Ohio, AGL	122	87% / 13%	14	11%
Tulsa Community College	Oklahoma, ASW	75	77% / 23%	7	9%
University of Nebraska – Omaha	Nebraska, ACE	149	86% / 14%	16	11%
Utah State University	Utah, ANM			22	
Utah Valley University School of Aviation Sciences	Utah, ANM	407	94% / 6%	29	7%
Western Michigan University	Michigan, AGL	862	88% / 12%	40	6%
Total participants; average gender breakdown		7,928	85% / 15%	607	

Note. PCATDs may also be available at institutions in laboratories but may not have been specified. Institutions with a low percentage rate (5% or less) were removed from the data. FAA Regions: ACE = Central Region, AEA = Eastern Region, AGL = Great Lakes Region, ANE = New England Region, ANM = Northwest Mountain Region, ASO = Southern Region, ASW = Southwest Region.

The following schools were invited, agreed to participate, but did not have high enough response rates when data collection closed: Baylor University (Texas, 60 flight students, 5% response rate), Community College of Allegheny County (New Jersey, 3 responses), Delta State University (Mississippi, 190 students, 5% response rate), Embry-Riddle Aeronautical University – Prescott (Arizona, 608 students, 4%), Florida Institute of Technology (Florida, 3 responses), Gateway Technical College (Wisconsin, 25 students, 4% response rate), Marywood University (Pennsylvania, 1 response), Middle Tennessee State University (Tennessee, 724 students, 4% response rate), Oklahoma State University (Oklahoma, 327 students, 2% response rate), Texas Southern University

(Texas, 1 response), University of Dubuque (Iowa, 315 students, 4% response rate), and University of Oklahoma (Oklahoma, approx. 300 students, 4% response rate).

The following schools were invited, initially agreed to participate, but did not have any responses when data collection closed: Bridgewater State University (Massachusetts), Delaware State University (Delaware, 91 flight students), Middle Georgia State University (Georgia), Tennessee State University (Tennessee), and University of North Dakota (North Dakota, approx. 1,600 students).