Summer 2023

Identification and Validation of a Predicted Risk-Taking Propensity Model Among General Aviation Pilots

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Thesis Submitted to the College of Aviation in Partial Fulfillment of the Requirements

for the Degree of Master of Science in Aviation

Embry-Riddle Aeronautical University

Daytona Beach, Florida

July 2023

Identification and Validation of a Predicted Risk-Taking Propensity Model Among General Aviation Pilots

By

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Abstract

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Title: Identification and Validation of a Predicted Risk-Taking Propensity Model Among General Aviation Pilots

Institution: Embry-Riddle Aeronautical University

Degree: Master of Science in Aviation

Year: 2023

Risk-taking, a persistent topic of interest and concern in aviation, has been linked with unsafe behaviors and accidents. However, risk-taking propensity is a complex construct that encompasses numerous factors still being researched. Even within the limited research available about the factors affecting pilots' risk-taking propensity, studies have yielded inconsistent results. Therefore, this quantitative study explores existing and novel factors that predict the propensity for risk-taking among general aviation (GA) pilots in the United States.

This study, conducted in two stages, involved developing a prediction model using backward stepwise regression to predict pilots' risk propensity, followed by model fit testing using additional sampling to validate the predicted model. Data was gathered using surveys from multiple local Experimental Aircraft Association (EAA) chapters in Central Florida and from Embry-Riddle Aeronautical University, Daytona Beach campus. In Stage 1, the model was constructed based on data obtained from 100 participants. Stage 2 involved validating the model using responses from another 100 participants who answered the same set of questions as in Stage 1. Model validation encompassed three methods: correlation analysis, *t*-test, and cross-validity coefficient. The results from these analyses demonstrated a strong fit between the regression model and the Stage 2 data, affirming the accuracy of the prediction model.

The analysis identified a model comprising seven significant predictors among a set of 12, accounting for 76% of the variance, with an adjusted R^2 of 75%, influencing the risk-taking propensity among GA pilots. These predictors included age, total flight hours, number of flight ratings, number of hazardous events, self-efficacy, psychological distress, and locus of control. Model prediction and cross-validation were employed to enhance the findings' rigor and generalizability. Practical applications and suggested areas for future studies are also discussed.

Keywords: Risk-taking propensity, aviation, backward elimination stepwise regression, cross-validation and model fit, McDonald's omega

Dedication

I would like to dedicate this thesis to my dear parents and my loving wife, Melody Samu. This work stands as a testament to their constant support, encouragement, understanding, and endless patience, which have been invaluable throughout this endeavor, shaping not only my academic achievement but also my character and resilience.

Acknowledgments

Conducting the necessary work and writing this research has been a tremendous academic pursuit. Nonetheless, it brings me great joy as I reflect on the invaluable support I have received throughout the process, for which I am profoundly grateful.

I extend my heartfelt appreciation to my committee chair, Dr. Jennifer E. Thropp, whose expertise, dedication, and insightful feedback have shaped my research and enhanced the quality of my writing. Most importantly, I am truly grateful for her support in my academic advancement and for pushing me to strive for excellence.

I also thank Dr. Scott Winter, my committee member, for his key contributions and constructive criticism of my statistical analysis and research methods that have helped refine my thesis. I am grateful for his knowledge, commitment to academic excellence, and prompt assistance with my concerns, which greatly aided my work.

I also want to extend my sincere gratitude to Dr. Donald Metscher and Ms. BeeBee Leong for their vital support during my graduate degree program. Their encouragement was instrumental in completing this degree and this research.

Completing this research would have been challenging without the help of my wife, Melody Samu, whose assistance during the data collection phase and in endlessly proofreading my work was vital to this project. I appreciate her love and support during late nights and early mornings, preserving my inner equilibrium in my academic journey.

I also thank my work colleague, Sang-A Lee, for her valuable help in the data collection process. Finally, I am immensely grateful to my loving family for the encouragement and moral support I received during my academic quest at Embry-Riddle.

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Chapter I: Introduction

A pilot's ability to make informed decisions is critical to aircraft safety. Even though pilots receive extensive training, and there are rules and models available to them in decision-making situations for the safe operations of an aircraft, most aviation accidents (60-85%) result from pilot error owing to mistakes in their judgment and decision-making handling the aircraft (Federal Aviation Administration [FAA], 2022; Jensen, 1997; Shappell et al., 2007; Wiegmann & Shappell, 2003). Per the National Transportation Safety Board (NTSB, 2022), accidents involving general aviation (GA) aircraft constitute nearly 83% of all aviation incidents in the U.S. each year, with pilots' loss of control in-flight (LOC-I) being the primary contributing factor. Majumdar et al. (2021) reported that most loss of control accidents between 2009 and 2017 was caused by pilot judgment, risk-taking propensity, and decision-making errors. Researchers have since shifted their focus away from pilot skillset deficiencies to factors influencing risk perception and risk-taking propensity, amongst other factors.

Pilots make decisions based on a complex interplay of psychological processes influenced by factors such as experience, cognition, context, motivation, intelligence, emotion, personality, and social dynamics (Mckinney, 1993). However, pilots' risk propensity influences decision-making by determining the extent to which they are willing to take chances when selecting different options. Uncertainty regarding the outcome of an action necessitates that pilots undertake a certain degree of risk, rendering decision-making and risk-taking interdependent (Sicard et al., 2003). Per Pauley and O'Hare (2006), effective management of risks is critical, encompassing the ability of pilots to recognize hazards, understand associated risks, and make informed aeronautical decisions based on calculated risks. Different risk-taking propensities affect how pilots make decisions within their abilities; thus, exploring all the factors that influence it is essential. Therefore, this research examines the determinants that influence the risk-taking propensity of GA pilots in the U.S.

Chapter 1 of this research paper thoroughly evaluates the central objective, problem statement, purpose statement, and fundamental factors that underlie this research's significance and practical implications on pilots' risk propensity. The information presented includes the account and relevance of the topic, research questions, hypotheses, study limitations, delimitations, and assumptions. To clarify the terminologies used in this research, Chapter 1 concludes with a summary of key terms and their operational definitions.

Statement of the Problem

Risk-taking continues to be an ongoing topic of interest and concern in aviation, drawing attention due to its connotation with the causation of injury. This study addresses the prevalence of risk-taking propensity among GA pilots in the U.S., which has been associated with unsafe behaviors and aviation accidents (Adams et al., 2002; Pauley et al., 2008a). Pilots with a tendency to take risks may make choices that put them in hazardous situations and increase the likelihood of accidents. Despite efforts to promote aviation safety through training and regulation, risk-taking behavior remains a significant challenge in the GA community. However, pilots' decision-making processes and risk-taking propensities present a challenge as they involve intricate psychological mechanisms and are predicted by a variety of interdependent variables that are still being investigated, rendering risk propensity a complex construct. While some research on pilots' perception of risk exists, there is a dearth of research on the factors that affect the risk-taking propensity of GA pilots. In addition, while many personality traits have been proposed as potential factors affecting a person's inclination to take or avoid risks (Atkinson, 1957; Zuckerman, 1979), there is currently no research investigating self-efficacy, locus of control, psychological distress, marital status, pilot experience, or past hazardous experiences as predictors. The present study lays the groundwork for further inquiry by examining potential predictors influencing risk inclinations among GA pilots.

Purpose Statement

The intent of this study was to enhance comprehension of the determinants influencing risk-taking propensity among the GA pilot community. Its purpose was to fill the gap in the research by incorporating a two-stage exploratory design approach in order to (a) create a predictive model based on multiple regression analysis to predict GA pilots' risk-taking propensity by considering social identity, social cognitive, and experiential factors, including the involvement in hazardous events as potential predictor variables, and (b) determine the validity of the regression model created in the previous step by using correlation analysis, *t*-test, and computing the cross-validity coefficient. By better understanding the factors that influence pilots' inclination towards risk-taking, this study seeks to contribute to improved aviation safety and reduce the prevalence of accidents and incidents caused by risk-taking behavior. It may also aid in developing effective intervention programs that help pilots manage risks prudently.

Significance of the Study

This research has the potential to assist the FAA in better understanding the factors that influence pilot risk-taking behavior, which they could use to educate pilots about the possible adverse consequences of risky behavior and aid them in developing policies, rules, and safety recommendations to increase GA safety. This research could benefit pilots as its results may shed light on their decision-making processes, enabling them to make informed and calculated choices during flight operations. The findings of this study could also benefit aviation training institutions as it could guide the development of targeted training programs meant to decrease risk-taking behavior among pilots. Also, aircraft manufacturers could utilize the findings to integrate safety measures and alerting systems that aid pilot decision-making and reduce instances of risky behavior. This prediction model could be of interest to aviation insurance companies to assist them in better understanding the risks involved in covering GA pilots and guiding their underwriting procedures. From a theoretical perspective, the findings from the examination of self-efficacy may either broaden or confirm the self-efficacy theory by Bandura (1977) and the theory of planned behavior by Ajzen (1991) by examining it within the context of aviation.

Although risk behavior and risk perception have been studied within behavioral and aviation sciences (Hunter, 2002a, 2006), there is comparatively less research on individuals' attitudes towards risk-taking, i.e., risk propensity and risk tolerance, especially among GA pilots. This study, therefore, seeks to bridge this gap by exploring the factors that can predict a pilot's risk-taking propensity during flight operations. Exploring the determinants of risk-taking propensity can help the aviation industry improve training, pilot selection and evaluation, as well as devise and execute intervention strategies that would personalize the risk to the pilot rather than treating it as an abstract statistical concept in order to mitigate the factors that contribute to most aviation accidents.

Research Questions (RQ)

The study investigated the following research questions:

R_1: Does age significantly predict risk-taking propensity scores among GA pilots while holding other factors constant?

R_2: Does gender significantly predict risk-taking propensity scores among GA pilots while holding other factors constant?

R_3: Does marital status significantly predict risk-taking propensity scores among GA pilots while holding other factors constant?

R_4: Does education level significantly predict risk-taking propensity scores among GA pilots while holding other factors constant?

R_5: Does ethnicity significantly predict risk-taking propensity scores among GA pilots while holding other factors constant?

R_6: Does locus of control significantly predict risk-taking propensity scores among GA pilots while holding other factors constant?

R_7: Does self-efficacy significantly predict risk-taking propensity scores among GA pilots while holding other factors constant?

R_8: Does psychological distress significantly predict risk-taking propensity scores among GA pilots while holding other factors constant?

R_9: Does the number of total flight hours significantly predict the risk-taking propensity among GA pilots while holding other factors constant?

R_{10}: Does the type of flight training curriculum significantly predict risk-taking propensity scores among GA pilots while holding other factors constant?

R_{11}: Does the number of flight certifications significantly predict risk-taking propensity scores among GA pilots while holding other factors constant?

R_{12}: Does the number of hazardous events experienced by GA pilots in the past five years as a pilot in command (PIC) significantly predict their risk-taking propensity scores while holding other factors constant?

Research Hypotheses

The study investigated the following hypotheses:

H_{A1}: Age will significantly predict a GA pilot's risk-taking propensity while holding other factors constant.

H_{A2}: Gender will significantly predict a GA pilot's risk-taking propensity while holding other factors constant.

H_{A3}: Marital status will significantly predict a GA pilot's risk-taking propensity while holding other factors constant.

H_{A4}: Education level will significantly predict a GA pilot's risk-taking propensity while holding other factors constant.

H_{A5}: Ethnicity will significantly predict a GA pilot's risk-taking propensity while holding other factors constant.

H_{A6}: Locus of control will significantly predict a GA pilot's risk-taking propensity while holding other factors constant.

H_{A7}: Self-efficacy will significantly predict a GA pilot's risk-taking propensity while holding other factors constant.

H_{A8}: Psychological distress will significantly predict a GA pilot's risk-taking propensity while holding other factors constant.

H_{A9}: The number of total flight hours will significantly predict a GA pilot's risk-taking propensity while holding other factors constant.

H_{A10}: The type of flight training curriculum will significantly predict a GA pilot's risk-taking propensity while holding other factors constant.

H_{A11}: The number of flight certifications will significantly predict a GA pilot's risk-taking propensity while holding other factors constant.

H_{A12}: The number of hazardous events experienced by GA pilots in the past five years as a PIC predicts their risk-taking propensity while holding other factors constant.

* Null hypotheses are assumed but not presented here for brevity.

Delimitations

The scope of this study was delimited to GA pilots who are FAA-certified private, commercial, and instructor pilots but excluded pilots with only rotary wing certification and active Part 121 airline pilots. Secondly, the study focused only on GA pilots in the U.S., specifically Central Florida. Thirdly, the study was delimited to collect data using self-report survey questionnaires and did not use any other data sources such as interviews, published data, experiments, or deriving risk propensity scores from outcomes of behavioral tasks (Mata et al., 2018). Finally, this study was delimited to analyze direct associations between each explanatory variable and the response variable, risk-taking propensity, while not analyzing inter-variable relationships.

Limitations and Assumptions

The current study acknowledges specific limitations that should be considered by readers when drawing conclusions or making inferences based on its results. The sample participants for this study were mainly GA pilots from Central Florida, an area whose characteristics may differ from those of other states in the U.S., especially regarding differences in weather, types of training environments, number of flight schools, or other pilot experience factors. Thus, the current study may have limited generalizability and yield different results if the data collection were conducted among a random sample of pilots from multiple locations within the U.S.

Using self-reported data rather than data gathered from randomized controlled trials (RCT) means that the study relies on respondents' thoughts, feelings, and behaviors, which can be prone to inaccuracies. Due to participant misunderstanding, forgetfulness, or prejudice, the participants' responses, such as logged flight times or the number of self-reported past hazardous events, may be susceptible to errors. External validation of participant answers was not feasible due to confidentiality. The assumption was that the pilot participants would provide truthful and accurate responses. The confidentiality of the survey likely encouraged more truthful responses.

Another possible limitation of this research is response bias, which occurs when not all the participants understand or comprehend a question similarly. This effect is most evident when participants are expected to choose between "Strongly Agree" and "Agree"; the researcher cannot guarantee that each participant recognized the differences in these prompts similarly.

Summary

In Chapter 1, a broad overview of the main objective of this study, along with the statement of the problem, purpose statement, and the fundamental factors that underline the significance and practical implications of this study, were explained. The information covered in this chapter contains the background of the topic and its relevance, research questions, research hypotheses, delimitations, limitations, and study assumptions. Chapter 1 concludes with a summary of key terms and operational definitions of terms used.

Operational Definition of Terms

Education Level	The stage of formal learning an individual has completed, for instance, high school, bachelor’s degree, master’s degree, etc.
Ethnicity	The cultural background or descent that a person identifies with, such as African American, Asian, American Indian, Caucasian, Hispanic, etc.
Locus Of Control	How much an individual believes that his or her actions control the events in their life. One may possess either an internal or external locus of control (Rotter, 1954).
Marital Status	A person’s state of relationship, such as single, married, divorced, etc.

Hazardous Event	A potentially dangerous event or incident that a pilot has experienced that may not have necessarily led to an actual accident as per defined in 49 CFR § 830.2.
Pilot Certifications	Count of the different types of pilot certifications earned, such as private, commercial, instructor, etc.
Psychological Distress	A feeling of emotional strain from being under pressure, which can affect a person's motivation, performance, and reaction. It was measured using the average stress score derived from a general health questionnaire (Goldberg & Williams, 1988).
Risk-Taking Propensity	A person's present inclination to engage in or avoid risks, which is considered as a person's trait that can change over time as a result of experience (Sitkin & Pablo, 1992).
Self-efficacy	A person's confidence in their ability to carry out an activity in a way that will lead to the desired performance outcomes (Bandura, 1977).
Total Flight Hours	Total amount a pilot has spent piloting an airplane.
Training Curriculum Type	Refers to either Part 141 or Part 61 flight training program in which the pilot has undergone training.

List of Acronyms

AOPA	Aircraft Owners and Pilots Association
EAA	Experimental Aircraft Association
ERAU	Embry-Riddle Aeronautical University
DV	Dependent Variable
FAA	Federal Aviation Administration
FARs	Federal Aviation Regulations
FSF	Flight Safety Foundation
GA	General Aviation
GAMA	General Aviation Manufacturers Association
GRiPS	General Risk Propensity Scale
IRB	Institutional Review Board
IV	Independent Variable
LOC	Locus of Control
LOC-I	Loss of Control In-Flight
NTSB	National Transportation Safety Board
PBC	Perceived Behavioral Control
SPSS	Statistical Package for Social Sciences
TPB	Theory of Planned Behavior

Chapter II: Review of the Relevant Literature

This chapter begins by providing an overview of the conceptual framework of risk propensity, reviewing the related literature, and comparing it with other risk-related concepts. The subsequent sections present an assessment of past literature on the selected social identity, social cognitive, and experiential factors, their interaction with risk-taking propensity, and previous findings within aviation and non-aviation contexts.

Risk Propensity Overview

Risk is the prospect of a danger arising from the uncertainty of an outcome (Battistelli & Galantino, 2019). For example, a pilot flying through a thunderstorm without accurate meteorological information or training is said to be taking a risk and is more likely to experience a catastrophe, potentially threatening the aircraft and passengers. Risk may be confused with uncertainty; although related, they have different meanings. *Uncertainty* is a situation in which the outcome of an occurrence is uncertain, while risk is the evaluation of the likelihood of a negative outcome. Uncertainty may exist without risk, while risk always entails some degree of uncertainty. Likewise, risk may also be confused with hazard. Hazard is a possible source of danger, including situations or environments that might cause harm. In contrast, risk is the possibility and effect of harm from exposure to a hazard.

Risk propensity, also conceptualized as a person’s tendency towards risk-taking, is described as a person’s present inclination to engage in or avoid risks and is seen as a person’s attribute that may change as a consequence of experience (Sitkin & Pablo, 1992; Sitkin & Weingart, 1995). Important choices are made in circumstances of partial knowledge; thus, it is challenging for pilots to gather the required task-relevant information and analyze all the possible outcomes in order to make prudent judgments, especially in a risky flight situation. In such circumstances, the risk propensity of pilots may play an essential role during decision-making. Research indicates that people differ in their willingness to take risks (Farmer, 1993; Fishburn, 1977); however, there are differing schools of thought about the nature of this trait and its effect on decision-making. Most risk propensity literature is organized around two theories: the *theory of individual differences* and the *prospect theory*.

According to the *prospect theory*, developed by Kahneman and Tversky (1979), individuals are more risk-averse while evaluating prospective gains and more risk-seeking when considering potential losses. A person is more prone to partake in risky behavior to avoid a perceived loss, which suggests that individuals place more emphasis on possible losses than potential rewards of the same size (Sulphey, 2014). The prospect theory also holds that individuals assess outcomes concerning a reference point, which may be a specific situation or past experience (Hanoch et al., 2006; Higbee, 1971; MacCrimmon & Wehrung, 1985; Scholer et al., 2010; Slovic, 1962; Tversky & Kahneman, 1986). Figner and Weber (2011) posited that taking risks is neither a singular occurrence nor one specific character trait. An essential postulate of the *prospect theory* is that a person's risk-taking is inconsistent and situation-specific. A person who accepts the danger in one context may avoid it in another.

Walmsley and Gilbey (2019) studied 132 commercial pilots in New Zealand to explore prospect theory in decision-making. It used an experimental design to explore pilots' risk-taking during uncertain weather and air traffic control (ATC) delay scenarios. Pilots were found to be risk-averse when monetary gains were at stake but preferred riskier routes when facing monetary losses. However, the same pilots were risk-averse in both loss and gain scenarios, with time as a factor. Facing uncertainties, pilots were risk-averse in poor weather situations than in ATC delays, where they felt more in control.

The alternate and traditional school of thought, called the *theory of individual differences* and supported by several psychometric studies (Berube, 1985; Frey et al., 2017; Kogan & Wallach, 1964; Harnett & Cummings, 1980; Highhouse et al., 2017; Sitkin & Pablo, 1992; Weber & Milliman, 1997; Zhang et al., 2018), asserts that risk propensity is a non-situation-specific trait that leads people to consistently exhibit risk-seeking or risk-averse inclinations across a wide range of settings. Thus, the *theory of individual difference* revolves around considering risk propensity as a trait unique to that person and personality (Zuckerman et al., 1978). Weber and Milliman (1997) posited that individuals' basic risk preferences and attitudes tend to stay consistent across settings, highlighting the stability of cross-domain risk preferences. Proponents of the *theory of individual difference* hold that propensity to engage in risks when making decisions during uncertain situations is a person's predisposition or trait that goes beyond situational conditions. For example, Berube (1985) considered risk propensity as an inherent trait that may be stable in all situations. Taylor and Dunnette (1974) believed that risk propensity is a matter of predispositions and a genetic trait. Weber and Milliman (1997) and Blais and Weber (2006) discovered that risk preferences are consistent across situations. According to March and Shapira (1987), more experienced individuals may selectively focus on their past abilities to overcome obstacles, making them more willing to take risks than less experienced individuals. A recent investigation by Crawford et al.

(2021) and the more established study by Knowles et al. (1973) identified risk propensity as a persistent characteristic across fields.

This paper considers the risk-taking propensity construct as an individual's general predisposition and a non-domain-specific trait. However, unlike previous conceptualizations of this construct as a constant and stable trait (Fischhoff et al., 1981; Rowe, 1977), this paper considers risk propensity as an attribute that is persistent (Sutherland, 1989) or enduring (Goldenson, 1984), stable, yet changeable or learnable (Corsini & Osaki, 1994; Sitkin & Weingart, 1995) over time through experience or training intervention.

Risk Propensity and Risk Perception

Although risk perception and risk propensity are words often used interchangeably, they refer to distinct concepts. Sitkin and Pablo (1992) define risk perception as a person's feelings and appraisal of the risk present in a situation. A person's risk perception is impacted by their intuitive judgment and subjective emotions (Slovic, 1987). According to Sitkin and Pablo (1992), the association between risk propensity and the risky behavior of an individual is mediated by risk perception. Risk propensity reflects a general orientation towards risk-taking. In contrast, risk perception focuses on evaluating a particular risk situation. Risk propensity is an individual's willingness to undertake risks; however, risk perception is a person's subjective evaluation of the severity and likelihood of a potentially harmful outcome. Risk propensity is a person's personality characteristic that determines their comfort level with uncertainty and potential loss. In contrast, risk perception is a cognitive process that assesses the potential impact of a decision. This study primarily focuses on risk propensity.

The subsequent section of the study explores the predictors of risk-taking propensity. It examines the association between social identity factors and risk-taking propensity, social cognitive factors and risk-taking propensity, and experiential factors and risk-taking propensity. It demonstrates how previous research serves as a foundation for the current investigation, including the choice of the explored factors.

Social Identity Factors and Risk-Taking Propensity

Individuals' risk-taking tendencies have been associated with social identity factors such as age, gender, education, race/ethnicity, marital status, and other related characteristics. These factors will be explored below.

Age

The propensity of individuals to take risks has been studied in relation to age. Yao et al. (2011) and Gibson et al. (2013) found that older financial investors tend to take fewer financial risks compared to younger ones, while Hallahan et al. (2004) found this association to be nonlinear. However, Larkin et al. (2013) found no link between age and risk-taking behavior among financial investors in Ireland. Regarding driving fully-automated vehicles, Hulse et al. (2018) discovered that younger people are more prone to take chances, consistent with Schoettle and Sivak (2014), who discovered that older people had a lower risk-taking propensity. Shook et al. (2021) showed that older individuals exhibit less risk-taking inclinations and greater dispositional awareness regarding health and safety, such as drug use and not wearing seatbelts, than younger individuals.

The studies above within non-aviation contexts share one thing in common: there is a negative association between age and the risk-taking propensity of individuals. This relationship may be due to a combination of factors. Age and experience may make people more cautious and risk-averse, and these individuals may prioritize stability and security over risk-taking and new experiences (Carstensen et al., 1999; Lang & Carstensen, 2002; Löckenhoff & Carstensen, 2007; Peters et al., 2007). Older individuals may also feel compelled to conform to established roles and behaviors that value caution and stability above risk-taking and exploration (Mamerow et al., 2016). Younger adults exhibit lower dispositional mindfulness than older adults, which is linked to a higher tendency to take risks (Shook et al., 2021).

The consequences of higher risk-taking tendencies are undesirable; however, these consequences in an aviation and flight context that typically affects the lives of more than one individual are especially severe. Yalçın et al. (2016) conducted a study among 308 Turkish helicopter pilots to examine their risk perception and the association between risky flight decision-making and flight experience. The study showed a positive correlation between pilots' age and their inclination towards risk-taking (high maneuver, altitude, and daily life risk) through structural equation modeling. On the contrary, Ison (2015) conducted a comparative analysis between groups of aviators who have been in accidents and those who have not, examining total hours, certification levels, and demographics. Using the accident data (n = 19,821) from the NTSB database, the study found a negative relationship between age and involvement in accidents. Younger pilots were more risk-taking and had more accidents than older pilots.

Sicard et al. (2003) conducted a descriptive study to evaluate the risk-taking propensity among military and commercial pilots. It used a sample of 96 French pilots and measured risk propensity using the Evaluation of Risk (EVAR) scale. Although the results from the *t*-test indicated no difference in risk propensity among the two age groups, the Pearson coefficient showed a significant negative correlation between age and one of the risk-taking propensity dimensions, i.e., energy, which is used to measure a person's level of physical or emotional arousal in response to risky behaviors or situations, indicating their degree of risk propensity.

The results of the Walmsley and Gilbey (2019) study on prospect theory discussed earlier showed no difference in pilots' risk-taking propensity with respect to their demographics (age, certifications, and flight hours). However, the small sample size and experimental design that cannot replicate real-world situations restrict the generalizability of the research's findings outside the New Zealand flying school that served as the sample. Li et al. (2003) used existing accidents from the NTSB between 1987 and 1997 to assess the link between pilot age and flight safety and found no link between age and crash risk, which may reflect the presence of a "healthy worker effect" owing to stricter medical standards and regular physical check-ups that pilots must undergo.

There are two opposing ways aging can affect pilots' safety performance. On the one hand, age-related health issues and cognitive declines may impair piloting skills and increase the probability of accidents, but on the other hand, aging may reduce crash risk due to increased expertise, safer behavior, and job independence (Fjell & Walhovd, 2010; Li et al., 2003; Samanez-Larkin & Knutson, 2015). Due to varying viewpoints and mixed research findings, it was pertinent to include age as a predictor variable to examine whether risk-taking propensity responds differently to age among fixed-wing GA pilots.

Gender

Gender differences can influence the risk-taking propensity of an individual. Yordanova and Alexandrova-Boshnakova (2011) surveyed a group of 382 Bulgarian investors to examine how gender affects the risk-taking propensity of entrepreneurs, reporting that compared to their male counterparts, female investors exhibited a lower inclination towards risk. Research by Hallahan et al. (2004), Larkin et al. (2013), and Novokmet et al. (2021) also concluded that men had higher risk propensity than females. Anbar et al. (2010) conducted research among investment managers and investors and reported that females were more hesitant to take risks than males. However, similar research by Masters (1989) and Nelson (2015) showed no relationship between gender and propensity toward risk-taking.

According to research (Guszkowska & Bodak, 2010), males tend to be more prone to participating in risky behaviors with physical repercussions, while females exhibit less of a tendency towards seeking out thrilling experiences than their male counterparts. Hulse et al. (2018) discovered that male participants were more risk-taking while operating fully autonomous vehicles than female participants, consistent with Schoettle and Sivak's (2014) survey. This could be because autonomous vehicles are associated with traits typically exemplified by men, such as independence, competitiveness, and entrepreneurship, according to Hulse et al. (2018). Duell et al. (2017) studied adolescent risk-taking propensity across different cultures regarding involvement in intoxicated driving, traveling with a drunk driver, engaging in sexual activity without proper protection, and smoking. As part of their extensive study among 5,227 individuals, the results from their data analysis indicated that males have a higher risk-taking propensity than females in health risk behaviors. A similar result was shown by Allen et al. (2013), who indicated that men had a 3.5 times higher risk-taking propensity than females regarding cocaine exposure.

A study by Byrnes et al. (1999), who directed a meta-analysis using 150 research papers to explore the risk propensities between genders, found that males showed more risk-taking propensity than females. However, the effects of gender on risk propensity differed between domains such as physical and intellectual risk-taking and smoking. It also found that the differences between genders are attenuated as people age.

Much of the literature described above conveys that men exhibit more risk-taking behavior than women. Men’s greater risk-taking may be attributed to their tendency towards overconfidence or other biological factors (Barber & Odean, 2001). Apicella et al. (2008) posit that male risk-taking behavior may be influenced by testosterone, with higher levels of salivary testosterone and facial masculinity correlating with increased aggression, sensation-seeking, and risk propensity. The reasons for this difference may be diverse and intricate and require more research.

In aviation, Ison (2015) compared groups of pilots who have been in accidents and those who have not. Using the NTSB accident database, the study found that female pilots were less involved in flight-related risks than male pilots. However, because the number of females in the sample was low, the results lacked statistical power. There is a dearth of published research and a lack of consensus on the role of gender in aviation risk propensity within the GA pilot community, making it a valuable topic to investigate.

Marital Status and Number of Dependents

Several studies have researched how marital status and the number of family dependents affect individuals' risk propensity. Hallahan et al. (2004) conducted empirical research among 20,000 individuals to find the association between their investment portfolio risk-taking attitude and social identity characteristics, including marital status. They found that single investors were more risk-taking than those married. These results were also supported by similar research by Nosita et al. (2020). Irandoust (2017) and Chaulk et al. (2003) posit that having more dependents, including children, reduces individuals' risk tolerance. However, Grable (2000) conducted a similar study about monetary risk-taking among 1,075 participants but discovered that married individuals tend to take more risks than single ones. Similar results were exhibited by Masters (1989), who showed that single investors were less risk-taking than married ones. On the contrary, similar research by Larkin et al. (2013) and Gibson et al. (2013) posited that marital status is not a predictor for risk-taking. These results (Gibson et al., 2013; Grable, 2000; Larkin et al., 2013; Masters, 1989) contradict past research that indicates that single investors were more risk-taking than those who were married.

Perrotte et al. (2021) assessed the influence of sociodemographic variables in health-related risk-taking behaviors, including heavy drinking and traveling without a seatbelt. The study results indicated that married individuals had a lower risk-taking propensity than single participants. Marriage is linked to increased responsibility and a more cautious attitude toward decision-making, which may cause married people to take fewer risks.

In environmental disaster management, Dash (2002) conducted a study to examine the factors determining individuals' decision-making to evacuate during a hurricane. The study showed that family composition and the number of dependents impact an individual's inclination to evacuate during an emergency. In addition, children in the household motivate individuals to evacuate (by 1.8 times), indicating a lower risk-taking propensity. These results were also supported by similar research by Irandoust (2017). Therefore, having children and dependents can influence the decision-making process.

Karachalios (2022) researched risk-taking behavior among airshow pilots in the field of aviation. Using a convergent mixed-method approach and a combination of online surveys, focus groups, and field observations of air show performers, the research found that being married was positively associated with the risk-taking behavior of air show pilots. Married pilots tend to prioritize family issues, which can decrease their mindfulness toward flying and increase their willingness to take risks.

Education

The association between education level and risk propensity is multifaceted. On the one hand, some research (Karachalios, 2022; Novokmet et al., 2021) indicates that people with a greater degree of education typically exhibit a greater inclination towards risk aversion than those with a lower level of education. This may be because individuals with higher levels of education are better equipped to evaluate risks and make informed decisions. Conversely, other studies (Grable, 2000; Rabbani et al., 2021) have shown that those with more education may be more willing to take risks. Those with more education may be more comfortable taking on more risks in their field of expertise.

Grable's (2000) study of 1,075 participants discovered that higher education and investment knowledge were linked with a greater risk-taking propensity in finance. Shusha (2017) discovered similar findings in a study among Egyptian investors, as did Larkin et al. (2013), Rabbani et al. (2021), and Yao and Curl (2011). However, Novokmet et al. (2021) found that higher formal education was related to lower risk-taking propensity, whereas Gibson et al. (2013) found no association between education and risk propensity.

Karachalios (2022) found that higher education among aerobatic pilots was linked with higher mindfulness, robust safety culture, and lower risk-taking propensity among air show pilots. Air show performers with greater education and knowledge have a better comprehension of risk assessment procedures, theoretical safety implications, and accountability to aviation authorities. This viewpoint is contradicted by Chionis and Karanikas (2018), who hold that those professionals in aviation with postgraduate degrees are less risk-averse than their counterparts with a bachelor's degree or less. However, the aviation professionals stated here are not pilots but aviation engineers and technicians. The investigation into the impact of education on the risk-taking tendencies of GA pilots is valuable and deserves exploration.

Race and Ethnic Background

Risk propensity may be influenced by race or ethnic background. In a longitudinal study of adolescents from the Washington, D.C. area, Collado et al. (2017) employed the Balloon Analogue Risk Task-Youth (BART-Y) laboratory evaluation to measure risk-taking propensities in substance abuse, sexual behavior, crime, and health compromises. The study found that African American youths exhibited a lower propensity for risk-taking than their white counterparts. However, Rabbani et al. (2021) conducted research among pre-retiree baby boomers using preexisting online data available from the Bureau of Labor Statistics (BLS) to measure their financial risk-taking attitude and tolerance. The results showed that African Americans were significantly more risk-taking than white participants in financial investment decisions. In studying cultural, cognitive and personality traits, Czerwonka (2017) showed that the risk-taking propensity among Polish students was much higher than their American counterparts.

Perrotte et al. (2021) explored the socio-demographic factors of individuals and their health-related risk-taking behaviors. Their study discovered that ethnicity plays a significant role in risk-taking tendencies. Specifically, Hispanics exhibit lower risk-taking behavior than non-Hispanic whites. According to the findings, Hispanics perceive health risks to be more dangerous compared to non-Hispanic whites. Dash's (2002) study examining the factors determining individuals' decision-making to evacuate during a hurricane event showed that African American and Hispanic ethnicities are less likely to evacuate, showing their greater risk-taking propensity than whites. Mehta et al. (2017) and Ragbir et al. (2018) reported that ethnicity is crucial in determining an individual's propensity to take risks. Mehta et al. (2017) found that American participants were more willing to fly in autonomous aircraft than Indian participants. Ragbir et al. (2018) discovered that American participants expressed negativity towards autonomous commercial flights, except in ideal conditions, while Indian participants were generally positive towards autonomous commercial flights, except in extreme conditions.

Regarding risk-taking in aviation, cultural factors can play a role in a person's risk propensity. People from collectivist societies such as Mexico and China are less likely to take risks than individualistic societies such as the United States and Western Europe. Certain cultures encourage conformity, prudence, and respect for those in authority, which may lead to a more risk-averse approach to flight (Hofstede, 2001). Other cultures may value innovation, initiative, and independence, leading to a more risk-taking aviation attitude.

Experiential Factors and Risk-Taking Propensity

Pilot experience is a significant factor in aviation safety and affects the risk-taking inclinations of pilots. O'Hare (1990) conducted research among a sample of GA pilots to examine their risk-taking propensity, confidence in their skills, and risk judgments. Using a computerized assessment of aeronautical decision-making during a visual flight rules (VFR) scenario in less-than-ideal weather, the study indicated that young pilots (age 30 and below) and more experienced pilots, i.e., with higher total flight hours, had a higher propensity to take risks than those with fewer hours. More experienced pilots scored high on the "personal invulnerability" dimension, which is frequently linked with accidents (O'Hare, 1990). This phenomenon was also supported by the research of Booze (1977), indicating a positive relationship between aircraft accident rates and total flight time. Per Booze (1977), experienced pilots are likelier to take risks or fly in hazardous situations.

Thomson et al. (2004) compared the risk-taking tendencies of novice and experienced helicopter pilots regarding regular flight missions. In a correlation study involving 64 pilots, it was discovered that there were substantial differences in how the two groups perceived relative hazards, with the more experienced pilots' perception of risk correlating more strongly and veraciously with actual risk. According to Thomson et al. (2004), flight hours positively correlate with risk-taking tendencies, leading experienced pilots to make risky decisions. This phenomenon may be due to their overconfidence, which is based on the fact that they perform their job well.

In contrast, Goh and Wiegmann (2002) studied aircraft accident data from the NTSB database to examine GA accidents related to VFR flights into instrument meteorological conditions (IMC) between 1990 and 1997 and compared it to non-weather-related GA accidents. The report indicated that VFR in IMC-related accidents was associated with pilots with fewer total flight hours. This association could imply that these pilots have a greater propensity to take risks, but it could also be attributed to their limited flight experience. The findings concur with Golaszewski (1983) and Li et al. (2003), who also reported a negative association between accident rates and flight time. In addition, Burian et al. (2000) conducted empirical research to explore the factors related to planned continuation errors (PCE) and risk-taking among pilots as reported in the Aviation Safety Reporting Standards (ASRS) database. By sampling 276 ASRS reports involving weather-related incidents, the study indicated that private pilots with relatively low flight hours had more PCEs, followed by flight instructors, commercial pilots, airline pilots, and flight engineers. Per Burian et al. (2000), more PCEs among less experienced pilots happen due to various factors such as inadequate knowledge, poor situational awareness, and the need to trust what their eyes tell them, especially in instrument flight. They tend to have a higher plan continuation bias. The results of the Burian et al. (2000) research parallel the research by Ison (2015) and Li et al. (2003), who showed a negative association between flight time and accident involvement. However, these results contrast the results of O’Hare (1990) and Booze (1977), which showed a positive association between risk-taking and flight hours.

Gilbert (1992) analyzed the association between flight hours and risk-taking propensity among 29 GA pilots in Europe. The results from the Spearman Rank correlation failed to indicate any association between flight hours and the risk-propensity factor. Another set of studies was carried out by Drinkwater and Molesworth (2010) among Australian GA pilots. Pilot participants were presented with a fictitious flight and weather scenario in a simulator and clear instructions. They were allowed to take off (go pilots) or turn around and land (no-go pilots). The results of a series of Mann-Whitney nonparametric tests showed no statistically significant differences in flight experience, age, or willingness to take risks in hazardous conditions between the two groups of pilots. Their research suggested neither pilot experience nor age was a reliable predictor of willingness to take risks.

The results above concerning flight experience hours and risk-taking propensity have yielded mixed results. Fischer et al. (2003) show that experienced commercial pilots have a more profound and complex understanding of flight risks than less experienced private pilots. This phenomenon could impact the pilots' propensity for risk, amplifying it for overconfident pilots who are willing to take risks due to their perceived expertise, or diminishing it for pilots whose experience has fostered their sense of awareness and wise decision-making abilities. When considering experience in terms of a difference in pilot certifications, which may indirectly imply a difference in flight hours, it is helpful to understand how pilots rate risks differently based on their number of FAA certifications and training backgrounds, i.e., Part 61 or Part 141. These areas warrant further investigation to bridge existing gaps in our understanding of the relationship between flight experience, certifications, and risk-taking propensity among pilots.

Hazardous Events

One of the exogenous variables associated with risk propensity posited by Sitkin and Pablo's (1992) and Sitkin and Weingart's (1995) model is outcome history. Outcome history refers to the degree to which a person perceives that their previous choices regarding risk have resulted in favorable or unfavorable outcomes. It represents a person's overall mental image of their performance in comparable past situations. Despite the belief that outcome history influences decision-making, many decision-making theories have neglected the role of outcome history. Nearly all research has concentrated on either individual risk orientation (MacCrimmon & Wehrung, 1985) or risk computation by decision-makers (Tversky & Kahneman, 1986), neglecting the potentially critical influence of previous decisions and their outcomes. This historical stance has been challenged by studies (March & Shapira, 1987; Thaler & Johnson, 1990) that have shown that a predisposition to take risks may be increased by having a history of success in taking chances in the past. While some regard risk propensity as a consistent feature over time, others contend that it varies with learning (Gerrans et al., 2012; Hung et al., 2010). As a person develops through time and accumulates experiences, risk propensity tends to attain persistence (Hung et al., 2010). This effect indicates that there might be substantial variances in risk propensity depending on experience.

Habituated Action Theory and Hazardous Events. Risk-related studies have researched people from a broad range of backgrounds and various social groups, including their risk preferences regarding health behaviors, financial and political decisions, and activities in response to technology and environmental threats (Rhodes, 1997; Singh & Kajol, 2021). Moreover, most of these and other studies indicate that risk assessment models predict a clear correlation between ongoing risky behavior and harm, i.e., individuals who engage in risky actions increase their probability of being harmed. This can be observed in individuals addicted to drugs, for example, who consume them, thereby continuing to put themselves at risk of dying from overconsumption.

In contrast to conventional risk-based research models, the theory of habituated action proposes that participating in high-risk conduct repeatedly without experiencing a negative consequence generally increases the risk-taking propensity and tolerance of that behavior (Inouye, 2014). Therefore, it is likely that actions previously seen as risky will become “normal” over time as a consequence of habit. For example, the theory of habituated action postulates that individuals with drug addiction would no longer perceive death from an overdose as a significant danger but rather embrace it as a daily habit. This is an essential concern because risky actions habituated or acclimatized over time may be regarded as less risky than beneficial if no repercussions have occurred (Rhodes, 1997). In other words, risk-taking may lead to more dangerous behaviors if there are no negative repercussions (Inouye, 2014). This repeated pattern of hazardous behavior followed by no negative repercussions would eventually become habitual, increasing risk-taking propensity with time.

One of the predictive factors of risk propensity considered in this study is a pilot’s involvement in hazardous events, which assesses the extent to which pilots were engaged in risky aviation situations. Collecting information from participants about the number of perilous incidents they have been involved in, such as a precautionary landing (to prevent an actual hazard), assumes a relationship exists between higher hazardous event scores and increased risk propensity. Considering this link in perspective of the habituated action theory, it is possible that if pilots' hazardous behaviors have become habitual, they would no longer see them as dangerous.

Studies on Hazardous Events. The literature linking exposure to hazardous events with risk propensity indicates mixed findings. Iversen (2004) conducted research examining the relationship between the inclination towards risk-taking and risky behavior among vehicle drivers by examining whether those who had been involved in an accident in the past engaged in more dangerous driving behavior. The research found that the risk-taking propensity increased among respondents who had experienced traffic collisions or accidents in the previous year. Compared to those without an accident history, the ones with a recent accident history engaged in unsafe driving practices such as breaking traffic laws, driving too fast or erratically, not wearing a seatbelt, driving under the influence, and not paying attention to one's surroundings while driving, especially around children.

During hurricane events, past experiences can both motivate and constrain individuals when deciding to evacuate (Dash, 2002). Those who have experienced the worst of a storm or calamity may be more inclined to evacuate to avoid going through it again. However, individuals who believe they successfully navigated a past hazard when in reality, the situation was not as dangerous as they thought, may be less likely to evacuate during a real threat.

Pauley et al. (2006, 2008a) conducted research to measure risk-taking and risk tolerance among GA pilots. The findings of the studies revealed that there was a significant positive association between risk tolerance and risk aversion in pilot groups and the number of hazardous events they encountered in the past 24 months, $r(27) = .40$, $p = .04$. The study by Pauley and O'Hare (2006) showed that the greater the number of past hazardous events in which the pilots were engaged, the more risk tolerant they are to take off in bad weather. However, the study by Pauley et al. (2008a) could not determine the direction of the relationship. Furthermore, these studies were conducted with a low sample size of 27, which may question the result's statistical power and effect size. According to Pauley et al. (2008a), pilots who have been in dangerous flight situations and come out of them without severe consequences may become immune to the risks and be willing to take on more risky situations in the future.

Another study by Pauley et al. (2008b) investigated the role of implicit processes in risk-taking and perception among aviators in New Zealand. According to the study's results, as pilots encounter an increased number of hazardous events, they tend to feel less anxious when dealing with adverse weather and become more inclined to take risks.

O'Hare and Chalmers (1999) surveyed 8,500 GA pilots in New Zealand to learn about their flying habits and potential risk factors associated with accidents. The study found that 27.2% of pilots admitted to encountering hazardous flight events (e.g., low fuel, stalls, entering IMC conditions on VFR flight, forced landing, etc.) at least once, and about four percent had done so at least four times. This suggests that pilots may have a greater likelihood of repeatedly making poor decisions related to risk-taking when they are exposed to hazardous situations and emerge unscathed, but further study is necessary to verify this phenomenon.

Joseph et al. (2013) conducted research among 275 army helicopter pilots to investigate the relationship between pilots' risk-taking tendencies, safety attitudes, and engagement in hazardous aviation events. Their study indicated a positive correlation between risk-taking tendency and pilots' past involvement in hazardous events; those with previous experience in hazardous events had a greater risk-taking propensity. The aforementioned studies contradict Hunter's (2002, 2005) research, which used the Hazardous Events Scale (Hunter, 1995), as they found no link between pilots' engagement in aviation incidents and their risk-taking propensity.

Social Cognitive Domain Factors and Risk-Taking Propensity

An individual's tendency to engage in risky behavior has been linked with several social cognitive domain factors, including their locus of control, psychological stress, and self-efficacy. These social cognitive domain factors can be crucial in shaping a person's risk-taking behavior.

Locus of Control

Locus of control (LOC), a psychological construct grounded on the social learning theory (Rotter, 1954), is based on the belief that a person's actions have the power to decide their future outcomes. Rotter (1954) proposed that an individual's locus of control can be classified as either internal, characterized by a belief that one has control over their life, or external, characterized by a belief that life is governed by fate or chance and beyond one's personal influence. People who possess an external locus of control do not expect to be rewarded for their actions or make an attempt to obtain rewards in future situations, whereas those with an internal locus of control often strive to acquire rewards and are able to succeed.

The locus of control construct has been demonstrated beneficial in predicting a wide range of behaviors and is an essential predictor of the risk-taking propensity among individuals. A study by Rabbani et al. (2021) in finance showed that locus of control has a significant negative association with investors' tendency to take risks. Those with external LOC had a lower risk tolerance than those with internal LOC. A similar study conducted by Ahmed (1984) in entrepreneurship confirms the same findings.

Salminen and Klen (1994) discovered an association between LOC and risk-taking behavior among Finnish employees in the construction and forestry industries, with individuals demonstrating greater external LOC engaging in riskier behaviors. Higbee (1972) found that participants with high perceived internal LOC made more dangerous military decisions than those with high external LOC during a tactical and negotiations game. In contrast, Cassell (1992) found no association between LOC and risk-taking propensity in higher education achievement.

When comparing the personnel in the domains mentioned above (i.e., finance, forestry and construction workers, military), GA pilots are more likely to experience emergency scenarios that require them to choose between many alternative options with limited time and potentially life-threatening consequences (Stewart, 2008). As a result, certain studies have concentrated on examining the impact of LOC on both accident occurrence and hazardous operational conduct. According to prior research (Hunter, 2002; Joseph & Ganesh, 2006; Vallee, 2006), pilots display greater internal LOC than external LOC, and there is a correlation (r = -.20) between the number of hazardous, non-fatal occurrences encountered and pilots' internal LOC score (Hunter, 2002). Compared to pilots with higher perceived internal LOC scores, those with lower scores encountered more hazardous aviation events. Furthermore, Wichman and Ball (1983) discovered that those with internal LOC were likelier to have self-serving biases than those with external LOC. Pilots with a greater internal LOC, for instance, consider themselves much more skillful and less prone to cause an accident compared to those with a higher external LOC.

Recent studies have analyzed how LOC correlates with aviation mishaps, situational awareness, and task load among ground vehicle operators. They discovered that LOC forecasted a variety of attitudes and actions that are congruent with aviation safety, such as willingness to take risks, risk management, multitasking, distraction management, and time management (Arthur et al., 1991; Ozkan & Lajunen, 2005; Stanton & Young, 2005).

Wichman and Ball (1983) administered Rotter's (1966) LOC scale to 200 GA pilots and found that more pilots had internal LOC orientation than the study conducted by Rotter himself in 1966. They also found that those with high internal LOC and of higher age attended more safety clinics than those with external LOC, indicating a higher orientation toward safety. These pilots proactively dealt with mitigating hazards instead of making light of them.

You et al. (2013) conducted a study among 193 Chinese airline pilots to verify the link between flight time, locus of control, safety operation behavior, and risk-taking as a mediator. Using structural equation modeling, they found that internal LOC was directly linked to safety operation behavior, with risk-taking as a mediating variable and flight time as a moderating variable. In other words, those with high internal LOC are more likely to prioritize safety, suggesting that they have a lower risk-taking propensity and are prepared to take charge in risky scenarios.

Individuals with a higher internal LOC can better appraise complex situations appropriately (Crisp & Barber, 1995). One's LOC may influence the assessment of scenarios; however, it does not necessarily impact their tendency to take risks. A more reasonable assumption would be that those with internal LOC, who are more aware of the risk, would choose less risky options than those with external LOC.

Research on LOC within aviation is limited, and little is known about the link between LOC and risk-taking propensity, especially among GA pilots. Although these studies within aviation suggest that pilots with internal LOC are risk-averse, additional study is required to support this proposition. Findings from the studies mentioned above also indicate that, in specific domains, individuals with internal LOC are more risk-taking. Enhancing the knowledge base by incorporating LOC as an explanatory variable in this research might give further insight into how it affects risky behavior among GA pilots.

Locus of Control Scale (Rotter, 1966). In this research, LOC is assessed as a respondent's perception of their ability to influence outcomes of life. The variable of LOC is derived by adding the scores of 29 loci of control questions (Rotter, 1966). Higher scores relate to an orientation toward the external LOC. Those with an external LOC inclination think that life outcomes are determined mainly by chance, luck, and the influence of others. In contrast, those who trust internal factors like their own actions have an internal LOC orientation (Rotter, 1966). Other aviation research has utilized this scale (Lester & Bombaci, 1984; Shirshekar, 2021; Smith, 1994; Wichman & Ball, 1983).

Psychological Distress

Multiple qualitative and quantitative studies have indicated that psychological distress has a substantial role in the risk judgment of individuals (Kotvis, 2012; Scott-Parker et al., 2011; Wang et al., 2021). According to Kahneman (1973) and Li and

Ahlstrom (2020), people are more susceptible to compromising their rationality and downplaying risks during distress and are more receptive to risky behaviors. Research by Ness and Klaas (1994) shows that individuals with heightened affective states, such as stress, anxiety, and fear, are likely to deviate from rational decision-making and demonstrate a greater predisposition to take risks.

Other studies (Lerner & Keltner, 2000; Steiner & Driscoll, 2005) have also discovered that distress and anger increase risk propensity and, as a result, mitigate the dread of the outcomes of hazardous actions. Furthermore, studies (Isen & Geva, 1987; Mano, 1992) have shown that the anticipation of contentment after a stressful choice might polarize judgment and increase the favorable appraisal of the decision outcome. This is an essential factor to be considered in this study, because when pilots, especially inexperienced ones, are faced with a stressful situation, such as bad weather, they may face an aroused affective state and may end up displaying a high risk propensity to initiate a poor decision.

High stress levels are associated with an increased tendency towards risky driving manners (Scott-Parker et al., 2011). Financial investors are inclined to take more risks during stressful conditions, especially in the gain territory, compared to the loss territory (Kotvis, 2012), which is congruent with the expected utility theory. However, stress can also attenuate risk-taking, especially in individuals with low risk-seeking inclination (Wang et al., 2021).

The research mentioned above exhibits mixed results in non-aviation contexts. However, there needs to be more literature on the correlation between risk propensity and psychological distress within the aviation field. Given the aviation industry's unique stressors and high-risk environment, it is significant to understand how psychological distress may impact GA pilots' risk-taking. Thus, this study seeks to bridge the gap in the literature by including psychological distress as a predictor variable.

Self-Efficacy

This subsection of the paper introduces the concept of self-efficacy, discusses its theoretical underpinnings, reviews previous research on its relationship to risk propensity, investigates how self-efficacy can affect pilot performance, and lastly, reviews its relationship to other social cognitive domain factors, including psychological stress, experience, and flight experience, in the framework of the current research.

Theory of Self-Efficacy. Psychologist Albert Bandura (1977, 1986, 1997) used "self-efficacy" to describe a person's belief and mindset about their competence to carry out the actions required to achieve specified objectives. It is one's self-confidence or trust regarding their capacity to do a specific task. Although other authors have defined this concept, Bandura (1977) distinguishes between efficacy and outcome expectations. An efficacy expectation is characterized as an individual's belief or confidence that they can effectively perform the action necessary to create the desired results. In contrast, outcome expectancy is an individual's expectation that a specific action will result in a particular result. These are essential differentiations because individuals may grow to feel that a given course of action would yield certain consequences (outcome expectancy) but may doubt their ability to undertake such activities (efficacy expectation). The outcome expectancy will not evoke actions if the individual has poor self-efficacy regarding their capacity to conduct the necessary action (Bandura, 1977).

Suppose a pilot has a high efficacy expectation about conducting a specific flight task, such as an instrument approach. In that case, he or she believes it can be accomplished, but the outcome expectancy to perform the flight task may be low due to its complexity. However, if the pilot has been repeatedly trained for that particular task, he or she may develop a high outcome expectancy. The same pilot may be worried about performing that task on a multi-engine aircraft instead. In this situation, the pilot may have high outcome expectancy but low efficacy expectations. Based on their real-life experiences, individuals form a generalized expectancy regarding their outcome expectancies, according to Bandura (1982). To deal with specific situations, people create certain beliefs about their capabilities.

Bandura's (1977) conceptualization of self-efficacy considers an individual's views about their capabilities and beliefs about the environment around them. Thus, this self-efficacy theory may have been the favored reference for self-efficacy research because it offers the link between the person and society that social scientists seek. However, it is necessary to note that a person's degree of self-efficacy has little to do with his or her actual competence level but rather with how that individual assesses his or her skills to do various behaviors (Bandura, 1982; Schunk & Pajares, 2004). Self-efficacy pervades all human endeavors and affects the capability to handle issues effectively and the choices most likely to be made. People's actions, feelings, and motives are more heavily influenced by their self-efficacy beliefs than by their actual level of skill. Highly self-efficacious people are more inclined to participate in specific actions when they feel they can succeed, while low self-efficacious people are more likely to avoid them (Bandura, 1977, 1986). Regarding the present study, pilots who strongly believe in their piloting skills might perceive a hazardous aviation situation as low-risk. Conversely, pilots who lack confidence in their abilities could perceive the same circumstance as high-risk. Pilots might be in danger if their self-efficacy about their performance is overestimated, leading to overconfidence (Linnenbrink & Pintrich, 2003).

Theory of Planned Behavior (TPB). One of the most significant and extensively employed concepts for investigating human behaviors is the theory of planned behavior (Ajzen, 1991; Cook et al., 2005). The theory has three core components as factors that shape a person's intention or attitude leading to an actual behavior: subjective norms (those rules of behavior one believes that others expect), attitudes (the degree to which someone sees something favorably or negatively) and perceived behavioral control (the degree of control individuals perceive they have over a situation, which is based on prior experience, predicted obstacles, and hurdles). Per Ajzen and Driver (1992), when the three components of the TPB are evaluated together, the more positive an individual's subjective norm and attitude toward a behavior is, and the greater their perceived behavioral control, the more their behavioral intention to conduct a particular behavior.

The TPB framework presents a theoretical model for describing the factors that affect a person's intention to engage in a behavior, although it is unclear if the intention will lead to a behavior. Ajzen and Driver (1992) believe that an individual's intentions shape the factors that motivate their actions. The level of effort an individual is willing to exert and their desire to achieve success can be inferred from their intentions. TPB claims that subjective norms, attitudes toward a behavior, and perceived behavioral control accurately predict intentions. According to Ajzen (1991), intentions are the immediate precursor to behavior, and perceived behavioral control is a crucial factor to consider when predicting individual behavior.

Pilots' unsafe behavior stems from their deliberate intentions, and unsafe behavioral intention refers to someone who still wants to perform the behavior despite knowing that it violates his or her safety minimums and relevant safety regulations. The TPB model is used to systematically analyze the influencing risk-taking intentions that may cause pilots to get involved in unsafe behaviors.

It is also worth stating that not all of the three predictor variables of the TPB model are required in every situation. Attitudes alone can play a significant role in shaping intentions in some scenarios, while in others, both attitudes and behavioral control can influence intentions. To anticipate a person's behavior, it may be enough to just look at their intentions, while in other cases it may be necessary to look at their intentions as well as perceptions of behavioral control. Furthermore, perceived behavioral control can also have a direct influence on behavior. According to Ajzen (1991), perceived behavioral control is employed to address situations in which individuals do not have full volitional control over the behavior under examination due to external influences. Of the three components of TPB model, only perceived behavioral control is able to directly lead a person toward a behavior without intention. Amongst the three elements, perceived behavioral control, therefore, received the focus in this study to examine how it associates with the risk propensity of pilots.

Perceived Behavioral Control. Perceived behavioral control relates to individuals' perceptions about their ability to execute a particular behavior, their resources, and their belief that they can overcome obstacles (Ajzen, 1991). Certain pilots, for example, may feel that they have the self-confidence in their capacity to cope with a potentially risky situation if they believe that the possible predicament of that situation is manageable, believe that they have the necessary training and abilities to deal with it, and are confident in their capacity to tackle it. According to the theory of planned behavior, such pilots are likely to exhibit greater perceived behavioral control of the risky situation. They will perceive what they face as a low-risk situation. On the other hand, if such pilots suppose they do not have the required abilities or training to manage the situation and perceive they would face problems tackling the event, they will assess their performance as inadequate and their behavioral control as poor. Such pilots will certainly have a lower propensity to take risks.

Perceived behavioral control is as critical as any other factor in determining an individual's self-efficacy (Ajzen, 1991; Ajzen, 2002). Self-efficacy has to do with individuals' beliefs regarding their own abilities to perform a certain behavior to achieve a goal or complete a task (Bandura, 1991). Although perceived behavioral control focuses on a person's intention rather than the ability to conduct a particular behavior, both theories focus on a person's perceived ability to carry out a behavior. When seen through the lens of the present study, perceived behavioral control and its related variables, in conjunction with the self-efficacy of pilots, may aid in understanding some of the factors influencing GA pilots' propensity to take risks. For this reason, in the present study, pilots' self-efficacy was examined as a potential component that may be related to pilots' risk-taking propensity.

Self-Efficacy and Pilot Performance. A high degree of self-efficacy has been related to a broad range of beneficial outcomes, including the ability to press on during uncertainties and achieve high levels of success and performance (Honicke et al., 2020). Usher et al. (2019) discovered that students with higher academic self-efficacy outperformed those with lower academic self-efficacy. It impacts how much effort is exerted and how long an individual maintains it to achieve desired results (Ilgen, 1994). Self-efficacy is linked to various work outcomes, including training proficiency and job performance (Martocchio & Judge, 1997). Plenty of research, including systematic reviews conducted by Bandura and Locke (2003), points to a link between performance success and self-efficacy. Per Lightsey (1999), self-efficacy beliefs influence how individuals expend their efforts, how persistent they are in achieving objectives, their endurance during setbacks and challenges, their level of stress and affect, and their behavior choices at work and in social interactions.

However, high self-efficacy might harm one's performance (Bandura & Jourden, 1991; Vancouver et al., 2002). Bandura and Jourden (1991) posit that high self-efficacy may create complacency, diminishing the efforts required for higher performance. This postulation implies that highly self-efficacious GA pilots have an elevated risk-taking propensity as they may perceive a high-risk situation as low-risk. In other words, GA pilots with high self-efficacy may misread danger in a potentially risky circumstance by underrating risk and overrating their capacity to cope with it.

Goh and Wiegmann (2001) researched factors influencing pilots' choices to take weather-related risks. There was no difference in experience or training between pilots who flew into deteriorating weather and those who diverted. Pilots who continued into bad weather displayed greater self-efficacy in their skills and higher willingness to take risks, and they underestimated the hazards of weather and pilot error. Additionally, empirical research conducted by O'Hare and Smitheram (1995) regarding aeronautical decision-making showed that pilots who rated their skills more highly and were overconfident in their flying skills tend to make riskier weather decisions. This phenomenon also indicates that such pilots lack awareness of the hazards associated with their activities.

Self-Efficacy Interactions with Past Experience and Stress. One of the primary information sources for developing self-efficacy is an individual's past experience with successes and failures (Artino, 2012; Schunk & Pajares, 2004; Williams & Williams, 2010). For instance, aviators who have once survived an unplanned aviation situation, such as bad weather, might consider similar flights or adverse weather scenarios low-risk and may likely continue rather than turn around or divert to another airport if they experience a similar trip in the future. Their self-efficacy increases due to their past experiences (Bandura, 1997). Moreover, as a cognitive element, self-efficacy may influence the association between pilots' flight experience and risk-taking propensity, which will be investigated in this study.

Another source that influences one's self-efficacy is their current emotional and physiological state (Artino, 2012). This includes their general mood, anxiety, or psychological stress level (Bandura, 1997; Ormrod, 2012). Individuals perceive stress symptoms (e.g., elevated heart rate, hyperventilation, sweating, and feelings of worry and panic) as signals of vulnerability during challenging activities (Bandura, 1997). To illustrate this point, consider a GA pilot who is apprehensive or tense on a cross-country flight and interprets this as a lack of ability (or efficacy) to perform the required operations, even though the reason for this stress is unrelated to the flight (Artino, 2012;

Bandura, 1997; Ciani et al., 2009). Low self-efficacy may lead to poor pilot performance due to psychological stress. Therefore, in the current research framework, psychological stress may influence the risk propensity of pilots.

Choice of Self-Efficacy Scale. When the self-efficacy concept was first introduced, Bandura (1977) presented it in a situation-specific manner, which suggests that different measurements of self-efficacy are necessary for different contexts. For instance, a flight instructor's self-efficacy in instructing student pilots may differ from his or her self-efficacy regarding effectively handling an aircraft in an emergency. To broaden the scope of self-efficacy, this study focuses on a generalized form of self-efficacy, which Tipton and Worthington (1984) described as people's perceptions of their ability to perform diverse activities in various circumstances. The present study assesses self-efficacy from a broad rather than a situation-specific viewpoint.

Summary

The body of research referenced in this section demonstrates the extent to which risk-taking propensity and its associated predictive factors have been examined in aviation and other professional domains. This chapter began with an overview of the risk propensity conceptual framework, an examination of related literature, and a comparison with concepts related to risk, followed by a literature review on social identity, social cognitive, and experiential components, an examination of the influence of these characteristics on risk-taking propensity, and prior results in aviation and non-aviation settings. The relationship between risk-taking among pilots and social identity factors, including age, gender, marital status, race/ethnicity, and education, has produced varied results in previous research. Some studies have suggested that flight experience hours and exposure to hazardous events can influence pilots' propensity for risk-taking. There was a dearth of literature on the association between training curriculum, the number of FAA certificates, psychological distress, and pilots' risk-taking. Social cognitive factors such as locus of control and self-efficacy are also explored, indicating their potential impact on risk-taking behavior.

Chapter III: Methodology

This chapter discusses the study methodology and design that was utilized. The sections included here describe the selected research method employed, the target population and sample, power analysis, data collection process, measurement instrumentation, statistical data analysis, and reliability and validity assessment.

Research Method Selection

The primary research methodology employed in this quantitative study was a survey. Data was collected using paper-based surveys to study the influence of social identity, social cognitive, and experiential predictor variables on the risk-taking propensity scores among fixed-wing GA pilots in the U.S. This quantitative method was suitable for this study as it allowed the researcher to objectively measure the risk propensity of GA pilots and identify the factors that influence their behavior. In addition, including numerical data enabled the data to be analyzed using statistical techniques such as multiple regression to generate a regression equation that may predict risk propensity, which may help create strategies to reduce risks related to GA operations.

Population and Sample

Population

With the objective of developing a prediction model to investigate the factors that predict the risk-taking propensity of GA pilots, the primary target population for this study was FAA-certified fixed-wing GA pilots in the U.S. These pilots operate under FAA's 14 CFR (Code of Federal Regulations) Part 91, and include airplane private pilots, commercial pilots, and certified flight instructors, regardless of their ratings and endorsements.

Sampling Frame and Strategy

The sampling frame for the study was the GA pilot population at multiple Experimental Aircraft Association (EAA) local chapters in Central Florida and the ERAU campus at Daytona Beach, who were willing and able to participate in this study. The sampling strategy employed was nonprobability convenience sampling using surveys. This strategy enabled the researcher to obtain data quickly and easily from readily available participants at the above locations. Including samples from multiple locations outside the ERAU campus improved the study's reliability and better represented pilot demographics, including gender, age, and pilot experience.

A Priori Power Analysis

Before conducting the study, an a priori power analysis was carried out using the G*Power 3.1.9.7 software to determine the sample size required for detecting an effect, if present, and to ensure data validity (Liu, 2014). According to G*Power analysis, with 12 predictors, an effect size of .2, an alpha level of .05, and a beta power of .8, the required sample size was estimated to be 98 participants (at minimum) for each stage to detect a statistically significant effect with a power of 0.8. Moreover, the generally recommended ratio of observations to independent variables is 5 to 1 for multiple regression (Hair et al., 2018). A total of 200 participants (100 per stage) were gathered for the construction of the regression equation and model validation.

Data Collection Process

The primary source of data was a set of surveys administered to GA pilots who were willing and able to participate in this study. The following sections outline the procedures employed to prepare the data for analysis and will begin by discussing the research design and procedures, the sampling materials used to gather data, and the sources of data, which details the various methods employed to gather the necessary information for this research.

Research Design and Procedures

This research study utilized a quantitative, non-experimental exploratory correlational design, employing descriptive and inferential statistics to test each null hypothesis statement. An exploratory correlational research design helped the researcher to examine the strength and direction of the relationship between multiple factors associated with GA pilots (such as experience, age, gender, training, etc.) and their propensity to take risks, which supported the objective of this study. The chosen design was also the most suitable option for predicting and achieving an optimal model fit.

The majority of the participants for this study were primarily recruited by verbally announcing and inviting them to participate in the survey during the monthly member meetings at local EAA chapters in Central Florida, where pilots who met the eligibility criteria are likely to frequent. Care was taken not to provide excessive details that could bias participant responses. The researcher also reached out to participants from the ERAU campus at Daytona Beach, specifically at locations such as the Aviation Learning Center within the College of Aviation, a place frequently visited by GA pilots, to recruit them for the study. Participants were provided with a printed copy of the survey, which included a brief outline of the study approved by the Institutional Review Board (IRB) and a consent form they had to sign before beginning the survey.

Furthermore, to ensure confidentiality, it was ensured that no one except the researcher would have access to participants' information, which was expected to boost response rates. The survey required approximately 20 minutes to complete. After receiving the completed paper surveys, the researcher quickly scanned through all the pages to verify that no questions had been accidentally skipped.

Apparatus and Materials

To collect data, four self-report scales and one inventory were utilized: the General Risk Propensity Scale (GRiPS) developed by Zhang et al. (2018), the New General Self-Efficacy Scale (GSE) by Chen et al. (2001), Rotter's (1966) Internal-External Locus of Control Scale (I-E LCS), the General Health Questionnaire (GHQ-12) by Goldberg and Williams (1988), and one social identity inventory. Participants were compensated $15 upon completion of the survey. Microsoft Excel was used to sort and organize the raw data, and IBM SPSS software version 28 was utilized for data analysis.

Sources of the Data

The primary data source for this research was surveys collected in person from GA pilots in Central Florida who were willing to contribute to the research. The surveys included standardized scales and inventories described earlier. Surveys were considered a suitable primary data source for this study due to their ability to gather data from large sample sizes and their ease of administration on paper. Surveys are also recognized for their high external validity. A sample of the survey utilized is presented in Appendix B.

Ethical Considerations and IRB Application

All the materials that were used for the survey, including the survey itself, the instruments, and the informed consent form, were reviewed by ERAU's IRB to verify compliance with human research ethical standards. Participation in this study was voluntary. To participate, respondents had to be at least a private pilot and 18 years of age. Participants had to approve the informed consent form to continue with the study.

The risk associated with participating in the present study was no more than would be encountered in daily life. All data was kept confidential, including any personally identifiable information. The responses from paper surveys were manually entered into a digital format. The hard copies were collected and stored inside the College of Aviation School of Graduate Studies office locker to ensure confidentiality and prevent unauthorized access. This digitized data was saved in a secure database. Data was processed and analyzed using SPSS software to identify response trends and patterns. The survey responses were utilized only to generate and validate the predicted model. Appendix A contains a copy of the IRB approval.

Measurement Instrument

This section discusses the constructs, variables, and scales used in the study. The scales used are standardized and validated and have been previously used in similar studies, which will be further elaborated below.

Constructs

The constructs used in this research are risk-taking propensity, self-efficacy, psychological distress, and locus of control. Risk propensity is a psychological construct of risk-taking behavior and can be inferred from an individual's inclination to engage in risky behaviors that can change with time because of experience (Sitkin & Pablo, 1992). It is considered a non-domain-specific trait that is persistent (Sutherland, 1989) or enduring (Goldenson, 1984), stable, yet changeable or learnable (Corsini & Osaki, 1994; Sitkin & Weingart, 1995) over time through experience or training intervention. Self-efficacy is another well-recognized construct in psychology that cannot be directly observable. It is an individual's belief in their ability to carry out a particular activity or achieve a particular objective (Bandura, 1977). As a construct, self-efficacy can be used to describe and predict behaviors and outcomes in various domains, including aviation. Another construct used in this study is locus of control, which is a dimension of personality that refers to an individual's belief about the degree to which they have control over their lives and the events that affect them, and can be assessed using standardized scales such as Rotter's (1966) locus of control scale. Lastly, psychological distress is a construct that describes a range of negative sensations and symptoms that affect an individual's psychological health and well-being, and it can be assessed using standardized scales such as the GHQ-12 (Goldberg & Williams, 1988). The following section will present a synopsis of the dependent and explanatory variables used and how they are measured.

Variables and Scales

Dependent Variable. The dependent variable in this study is the risk-taking propensity score of pilots. In this research paper, *risk propensity* is operationally defined as a person's present tendency to either embrace or avoid risks and is seen as a personality trait that can potentially evolve over time due to experience (Sitkin & Pablo, 1992; Sitkin & Weingart, 1995). Risk propensity was quantified using the General Risk Propensity Scale, or GRiPS, developed by Zhang et al. (2018). The GRiPS scale contains eight questions. The participants scored each question on a scale of one to five, where one indicates *strongly disagree*, two indicates *disagree*, three indicates *neutral*, four indicates *agree*, and five indicates *strongly agree*. This scale was treated as a continuous variable by averaging the eight Likert-type questions into a single score for each pilot, as is a standard statistical procedure (Brown, 2011). The GRiPS scale is unidimensional, meaning that all the questions are related to the same underlying factor or construct of risk propensity (Zhang et al., 2018). It is possible to add up all the individual items of the scale and divide by the number of items to obtain a single score of an individual's inclination toward taking risks.

Explanatory Variables. The explanatory variables are classified into social identity, social cognitive, and experiential factors. The social identity data that were gathered from the participants included age, gender, education level, ethnicity, and marital status. Gender, ethnicity, and marital status are categorical variables measured on a nominal scale. Age is a continuous variable that is measured using a ratio scale, and level of education is measured on an ordinal level.

The social cognitive factors include self-efficacy, locus of control, and psychological stress, all continuous variables measured using an interval scale. The broad construct of *general self-efficacy* (GSE) is not directly observable. However, it can be conceptually defined as a person's confidence in their ability to plan and perform the courses of action necessary to handle potential situations (Bandura, 1977). The GSE questionnaire contains eight statements that measure a person's self-efficacy level based on a five-point Likert scale with responses including *strongly disagree*, *disagree*, *neutral*, *agree*, and *strongly agree*. This scale has been validated in previous studies (Chen et al., 2001; Felix, 2018; Juárez & Contreras, 2008; Sampson et al., 2021) and demonstrates good psychometric and unidimensional properties for use in this study.

Locus of control is operationally defined as the extent to which individuals suppose they have some influence over the results of the circumstances they encounter (Rotter, 1954; Rotter, 1966). Rotter's unidimensional continuum scale ranges from a strong internal locus of control belief on one end to a strong external locus of control belief on the other end. Internal LOC persons believe they can influence the result of a situation, whereas external LOC persons ascribe outcomes to chance, luck, or other people. The locus of control scale has 29 items (with six filler questions intended to make the test more ambiguous), where respondents select the statements they most agree with from two options (A or B) for each question. One point is given for each response that reflects an external locus of control, as predetermined by the scale's answer key. Therefore, a low score (0-11) indicates an internal locus of control, and a high score (12-23) denotes an external locus of control.

Psychological distress is defined as an individual's overall psychological well-being, including psychosomatic indications, severe depression, worry and sleeplessness, and social dysfunction (Forgaty, 2005). The Goldberg and Williams (1988) 12-item general health questionnaire (GHQ-12) is a self-reported psychological health questionnaire used to assess stress with responses scored on a Likert scale from zero to three. The scale has acceptable psychometric properties to function as a unidimensional scale (Corti, 1994; Goldberg et al., 1997; Liang et al, 2016; Rey, 2014; Ye, 2009). The first half of the questionnaire, containing items representing poor psychological health, is scored such that zero indicates *not at all*, one indicates *no more than usual*, two indicates *rather more than usual*, and three indicates *much more than usual*. The second half of the questionnaire, containing items representing good psychological health, is scored such that zero indicates *better/more so than usual*, one indicates *same as usual*, two indicates *less than usual*, and three indicates *much less than usual*. Thus, a low score signifies a low amount of stress, whereas a high score signifies a high amount of stress.

The experiential factors include: number of total flight hours, training curriculum, number of FAA certificates held, and number of hazardous events experienced in the past five years. A *hazardous event* is operationally defined as a pilot action that may cause or contribute to an unforeseen or undesirable occurrence, such as an accident. All of these variables are continuous except for the type of training curriculum, which is a categorical variable measured using a nominal scale. All categorical variables were dummy coded appropriately for use in the statistical analysis.

Data Analysis Approach

This research seeks to enhance the comprehension of the factors that impact risk-taking propensity within the GA pilot community. Preliminary data analysis ensured that all entries were accurately transferred into MS Excel. The data was then sorted, arranged, and examined for missing information or unengaged responses. This was followed by the recoding of categorical variables to ensure they were standardized, grouped, or aggregated, enabling meaningful interpretation and comparison across different levels or categories within the dataset. The following sections will discuss the data analysis methodology employed in this study, which will encompass information about participant demographics, reliability and validity assessment, examination of regression assumptions, and the data analysis process.

Participant Demographics

The participants in this research were pilots with a minimum of a private pilot certificate and who were at least 18 years of age. A priori power analysis determined a minimum sample size of 98 per stage, but a sample size of 100 per stage was utilized. Appropriate descriptive statistics were computed for participants' age, gender, marital status, education level, ethnicity, flight hours, number of flight ratings, training curriculum, number of hazardous events, self-efficacy scores, locus of control scores, psychological distress scores, and the dependent variable, risk-taking propensity scores, and is outlined in Table 1. Various regression assumptions, including normality, linearity, and homoscedasticity, were also tested, and will be discussed in the subsequent section.

Reliability and Validity Assessment Methods

According to Field (2018) and Hair et al. (2010), reliability refers to the extent to which an instrument generates consistent measurements. This study employed pre-existing instruments, which have been examined for reliability. Cronbach's alpha, a measure that assesses how well items in a scale are interrelated in assessing the same concept, was used to measure the internal consistency of this research's instruments (Cronbach, 1951). It is desirable for Cronbach's alpha to be within the acceptable range from .7 to an upper limit of .95 (Powell & Dompier, 2014; Tavakol & Dennick, 2011). Before including the instruments in this research, their internal consistency values were verified by referring to results from previous studies.

The General Risk Propensity Scale (GRiPS) was earlier reported to have an overall reliability coefficient of $\alpha = .92$ (Zhang et al., 2018). The scale used to measure self-efficacy by Chen et al. (2001) had a reliability coefficient of .85 and repeatedly showed superior predictive and content validity compared to similar instruments. The Rotter (1966) Internal-External Locus of Control scale reported a reliability coefficient of .79, as reported by Rinn et al. (2014), .91 by Afolabi and Dennis (2019), .77 by Tong and Wang (2006), and .71 by Akça and Yaman (2010), with a .83 test-retest reliability. The

Goldberg and Williams (1988) general health questionnaire to evaluate participants' psychological health had a reliability coefficient of .94 (Lesage et al., 2011).

Validity is about whether or not an instrument effectively measures what it is intended to measure and the degree to which conclusions can be drawn from the results obtained (Hair et al., 2010; Vogt, 2005). Reliability and validity are interdependent; even if a model is reliable, it is of limited value in predicting results if it does not accurately predict them. The survey instruments employed in this study not only demonstrated sufficient validity and psychometric properties through their use in previous research but were also assessed for face and content validity based on initial reviews by subject matter experts, including pilots and Ph.D. holders in human factors and research methods, to ensure they measured what they purported to measure. The feedback obtained from these experts confirmed that the survey instruments demonstrated sufficient validity to proceed with the primary data collection.

Regression Assumptions

After confirming that the selected statistical method was the most appropriate for the study, and after the categorical variables were dummy coded, the study design also had to uphold the assumptions for multiple linear regression to produce valid results.

1. Assumption #1: The dependent variable of interest uses a continuous scale.
2. Assumption #2: The total number of explanatory variables is at least two.
3. Assumption #3: Each observation in the study is independent of the others.
4. Assumption #4: Each of the explanatory variables has a linear relationship with the dependent variable.
5. Assumption #5: The data points are homoscedastic.

6. Assumption #6: No multicollinearity - there are no significantly associated pairs of explanatory variables in the data.
7. Assumption #7: The dataset does not contain any spurious outliers.
8. Assumption #8: The data's residuals or errors exhibit a normal distribution.

The first assumption states that the dependent variable assumes continuous values. In this study, risk-taking propensity is the dependent variable, and it was measured using the General Risk Propensity (GRiPS) Likert scale by Zhang et al. (2018). Despite the common understanding of Likert scales as ordinal scales, this study used them as interval scales since each was coded to provide a single number (Joshi et al., 2015). The second assumption states that the study must incorporate more than two explanatory variables. This research examines 12 explanatory variables, including age, gender, marital status, level of education, ethnicity, locus of control, psychological distress, self-efficacy, number of hazardous events encountered, number of flight certifications, training curriculum, and total flight hours.

The third assumption states that the study's observations must be independent. Because the observation of one explanatory variable does not depend on or affect the observation of another, the observations in this research are independent of one another. This assumption was verified using the Durbin-Watson statistic generated by SPSS. Assumption four asserts that the study's explanatory and dependent variables have a linear relationship. The literature reviews across various domains considered in this study have shown that the explanatory variables utilized in this study exhibit a linear relationship with risk propensity (Goh & Wiegmann, 2002; Ison, 2015; O'Hare, 1990; O'Hare & Chalmers, 1999; Pauley et al., 2006; Sicard et al., 2003).

The fifth assumption states that the data points in the study must be homoscedastic. To check for homoscedasticity, residuals were plotted on a scatterplot to look for similarity in variance between the explanatory variables. The sixth assumption about multicollinearity mentions that there should not be a correlation between any two explanatory variables in any way. Multicollinearity was verified by examining the correlation coefficients and the tolerance/VIF values in SPSS (Daoud, 2017). The seventh assumption purports that there are no spurious outliers in the dataset. This assumption was tested in SPSS to spot any outliers before data analysis. Mahalanobis' distance was computed to check for significant outliers. The eighth assumption pertains to the normality of the residual errors. This assumption was verified by examining the residual plot generated using SPSS.

Data Analysis Process

The study's statistical procedures used backward elimination multiple linear regression analysis and model fit testing. Linear regression was selected for its appropriateness and functional benefit of generating an equation to better understand the various predictors influencing GA pilots' propensity to take risks. Multiple regression was utilized in this research to gain a more comprehensive knowledge of the variables influencing risk-taking propensity since it allowed for exploratory research, the development of a model for risk-taking propensity, and testing the model for predictive value. Analysis of variance (ANOVA) and *t*-tests were inappropriate because they examine the differences between groups, whereas the aim of this study was to build a prediction equation. The factors considered for this study are age, gender, marital status, education level, ethnicity, locus of control, self-efficacy, psychological distress, flight hours, training curriculum, number of FAA ratings, and hazardous events involvement, all chosen based on past literature. A set of pre-existing surveys quantified the self-efficacy, locus of control, psychological distress, and risk propensity constructs into scores that aided data entry into SPSS 28 software.

Stage one of the data analysis process involved performing multiple regression analysis using the backward elimination method to analyze data, which was done by regressing risk-taking propensity scores on social identity factors (age, gender, marital status, education level, ethnicity), social cognitive domain factors (locus of control, psychological distress, and self-efficacy), and experiential factors (total flight hours, type of training curriculum, number of FAA ratings, and involvement in hazardous events) to formulate a regression equation and coefficient for each explanatory variable. Multiple regression analysis was conducted by considering its underlying assumptions, i.e., linearity, multicollinearity, independence of residuals, homoscedasticity, reliability of explanatory variables, and distribution of the residuals, which was discussed earlier in this chapter.

Stage two of the data analysis process involved model fit testing to evaluate the validity of the model generated in the first stage. Several studies (Anania et al., 2021; Lamb et al., 2020; Ragbir, 2021) have utilized model fit testing and cross-validation to assess and enhance the equation's predictive ability on an independent sample. Although a regression equation may find the best fit for the data at hand, cross-validation helps increase the predicted model's generalizability (Green & Tull, 1978; Kozak & Kozak, 2003; Steckel & Vanhonacker, 1993).

This study employed a single cross-validation data splitting technique wherein the researcher randomized the initial dataset and then split it into two equal halves: the training dataset and the validation dataset. As previously mentioned, the training dataset generated the model and made predictions on the dependent variable values to be used on the validation dataset. Next, the researcher compared the actual and predicted values of the validation dataset to examine the model's predictive validity. This cross-validation step was done using three methods. The first method consisted of a *t*-test that compared the actual and predicted risk propensity scores from stage two pilot data. The second method involved conducting a Pearson correlation between the risk propensity scores obtained from the actual and predicted data of the stage two dataset. The final method consisted of a cross-validated R-squared (R^2).

Summary

The objective of this chapter was to describe the intended methodology for conducting this research study. The key areas covered were an outline of the selected research method and design, the identified target population and sample, the process of collecting data, the instruments used, and the data analysis and statistical strategy used. It also included an outline of the human-subject aspects, including the participants' eligibility criteria, data confidentiality, and legal and ethical considerations. The following chapter will include the outcome results of this research.

Chapter IV: Results

The purpose of this research was to explore what factors predict the risk-taking propensity of GA pilots in the U.S. The overall objective was to develop a prediction model that would assist the aviation industry in understanding the individual factors that influence a GA pilot's risk propensity and its implications. The findings of the data analysis conducted, along with descriptive and inferential statistics, are summarized and discussed in this section of the report. Microsoft Excel and IBM's SPSS software were used throughout the data analyses that were performed.

The statistical method employed to analyze the research data was multiple linear regression using a survey-based predictive correlational design. The research was carried out in two phases: The first stage included the development of a regression equation that was used to predict the risk propensity of GA pilots (dependent variable), and the second phase involved model fit testing to evaluate the model predicted in the first stage.

Demographics Results

As part of the study, demographic information was gathered from participants, which encompassed their age, gender, highest level of education attained, ethnicity, and marital status. The overall sample for this study consisted of 200 participants, with the majority (89%) being male and aged between 18 and 89. The participants came from diverse ethnic backgrounds, with the majority (69%) self-identifying as white. Additionally, 52% had earned a bachelor's or a graduate degree, and 53% were married or in a domestic partnership.

Descriptive Statistics

All the data for this study were collected at the same time. However, since it was randomly split into two datasets for the two-stage analysis, it is presented separately for each stage, along with the corresponding number of participants and central tendency measures. Table 1 summarizes the descriptive statistics for all variables used in each stage of the study.

Table 1

Summary of Stage 1 and Stage 2 Descriptive Statistics

Variable	Stage 1				Stage 2			
	n (%)	*M*	*SD*	*Skew*	*n (%)*	*M*	*SD*	*Skew*
Age	100 (100%)	49.1	22.99	-1.04	100 (100%)	49.3	23.14	-0.07
Total flight hours	100 (100%)	3344	5829	2.22	100 (100%)	3133	6073	2.62
Risk propensity score (1-5)	100 (100%)	2.90	0.57	-0.46	100 (100%)	2.98	0.56	-0.04
Locus of control score (0-23)	100 (100%)	9.07	4.14	0.14	100 (100%)	9.43	4.40	0.32
Self-efficacy score (1-5)	100 (100%)	3.93	0.64	-0.77	100 (100%)	4.03	0.59	-0.94
Psych. distress score (0-36)	100 (100%)	7.4	4.50	0.51	100 (100%)	8.54	4.45	0.12
Gender								
– Male	90 (90%)				87 (87%)			
– Female	10 (10%)				13 (13%)			
Marital status								
– Married	49 (49%)				56 (56%)			
– Unmarried	51 (51%)				44 (44%)			
Highest education level								
– Less than bachelor’s degree	44 (44%)				52 (52%)			
– 4-year bachelor’s degree	36 (36%)				33 (33%)			
– Master’s, Ph.D. or higher	20 (20%)				15 (15%)			
Ethnicity								
– White	68 (68%)				69 (69%)			
– Non-white	32 (32%)				31 (31%)			
Flight training curriculum								
– Part 61	54 (54%)				54 (54%)			
– Part 141	46 (46%)				46 (46%)			
Flight ratings								
– Private	33 (33%)				46 (46%)			
– Commercial	31 (32%)				24 (24%)			
– Flight instructor	36 (36%)				30 (30%)			

Table 1

Summary of Stage 1 and Stage 2 Descriptive Statistics

Variable	Stage 1				Stage 2			
	n (%)	*M*	*SD*	*Skew*	*n (%)*	*M*	*SD*	*Skew*
Number of hazardous events								
– 0	83 (83%)				83 (83%)			
– 1	4 (4%)				8 (8%)			
– 2	3 (3%)				2 (2%)			
– 3	8 (8%)				2 (2%)			
– 4	2 (2%)				5 (5%)			
– 5+	0 (0%)				0 (0%)			

Dummy Coding

All the categorical variables used in this study were dummy coded in order to be used for data analysis. For the categorical variable gender, a dummy-coded variable was used to represent the comparison between males and females, with male category serving as the reference group. To address the issue of uneven sample sizes and limited variability in marital status, a dummy-coded variable was created to compare married individuals with those who were not married. The unmarried category includes those who were separated, divorced, widowed, or never married. The married category was the reference group. The categorical variable education was dummy coded to allow the researcher to compare the educational attainment levels of participants who had completed a 2-year college degree or less, a 4-year college degree, or a graduate degree (either a master’s or a doctoral degree). The 4-year college degree was chosen as the reference group for this comparison. Likewise, the categorical variable ethnicity was dummy coded to allow the researcher to compare participants who identified as white or non-white, with white as the reference group. Lastly, flight training curriculum was dummy coded, which allowed comparison between participants who were most recently trained under either Part 61 or Part 141 regulations, with Part 61 as the reference group.

Incomplete and Missing Data

When there is missing data in a survey, it may lower the statistical power of the research and lead to skewed estimates, which can lead to erroneous findings (Kang, 2013). Since participation was voluntary, participants had the right to discontinue the survey at any time without penalty. Despite this voluntary nature, it is important to note that this study achieved a 100% response rate without any incomplete surveys.

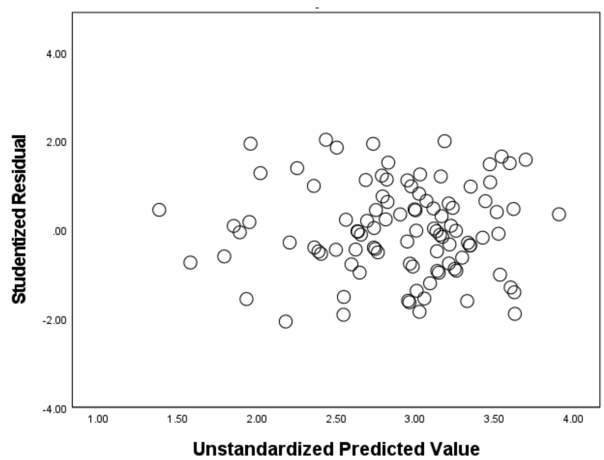
Assumptions of Regression

In order for the design to be capable of producing meaningful findings, it must satisfy all the eight assumptions that are associated with multiple linear regression. Assumption 1, that the dependent variable of interest must use a continuous scale, and assumption 2, that the total number of independent variables is at least two, were met in this study. Assumption 3, that the study's observations are independent of one another, was not violated since residuals were independent, as assessed by a Durbin-Watson statistic of 1.994 in the stage 1 dataset, within the recommended range of 1.5 to 2.5 (Fields, 2009).

Assumption 4 about the linear relationship between the dependent and independent variables was tested by first analyzing the unstandardized predicted values graphed against the studentized residuals and then by analyzing the partial regression plots for each independent variable. In Figure 1, the residual scatterplot depicts a horizontal band pattern, indicating a likely linear relationship between the dependent and independent variables. A visual inspection of the partial regression plots, as recommended by Laerd (2019), is shown in Appendix C for each independent variable and reveals that the data fulfills the fourth assumption, indicating a linear relationship.

Figure 1

Studentized Residual by Unstandardized Predicted Value of Risk Propensity



Assumption 5, about homoscedasticity of data points, was not violated, as the standardized residuals and the predicted values were analyzed using a scatterplot as depicted in Figure 1, indicating that the data points were random with no patterns. The spread of the projected values does not increase for either small or large values. Assumption 6 about multicollinearity between independent variables was not violated and was verified by examining the correlation coefficients and the tolerance/VIF values in SPSS. A collinearity issue may exist if the tolerance value is below 0.1, corresponding to a VIF larger than 10 (Hair et al., 1995). In this study, the tolerance value and the VIF were below their cut-off values of 0.1 and 10, respectively, as indicated in Table 4. Assumption 7, that there should not be any spurious outliers in the dataset, was not violated since no outliers were present in any variable, as confirmed by the Mahalanobis Distance test values not exceeding their critical values using the criterion $\alpha = .001$. Assumption 8, regarding the normal distribution of residual errors, was visually verified using an SPSS-generated histogram and P-P plot and is depicted in Figures 2 and 3.

Figure 2

Regression Standardized Residual Histogram

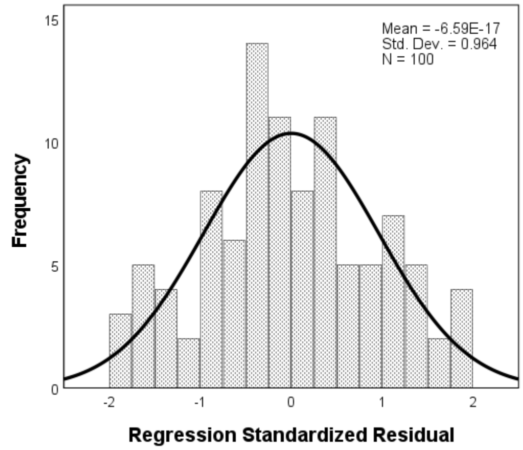
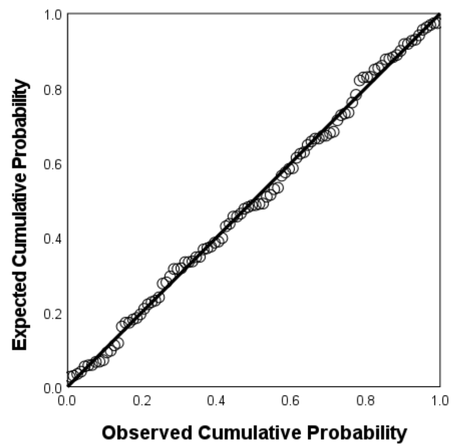


Figure 3

Normal Probability Plot (P-P Plot)



Reliability and Validity Assessments

The internal reliability of the instruments in this study was assessed using Cronbach's alpha and Guttman's split-half reliability coefficient. Cronbach's alpha is a statistic for analyzing internal consistency, showing the degree to which items within an instrument are correlated or measure the same underlying construct (Hair et al., 2010; Tavakol & Dennick, 2011). Cronbach's alpha of above .7 shows good reliability of items that are measured (Nunnally, 1978). Guttman's split-half test evaluates test-retest reliability and was proposed by Guttman in 1945. Additionally, McDonald's omega was calculated as an extra measure of internal consistency. The risk propensity scale used in both stages showed excellent internal consistency, with Cronbach's alphas of .95 and .93. The Guttman coefficient yielded slightly higher values of .96 for both stage one and stage two. This result demonstrates that the employed scale possesses adequate psychometric properties, justifying its use in ongoing research. Table 2 provides a summary of the consistency and reliability analyses conducted on the remaining scales used in this study. The results indicate that these scales demonstrated high reliability, confirming their suitability for assessing their respective constructs.

Table 2

Summary of Stage 1 and Stage 2 Internal Consistency and Reliability Analyses

Variable	Stage 1			Stage 2		
	Alpha	Omega	Guttman	Alpha	Omega	Guttman
General Risk Propensity	.95	.95	.96	.93	.93	.96
New General Self-Efficacy	.93	.92	.93	.92	.92	.93
General Health Questionnaire	.83	.82	.91	.84	.83	.87
Locus of Control	.73	.71	.80	.78	.77	.83

Data Analysis Results

The data analysis for this study was performed in two phases. The first phase entailed creating a regression model, and the second involved assessing the model's fit. The purpose was to investigate potential determinants of a pilot's risk-taking propensity. This was made possible by creating two independent datasets to be used in each step of the process. As previously mentioned, the initial dataset was randomized and then split into two equal halves to facilitate the two-stage analysis conducted in this study.

Stage 1: Model Development

In the first phase of this research, a multiple linear regression equation was created using data from 100 participants and utilized to forecast the risk-taking propensity of GA pilots. Twelve predictors were analyzed: age, gender, marital status, level of education, ethnicity, locus of control, psychological distress, self-efficacy, total flight hours, training curriculum, number of flight ratings, and the number of hazardous events experienced in the past five years. The study used a backward elimination multiple regression method to identify a parsimonious set of predictors of pilots' risk-taking propensity. The benefit of this method is that it eliminates the predictors that do not statistically contribute to the model but retains the ones that do. Table 4 presents the beta weights and significant values of the final model. The following describes the details of the risk propensity regression analysis.

Age, total flight hours, number of flight ratings, number of hazardous events experienced, self-efficacy, psychological stress, and locus of control were significant predictors that were included in the final model. The following multiple regression model was obtained:

$$\hat{Y} = 2.663 - .009X_1 - .017X_2 - .135X_3 + .074X_4 + .140X_5 + .019X_6 + .031X_7$$

Risk propensity score = 2.663 - .009 (*age*) - .017 (*total flight hours*) - .135 (*number of flight ratings*) + .074 (*number of hazardous events*) + .140 (*self-efficacy score*) + .019 (*psychological stress score*) + .031 (*locus of control score*)

The predicted variable $\hat{Y}$ represents the risk-taking propensity of pilots, which is the dependent variable. The independent variable X_1 represents age, X_2 represents total flight hours, X_3 represents the number of FAA flight ratings, X_4 represents the number of hazardous events, X_5 represents self-efficacy, X_6 represents psychological stress, and X_7 locus of control.

The R^2 for the overall regression model was 76.4% with an adjusted R^2 of 74.6%, which is a large effect size, per Cohen (1988). The resulting regression equation shows that variables age, total flight hours, number of flight ratings, number of hazardous events, self-efficacy score, psychological stress score, and locus of control score explained 76% of the variation from the dependent variable, risk-taking propensity. ANOVA was performed to determine whether the regression equation is significantly better at predicting scores in the DV compared to using the mean. Utilizing the current sample, it was determined that the effect differed significantly from zero, $F(7, 92) = 42.60$, $p < .001$. This means that the resulting variables significantly predicted risk propensity. The summary of the ANOVA table is listed in Table 3 and the coefficients of the seven significant predictors in the first stage are listed in Table 4.

Table 3

ANOVA Table

Final Model		*SS*	*df*	*MS*	*F*	*p*
7	Regression	24.923	7	3.560	42.600	< .001
	Residual	7.689	92	.084		
	Total	32.612	99			

Note. Dependent Variable: Risk-Taking Propensity
Predictors: (Constant), Age, Flight Hours, Number of Flight Ratings, Number of Hazardous Events, Self-Efficacy, Psychological Distress, and Locus of Control.

Table 4

Regression Coefficients from Stage 1 (N = 100) for Risk-Taking Propensity

						Collinearity Statistics		Correlations		
Predictors (Model 7)	*B*	*SE B*	β	*t*	*p*	Tol.	VIF	Zero-order	Partial	Part
(Constant)	2.663	.333		7.98	<.001					
Age	-.009	.002	-.353	-4.68	<.001	.450	2.224	-.662	-.439	-.237
Flight Hours	-.017	.008	-.171	-2.09	.039	.384	2.607	-.712	-.213	-.106
Flight Ratings	-.135	.041	-.196	-3.30	.001	.725	1.380	-.284	-.325	-.167
Hazardous Events	.074	.030	.131	2.49	.015	.921	1.086	.237	.251	.126
Self-Efficacy	.140	.066	.156	2.13	.036	.475	2.105	.634	.217	.108
Mental Distress	.019	.008	.147	2.48	.015	.733	1.364	.530	.251	.126
Locus of Control	.031	.009	.224	3.34	.001	.568	1.760	.646	.329	.169

Note. Dependent Variable: Risk-Taking Propensity

Stage 2: Model Validation

The objective of stage two was to use a separate sample of participants (n = 100) to evaluate the model fit and the prediction ability of the regression model developed in stage one. It helps to validate the prediction equation and ensure that both samples come from the same population. Here, the risk-taking propensity scores of GA pilots were predicted using the regression equation developed in the first stage. These predicted risk propensity scores were then compared to the actual risk propensity scores in the second stage. A t-test, a correlation analysis, and a cross-validated R^2 analysis were used to compare the scores in both stages.

T-Test

A t-test was performed to assess the correspondence between the predicted risk propensity scores computed utilizing the model developed in stage one on the stage two dataset and the observed risk propensity scores in the stage 2 dataset. The independent samples t-tests showed that there was no statistically significant distinction between the predicted values of risk propensity (M = 2.97, SD = 0.47) and the observed values (M =

2.98, *SD* = 0.56), *t*(198) = -0.13, *p* = .901. The absence of a significant difference in the means implies that the equation established in stage one is a reliable model for predicting risk-taking propensity among GA pilots. The findings are depicted in Table 5.

Table 5

T-Test Between Actual and Predicted Risk-Taking Propensity Scores (Stage 2)

Levene's Test for Equality of Variances		*t*-test for Equality of Means					95% CI	
F	*p*	*t*	d*f*	*p*	Mean Difference	*SE*	*LL*	*UL*
2.92	.089	-0.13	198	.901	-.01	.07	-.15	.14

Note. Equal variances assumed.

Correlation Analysis

A Pearson's correlation analysis was carried out to validate the linearity of the relationship between the predicted and observed risk-taking propensity scores by comparing them. The results showed a significant relationship between the two scores, *r*(98) = .85, *p* < .001. The cross-validation coefficient provides further support for the model's fit, as a strong and positive correlation exists between the predicted and observed scores.

Cross-Validated R^2

A cross-validated R^2 analysis was carried out to compare the predicted risk propensity scores with the observed risk propensity scores. The following formula was used to compute the squared cross-validity coefficient.

$$R_{cv}^2 = 1 - \left(\frac{N - 1}{N}\right)\left(\frac{N + k + 1}{N - k - 1}\right)(1 - R^2)$$

In the above equation, N is the sample size, R^2 is the observed squared multiple correlation, and k is the number of fixed predictors in the final model (Pedhazur, 1997). The stage 2 cross-validity coefficient is determined utilizing the aforementioned formula:

$$.725 = 1 - \left(\frac{100 - 1}{100}\right)\left(\frac{100 + 7 + 1}{100 - 7 - 1}\right)(1 - .764)$$

In stage 2, where $N = 100$, $k = 7$, and $R^2 = .764$, the resulting cross-validity coefficient is .725. The proximity of the original R^2 from stage one and the cross-validated R^2 provides evidence for an acceptable model fit (Cohen, 1988; Field, 2013). The closeness in the two R^2 values suggests how well the predicted model from stage one would be generalizable to additional samples obtained from the population. Table 6 contains a summary of the statistics pertaining to the model fit.

Table 6

Stage 2 Model Fit Using Observed Versus Predicted Risk-Taking Propensity

	T-Test			Correlation		Original R^2	Cross-Validated R^2
	t	*df*	*p*	*r*	*p*		
Risk-Taking Propensity	-.125	198	.921	.848	<.001	.764	.725

Hypothesis Testing Results

The research questions and the corresponding hypotheses were introduced in Chapter 1. To facilitate testing, these hypotheses have been reformulated in null form. Table 7 summarizes the null hypotheses and their outcomes, indicating whether they were rejected or retained. Null hypotheses were rejected at a p-value of less than 0.05, a commonly used level of statistical significance.

Table 7

Hypothesis Testing Results Summary

Null Hypotheses	*p*	H_o decision
H_{o1}: Age will not significantly predict a GA pilot’s risk-taking propensity, holding all other variables constant.	< .001	Rejected
H_{o2}: Gender will not significantly predict a GA pilot’s risk-taking propensity, holding all other variables constant.	.124	Retained
H_{o3}: Marital status will not significantly predict a GA pilot’s risk-taking propensity, holding all other variables constant.	.907	Retained
H_{o4}: Education level will not significantly predict a GA pilot’s risk-taking propensity, holding all other variables constant.	.142	Retained
H_{o5}: Ethnicity will not significantly predict a GA pilot’s risk-taking propensity, holding all other variables constant.	.295	Retained
H_{o6}: Self-efficacy will not significantly predict a GA pilot’s risk-taking propensity, holding all other variables constant.	.036	Rejected
H_{o7}: Locus of control will not significantly predict a GA pilot’s risk-taking propensity, holding all other variables constant.	.001	Rejected
H_{o8}: Psychological distress will not significantly predict a GA pilot’s risk-taking propensity, holding all other variables constant.	.015	Rejected
H_{o9}: The number of total flight hours will not significantly predict a GA pilot’s risk-taking propensity, holding all other variables constant.	.039	Rejected
H_{o10}: The type of flight training curriculum will not significantly predict a GA pilot’s risk-taking propensity, holding all other variables constant.	.595	Retained
H_{o11}: The number of flight certifications will not significantly predict a GA pilot’s risk-taking propensity, holding all other variables constant.	.001	Rejected
H_{o12}: The number of hazardous events experienced by GA pilots will not predict their risk-taking propensity, holding all other variables constant.	.015	Rejected

Summary

Chapter 4 of this study provided a thorough overview of the findings from the regression and model fit analyses. This study aimed to explore what factors predicted the risk-taking propensity of GA pilots in the U.S., which was executed in two stages. In the first stage, a regression equation was developed to predict the risk propensity of pilots. Employing the backward elimination multiple regression method, the final model incorporated seven predictors: age, total flight hours, number of flight ratings, number of hazardous events experienced, self-efficacy, psychological distress, and locus of control. In the second stage, model fit testing was conducted to validate the model developed in the previous stage using three metrics: a *t*-test, cross-validated R^2, and correlation. All three tests confirmed an acceptable model fit.

Chapter 5: Discussion

This study aimed to explore the determinants that influence the risk-taking propensity of GA pilots. Despite the presence of highly experienced pilots and the industry's best efforts in increasing aviation safety awareness to minimize accidents through high training standards, pilot error remains the leading cause of general aircraft accidents, often attributed to poor decision-making and errors in judgment, which an individual's risk-taking may influence. Risk-taking is multifaceted and necessitates further investigation to better understand its nature and identify and address the root causes of pilot error to improve aviation safety. In other words, it is essential to recognize the factors that influence a pilot's decision-making process, including their propensity for risk-taking, and how these can be mitigated or eliminated to reduce the incidence of accidents.

Using a backward elimination stepwise multiple regression analysis, this study developed a regression equation with seven significant predictors: age, total flight hours, number of FAA flight ratings, number of hazardous events experienced, self-efficacy, psychological distress, and locus of control. Two independent stages comprising 100 participants each were used to build and validate the model. The overall findings strongly supported the model's strength and validity, as it accounted for a large portion of the variance in the data. Despite the significant explanatory power of the model, further research in this field can help not just replicate the results but also contribute to refining the model, considering the diverse reasons for risk-taking behavior.

In this chapter, the results presented in Chapter 4 are elaborated upon, and this study's future implications are discussed. This entails analyzing the hypotheses, discussing the predictors from the model, and determining whether the collected data support each. In addition, this section will emphasize this study's practical applications and limitations and suggest areas for future research.

A Discussion of Predictors in the Study

The initial premise that age will significantly predict a GA pilot's risk-taking propensity while holding all other variables constant was supported by the findings of this study, demonstrating a significant inverse relationship between age and the inclination of pilots to take risks. This finding aligns with previous literature that older pilots generally make fewer errors and poor risky decisions than younger pilots (Ison, 2015; Sicard et al., 2003). However, the findings contrasted with Yalçın et al.'s (2016) study, which examined helicopter pilots outside the U.S. Similarly, it differed from the findings of Li et al. (2003), likely due to variations in data collection methodology using older pre-existing data. Likewise, Walmsley and Gilbey's (2019) study exhibited the same inconsistency, possibly due to limited generalizability caused by the study's experimental design confined to a New Zealand flying school sample.

Aging may reduce crash risk due to increased expertise, safer behavior, and job independence (Fjell & Walhovd, 2010; Samanez-Larkin & Knutson, 2015). Per Blais and Weber (2006) and Weber et al. (2002), changes in risk perceptions across adulthood may also explain age-related differences in risk-taking propensity, as observed in this study. Josef et al. (2016) posit that significant cognitive, biological, and life events during early and late phases of life, such as marriage or retirement, may influence the stability of individual risk-taking propensity.

Concerning gender-based differences in pilots' risk-taking propensity, the study was consistent with Masters (1989) and Nelson (2015) in a non-aviation context, who found no general differences in risk-taking inclinations between men and women. According to Masters (1989), previous research suggesting that females are more risk-averse than males contradicts his current finding. He suggests that gender differences in risk-taking propensity may have diminished over time, cautioning researchers against stereotyping based on sex. Nelson (2015) holds that stereotyping based on gender can lead to invalid generalizations and distort one's understanding of reality.

This study indicates that females and males in aviation exhibit similar risk-taking tendencies, contradicting Ison's (2015) research on pilots involved in accidents, which found that females were less risk-taking than males. A possible explanation for this inconsistency is that the proportion of females in the dataset used in both studies was considerably smaller than that of males, reducing the statistical power to detect gender-based differences. However, it is essential to note that the lack of a substantial gender impact in this study does not rule out its relevance in other circumstances or in conjunction with other factors.

In exploring the predictors of GA pilots' risk-taking propensity, the proposition that marital status predicts risk-taking propensity was dismissed as it did not contribute significantly to the model's predictive power. The absence of a relationship between marital status and risk-taking behavior agrees with the research of Larkin et al. (2013) and Gibson et al. (2013) in a non-aviation context. This study's findings, however, contradict Karachalios' (2022) research, which indicated that married pilots took more risks than unmarried pilots. One possible explanation is that Karachalios' study focused on airshow pilots, whose intentions and behaviors may differ from those of GA civilian pilots. Furthermore, the methodology and sample size significantly varied between the two studies, as Karachalios' study relied on qualitative data from semi-structured interviews with only 12 airshow pilots. However, there may be a third variable among the variables considered or not considered in this study, such as emotional well-being, that may mediate the relationship between marital status and risk-taking propensity. Likewise, there may also be factors among the ones considered in this study or ones beyond this study, such as social identity or personality factors, that moderate the relationship between marital status and risk-taking. Further research may be beneficial in exploring the potential role of marital status in predicting the outcome variable.

Past literature has suggested that higher education can be pivotal in fostering a healthy attitude toward risk-taking. The present study hypothesized that a predictive effect exists between education and risk-taking among GA pilots. However, the results suggest that the formal education pilots receive has limited influence on their inclination towards risk. The findings align with Gibson et al. (2013), who found no association between education and risk propensity in a non-aviation context. This outcome implies that education alone is insufficient to bring about a behavioral change in an individual's ability to differentiate between risky and non-risky situations. This study disagrees with Karachalios (2022), who linked higher education among airshow pilots with lower risk-taking, but their characteristics and intentions differ from regular GA civilian pilots.

Another social identity factor analyzed was ethnicity and its ability to predict the risk propensity of pilots. While holding all other variables constant, the results failed to find statistical significance to support its predictive ability. It is important to note that two-thirds of the participants in this study were identified as white, which may have constrained the statistical power to detect any potential differences in risk-taking behavior between different ethnic groups. However, although ethnicity did not exhibit predictive power in the regression model, a *t*-test comparing risk propensities between white and non-white ethnic groups revealed that whites displayed higher risk-taking tendencies than non-whites, agreeing with previous research (Collado et al., 2017; Czerwonka, 2017; Mehta et al., 2017; Perrotte et al., 2021)

Pilot experience, measured by the total flight hours, was an important factor explored in this study. The hypothesis posited that the number of total flight hours would significantly predict risk-taking propensity among pilots. The findings corroborated this hypothesis, demonstrating a negative correlation between pilots' total flight hours and their inclinations toward risk-taking. The results are consistent with past literature (Burian et al., 2000; Goh & Wiegmann, 2002; Golaszewski, 1983; Ison, 2015; Li et al., 2003) that pilots with more flight hours tend to exhibit lower propensities for taking risks. Such pilots have more situational awareness and superior decision-making abilities, enabling them to make cautious and calculated judgments under challenging circumstances. Pilots' perceptions of the source of aviation accidents and injuries are influenced by their accumulated flight experience, and as experience is gained, their awareness of the importance of adhering to safety regulations is likely to increase (You et al., 2013). In addition, the confidence attained through flight hours can enable pilots to take a measured approach toward risk and prioritize safety over unnecessary risks.

Within the realm of pilot experience, an additional dimension is the type of flight training curriculum (Part 61 or Part 141). Based on the assumption that different curriculums may vary in their effectiveness and approach to risk management training, it was hypothesized that the type of flight training curriculum would significantly predict a GA pilot's risk propensity. The findings showed no difference between the curriculums, which suggests that curriculum type may not be a significant predictor of risk-taking behavior when considered in isolation from other variables. This may be because flight training must adhere to the requirements set forth in the Federal Aviation Regulations (FARs) and train students to the standards outlined in Part 61. Therefore, this compliance remains an important factor irrespective of the curriculum in place (Wallace, 2010).

The number of FAA flight ratings was explored as a potential predictor of risk-taking propensity. The results supported the hypothesis by indicating a negative correlation between the number of flight certificates and pilots' tendencies towards risk-taking, suggesting that those with fewer ratings exhibit a heightened willingness to engage in riskier flying behaviors. Put differently, pilots with more certifications may exhibit a more cautious and risk-averse attitude during flight. This phenomenon could be attributed to the extensive training and evaluation required to obtain multiple flight ratings, which instills a greater emphasis on flight safety, compliance with FARs, and disciplined aeronautical decision-making (ADM). Obtaining additional flight ratings may contribute to the cultivation of a safety-conscious mindset and reduce risky behaviors in flight operations.

The study examined the number of self-reported hazardous events experienced by pilots as a predictor of risk-taking propensity. The findings corroborated this hypothesis, demonstrating a positive correlation between the number of hazardous events a pilot has been exposed to and their risk-taking propensity. This finding aligns with past literature

(Joseph et al., 2013; O'Hare & Chalmers, 1999; Pauley et al., 2006, 2008a, 2008b) that those with previous experience in hazardous events had a greater risk-taking propensity. Hunter (2006) posits that pilots exposed to more hazardous events tend to rate them as lower risks. Risk-taking can lead to a cycle of increasingly dangerous behavior if negative consequences are not quickly realized. In this cycle, risk perception decreases, and tolerance for risk increases. As Rhodes (1997) states, habitual behaviors do not require risk assessment or calculation; they are simply performed. However, this positive relationship between hazardous events and risk-taking strengthens when involving psychological stress. A pilot who has encountered several hazardous events may view most aviation situations as less risky. However, when subjected to stress, this pilot will likely exhibit an even greater propensity for making risky decisions than when not under stress. Therefore, it is essential to implement stress management measures to support pilots, including fostering open communication, encouraging more voluntary reporting initiatives, promoting self-care, and providing resources and training programs, to help pilots recognize and cope with stressors.

Locus of control, an important construct explored extensively in the literature, holds profound implications for individuals' attitudes toward risk-taking. Grounded on Julian B. Rotter's (1954) social learning theory and the perceived behavioral control component of Ajzen's (2002) theory of planned behavior, the current study hypothesized that LOC would predict pilots' risk-taking inclinations. This hypothesis was upheld as the findings demonstrated a positive correlation between pilots' LOC scores and risk-taking propensity, i.e., higher external LOC scores were associated with higher risk-taking propensities. This finding aligns with the studies of Wichman and Ball (1983), Salminen and Klen (1994), and You et al. (2013), which report that pilots with an external LOC, i.e., those with the belief that outside forces control their outcomes, tend to have higher risk-taking inclinations compared to those with an internal LOC, i.e., those with the belief that they control their outcomes. Those with higher internal LOC are more adept at accurately assessing complex situations than those with external LOC (Crisp & Barber, 1995). External LOC individuals may feel that they have little control over their lives or the outcomes of their actions, resulting in more risk-taking inclinations (Johnson, 2018). They tend to desire novelty and exhibit sensation-seeking tendencies, which makes them prone to greater risk-taking.

The current study found statistically significant results when exploring the relationship between psychological distress and risk-taking propensity in GA pilots. The outcome suggests that pilots experiencing higher levels of psychological distress, including anxiety, depression, fear, or social impairment, may exhibit greater inclinations toward risky behavior and initiate poor decisions (Ormrod, 2012). Based on further data analysis, this postulation held especially true for pilots with less flight experience; when confronted with a stressful situation, they may experience heightened emotional arousal and exhibit a greater tendency to make risky decisions. Psychological distress is a serious issue given the aviation industry's unique stressors and high-risk environment, and it can negatively impact a pilot's performance and safety. Research (Baradell & Klein, 1993; Kolich & Wong-Reiger, 1999) has found that life stress was linked to poorer decision-making and information-processing ability, which suggests that in real-world tasks, such as piloting, stress-related thoughts may capture pilots' attention, divide their focus, and impair their working memory capacity, potentially leading to overlooking critical information and neglecting tasks (Young, 2008). While previous studies in non-aviation domains (Isen & Geva, 1987; Kotvis, 2012; Mano, 1992; Ness & Klaas, 1994; Scott-Parker et al., 2011) have shown a positive association between individuals' psychological health and their risk-taking inclinations, thereby influencing decision-making and performance, this study represents a novel effort in investigating the topic of risk-taking propensity specifically among GA pilots.

A pilot's level of self-efficacy was examined in this study as a predictive factor for risk-taking. The findings strongly supported the premise about the predictive capability of self-efficacy, as well as supported Bandura's (1977) self-efficacy theory. It also aligned with previous studies by Goh and Wiegmann (2001) and O'Hare and Smitheram (1995) that demonstrated that more self-efficacious pilots tend to have higher risk-taking inclinations than low self-efficacious pilots; such pilots are overconfident in their flying skills. Bandura and Jourden (1991) suggest that highly self-efficacious GA pilots may underestimate risks and overestimate their ability to cope with potential danger due to the complacency of high self-efficacy, increasing their risk-taking propensity.

While not explicitly investigated in this study, self-efficacy could potentially interact with experience and psychological distress, which are factors examined individually. According to Artino (2012), Schunk and Pajares (2004), and Williams and Williams (2010), an individual's past experiences with successes and failures serve as an important source of information for developing self-efficacy. Pilots who have previously survived inadvertent flight events may perceive similar future situations as low-risk, leading them to be less risk-averse about them. Past experiences contribute to an increase in their self-efficacy (Bandura, 1997). Additionally, as a cognitive factor, self-efficacy may impact the relationship between flight experience and risk-taking tendency, which has already been explored earlier in this study. Likewise, self-efficacy could also interact with psychological distress, including mood, anxiety, and stress levels (Artino, 2012; Bandura, 1997; Ormrod, 2012). Because stress symptoms are often perceived as vulnerability during challenging activities (Bandura, 1997), the resulting low self-efficacy due to psychological stress may lead to poor pilot performance.

Conclusions

The objective of the present study was to address a gap in the existing literature about risk-taking propensities among GA pilots. Pilot error continues to be the predominant factor in aviation accidents, albeit highly experienced pilots and increased safety awareness in the industry. Researching the intricate subject of risk-taking is necessary to gain a deeper comprehension of the factors that impact a pilot’s judgment and decision-making and to pinpoint the underlying reasons for pilot errors. While it was once assumed that experience alone was sufficient for pilots to exercise sound judgment, studies such as the current one on risk-taking propensity have shown that various factors can influence a pilot’s decision-making.

Using two independent stages comprising 100 participants each, this study developed a regression equation with seven significant predictors of a pilot’s risk-taking propensity: age, total flight hours, number of flight ratings, number of hazardous events experienced, self-efficacy, psychological distress, and locus of control. Some of these factors, but not all of them, have been examined in earlier research. The second stage of this research utilized an independent sample of 100 participants to verify the fit of the predicted regression model.

While the current study yielded robust support for the strength and validity of the model's explanatory power as it accounted for a substantial proportion of the variance observed in the data, replication of these findings in future research is encouraged to enhance confidence in the findings. Additionally, further investigations can contribute to refining the risk-taking propensity model by considering the diverse factors not included in this study. By delving deeper into the factors affecting pilots' risk-taking inclinations, researchers can uncover nuanced insights and expand the understanding of the complex nature of risk-taking behavior. This study represents a significant step in understanding existing and new factors contributing to pilots' risk-taking behaviors and their implications for aviation safety. The concept of sound judgment in aviation, as mentioned earlier, is closely related to risk-taking propensity.

Implications of the Findings

In terms of theoretical implications, the results of the present study expanded the number of variables predicting risk propensity among GA pilots. The results also provided sufficient evidence to support Bandura's (1977) self-efficacy theory and Ajzen's (1991) theory of planned behavior with respect to external LOC. The model's ability to explain the data confirms that using Chen et al.'s (2001) domain-free, general self-efficacy scale was appropriate and valid for measuring self-efficacy. This result implies that forthcoming studies in aviation can employ this scale for comparable research objectives. In addition, the study's findings with respect to past hazardous events confirmed the habituated action theory, which suggests that repeated engagement in high-risk behavior without adverse outcomes tends to be related to lower perceived risk associated with such behavior (Kasperson et al., 1988; Weyman & Kelly, 1999).

Pilots, as key stakeholders in aviation safety, can benefit from the results of this study by being made aware of their own risk-taking propensity based on factors such as past hazardous events, self-efficacy, and locus of control, among others. This awareness encourages safety-oriented behavior and informed decision-making, especially with go or no-go decisions, thus mitigating potential flight risks. Such self-awareness may also motivate pilots to seek training programs and continuously improve their risk management skills. Pilots may use the model to either perform routine pre-flight risk assessments or post-flight self-debriefs incorporating their encounters with hazardous events in previous flights to help them reflect upon and increase their awareness of their susceptibility to unwarranted inclinations and implicit attitudes towards risk-taking in future flights.

In addition, as part of pilot training, it may be beneficial for training entities to intentionally expose pilots to simulated hazardous events beyond what the FAA curriculum requires to instill in them a safety-oriented mindset incorporating proper risk-management techniques and adherence to checklists and standardized procedures when faced with challenging in-flight decisions. This goal can be accomplished through targeted scenario-based training (SBT), simulations, recurrent training, safety awareness programs, and strategies to minimize the likelihood of aircraft accidents (FAA, 2007).

The study indicated a positive association between psychological distress and risk propensity. A practical implication is for GA employers and flight schools to take proactive measures to support pilots by recognizing and understanding the different categories of stress they may face, such as acute (short-term), chronic (long-term), physiological (fatigue, illness, sleep), and psychological stress (social, emotional), and providing resources and guidance for effective stress management (FAA, 2009). This goal can be achieved by organizing regular pilot health-related training seminars and stress management clinics, which can serve as platforms for educating pilots about the different types of stress and equipping them with effective stress management techniques. Additional emphasis can be placed on training pilots in medical factors impacting their well-being and performance. Encouraging the routine use of checklists such as PAVE (Pilot, Aircraft, enVironment, External pressures) and IMSAFE (Illness, Medication, Stress, Alcohol, Fatigue, Eating) and setting personal minimums can further enhance risk management and help pilots assess their fitness for flight.

The current study's findings highlight the significant association locus of control has on pilots' risk-taking propensity. A practical implication is for flight schools and employers to develop training programs that enhance pilots' level of internality or externality. Specifically, pilots with a high degree of internality should be encouraged and trained to have confidence in their ability to identify and manage risky events. In contrast, pilots with a high degree of externality should receive training to manage their anxiety and improve their confidence levels, enabling them to operate the aircraft safely.

Age plays a significant role in aviation safety, as indicated by existing literature and the current study. Combined with the finding that also predicts risk propensity, the implication is that pilots can use this information to proactively self-assess any shifts or developments in their LOC orientation over time and whether they tend to attribute outcomes to external factors beyond their control. This knowledge is crucial as it can influence their risk attitudes and decision-making processes during flight operations. Older pilots tend to have a more internal LOC associated with lower risk propensity. The study indicates that older and more experienced pilots exhibit lower risk-taking, drawing upon their experiences and knowledge, thereby contributing to aviation safety. Recognizing the influence of age on risk-taking behavior, interventions can be designed to target specific age groups, providing tailored training and resources that promote a safety-conscious mindset throughout a pilot’s career. Similarly, pilots with a stronger external LOC may benefit from interventions that focus on enhancing their sense of internal control and personal responsibility for safety. By fostering a greater internal LOC orientation, pilots can be encouraged to make more informed and cautious decisions, leading to improved overall safety outcomes.

The study’s findings regarding age, LOC, psychological distress, and self-efficacy have significant implications for aircraft avionics and systems manufacturers. These insights can guide the development of human-centered flight instrumentation, automation, and cockpit displays that enhance safety by helping to reduce the risk of pilot-error-induced disasters. By leveraging technological advances, advanced human-centric cockpit systems can provide pilots with mission critical information, situational awareness, effective warnings, predictive aiding, and adaptive flight guidance, enabling them to make safer decisions and manage their risk-taking behavior during flight.

The study’s model revealed that pilots’ education level did not predict risk propensity, indicating that formal education does not significantly influence their inclination towards risk aversion or risk-taking. This finding may denote that formal education alone may not be the sole contributor to risk propensity and may be mediated by a third factor. Nonetheless, this finding encourages GA pilots to seek safety training through alternative channels such as FAA safety-related courses, workshops, seminars, webinars, and clinics designed to mitigate risk and enhance safety in aviation operations.

Finally, policymakers and aviation groups such as the FAA, Aircraft Owners and Pilots Association (AOPA), Flight Safety Foundation (FSF), EAA, and the General Aviation Manufacturers Association (GAMA), who create and administer GA pilot training programs, can develop safety-oriented training curriculum, safety guidelines, and risk management strategies. The findings of this research can also serve to inform policies, rules, currency, and proficiency requirements, as well as safety recommendations aimed at enhancing safety in flight operations.

Limitations of the Findings

The research's limited sample of GA pilots from the Central Florida area, chosen through convenience sampling, restricts the generalizability of the findings to the broader population of GA pilots in the U.S. There is also potential for sample bias as participants were selected based on their availability and willingness to participate. Future research may involve a more diverse sample of GA pilots from different regions in the U.S. to enhance the generalizability of the results. Stratified random sampling may ensure representative sampling of GA pilots in the U.S. Including flight data recorders or simulators, studies could enhance comprehension of pilot decision-making and reduce self-reported data biases.

This research employed a cross-sectional design, which depicts only a snapshot of risk-taking propensity and may hinder the researcher's ability to track risk-taking propensity changes over time. Alternative study designs, such as longitudinal studies, may be used by researchers in order to follow changes in risk-taking propensities over time and give more robust evidence of causation. Additionally, due to the study's correlational nature, it is impossible to draw causal inferences. However, the data collected from this nonexperimental study can serve as a foundation for future research, which could include manipulating specific parameters through randomized controlled experiments and analyzing their influence on pilot decision-making and risk-taking propensity. Furthermore, researchers may explore augmenting their results with qualitative data or pilot interviews to acquire a more in-depth knowledge of their decision-making processes and the factors that impact them.

The novel nature of this research necessitated the use of backward elimination stepwise regression to construct the prediction model. This statistical technique has limitations since semi-partial correlational values are used to evaluate significant predictor variables. Also, the method limits the re-entry of a dropped variable, although it may become significant later in the model. Future studies could utilize the manual entry of variables into the model to reinforce the theoretical aspect of the significant predictors.

Recommendations

The present research laid the groundwork for future researchers to develop. It aimed to explore the risk-taking propensity of GA pilots and its predictors. The results indicated that the tendency to take flight risks was associated with younger pilots with comparatively lower number of flight hours and ratings, high self-efficacy, higher levels of psychological distress, an external locus of control, and who have experienced more hazardous events.

Based on past literature, this study incorporated social identity factors, such as age, gender, marital status, race/ethnicity, and education; however, the results only partially aligned with earlier research, demonstrating the difficulty of interpreting risk propensity with the selected variables. Future studies could consider increasing the sample size and implementing a stratified probability sampling method that represents diverse segments of the GA population across various regions in the U.S. to enhance the generalizability and accuracy of the model.

While the present study utilized non-domain-specific scales to measure constructs such as risk-taking propensity and locus of control, future studies may replicate this research using aviation-specific scales. Employing an aviation-specific measurement scale specially designed to capture the nuances and intricacies of pilots’ risk-taking, self-efficacy, and locus of control can enhance the validity and reliability of the study.

While self-reported risk propensity data may be valuable, future research could include objective risk-taking measures like flight simulator tests to validate the self-reported data. In order to give more in-depth insights into the aspects that lead to pilot risk-taking behaviors, future research could also consider adopting a mixed-method approach to obtain data, including pilot interviews and focus groups.

Future research could explore not only the direct influence of individual factors on risk-taking, but also their interrelationships, utilizing a full structural equation model that analyzes latent and observable variables. While some predictors did not show significance in this study, future investigations could employ a varied sampling strategy, re-examine the predictors, and analyze complex interactions among them, shedding further light on pilot risk-taking behavior. Moreover, future studies can integrate new predictors, such as personality traits within the Five-Factor Model (FFM), which may exhibit either a direct or moderating relationship with risk propensity.

Understanding the determinants of pilots' risk propensity is a pivotal stride towards improving aviation safety. Deepening the knowledge of these predictors and their dynamic interplay with risk-taking offers valuable insights for pilots, policymakers, manufacturers, and flight instructors. This knowledge provides a framework for enhanced risk management and better-informed aeronautical decision-making to ensure a promising future of safer skies for pilots and passengers alike.

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Appendix A

Permission to Conduct Research

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

Principal Investigator: Joel Samu

Other Investigators: Research Advisor Dr. Jennifer Thropp, Committee Member Dr. Scott Winter

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

Project Title: Identification and Validation of a Predicted Model based on the Risk-Taking Propensity Factors Among General Aviation Pilots

Review Board Use Only

Initial Reviewer: Teri Gabriel **Date:** 12/08/2022 **Approval #:** 23-060

Determination: Exempt

Dr. Beth Blickensderfer Elizabeth L. Blickensderfer Digitally signed by Elizabeth L. Blickensderfer Date: 2022.12.13 16:00:06 -05'00'
IRB Chair Signature:

Brief Description:

The purpose of this study is to gain a better understanding of the factors that influence risk-taking propensity among general aviation pilots to engage in risky flight behaviors. This study will be conducted using a set of five surveys of general aviation pilots who are at least 18 years of age and have a private pilot certificate but no airplane transport pilot (ATP) certificate. The survey will be administered using paper- and web-based survey formats.

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.)

EMBRY-RIDDLE
Aeronautical University

31 March 2023

Modification of Previously Approved IRB

Campus:	Daytona Beach	College:	COA
Applicant:	Joel Samu	Degree Level:	Master
ERAU ID:	2578549	ERAU Affiliation:	Student
Project Title:	Identification and Validation of a Predicted Risk-Taking Propensity Model Among General Aviation Pilots		
Principal Investigator:	Joel Samu		
Submission Date:	03/31/2023		
Beginning Date:	03/31/2023		
IRB Approval #:	23-060		
Type of Funding Support:	Partially funded by Spark Grant		

Modification of Approved IRB
APPROVAL

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

IRB Approver Signature: Teri Gabriel, IRB Director

Date of Approval: April 3, 2023

Questions

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

Other

1) Title: Identification and Validation of a Predicted Risk-Taking Propensity Model Among General Aviation Pilots
2) Participant recruitment locations include local EAAs in Central Florida (such as 1551, 1632, 812, 288, etc.), ERAU DB campus and classrooms, and Downwind Cafe.

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

Yes

Will the Informed Consent Form change?

No

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

No

Appendix B

Data Collection Device

INFORMED CONSENT

Identification and Validation of a Predicted Risk-Taking Propensity Model among General Aviation Pilots

Purpose of this Research: I am asking you to participate in a research project to explore the risk-propensity factors among general aviation pilots in the United States. You will be asked to complete a set of 5 questionnaires measuring multiple factors, including self-efficacy, locus of control, stress, experience, and socio-identity factors. The total time of your participation is estimated to be about 20 minutes.

Risks or discomforts: The risks of participating in this study are no greater than what is experienced in daily life.

Benefits: While there are no direct benefits to you in participating in this study, your inputs will help the general aviation pilot community, including training institutions, to understand how these factors may influence the risk-taking tendencies of pilots, which therefore can be used to develop intervention programs and risk-reduction strategies to improve aviation safety.

Confidentiality of records: Your individual information will be protected in all data resulting from this study. Your responses to this survey including any personally identifiable information will be kept confidential. To protect the confidentiality of your responses, data in digital form will be keyed into a password-protected file on a password-protected computer and later destroyed three months after it has been analyzed. Likewise, personally identifiable information on the paper-based surveys will be blacked out with a black ink marker once the data is transferred digitally. No one other than the researcher (myself) will have access to any of the responses. Information collected as part of this research ***will not be used*** or ***distributed*** for future research studies.

Compensation: Participants who complete the survey will be compensated $15 for their time. No compensation will be provided if the survey is terminated by the participant before completing it.

Contact: If you have any questions or want additional information about this study, please get in touch with Joel Samu, samuj@my.erau.edu, or the faculty member overseeing this project, Dr. Jennifer Thropp, throppj@erau.edu. For any concerns or questions as a participant in this research, contact the Institutional Review Board (IRB) at 386-226-7179 or email at teri.gabriel@erau.edu.

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

CONSENT. By signing below, I certify that I am a resident of the U.S. am at least 18 years old and have at least an FAA Private Pilot Certificate but not an ATP certificate, understand the information on this form, and voluntarily agree to participate in the study. A copy of this form can also be requested from Joel Samu, samuj@my.erau.edu

Signature or Initials ____

SURVEY

Part 1 of 5

Please mark the appropriate box

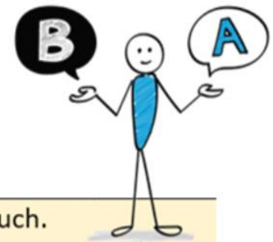
	Strongly Disagree 1	Disagree 2	Neutral 3	Agree 4	Strongly Agree 5
1. I will be able to achieve most of the goals that I have set for myself.					
2. When facing difficult tasks, I am certain that I will accomplish them.					
3. In general, I think that I can obtain outcomes that are important to me.					
4. I believe I can succeed at most any endeavor to which I set my mind.					
5. I will be able to successfully overcome many challenges.					
6. I am confident that I can perform effectively on many different tasks.					
7. Compared to other people, I can do most tasks very well.					
8. Even when things are tough, I can perform quite well.					

Part 2 of 5

Please mark the appropriate box

	Strongly Disagree 1	Disagree 2	Neutral 3	Agree 4	Strongly Agree 5
1. Taking risks makes life more fun.					
2. My friends would say that I'm a risk taker.					
3. I enjoy taking risks in most aspects of my life.					
4. I would take a risk even if it meant I might get hurt.					
5. Taking risks is an important part of my life.					
6. I commonly make risky decisions.					
7. I am a believer of taking chances.					
8. I am attracted, rather than scared, by risk.					

Part 3 of 5



For each of the 29 questions select (✓) the statement A or B that you agree with the most:

1
a. Children get into trouble because their parents punish them too much.
b. The trouble with most children nowadays is that their parents are too easy with them.

2
a. Many of the unhappy things in people's lives are partly due to bad luck.
b. People's misfortunes result from the mistakes they make.

3
a. One of the major reasons why we have wars is because people don't take enough interest in politics.
b. There will always be wars, no matter how hard people try to prevent them.

4
a. In the long run people get the respect they deserve in this world.
b. Unfortunately, an individual's worth often passes unrecognized no matter how hard he tries.

5
a. The idea that teachers are unfair to students is nonsense.
b. Most students don't realize the extent to which their grades are influenced by accidental happenings.

6
a. Without the right breaks one cannot be an effective leader.
b. Capable people who fail to become leaders have not taken advantage of their opportunities.

7
a. No matter how hard you try some people just don't like you.
b. People who can't get others to like them don't understand how to get along with others.

8
a. Heredity plays the major role in determining one's personality.
b. It is one's experiences in life which determine what they're like.

9
a. I have often found that what is going to happen will happen.
b. Trusting to fate has never turned out as well for me as making a decision to take a definite course of action.

10	a.	In the case of the well-prepared student there is rarely if ever such a thing as an unfair test.
	b.	Many times, exam questions tend to be so unrelated to course work that studying is really useless.
11	a.	Becoming a success is a matter of hard work, luck has little or nothing to do with it.
	b.	Getting a good job depends mainly on being in the right place at the right time.
12	a.	The average citizen can have an influence in government decisions.
	b.	This world is run by the few people in power, and there is not much the little guy can do about it.
13	a.	When I make plans, I am almost certain that I can make them work.
	b.	It is not always wise to plan too far ahead because many things turn out to be a matter of good or bad fortune anyhow.
14	a.	There are certain people who are just no good.
	b.	There is some good in everybody.
15	a.	In my case getting what I want has little or nothing to do with luck.
	b.	Many times, we might just as well decide what to do by flipping a coin.
16	a.	Who gets to be the boss often depends on who was lucky enough to be in the right place first.
	b.	Getting people to do the right thing depends upon ability, luck has little or nothing to do with it.
17	a.	As far as world affairs are concerned, most of us are the victims of forces we can neither understand, nor control.
	b.	By taking an active part in political and social affairs the people can control world events.
18	a.	Most people don't realize the extent to which their lives are controlled by accidental happenings.
	b.	There really is no such thing as "luck."
19	a.	One should always be willing to admit mistakes.
	b.	It is usually best to cover up one's mistakes.

20	a.	It is hard to know whether or not a person really likes you.
	b.	How many friends you have depends upon how nice a person you are.
21	a.	In the long run the bad things that happen to us are balanced by the good ones.
	b.	Most misfortunes are the result of lack of ability, ignorance, laziness, or all three.
22	a.	With enough effort we can wipe out political corruption.
	b.	It is difficult for people to have much control over the things politicians do in office.
23	a.	Sometimes I can't understand how teachers arrive at the grades they give.
	b.	There is a direct connection between how hard I study and the grades I get.
24	a.	A good leader expects people to decide for themselves what they should do.
	b.	A good leader makes it clear to everybody what their jobs are.
25	a.	Many times, I feel that I have little influence over the things that happen to me.
	b.	It is impossible for me to believe that chance or luck plays an important role in my life.
26	a.	People are lonely because they don't try to be friendly.
	b.	There's not much use in trying too hard to please people, if they like you, they like you.
27	a.	There is too much emphasis on athletics in high school.
	b.	Team sports are an excellent way to build character.
28	a.	What happens to me is my own doing.
	b.	Sometimes I feel that I don't have enough control over the direction my life is taking.
29	a.	Most of the time I can't understand why politicians behave the way they do.
	b.	In the long run the people are responsible for bad government on a national as well as on a local level.

Part 4 of 5

Please mark the appropriate box

How often have you...	Not at all 0	No more than usual 1	Rather more than usual 2	Much more than usual 3
1. lost much sleep over worry?				
2. felt constantly under strain?				
3. felt you could not overcome your difficulties?				
4. been feeling unhappy and depressed?				
5. been losing confidence in yourself?				
6. been thinking of yourself as a worthless person?				

How often have you...	Better/ more so than usual 0	Same as usual 1	Less than usual 2	Much less than usual 3
7. been able to concentrate on whatever you are doing?				
8. felt that you are playing a useful part in things?				
9. felt capable of making decisions about things?				
10.been able to enjoy your normal day-to-day activities?				
11.been able to face up to your problems?				
12.been feeling reasonably happy, all things considered?				

Part 5 of 5

1. Please tick *all* the FAA fixed-wing pilot ratings you *currently* have:

Private Pilot, Airplane:	☐ Single-Engine		☐ Multi-Engine
Instrument Rating, Airplane:	☐ Single-Engine		☐ Multi-Engine
Commercial Pilot, Airplane:	☐ Single-Engine		☐ Multi-Engine
Flight Instructor, Airplane:	☐ CFI	☐ CFI-I	☐ MEI

2. In the past 5 years, while flying GA aircraft, have you experienced any serious incidents or accidents (as a flight crew member)?

☐ None	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5+

3. In the past 5 years, while flying GA aircraft, how many times have you experienced the below (as a flight crew member?

	None	1	2	3	4	5+
a. Low fuel situation						
b. Precautionary or forced landing to an airport other than your original destination						
c. Precautionary or forced landing away from an airport						
d. Inadvertently stalled an aircraft						
e. Became so disoriented that you had to land or call ATC for assistance in determining your location						
f. Had a mechanical failure which jeopardized the safety of your flight						
g. Had an engine quit because of fuel starvation, either because you ran out of fuel or because of an improper pump or fuel tank selection						
h. Flown into areas of instrument meteorological conditions when you were not on an instrument flight plan						
i. Turned back or diverted to another airport because of bad weather while on a VFR flight						

4. Please select the type of FAA environment you have been trained/are training in:

Private Pilot Airplane:	☐ Part 61	☐ Part 141
Commercial Pilot Airplane:	☐ Part 61	☐ Part 141

5. Total flight hours:

6. Pilot-In-Command (PIC Hours):

7. What is the *highest* level of school you have **completed**?

☐ Less than high school diploma	☐ High school diploma or equivalent (e.g. GED)	
☐ Some college but no degree	☐ Associate degree	
☐ Bachelor's degree	☐ Master's degree	☐ Ph.D. or higher

8. Are you now married, widowed, divorced, separated, or never married?

☐ Married	☐ Separated	☐ Divorced	☐ Widowed	☐ Never married

9. How many children are you parent or guardian for that live in your household (aged 17 or younger only)?

☐ None	☐ 1	☐ 2	☐ 3	☐ 4	☐ 5+

10. Please select your ethnic background:

☐ White or Caucasian
☐ Black or African American
☐ Hispanic or Latino
☐ Asian or Asian American
☐ American Indian or Alaska Native
☐ Native Hawaiian or other Pacific Islander
☐ Another/Multiple race(s) – please specify: ____________________________

11. What is your gender?

☐ Male	☐ Female

12. What is your age?

Thank You for Your Responses

Appendix C

Partial Regression Plots

Partial Regression Plots for Age, Total Flight Hours, Number of Flight Ratings, Number of Hazardous Events, Self-Efficacy, Psychological Distress, and Locus Of Control