

Summer 2022

Determining Contributing Factors for Passenger Airline Pilot Perceived Fatigue

Heidi C. Kim

Embry-Riddle Aeronautical University, kleincd8@my.erau.edu

Follow this and additional works at: <https://commons.erau.edu/edt>

Scholarly Commons Citation

Kim, Heidi C., "Determining Contributing Factors for Passenger Airline Pilot Perceived Fatigue" (2022).
PhD Dissertations and Master's Theses. 681.
<https://commons.erau.edu/edt/681>

This Dissertation - Open Access is brought to you for free and open access by Scholarly Commons. It has been accepted for inclusion in PhD Dissertations and Master's Theses by an authorized administrator of Scholarly Commons. For more information, please contact commons@erau.edu.

Determining Contributing Factors for Passenger Airline Pilot Perceived Fatigue

Heidi C. Kim

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

Embry-Riddle Aeronautical University

Daytona Beach, Florida

August 2, 2022

© 2022 Heidi C. Kim

All Rights Reserved.

Determining Contributing Factors for Passenger Airline Pilot Perceived Fatigue

By

Heidi C. Kim

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

David A. Esser Digitally signed by David A. Esser
Date: 2022.09.12 11:16:12 -04'00'

David A. Esser, Ph.D.
Committee Chair

Scott Winter Digitally signed by Scott Winter
Date: 2022.09.14 08:05:11
-04'00'

Scott R. Winter, Ph.D.
Committee Member

Steven Hampton Digitally signed by Steven Hampton
Date: 2022.09.17 11:51:51 -04'00'

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

Kimberly J. Szathmary Digitally signed by Kimberly J. Szathmary
Date: 2022.09.14 11:32:25
-04'00'

Kimberly J. Szathmary, Ph.D.
Committee Member

Alan J. Stolzer Digitally signed by Alan J. Stolzer
Date: 2022.09.19 09:06:15 -04'00'

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

Lon Moeller Digitally signed by Lon Moeller
Date: 2022.09.19 10:39:14 -04'00'

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

OSTROWSKI.KRIS.A Digitally signed by
OSTROWSKI.KRIS.ANTHONY.1
255132640
Date: 2022.09.14 10:58:19 -05'00'
NTHONY.1255132640

Kris A. Ostrowski, Ph.D
Committee Member (External)

August 2, 2022

Signature Page Date

Abstract

Researcher: Heidi C. Kim

Title: Determining Contributing Factors for Passenger Airline Pilot Perceived Fatigue

Institution: Embry-Riddle Aeronautical University

Degree: Doctor of Philosophy in Aviation

Year: 2022

Fatigue is a recurring concern for pilots and continues to be a common contributing cause of aircraft accidents. The purpose of the dissertation was to determine factors that influence fatigue in commercial airline pilots. The ability to accurately associate fatigue in pilots before a flight begins could have a profound and meaningful impact on aviation safety. Seven factors were identified in the literature review as having possible predictive capabilities of perceived fatigue in pilots working for passenger carriers, including *time awake, perceived stress, sleep quality, hours of sleep, age, typically scheduled start time, and hours on duty*.

An electronic survey instrument was used to gather quantitative data from U.S. passenger-carrying airline pilots. Data collected from 271 responses were randomly assigned to two separate groups. First, a regression equation was created utilizing half of the data collected from a survey instrument. The regression identified that *age, hours on duty, and sleep quality (JSS) were significant independent variables (IVs) contributing to fatigue*. Next, the regression equation was used to create predicted values of perceived fatigue. Then the second half of the dataset was used to validate if the equation could be utilized to identify contributing factors for passenger airline pilots' perceived fatigue.

Data were created with the regression equation and compared to perceived fatigue. The model was a moderate fit for the second data set.

The analysis identified age as a negative predictor, indicating that fatigue (FSS) decreases as *age* increases. *Age* also had the smallest effect size of the significant IVs. These two items, while counterintuitive, are possibly explained by variances in schedules between pilot seniority. *Sleep Quality* (JSS) had the most significant effect on fatigue, while *hours on duty* had a larger effect than age but a smaller effect than *sleep quality*. Four variables studied were not significant predictors of fatigue and were not used in model creation: *time awake*, *perceived stress*, *hours of sleep*, and *typically scheduled start time*.

Safely operating a flight involves weighing the implications of fatigue and other possible hazards resulting in many possible predictive factors. Heinrich's domino theory was used to derive the fatigue factors in this dissertation. The significant predictor variables, *age*, *hours on duty*, and *sleep quality* form a potential "domino" for a fatigue-related accident. These fatigue factors may not cause an accident but could be a "domino" in a series of factors.

While some fatigue factors have been studied, the factors studied in this dissertation have not previously been studied in the same way by creating a model with this population. Additionally, previous fatigue studies have not typically researched U.S.-based passenger-carrying pilots. Analyzing risks associated with fatigue in passenger-carrying pilots at commercial airlines is particularly complex because many factors can influence fatigue, including scheduling software, union contracts, and norms and practices. Airlines and regulators could use the prediction equation to potentially reduce

fatigue-related risks. The equation created can predict fatigue in advance of scheduled flights and serve as a starting point for future fatigue researchers.

Keywords: aviation, commercial pilots, airline pilots, domino theory, fatigue, flight safety

Dedication

I dedicate this dissertation to my husband, Captain Alex Kim. Thank you for sticking by through the many adventures we have had while writing this dissertation. Moving from Cedar Rapids, IA, to Albuquerque, NM, to Havre De Grace, MD, to Euless, TX, was no small challenge. We also survived five job changes for me and three for you. I know that homework time was not always fun, but I am here today because of your “Just get it done already” attitude.

I took the qualification exam for this dissertation the day that you had a vertebral artery dissection while running on an overnight with Allegiant. This caused an ischemic stroke and a secondary hemorrhagic stroke. There were many days I did not think you would be around to see me finish this dissertation. I had to use my CFI skills to teach you to drive again and my human factors brain to understand the visual impairment challenges of hemianopsia. I am so proud you are back in the aviation world, teaching others to fly digital penguins.

The completion of this dissertation marks the beginning of a new and much happier adventure for us together. Together we get to teach our future aviator essential things like how important education is, why you do not throw food, how to pet the dog nicely, manners, and maybe even how to fly. Baby Niko Kim was born 6/1/2022.

Acknowledgments

This dissertation would not be complete without the support and encouragement of so many. Dr. Esser, thank you for sticking it out through this long process. Your encouragement made completion possible. Dr. Cuevas, thank you for your helpful advice on academics, human factors, and life. Dr. Winter, thank you for making my complicated statistical analysis less painful. I am also thankful for the many comments from my other committee members, Dr. Ostrowski and Dr. Szathmary. Your comments led to vast improvements in my written work. Thank you to my Cohort 6 and 7 classmates who beat me in the race to become a Ph.D. Your advice made a difference to me.

The support and encouragement of my family through the dissertation process made the most difference. Alex, thank you for the sacrifices involved in producing this document. Rudder, thank you for being my dissertation emotional support golden retriever. Finally, to my parents, thanks for always believing in me; you have your first doctor in the family.

Table of Contents

	Page
Signature Page	iii
Abstract	iv
Dedication	vii
Acknowledgments.....	viii
List of Tables	xiii
List of Figures	xiv
Chapter I: Introduction.....	1
Sleep and Fatigue Physiology.....	3
Fatigue Laws for Flight Crews	4
Statement of the Problem.....	6
Purpose Statement.....	6
Significance of the Study	7
Research Questions	8
Delimitations.....	9
Limitations and Assumptions	10
Summary.....	12
Definitions of Terms	12
List of Acronyms	17
Chapter II: Review of the Relevant Literature.....	19
Fatigue.....	21
Fatigue as an Aviation Concern.....	21
Fatigue Proofing.....	23

Fatigue Factors.....	25
Airline Fatigue Regulations	37
Fatigue Regulations: Expanded	37
Cargo Carve-Out.....	38
14 CFR 121 cf 14 CFR Part 117.....	40
Regulatory Gaps.....	45
Gaps in the Literature.....	46
Theoretical Framework.....	48
Heinrich’s Domino Theory.....	49
Research Model	57
Summary.....	58
Chapter III: Methodology	60
Research Method Selection.....	60
Population/Sample	61
Population and Sampling Frame.....	61
Sample Size.....	63
Sampling Strategy.....	63
Data Collection Process	64
Design and Procedures.....	65
Apparatus and Materials	66
Sources of the Data	67
Ethical Consideration.....	67
Measurement Instrument	68

Variables and Scales	69
Data Analysis Approach	71
Participant Demographics.....	71
Reliability Assessment Method	72
Validity Assessment Method	72
Data Analysis Process/Hypothesis Testing.....	74
Summary.....	77
Chapter IV: Results.....	78
Pilot Study.....	78
Demographics Results	79
Group 1	79
Group 2	84
Internal Consistency and Reliability.....	88
Demographics Results	89
Multiple regression Analysis	95
Stage 1.....	96
Stage 2.....	97
Summary.....	100
Chapter V: Discussion, Conclusions, and Recommendations	101
Discussion.....	101
Significant Predictor Variables.....	102
Non-Significant Predictor Variables.....	104
Conclusions.....	105

Theoretical Contributions	105
Practical Contributions.....	107
Limitations of the Findings.....	109
Recommendations.....	110
Recommendations for Professional Pilots	110
Recommendations for Future Research Methodology	112
Recommendations for Future Research	112
Summary.....	114
References.....	115
Appendix A Permission to Conduct Research.....	126
Appendix B Data Collection Device.....	128
Appendix C Subject Matter Experts	136
Appendix D Partial Regression Plots.....	139

List of Tables

Table	Page
1 Fatigue Factors Literature Support.....	58
2 Summary of Group 1 Statistics	83
3 Summary of Group 2 Demographic Statistics.....	87
4 Summary of Group 1 and Group 2 Cronbach's Alpha.....	88
5 Model Summary with Durbin-Watson Test	90
6 Summary of Correlations Between Variables	92
7 Summary of Collinearity Statistics.....	93
8 Coefficients	96
9 ANOVA Model	97
10 T-Test of Actual and Predicted Scores of Fatigue	98
11 Correlational Analysis Between Actual and Predicted Fatigue Scores.....	99

List of Figures

Figure		Page
1	Five Factors in the Accident Sequence	51
2	Aircraft Flown by Group 1 Participants	81
3	Type of Flying by Group 1 Participants	81
4	Aircraft Flown By Group 2 Participants	85
5	Aircraft Flown By Group 2 Participants	85
6	Studentized Residuals and Unstandardized Predicted Values of Fatigue	91
7	Frequency Distribution Histogram of Residuals for FSS.....	94
8	Normal Probability Plot of Standardized Residual of FS.....	95
9	Scatter Plot of Actual FSS by Predicted Value FSS	98

Chapter I: Introduction

The National Transportation Safety Board (NTSB) produces the Most Wanted List of Transportation Safety Improvements each year. Reducing fatigue-related accidents is a prominent issue in aviation safety (NTSB, 2019). The NTSB (2019) describes the severity of the fatigue problem by classifying fatigue as “a pervasive problem in transportation that degrades a person’s ability to stay awake, alert, and attentive to the demands of safely controlling a vehicle, vessel, aircraft, or train” (p. 1). Fatigue is an important focus area for the NTSB, with over 40 recommendations to reduce fatigue-related risks across several transportation modes (NTSB, 2019). Avers and Johnson (2011) described fatigue as “a multidimensional construct commonly described as sleepiness or a general tired feeling resulting from extended wakefulness, insufficient sleep, or circadian disruption” (p. 88).

Fatigue has been a recurring concern for transportation-related accidents, and it remained so throughout 2020 (NTSB, 2019). Much of the foundational fatigue research in the aviation industry was conducted between 1990 and the early 2000s. NASA fatigue-related studies (Gander et al., 1998) were conducted before establishing 14 C.F.R Part 117 (2012) rest rules. Due to the age of the NASA fatigue studies and minimal other consistent, widespread studies (Gander et al., 1998), there is substantial opportunity for additional research since 14 C.F.R Part 117 went into effect. Fatigue-related factors are absent from the FAA’s 2020 annual list of technical research topics. Increased focus on other topics such as unmanned aircraft, commercial space flight, and complex automation have instead become more dominant (FAA, 2020). While some aviation fatigue research

continues, no predictive methods were identified that could be used among the U.S. airline pilot population prior to a flight.

Estimates from the NTSB suggest that approximately 23% of major aviation-related accidents are related to fatigue as a primary cause, contributing cause, or finding identified in the accident investigation (Marcus & Rosekind, 2017). However, the actual number could be much higher due to underreporting fatigue in aviation incidents and accidents. Fatigue is not a unique concern to the aviation industry; the maritime industry, for example, has also noted fatigue effects. The maritime industry estimates that ship groundings are 23% more likely to occur in fatigued naval operators (Akhtar & Utne, 2015). Although ship groundings do not necessarily cause fatalities in the maritime industry, similar contributing factors in aviation could have fatal consequences.

A consensus group of international fatigue scientists, who primarily study human performance, safety, and accidents in transportation, identified “the major causes of fatigue are: (a) the time of day of the transport operation (e.g., night/early morning), (b) a long duration of wakefulness, (c) inadequate sleep, (d) pathological sleepiness (sleep apnea), (e) prolonged work hours (not necessarily operating a vehicle)” (Akerstedt, 2000, p. 395). Identified fatigue factors presumably would aid in predicting fatigued pilots, further improving aviation safety. While some aspects of Heinrich’s domino theory have lost relevance (Dekker, 2019), Heinrich stressed that accidents and incidents could be prevented (Heinrich et al., 1980). Utilizing fatigue factors to improve aviation-related fatigue predictability could reduce aviation accidents and incidents. The identified fatigue factors impact personnel in other modes of transportation, but there are issues unique to

aviation (Drongelen et al., 2017; Marcus & Rosekind, 2017). Problems related to operational difficulties and rest scheduling can occur in all modes of transportation.

Although fatigue is a problem across various modes of transportation, the full impact of fatigue is sometimes underreported (Caldwell, 2004; Drongelen et al., 2017). Underreporting fatigue could be exacerbated by fears of negative consequences on medical certification, income, and career advancement. Overt factors in incidents and accidents could confound the identification of fatigue as a contributing factor.

Sleep and Fatigue Physiology

Longer flights present complex issues concerning fatigue. As identified by research, flight crew members have episodes of micro-sleep during long-haul operations (Capon et al., 2003). Micro-sleep is a short burst of sleep that is only a few seconds long (Colino, 2018). Due to the frequency of micro-sleep occurrences (Capon et al., 2003), micro-sleep likely occurs on both long-haul and short-haul flights, despite short-haul flights likely transiting fewer time zones. Despite some operational differences, crews can still be subjected to continuous-duty overnight operations where the same crew conducts a late-night flight and an early-morning flight during the same period (Capon et al., 2003; Co et al., 1999; Lamp et al., 2019; Sallinen et al., 2017).

Quality Sleep is vital to several essential body functions, including cardiovascular and metabolic health, regulating emotions, brain development and activity (Drongelen et al., 2017; Mukherjee et al., 2015), and general quality of life. Medical disorders such as obstructive sleep apnea, insomnia, or other underlying health and medication concerns can harm health and wellbeing (Drongelen et al., 2017). A lack of sleep has been

attributed to psychiatric illness, depression, and mental disorders (Mukherjee et al., 2015).

The detriments of a lack of sleep have most frequently been studied by disrupting sleep and examining the consequences. These experiments have identified that sleep is critical to vigilance, alertness, and sustained attention. A 2006 (Rosekind et al.) study focused on alertness management to combat fatigue in pilots' operational settings. Of the 213 airline pilots surveyed (23% response rate), 38% indicated that fatigue was a severe problem in aviation. An additional 45% reported it was at least moderately a problem. 100% of respondents named concentration a primary problem affecting them in the operational environment. Of these respondents, 90% reported noting vigilance degradation, and 86% noticed a reduction in decision-making abilities (Rosekind et al., 2006).

Fatigue Rules for Flight Crews

Pilot fatigue has been an underlying safety concern since aviation's beginning (Rudari et al., 2014). Despite complex crew rest rules, 90% of pilots attribute scheduling factors to fatigue's most frequent cause. Recommendations for improving crew scheduling included reducing duty duration, limiting the conduct of continuous-duty overnights, increasing rest, consistency of day versus night duties, report time management, and improved reserve practices (Co et al., 1999; Drongelen et al., 2017). Flight crew alertness and fatigue levels can be negatively impacted by unpredictable pilot scheduling, excessive flight duty periods, short off-hour work periods, and inconvenient layovers (Caldwell, 2012). Dinges et al. (1999) explained that factors such as fatigue and

circadian physiology could be more beneficial if incorporated into regulatory and industry scheduling practices.

Aircraft design improvements have allowed for increased flight durations. Concern about pilot fatigue has motivated the U.S. Congress to push for regulatory changes. Substantial changes to regulations were made by creating 14 C.F.R Part 117 on January 4, 2014. The regulation changes implemented with 14 C.F.R Part 117 were the first aviation requirements designed to consider natural circadian rhythms, fatigue, and crossing various time zones (Rudari et al., 2014). Despite the new addition of 14 C.F.R 117, many gaps in addressing fatigue in commercial aviation persist. Additionally, 14 C.F.R 117.1 (2012) does not apply to cargo operations and, as a result, states the following:

- (a) This part prescribes flight and duty limitations and rest requirements for all flight crewmembers and certificate holders conducting passenger operations under part 121 of this chapter. (p. 1)

This rule only applies to passenger carriers, leaving cargo carriers exempt from the regulation (*Flight and Duty Limitations and Rest Requirements*, 2012). Title 14 C.F.R 117 creates substantial differences in scheduling practices between cargo and passenger carriers, subjecting crews to varying fatigue levels based on what the aircraft is carrying.

The remainder of 14 C.F.R 117 regulates fatigue-related actions by passenger carriers and their pilots. Each flight crewmember must report for duty rested and prepared. Flight crew members reporting for a flight who self-report as fatigued will not be assigned to flight duty (FAA, 2012). 14 C.F.R 117 prescribes the foundation of a

fatigue risk management system (FRMS). It also covers flight duty period limits, rest periods, reserve, and nighttime operations.

Statement of the Problem

Fatigue can have devastating consequences on pilot performance (Caldwell, 2004; Drongelen et al., 2017). Despite fatigue recommendations dating back to 1967 by the NTSB (Case Analysis and Reporting Online, 2021) to reduce fatigue-related accidents and incidents within aviation, fatigue remains a substantial risk to aviation safety. The aviation industry has identified fatigue as a reoccurring safety problem, leading to increased accidents, incidents, and aviation safety-related occurrences. While fatigue contributing factors have been researched across other modes of transportation, such as vehicle and ship-based research (Bal et al., 2015; Akhtar & Utne, 2014; May & Baldwin, 2009), minimal research has been conducted into exploring contributing fatigue factors in U.S. based passenger-carrying airline pilots. Connections between fatigue factors and airline pilots remain unclear due to limited research.

Purpose Statement

The primary purpose of the dissertation was to determine factors that influence fatigue in commercial airline pilots. Research has been conducted indicating that pilots do have some level of fatigue, particularly on long-haul flights (Cabon et al., 2003; Co et al., 1999; Lamp et al., 2019; Sallinen et al., 2017). However, few studies have focused on the factors leading to a fatigued flight in U.S.-based passenger-carrying pilots. Therefore, this research seeks to determine fatigue factors in commercial pilots.

Fatigue factors surveyed include stress, sleep, pilot schedules, and age. Any factor that can be identified before a flight occurs to predict fatigue could aid the pilot, airlines,

and regulators to a safe flight outcome. Based on findings, this research provides data that can improve scheduling algorithms and rest regulations.

Significance of the Study

The ability to accurately predict fatigue based on sleep and schedule in pilots before a flight could have a profound and meaningful impact on aviation safety. Findings learned from this study will potentially shape Federal Aviation Regulations (FAR), airline operations, and, most importantly, impact crew and passengers' lives. A benefit of identifying significant fatigue causal factors is using those factors to determine the association with fatigue.

Today, fatigue identification is primarily made using historic fatigue data scheduling-based tools. Previous research has been limited to physiological monitoring devices in flight to predict fatigue-like scenarios (Berberich & Leitner, 2017; Wilson et al., 2019). Identifying the fatigue factors in U.S.-based passenger-carrying pilots that can be used as causal factors of fatigue without physiological monitoring devices has not been previously studied using a regression model. The data identified in this dissertation could be used to predict fatigue more accurately prior to departure without physiological monitoring devices. Regulatory authorities, passenger airlines, and airline pilots could benefit from these findings. Unfortunately, the researcher could not identify fatigue research designed to determine if FAR Part 117 changes have been effective.

Heinrich's domino theory was used as the theoretical basis to derive fatigue factors in this dissertation. The significant predictor variables form a potential "domino" for a fatigue-related accident. Heinrich's domino theory suggests that accidents can be

mitigated by limiting or removing the dominos, or in the case of this research, causal variables.

With limited information available to regulators on the success of regulatory changes, authorities are left without adequate data to drive future changes. Data can aid those writing regulations in making data-based decisions. Fatigue Analysis, conducted as a part of an FRMS, is the process of collecting and gathering data to allow U.S.-based passenger airlines (often with agreement from pilots' unions) to modify schedule programming algorithms to reduce fatigue. Fatigue analysis described under AC 120-103A also recommends gathering the latest scientific research and conducting operation-specific human factors research (FAA, 2013). With data-based changes to regulations and airline scheduling policies, pilot fatigue levels will be reduced with information gained from this research.

Research Questions

This dissertation examined one overarching research question: What factors can be identified to predict perceived pilot fatigue in U.S. based passenger-carrying airline pilots? Fatigue factors of age, sleep, stress, and schedule are used to answer the following specific research questions:

1. Is time awake a significant predictor of perceived pilot fatigue when controlling for perceived stress, sleep quality, hours of sleep, age, typically scheduled start time, and hours on duty?
2. Is perceived stress a significant predictor of perceived pilot fatigue when controlling for time awake, sleep quality, hours of sleep, age, typically scheduled start time, and hours on duty?

3. Is sleep quality a significant predictor of perceived pilot fatigue when controlling for time awake, perceived stress, hours of sleep, age, typically scheduled start time, and hours on duty?
4. Are hours of sleep a significant predictor of perceived pilot fatigue when controlling for time awake, perceived stress, sleep quality, age, typically scheduled start time, and hours on duty?
5. Is age a significant predictor of perceived pilot fatigue when controlling for time awake, perceived stress, sleep quality, hours of sleep, typically scheduled start time, and hours on duty?
6. Are hours on duty a significant predictor of perceived pilot fatigue when controlling for time awake, perceived stress, sleep quality, hours of sleep, typically scheduled start time, and age?
7. Is typically scheduled start time a significant predictor of perceived pilot fatigue when controlling for time awake, perceived stress, sleep quality, hours of sleep, age, and hours on duty?

Delimitations

The dissertation focuses on pilot self-reportable fatigue factors that could be used as a prediction factor before a flight. For this research, physiological monitoring is not used. When used actively, physiological monitoring can only be used after a flight has already begun and would be challenging to utilize for fatigue prevention of an individual pilot. Devices such as an electrocardiogram (ECG) have been frequently used in studies to detect fatigue in pilots (Wilson et al., 2019). Invasive technology, including physiological monitoring devices, is cumbersome, expensive, and often requires batteries

or external power (Quintana & Heathers, 2014). The utilization of ECG and physiological monitoring devices could prove cost-prohibitive and cumbersome. Existing studies have not provided a non-invasive, individualized method of determining fatigue before a flight.

The impacts of COVID-19 have been problematic for the airline industry and were a potential confounding variable for the study. Some airlines have had reduced schedules, furloughs, or extended leaves. While this could skew data, an item on the questionnaire was added to limit the effects of various types of pilot leaves. Pilots on more than a one-week voluntary leave, extended leave, or furlough were discontinued from providing further input into the survey tool.

Because the dissertation involved active airline pilots with FAA medical certificates, pathological sleepiness, including illnesses or sleep disorders not approved under an FAA medical certificate, was not included. Untreated sleep disorders are potentially medically disqualifying, according to the *Guide for Aviation Medical Examiners* (FAA, 2019a). To have a more homogeneous group of participants, only U.S. Part 121 crew members were utilized within this dissertation; Part 135, cargo, and other U.S. airline crew members were not included. Finally, task-related fatigue factors were not a focus of this research because it is likely that observational research would have to be utilized instead of the methodology chosen. Participants were required to all fly for U.S.-based 121 passenger airlines so that job-related tasks are similar.

Limitations and Assumptions

This dissertation relies on accurate, honest responses to survey questions. Survey participants may hesitate to answer honestly because answers could have implications for

their company or their medical certification if misused. Participants were advised that preserving their anonymity and confidentiality was of the utmost importance. The participants were all volunteers who may withdraw from the survey with no ramifications.

Because all data were self-reported, bias is possible. Response bias is a condition that occurs during the survey process for surveys that ultimately affects the way the participant responds. For example, bias can occur due to the fear of retaliation described above. Another cause of bias is if the participant sees him or herself differently or wants to report a more satisfactory condition. The challenge with response bias is overestimating or underestimating the situation (Lavrakas, 2008). The researcher attempted to overcome challenges related to response bias by ensuring that questions were short and precise. Subject matter experts vetted the questions for clarity and ease of understanding. Additionally, a small pre-test and pilot study validated the survey instrument.

Sampling errors are a potential limitation of this dissertation. Due to the timeframe required to collect data, this dissertation relied on convenience sampling. The sampling frame was primarily located through virtual social networks frequented by airline pilots. While the survey filters out non-pilots or pilots who do not meet dissertation qualifications, it cannot be guaranteed who ultimately participated. By reviewing data collected for outliers, the effects of a participant who does not meet qualifications should be lessened.

Statistics used in this study determined factors that could contribute to pilot fatigue; however, determining causation of fatigue factors is not the purpose of the study.

The study focuses on correlation rather than causation. Determining the exact causes of fatigue requires additional analysis and multiple independent studies beyond this dissertation. Due to the time and complexity involved in determining the cause of factors, this determination is not possible within the proposed timeline. Despite being unable to determine causation, contributing fatigue factors identified are helpful for future research on predictive fatigue in U.S.-based passenger-carrying airline pilots.

Summary

Aviation accidents and incidents, pilot-reported occurrences, and operational research indicate that fatigue remains a problem (Caldwell, 2004; Drongelen et al., 2017). Additionally, the hazards of fatigue have already had devastating consequences on the safety of the air travel system. This research examined factors that could be identified in pilots to predict fatigue. Once predictive fatigue factors are determined, they can be used to create methods for determining specific fatigue risks.

Chapter II reviews fatigue and fatigue-related issues in transportation. Only U.S.-based regulations were discussed because of the variance of regulations concerning crew rest. Chapter III explains the quantitative methodology used to collect and analyze data. Chapter IV reviews the data collected and analyzed from the survey tool. Chapter V discusses findings in Chapter IV, identifies theoretical and practical contributions, and provides recommendations for the future.

Definitions of Terms

14 C.F.R 117

A section in Title 14 of the Code of Federal Regulations, Chapter 117, primarily focuses on

	flight and duty limitations and rest requirements for flight crew members.
14 C.F.R 121	A section in Title 14 of the Code of Federal Regulations, Part 121 specifies the operational requirements for the domestic, flag, and supplemental operations.
Alertness	Alertness is “the state of being awake, aware, attentive, and prepared to act or react” (American Psychological Association, 2020).
Cargo Carrier	14 C.F.R 121 Air Carrier, whose primary mission is exempt from 14 C.F.R 117.1.
Circadian Fatigue	Circadian fatigue is one of the three types of fatigue. Circadian Fatigue is “the reduced performance during nighttime hours, particularly during an individual’s ‘window of circadian low’” (WOCL) (FAA, 2012, p. 2).
Circadian Rhythm	Circadian rhythms are “physical, mental and behavioral changes that follow a daily cycle. They respond primarily to light and darkness in an organism’s environment. Sleeping at night and being awake during the day is an example of a light-related circadian rhythm” (National Institute of General Medicine Sciences, 2020, para. 1).

Cumulative Fatigue	Cumulative fatigue is one of the three types of fatigue. Cumulative Fatigue is “fatigue brought on by repeated mild sleep restriction or extended hours awake across a series of days” (FAA, 2012, p. 2).
Fatigue	According to the FAA (2012, p. 2), “fatigue is characterized by a general lack of alertness and degradation in mental and physical performance.”
Flight Crew Member	14 C.F.R 1.1 defines a flight crew member as a pilot, flight engineer, or flight navigator assigned to duty in an aircraft during flight time.
Flight Duty Period	14 C.F.R 117.3 defines a flight duty period as a period that begins when a flight crew member is required to report for duty with the intention of conducting a flight, a series of flights, or positioning or ferrying flights, and ends when the aircraft is parked after the last flight, and there is no intention for further aircraft movement by the same flight crew member. A flight duty period includes the duties performed by the flight crew member on behalf of the certificate holder that occur before a flight segment or between flight segments without a required intervening rest period. Examples of tasks that are part of the flight duty period include

deadhead transportation, training conducted in an aircraft or flight simulated, and airport/standby reserve if the above tasks occur before a flight segment or between flight segments without an intervening required rest period.

Human Factors

Human Factors is “the scientific discipline concerned with the understanding of interactions among humans and other elements of a system, and the profession that applies theory, principles, data, and methods to design to optimize human well-being and overall system performance”

(International Ergonomics Association, 2020, para. 1).

Long-haul [Flight(s)]

The definition of a long-haul flight can vary between various countries and operators. However, 14 C.F.R 117 Table A indicates the maximum flight time limits for nonaugmented operations is any flight time exceeding 8 or 9 hours, depending on report time. While it is not always the case, these flights often cross continents or large oceans, cross many time zones when traveling east to west, and are on larger wide-body aircraft. An example of a

	long-haul flight is the United States to Asia or Europe.
Network Driven Sampling	For this research, network-driven sampling is a method of data collection that uses multiple methods of social media to gather data, including “Facebook, Twitter, and LinkedIn in order to create a more representative sample” (Pettit, 2019).
Passenger Airline Pilots	For this research, passenger airline pilots are pilots who primarily fly U.S.-based passenger airlines operating under 14 C.F.R 121.
Reserve	Reserve is a period of scheduled on-call activity for a pilot designed to “cover trips that are not staffed because of a sick call, family emergencies, a weather disruption, or some other reason that the original pilot can’t complete the assignment” (Aircraft Owners and Pilots Association, 2017, para. 3).
Sleep	Sleep is “regulated by a homeostatic and circadian process. Together, these two processes determine most aspects of sleep and related variables like sleepiness and alertness” (Deboer, 2018, p. 68). In addition, sleep also substantially affects learning, memory, and cerebral changes (Maquet, 2001).

Sleep Debt	Sleep debt, applied to the flight crew, is a term used when a crew member has less than 8 hours of sleep over several days. Sleep debt is not relieved at a rate of 1:1. The amount of sleep required to make up for the deficit is less than the total amount of sleep missed. However, resolving sleep debt may require more than an 8-hour sleep opportunity (FAA, 2012).
Transient Fatigue	Transient fatigue is one of the three types of fatigue. Transient Fatigue is “acute fatigue brought on by extreme sleep restrictions or extended hours awake within 1 or 2 days” (FAA, 2012, p. 2).
Window of Circadian Low	The FAA (2012) defines the window of circadian low as typically between 2:00 a.m. and 05:59 a.m.

List of Acronyms

ALPA	Airline Pilots Association
ECG	Electrocardiogram
FAA	Federal Aviation Administration
FAR	Federal Aviation Regulation – 14 C.F.R
FDP	Flight Duty Period
FRMS	Fatigue Risk Management System
NASA	National Aeronautics and Space Administration
NDS	Network Driven Sampling

NPR Notice of Proposed Rulemaking
NTSB National Transportation Safety Board

Chapter II: Review of the Relevant Literature

“My mind clicks on and off. . . . I try letting one eyelid close at a time when I prop the other open with my will. But the effort’s too much. Sleep is winning. My whole body argues dully that nothing, nothing life can attain, is quite so desirable as sleep. My mind is losing resolution and control” (Lindbergh, 1953, p. 233). Lindbergh described the hazards of fatigue on his journeys. His flights occurred before duty limits, rest requirements, or flight scheduling software. Fatigued pilots operating airplanes in varying states of sleepiness are not a new problem.

By the 1930s, scientists understood that transitioning to multiple time zones could increase fatigue. New scientific knowledge on fatigue led to the first aircrew duty hour and flight time limitations in the Civil Aeronautics Act of 1938 (Caldwell, 2005). Few regulatory changes to pilot aircrew duty hours and flight time limitations occurred between 1938 and the addition of 14 C.F.R Part 117 in 2014.

Several recent accidents have brought attention to fatigued U.S. passenger airline pilots operating flights. For example, in February 2009, a Colgan Air DHC-8-400 regional jet crashed five miles from Buffalo Niagara International Airport (KBUF) while performing an instrument approach. The accident killed four crew members, 45 passengers, and one person on the ground (National Transportation Safety Board, 2010). Peter Garrison (2010), an American journalist, explained this flight received:

An unusual amount of media scrutiny, in part, because of what the NTSB’s report revealed about the captain’s history of failed flight checks and about the seemingly bizarre lifestyle of the first officer, who lived in Seattle, commuted

across the country for work, slept when and where she could and was paid a bit more than \$15,000 a year for her pains. (p. 1)

Although many in the aviation industry are familiar with pilots commuting long distances to work, the U.S. Public Broadcasting Service aired a documentary on pilot lifestyles that received national media attention immediately following this accident. The documentary explained pilot life in crash pads far away from their home and described long hours with low pay. A *crash pad* is a term frequently used in the airline industry, representing a rented, sometimes shared space used for rest when living in one location and working out of another. Long-distance commutes, living in hotels and crash pads, and meager pay concerned the traveling public. In addition, there was a growing public outcry about low wages, pilot fatigue, and flight training. This concern over the pilot lifestyle and fatigue ultimately translated into congressionally mandated changes to fatigue and rest rules for pilots (Caldwell, 2012; Garrison, 2010; Rudari et al., 2014; Taylor, 2014).

As a result of the Colgan crash, the NTSB identified three primary fatigue-related concerns to be addressed by Congress and the FAA. The NTSB highlighted the need for continued accident and incident investigations on human fatigue's dangers within 14 C.F.R Part 121 airline operations (NTSB, 2010). Previous work was not extensive enough or specific enough to airline operational environments. Second, the NTSB addressed the need to incorporate fatigue-related factors into company policies, scheduling practices, and crew member reporting responsibilities related to fatigue. Finally, the NTSB discussed the need for changes to federal flight and duty regulations to mitigate the dangers of fatigue in aviation. The NTSB also highlighted the need to

recognize fatigue factors in airline pilots (NTSB, 2010). The findings above indicate the continued need to investigate fatigue-related accidents and incidents.

Although not always typical, governmental changes for fatigue awareness started with a congressional mandate. The implementation of the NTSB's suggestions was the responsibility of the FAA. Congressional mandates left the FAA to decide precisely how to implement regulatory and policy changes for passenger and cargo carriers (Garrison, 2010; Taylor, 2014).

Fatigue is rarely the primary cause of an aircraft accident; however, fatigue is often a common contributing factor. For example, pilot fatigue can interact with pilot procedural deviations, increased workload, and difficulty maintaining sustained vigilance; when fatigue interacts with other factors, the overall likelihood of an incident or accident increases (Morris et al., 2018).

Due to the influence of fatigue in aviation, fatigue is the first topic covered in the literature review. Next, fatigue factors are discussed as the basis for the survey explained in this dissertation. Fatigue factors, used to predict individual variability, are thought to be the optimal method of predicting fatigue (Reifman, 2004). Thirdly, the literature review examines fatigue regulations and fatigue planning. Finally, the literature review draws attention to literature gaps and the theoretical basis for determining fatigue factors in aviation, Heinrich's domino theory, and modern explanations of Heinrich's theories.

Fatigue

Fatigue as an Aviation Concern

Approximately 20% of all NTSB investigations between 2001 and 2012 involved fatigue. In these cases, fatigue was identified as a finding, contributing factor, or probable

cause (NTSB, 2016). More than 300 U.S. aviation-related fatalities have been attributed to fatigue. These cases were attributed to a lack of sleep, circadian rhythm differences, and excessively long duty days (Avers & Johnson, 2011). In addition to the toll on human life, aircraft damage due to fatigue can cost millions of dollars, even from just a single event.

The United States Air Force Safety Center (USAFSC) mission includes developing, implementing, executing, and evaluating Air Force aviation mishap prevention, investigation, and awareness. The USAFSC estimates that 8% of Air Force Class A mishaps were a causal result of fatigue; however, estimates that include fatigue as a contributing factor are likely higher (Morris et al., 2018). A Class A accident occurs when the cost of damages to public or private property is \$2,000,000 or more, a Department of Defense aircraft is destroyed (excluding UAS), or when an injury to persons includes total permanent disability or fatality (Department of Defense, 2011). The financial limits for a Class A accident can change from year to year and are subject to change based on economic valuation. More concerning for USAF military pilots is that 25% of night tactical fighter Class A accidents between 1974 and 1992 identified fatigue as a contributing factor (Morris et al., 2018). The research suggested a notable increase in fatigue risk for night flights. Although this statistic is specific to military applications, it likely has applications in civilian flying. Fatigue findings in military pilots have largely mirrored fatigue findings in their civilian counterparts (Caldwell, 2005).

When examining human factors related to commercial airline accidents between 1978 and 1999, 20% of accidents occurred with pilots with ten or more hours of flight duty time (Goode, 2003). This resulted in pilots with 10 to 12 hours of duty time having

an accident rate 1.7 times higher [$X^2(4, n = 8) = 1.65, p = .15$] than all pilots on average [$X^2(4, N = 55) = 1.0, p = 1.0$]. Pilots with over 13 or more hours of duty time [$X^2(4, n = 3) = 5.62, p = .05$] had over 5.5 times greater likelihood of having an accident (proportionally). With an increase in flight duty time, a higher probability of an accident was also identified in human-factors-related accidents (Goode, 2003).

When Indian Air Force pilots were surveyed, 34% ($n = 28$) of participants indicated they felt sleepy in the cockpit (Taneja, 2006). Furthermore, nearly 40% ($n = 30$) of pilots surveyed believed falling into microsleep was common on the flight deck. Even more concerning, almost 25% ($n = 38$) of fighter pilots thought micro-sleep on the flight deck was common (Taneja, 2006).

Fatigue Proofing

Fatigue proofing is used in various industries and applications to reduce fatigue-related risks in roles that cannot substantially reduce working hours (Dawson et al., 2017). In aviation, fatigue proofing is primarily applicable to long-haul flights because reducing working hours is not possible on these flights in some cases (Sallinen et al., 2017). Fatigue proofing is regularly used in the U.S. military and some emergency services professions. In the military, soldiers may be provided with caffeine or other pharmaceutical alertness aids to help them stay awake on extremely long missions (Dawson et al., 2017).

Using stimulants or alertness-promoting products is a technique used to lower the risk of acute fatigue. Sallinen et al. (2017) examined Flight Duty Periods (FDP) on U.S. airline short-haul and long-haul flights researching alertness-promoting products, like coffee, tea, energy drinks, or the use of snuff and suggested alertness-promoting products

are frequently used among pilots on long-haul and short-haul flights. Alertness-promoting products were reported 98%-100% ($N = 701$) of all flights. When examining alertness-promoting products on long-haul flights, 55%-71% ($n = 383$) of pilots used alertness-promoting products while flying an outbound flight. Approximately 50%-73% of pilots used alertness-promoting products while flying a long-haul inbound flight (Sallinen et al., 2017).

Fatigue-proofing strategies include approaching tasks and problems differently by slowing down the speed at which the task is completed, rotating personnel in and out of complex tasks, delegating and splitting duties to reduce workload, cross-checking for errors using checklists, increasing verbalization and communication, and increased social interaction. Despite the apparent usefulness of these fatigue-proofing strategies, cultural pressure can still prevent accurate disclosure of perceived fatigue to peers and supervisors. Without a willingness to disclose fatigue in a timely method, the application of some of these fatigue-proofing strategies may be more challenging to use (Dawson et al., 2017).

In a fatigue survey conducted by Zaslona et al. (2018), a small group of pilots reported that “fatigue is never an issue” or that they “just live with it” (Zaslona et al., 2018, p. 9). It was not clear from Zaslona’s research if these pilots had differing routes or fatigue management strategies than their peers (Zaslona et al., 2018). Some of these reports could be attributed to pilots not fully appreciating the effects of fatigue on pilot performance by failing to identify their fatigue factors.

Fatigue Factors

Fatigue factors can be used in the process of evaluating fatigue. The European Sleep Research Society (ESRS) is a body of international non-profit sleep researchers who focus on all aspects of sleep research and sleep medicine. In 2000, the ESRS published a consensus statement on fatigue and accidents in transport operations. This consensus statement published in the *Journal of Sleep Research* forms an idea of which fatigue factors are most important in preventing fatigue. The researchers contend that fatigue compromises public and environmental safety, health, and productivity, regardless of the profession (Akerstedt, 2000). The researchers further identify the major causes of fatigue as the time of the day, a long duration of wakefulness, inadequate sleep, pathological sleepiness, and prolonged work hours.

Fatigue factors have also been extensively studied in motor vehicle operators. Methods of counteracting and predicting fatigue in drivers led to research on fatigue factors. Driver fatigue factors have been previously categorized into task-related fatigue and sleep-related fatigue. Task-related fatigue factors include low visibility, high traffic, and monotonous driving conditions. While task-related fatigue factors also influence pilots, task-related fatigue factors in pilots would likely be different. Task-related fatigue factors were not a focus of this research due to time limitations for dissertation completion. Sleep-related fatigue factors for drivers include the time of day (Circadian effects), sleep deprivation, sleep restriction, and untreated sleep disorders. Rumble strips, automated lane departure, forward collision technology, and adaptive driving tools were designed to address the dangers of fatigue. Sleep deprivation and sleep restriction can be

influenced by schedules, sleep quality, and sleep quantity (May & Baldwin, 2009). It is expected that these same sleep influencers are also applicable to pilots.

In a previous fatigue factors study involving Chinese airline pilots, pilots were asked about their subjective and overall fatigue factors (Dai et al., 2018). Sleep quality and workload were found to correlate with subjectively perceived pilot fatigue.

Significant differences between the fatigue scores of international pilots ($n_1 = 40$, $M = 3.8$, $SD = 1.2$) and domestic pilots ($n_2 = 20$, $M = 3.13$, $SD = .92$), $t(.6) = 2.204$, $p < .05$ were also noted. The effect size for the analysis ($d = .6$) was found to exceed Cohen's (1988) convention for a large effect size ($d = .8$). Chinese international pilots reported having increased fatigue compared to domestic pilots (Dai et al., 2018).

The exact breakdown of possible fatigue factors varies based on the research type and the environment. In a study of 502 airline pilots, Drongelen et al. (2017) found risk factors that could be identified in a person's work, health, sleep, and lifestyle. While several potential fatigue factors were identified, gender was found not to influence fatigue level and could not be recognized as a fatigue factor. Younger pilots 21-30 years old (OR = Ref.) were at a lower risk for developing fatigue compared to older pilots; however, differences were less pronounced among older pilots: 31-40 (OR = 3.36, 95% CI = 1.32, 8.53), 41-50 (OR = 4.19, 95% CI = 1.40, 12.47), and 51-60 (OR = 3.57, 95% CI = .91, 13.98). Long-haul pilots also noted far more fatigue than short-haul pilots: OR = .74 (95% CI = .36, 1.5) and OR = 3.36 (95% CI = 1.32, 8.53), respectively (Drongelen et al., 2017). Drongelen et al. (2017) utilized the Jenkins Sleep Scale (JSS) to measure sleep in pilots, common in the aviation industry (Drongelen et al., 2014; Drongelen et al., 2017; Reis et al., 2016).

Sleep quality, sleep duration, and work-life balance seemed to be possible fatigue factors. In addition, many other lifestyle factors were also included in this study, including the amount of physical activity, alcohol consumption, Body Mass Index (BMI), chronic disease, health, and sleep medication, all identified as risk factors for fatigue (Drongelen et al., 2017). However, because airline pilots must possess a valid first-class medical, this research did not investigate lifestyle fatigue factors. Nevertheless, some lifestyle fatigue factors still occur in pilots, including those with a current medical certificate.

Circadian Rhythm and Stress. Circadian rhythms are “physical, mental, and behavioral changes that follow a daily cycle” (National Institute of General Medical Sciences, 2020, para. 1). Circadian rhythm is impacted by light. Light sensitivity impacts crews who sleep or fly opposite their typical day or night cycles. Periodic day or night cycle disruptions are primarily responsible for acute fatigue (Dai et al., 2018). However, chronic fatigue is also possible for pilots who fly across many time zones and do so regularly for their job (Dai et al., 2018; Drongelen et al., 2017). Circadian rhythm disruptions are more common when crossing multiple time zones. Circadian rhythm disruptions are less likely to occur on North/South flights, which may stay in the same time zone or differ by a much smaller number of time zones from their starting location.

On long-haul flights, fatigue is mitigated by having extra crew members to allow sleep rotations. This strategy is primarily accepted to reduce flight crew fatigue on long-haul flights. Despite the widespread acceptance of in-flight sleep, the *sleep quality* in-flight is far more imperfect than that received on the ground (Van Den Berg et al., 2020). Pilots experience many physical and mental fatigue problems that are not experienced by

other types of shift workers. Vibration, pressure changes, low humidity levels, cabin noise, random work times, and extended flight durations can cause poor-quality sleep (Dai et al., 2018).

Airline pilots flying long-haul routes noted that the single most prominent influencer in their sleep is the timing of their rest breaks (Zaslona et al., 2018). Rest break timing impacted both the quality and quantity of crew rest inflight. Pilots who had their rest breaks at times would usually be awake and noted more difficulties sleeping (Zaslona et al., 2018). Scheduling practices for rest break timing are company and pilot-dependent and do not follow a universal pattern.

Pilots flying long-haul flights can fly a series of flights across many time zones. Gander et al. (2016) examined 39 U.S.-based B747-400 pilots flying trips from 9 to 13 days with multiple flights between the United States and Asia. Total in-flight sleep, sleepiness, and task performance were evaluated. Task performance scores identified by Gander et al. (2016) on flights later in a trip sequence improved significantly on flights from the U.S. to Japan: $F(3, 23.3) = 3.30, p < .05$. Although route variability impacted the study, Gander et al. (2016) attributed the improvements later in a trip sequence to circadian rhythm adaptation. Circadian rhythm adaptation to local time led to an increase in task performance. Some routes were more disruptive to circadian rhythm than others. Even with adjustments in circadian rhythm, this flight pattern still resulted in extreme circadian disruption to pilot sleep patterns (Gander et al., 2016).

Samel, Wegmann, and Vejvoda (1997) studied 50 U.S.-based pilots who flew routes between Europe and the United States. Pilots answered a questionnaire on stress factors and psychophysiological factors. A questionnaire on the perceived task load

during the flights was also provided. Surveys were completed by pilots one hour before the flight and at one-hour intervals throughout the flight. Overall ratings indicated that outgoing flights to the United States were less stressful than returning flights to Europe. Night flights also received a more stressful rating than day flights. Pilot *stress* can be caused by several factors, including social isolation, close confines of the flight deck, sleep difficulties, labor disagreements, company disagreements, and having extended hours away from family and friends.

Evaluating stress is important in determining pilot fatigue based on the connections noted above between fatigue, circadian rhythm, and stress. Stress has been previously measured in aviators utilizing the Perceived Stress Scale (PSS). The PSS is one of the most widely used and validated *stress* measuring methods (Hellhammer et al., 2010). Kirschner, Young, and Fanjoy (2014) also used the PSS scale on aviators to determine *stress* levels in collegiate flight programs.

Scheduling and the Impact of Circadian Factors. While flight schedules for U.S. commercial flights are typically pre-configured to allow for adequate rest, operational issues such as weather, maintenance, and air traffic control/airport delays can further complicate schedules. Pilot trips can vary in length, often lasting several days. Each day can have a different quantity and duration of hours worked, affecting time on duty. Each day can also have different overnight locations with hotels of varying quality. A complex combination of factors impacts fatigue for flight crew due to schedule and pilot workload (Caldwell, 2005).

Long-haul flights require additional care in scheduling, given duty time restrictions (Dawson et al., 2017). In addition, long shift flights often result in additional

crew member configurations to compensate for shift length. Improving flight crew schedules to reduce fatigue involves two components. Issues that must be addressed in flight scheduling include maintenance, crew bidding, and route planning. The second piece of flight scheduling that requires improvement to reduce fatigue is the actual crew scheduling. Scheduling software often has built-in logic to create schedules based on pre-defined limits. Monitoring crew scheduling for significant circadian rhythm disruptions and ensuring vital rest is essential to reducing flight crew fatigue (Drongelen et al., 2017; Yildiz et al., 2017).

Circadian rhythm disruptions can profoundly impact individual fatigue, increasing the likelihood of errors. In a study examining 24-hour patterns of skill-based errors in aviation mechanics, 915 mechanics responded ($N = 5,200$) (Hobbs et al., 2010). During a 24-hour period, the peak in total maintenance errors occurred at 2 a.m. After fitting a 24-hour fundamental and 12-hour harmonic sinusoidal curve to the skill-based and total error data, the analysis indicated that skill-based errors occurred primarily between 2:30 a.m. and 3:00 a.m. (Hobbs et al., 2010). This study included mechanics who regularly worked all shifts, suggesting that even those who typically work night shifts may not be ideally adapted to overnight work. Likely, an increase in total errors, especially skill-based errors, would also be seen during times opposite regular waking periods for flight crew members.

Three or four pilots are utilized in an additional crew member configuration to allow crew rotation and adequate rest during the flight. The exact multi-crew configuration is specific to the scheduled *start time*. Trips scheduled with flight duty periods between 13 and 19 hours require between three and four pilots; flights shorter

than 13 hours generally only require two pilots (Airline Pilots Association (ALPA), 2013). Because this duty restriction does not allow for any deviation, companies may send extra pilots to account for different operational occurrences.

In another study examining long-haul sleep on flights between the United States, Hawaii, and Japan, relief crews tended to get significantly more rest than the command crew responsible for landing the plane (Gander et al., 2016). This highlights one of the unique interactions between a pilot's scheduled flight and rest periods compared to their actual rest. Due to these flights' nature, some pilots can sleep in line with their circadian rhythm, while others do not.

Safety degradation during the night can also be seen in other forms of transportation. Stutts et al. (2003) found an association between sleep-related automobile crashes and those working a night shift, working two or more jobs, and working more than 60 hours a week. Additionally, drivers averaging less than five hours of sleep at night were five times more likely to be involved in a sleep-related crash ($n = 467$, 95% CI = 3.12, 9.88) versus a non-sleep-related crash ($n = 529$).

Finally, aging-related deterioration of biological systems influences transportation workers' performance, including similar influencers such as eyesight, perception, response to stimuli, and muscle strength (Holliday, 1995). For example, age-related degradation to the vision and other biological systems at night could influence fatigue factors. Existing U.S.-based passenger airline pilots are subject to age limits for conducting Part 121 flights.

Overnight flight duties impact airline pilots flying both short and long-haul flights. Subjective alertness was reduced during overnight flight duty periods regardless

of the flight length. In addition to scholarly research, airline pilots subjectively described possible reasons for alertness reductions as the monotony of flying, lower amounts of sleep over a given period and circadian rhythm misalignment (Sallinen et al., 2017).

Sleep Quality. Flight crews can spend many nights away from the comfort of their beds. Hotels can present widespread problems such as uncomfortable or loud climate control, noisy hallways and neighbors, and uncomfortable beds. In long-haul flights, flight crew sleeping conditions are shared and vary from designated bunk space to a business seat surrounded by passengers (Caban et al., 2003). As a result, both hotels and long-haul flights can result in crew members receiving inferior sleep quality.

To look for links between quality and quantity of sleep to sleepiness and overall safety, Lemke et al. (2016) examined sleep quality and quantity in long-haul truck drivers. Most of these drivers reported working over 11 hours a day ($n = 163$, $M = 62.7$). In addition, most of these drivers reported driving while sleepy.

Driver sleep quality is often tied to drivers reporting sleepiness while driving. Nearly 40% of drivers in this study reported never or rarely receiving good quality sleep ($N = 98$, $M = 38.2$) on their workdays. Additionally, 44% of the drivers said sleepiness affected their concentration while working ($N = 98$, $M = 38.2$) (Lemke et al., 2016).

Focus can be essential for pilots while conducting complex flight procedures.

Sleep Quantity. Most fatigue-related regulations focus primarily on sleep quantity instead of sleep quality. This is likely due to individual variability and the more limited ability of a company to control the sleep quality received by their employees. Alertness is typically one of the first abilities diminished by fatigue (Caldwell, 2005). Additionally, most scientists believe pilots should have a minimum of 8 hours of sleep

during their designated rest periods (Goode, 2003). Alternatively, scheduling practices can substantially impact the quantity of sleep. Sleep quantity has been previously associated with automobile accidents and accident risk (Lemke et al., 2016).

Kalsi et al. (2018) reviewed fatal sleepiness-related motor vehicle accidents and compared them to other fatal motor vehicle accidents in Finland. When considering sleep time, disease, blood alcohol content, drug use, body mass index, medications, age, and gender, the only significant difference in a logistic regression model between the two groups was total sleep time of fewer than 6 hours (OR = 3.81, 95% CI = 1.22, 11.85). Reduced sleep was the primary cause of fatal sleepiness-related motor vehicle accidents in Finland. U.S. pilots likely would have lower rates of drug-related sleepiness and untreated sleep apnea than those operating motor vehicles because they receive regular comprehensive medical examinations with FAA oversight. Sleep quantity was the most crucial indicator of Finish fatal sleepiness-related motor vehicle accidents (Kalsi et al., 2018) instead of other factors like disease, alcohol, drug use, BMI, age, or medications.

Measuring Fatigue. Historically, fatigue measurements have included self-reported ratings, cognitive-based tests, and physiological measurements. These fatigue measurement methods are well used in the U.S. aviation industry (Gander et al., 2015; Reis et al., 2013; Rizzo et al., 2019, Wilson et al., 2019). However, each measurement method has unique benefits.

Self-Reporting Fatigue. Pilots have been asked to self-report fatigue in previous studies during flight using survey methods. Gander et al. (2015) studied 70 Delta Air Lines pilots flying the B777 200-ER, four pilots from an unknown airline who also operated the B-777 200-ER, 41 Singapore airlines A340-500 pilots, and 52 South African

Airways A340-600 pilots regarding the impacts of fatigue in airline pilots. These pilots were asked to complete a Karolinska Sleepiness Scale (KSS). The scale assesses pilot sleepiness and alertness levels based on a scale of one to nine. The highest safety risk on the KSS is a nine, which indicates an individual is exceptionally sleepy and fighting sleep. A rating of a one on the KSS indicates the lowest safety risk because it suggests that the person was vigilant (Gander et al., 2015).

Another fatigue tool used was the Samn-Perelli Crew Status Check. The Samn-Perelli Crew Status Check uses a scale of one to seven. As with the KSS scale, a rating of one represents a vigilant and wide-awake individual. A rating of seven indicates a person is completely exhausted and unable to function effectively (Gander et al., 2015). Self-reported fatigue assessments measured through surveys have effectively estimated pilot fatigue.

The Fatigue Severity Scale (FSS) has been utilized in several fatigue evaluations in the transportation sector (Reis et al., 2013; Rizzo et al., 2019) and has been well studied outside of aviation. For example, Reis et al. (2013) utilized and validated the use of FSS in a study of Portuguese airline pilots. In this study, total fatigue was summed utilizing the FSS, and a percentage of fatigue was determined. The validation group had a total fatigue score of 86.5% ($N = 104$), while the main study group's total fatigue score was 89.3% ($N = 456$).

One issue with relying solely on self-reporting of fatigue is accuracy. A U.S. Air Force School of Aerospace Medicine fatigue survey, Crew Status Survey (CSS), noted that military pilots rarely assessed their fatigue as high risk (Bennett, 2016). CSS surveys seemed to have enough errors in completion that suggest the pilots finishing these

surveys may not have fully understood how to utilize this tool reliably. Bennett (2016) offers several reasons for these errors, including the perception of an activity required by management and a desire to be on time and not waste time on extra activities. Bennett (2016) attributed the lack of fatigue reporting using the CSS tool to errors in completing the survey, a lack of survey completeness, and different operational understanding between researchers and pilots. Educating participants on how to accurately rate their fatigue, such as within the survey tool used in this dissertation, can overcome some self-rating difficulties.

Physiological Monitoring and Cognitive Fatigue. Pilot fatigue evaluations can involve several types of physiological monitoring devices. Most of the physiological monitoring devices focus on heart-related measurements. Recent studies have included wrist or other wearable heart rate technology.

One new technique for gathering physiological measurements incorporated a photoplethysmogram (PPG) into an aviation headset. PPGs are used to detect blood volume changes utilizing pulse oximeters. Wilson et al. (2019) used 14 commercial pilots to determine if a PPG would follow a similar pattern in pilots to an electrocardiogram (ECG). ECG monitoring can be cumbersome, as it sometimes involves chest strap monitors. PPG monitoring proved helpful in measuring pilots' fatigue due to its accuracy combined with a less bulky device. When comparing ECG data to PPG data, a Pearson's Correlation was utilized (Wilson et al., 2019). This study also noted that PPG monitoring could measure workload or *stress* (Wilson et al., 2019). However, while PPG monitoring devices could be more easily incorporated into the aviation environment, they would be unable to predict pilot fatigue before a flight occurs.

Psycho-vigilance Tests (PVT)s are various cognitive tests with established, valid, and sensitive measurements (Rosekind et al., 2006). However, PVTs have not proved to be especially useful in measuring fatigue due to the widely variable results (Basner & Dinges, 2011; Ganger et al., 2016). In a study conducted by Granger et al. (2016), pilots were asked to complete subjective fatigue and sleepiness ratings and conduct a PVT. Flight legs analyzed in the study included predefined segments between East Coast USA and Japan ($n = 44$) and Japan and East Coast USA ($n = 38$). A series of ANOVAs were conducted to determine if any significant effects could be identified for the mean PVT response. When analyzing mean PVT response at top of descent (TOD), no significant effect was identified with *time awake* at TOD on the East Coast USA-Japan route: $F(1, 32.8) = .62, p = .4377$, or the Japan-East Coast USA route: $F(1, 29.7) = .79, p = .3815$. However, when analyzing the Japan-East Coast USA route, significance was identified between the mean PVT response speed at TOD and flight number in the trip sequence: $F(1, 30.8) = 7.47, p < .05$. However, this was not seen on the East Coast USA-Japan route: $F(1, 32.8) = .62, p = .4377$. While this study identified some significant effects, its variability in results between legs casts doubt on the usefulness of PVT response time in academic research.

Other Tracking Methods. Fatigue evaluations often utilize video-based recording as a method of determining fatigue. Video-based recording employs trained raters to observe fatigue levels. In a video-based recording pilot study conducted by Berberich and Leitner (2017), pilots' fatigue levels were evaluated using the Human-Factors-Consult (HFC) fatigue rating scale. This study's fatigue indicators were communication and coordination, instrument scanning, and physical signs.

It was difficult for study raters to remember specific behavior indicators of fatigue in participants during the study. The instructors, seated behind the student in the simulator, also had difficulty seeing study participants' faces to determine if they were fatigued. The researchers also noted that fatigue was masked by task-induced attention during flight phases, like takeoff and landing (Berberich & Leitner, 2017). Video-based monitoring and evaluation of fatigue regularly would be challenging to implement due to privacy concerns.

Airline Fatigue Regulations

Fatigue Regulations: Expanded

Fatigue regulations for pilots are codified in 14 C.F.R Part 121 and 14 C.F.R Part 117. The addition of 14 C.F.R Part 117 in 2014 was the first significant change to fatigue and flight time limitations in 60 years (ALPA, 2013). Combined with 14 C.F.R Part 117, AC 120-103A, released May 6, 2013, guides air carriers on the FAA's basic suggested concepts of a functioning FRMS for Aviation Safety to satisfy 14 C.F.R Part 117. This advisory circular focuses on fatigue education, fitness for duty, and implementing an FRMS for air carriers and their pilots.

Advisory Circular (AC) 120-103A describes fatigue tools, including sound fatigue education for pilots, better evaluation of individual fitness for duty before and during flight, and a robust FRMS for airlines. Fatigue tools include objective tools that use available information to provide the most accurate predictions available, accounting for individual and environmental factors that generally occur in an airline flight operation. Finally, these fatigue tools capture data with improved self-reporting data and self-monitoring for fatigue risk during and before a flight (Weiland et al., 2013).

Fatigue education and awareness training are required under 14 C.F.R Part 117 for 14 C.F.R 121 passenger operators. All employees, including flight crew members, dispatchers, scheduling, managers with oversight into those areas, and anyone with operational control, must receive fatigue education and awareness training, as described in AC 120-103A. It is essential to inform airline employees that fatigue is not a problem caused by a lack of motivation to work. Fatigue can be difficult to predict and cannot always be accurately self-reported (Caldwell, 2005). Therefore, the airline must evaluate and update its fatigue education and awareness training every two years.

Cargo Carve-Out

In early versions of 14 C.F.R Part 117, the FAA included all applicable domestic, flag, and supplemental operations within this regulation. Initially, they included all types of passenger and cargo operations in 14 C.F.R Part 117 because of the universal nature of fatigue, but upon publication, cargo operations were excluded. For example, the FAA found that, on average, people require at least 8 hours of sleep per day (Taylor, 2014), yet when 14 C.F.R Part 117 was published, U.S. cargo carriers were excluded.

FAA fatigue rules have largely left 14 C.F.R Part 135 operators unaffected. Over the last 45 years, more than 200 fatigue recommendations have been suggested for various transportation modes. Despite the attention on fatigue, many fatigue-related issues remain for pilots and transportation operators in various industries.

While FAA regulations have provided increased fatigue protections for pilots, such as 14 C.F.R Part 117, problems remain. Cargo and most business jet companies are exempt from these essential fatigue regulations. Passenger airline pilot fatigue is overwhelmingly the most frequently studied type of pilot fatigue due to several factors,

including increased encouragement by the company and academia for participation and a broader base of pilots to draw.

Since 2014 the NTSB has advocated for 14 C.F.R Part 117 to apply to cargo carriers because fatigue was a factor in many cargo-related accidents. Increased fatigue regulations for cargo carriers are made more critical with frequent overnight operations (The State of Airline Safety, 2019). In addition, the NTSB lobbied the FAA that even stronger restrictions were necessary for cargo carriers because those types of operations usually operate during the overnight hours (The State of Airline Safety, 2019).

Cargo carriers contested their inclusion in 14 C.F.R Part 117 was a new approach and treated all airlines as a “one size fits all” (Taylor, 2014, p. 415) approach rather than an approach customized to their operation. Cargo carriers argued that 14 C.F.R Part 117 fatigue and rest rules would have significant and costly effects on their companies. Many large cargo companies were quick to file comments explaining the adverse effects of 14 C.F.R Part 117 during the Notice of Proposed Rulemaking. While cargo companies mainly supported the cargo exclusion from fatigue regulations, cargo pilot unions opposed it, noting a lack of evidence to support the exemption. Pilot unions also noted that exemptions to 14 C.F.R Part 117 did not have any academic or scientific basis, as validated by the scholarly literature (CAPA, 2019).

After lobbying from cargo airlines, the FAA ultimately allowed cargo airlines to comply with flight duty and rest requirements, voluntarily excluding them from mandatory compliance to 14 C.F.R Part 117. Under a revision of 14 C.F.R Part 117, cargo carriers have no mandatory requirement to comply with any part of this regulation.

While some fatigue-related studies reviewed separated short-haul pilots from long-haul pilots, no studies separated the results of long-haul passenger airline pilots compared to long-haul cargo pilots. Crossing multiple time zones can be problematic because pilots may need to utilize various techniques such as daytime sleeping to overcome circadian rhythm disruptions. Airline pilots' unions contended that by exempting cargo carriers from this regulation, they are subject to a lower tier of safety instead of the same safety level that passenger airline carriers follow for fatigue and rest rules (CAPA, 2019).

Eight months after 14 C.F.R Part 117 was first published in 2013, the NTSB released its final report on an accident involving UPS Flight 1354. In this accident, the cargo carrier crash occurred short of a runway while performing a non-precision approach to Birmingham-Shuttlesworth International Airport (KBHM). The flight began at 0500 local time and impacted the ground approximately 45-minutes later. The NTSB identified several factors, including pilot communication errors, darkness/night operations, incomplete weather information gathered, and performance deficiencies in training for one of the pilots on board. Within the NTSB's investigation conclusions, the NTSB also identified increased fatigue levels in both the Captain and the First Officer as contributing factors to the accident (NTSB, 2014).

14 C.F.R 121 cf 14 C.F.R Part 117

Fitness for Duty. Several rules changed for air carriers under 14 C.F.R Part 117 were designed to supplement fatigue and rest regulations. One notable change emphasized fitness for duty rules, requiring pilots to acknowledge they are fit for duty before beginning their flight duty period. Each pilot must individually accept fitness for

duty; the pilot-in-command cannot do it on behalf of other flight crew members. Flight crew members who report being too fatigued to fly may not continue to operate subsequent flights (ALPA, 2013).

FRMS. As a part of 14 C.F.R 117, the FAA introduced an FRMS program to allow carriers to manage fatigue within their operation centrally. If the certificate holder gathers scientific data to show that proposed schedule changes will provide an equivalent level of safety, waivers can be approved. In addition, any airline seeking an exception to FAA rules must achieve an equivalent level of protection to the original rule and requires FAA approval (ALPA, 2013).

FRMS allows airlines to demonstrate that they can achieve an equivalent level of safety with scheduling alternatives to the rules contained in 14 C.F.R Part 117. The equivalent level of safety has sometimes been achieved through evidence testing. Evidence testing includes any objective research the airline can produce related to pilot fatigue. Fatigue monitoring devices, sleep diaries, and psychomotor vigilance tests are applied to pilots in controlled sleep conditions and the alternative proposed rest schedule. If an airline can demonstrate that an equivalent level of safety to the base condition is achieved, it is possible to seek FAA exceptions and differences to requirements defined in 14 C.F.R Part 117 (Wu et al., 2018).

By using an FRMS, airlines can make some modifications to their fatigue-related rules under the oversight of the FAA. This is based on an airline's operational needs discovered through the FRMS process. FRMS processes feature proactive and reactive fatigue reporting. Proactive reporting of fatigue encourages monitoring of fatigue-related trends in airline operations. Reactive fatigue reporting includes pilot fatigue reports and

accident/incident reports that include fatigue as a factor. Reactive reporting is essential to measuring and preventing fatigue in an airline by allowing changes to scheduling and operational rules within a company (Weiland et al., 2013).

The concepts of FRMS have been adopted in other industries, including medicine. Hospitals struggle with fatigue challenges among doctors and nurses. Difficulty filling medical positions on top of long shifts and a high number of night shifts can cause sleep deprivation and fatigue (Farquhar, 2017). Those advocating for FRMS systems in hospitals have struggled with adaptability and willingness to change scheduling practices based on FRMS alone (Farquhar, 2017).

Fatigue Modeling. Borbely's model is the first model developed for fatigue identification, which combined time of day and duration of sleep and wakefulness to assess fatigue. This model has advanced but remains the basic conceptual model for aviation and rail modes of transportation. The modern and most frequently used derivatives of Borbely's model today include the two-process model; sleep/wake fatigue predictor model; sleep activity fatigue and task effectiveness (SAFTE) model; fatigue audit inter-dyne (FAID) model; system for aircrew fatigue evaluation (SAFE) model; and the alert management program (AMP) model (Dai et al., 2018).

The most evident deficiency of the previously highlighted fatigue models is that they are not customized to the individual and assume variables for an average person (Weiland et al., 2013). Many models do not include factors specific to the airline's operational environment or pilot. Few studies have compared fatigue models against each other to determine which model is superior (Weiland et al., 2013). Fatigue models are often applied over-simplistically to prevent variability in the data produced due to

varying schedules. Weiland et al. (2013) provide for few model comparisons. Fatigue risk management indicators such as circadian rhythms, sleep quality, and subjective fatigue are these models' most crucial absent characteristics (Dai et al., 2018). Aviation needs to manage risks and mitigate their subsequent consequences.

It is essential to distinguish between the amount of fatigue experienced by a person and the fatigue-associated risk of a negative occurrence. As fatigue increases, fatigue-associated risk increases (Dai et al., 2018). Fatigue-associated risk includes accident likelihood, an accident's financial impact, and social and human cost. The study conducted by Dai et al. (2018) also noted that fatigue models are only accurate for the most average individual. Due to individual and operational factors, some individuals receive far less sleep than predicted by forecasting tools, and thus, the model may underestimate fatigue. The model can significantly underestimate the fatigue risk of these individuals due to design.

Darwent et al. (2015) examined the sleep behaviors of 347 commercial train conductors. Participants kept a sleep diary and used wrist activity monitors to calculate total sleep. This study used FAID to estimate fatigue across all shifts. FAID uses shifts and work/rest time history to generate a fatigue level score. The scores ranged from 0 to 243, but Australian rail regulations do not allow a rating higher than 90. The study ($N = 347$) found variability across a given fatigue level by roughly a factor of five when individual fatigue factors are considered (Darwent et al., 2015).

The U.S. Air Force primarily uses the Fatigue Avoidance Scheduling Tool (FAST) for mission planning and to minimize the effects on flight crew circadian rhythm (Darwent et al., 2015). The tool generates a fatigue risk assessment based on circadian

rhythm, homeostatic regulation, sleep/wake schedules, and mission location. Using this tool, flight schedules are provided based on fatigue associations. However, because of substantial individual differences, fatigue models are best used to proactively arrange schedules and improve a person's quantity of sleep but are not necessarily valuable for predicting fatigue levels (Darwent et al., 2015).

For schedules that use fatigue modeling, the only method for overcoming individual variability is individually inputting fatigue data, such as differences between actual and planned data, for each pilot. This type of fatigue prediction method has been suggested, given many military applications for fatigue modeling. With internet capabilities, it is now possible to use individual fatigue modeling for a larger group than before. Using individual fatigue data was previously thought to be too time-consuming for a massive operation like an airline due to the data entry required. A process that requires manual entry of fatigue levels that is not networked would slow a large operation (Reifman, 2004).

Flight Duty Period. Many flight-duty day-related changes were also made under 14 C.F.R Part 117. All overnight operations require at least 3 hours of rest during the flight duty period (FDP). FDP limits are based on the *start time* and the number of segments flown. Pilots must receive ten consecutive rest hours before beginning a reserve period. There are also cumulative hour maximums for FDP during any week, four weeks, or 365-day period. Title 14 C.F.R Part 117 also requires 10 hours of rest, of which 8 hours is uninterrupted sleep. Interruptions include company disturbances, like a call from crew scheduling, hotel disruptions, or a fire alarm in the middle of the night.

When comparing the above rules to 14 C.F.R Part 121 flight rules, the positive benefits of pilot fatigue reduction under 14 C.F.R 117 can be identified. Title 14 C.F.R Part 121 does not require fitness for duty, an FRMS program, or fatigue education. There are also calendar-based duty limits, but these duty limits are not as extensive as the duty limits identified by 14 C.F.R Part 117. For example, 14 C.F.R Part 121 requires 24 hours free from duty in seven days, and some fundamental limitations on-duty times daily and yearly. In addition, 14 C.F.R 121 allows rest periods to be reducible from 9 hours of sleep to 8 hours of sleep, whereas 14 C.F.R part 117 requires a rest period of at least 10 hours with 8 hours of uninterrupted rest (ALPA, 2013).

Regulatory Gaps

Scientific information about fatigue, sleep, circadian physiology, and shift work has expanded. When considering fatigue applications for 14 C.F.R Part 121 passenger airline pilots, gaps between fatigue research and fatigue regulation in the U.S. are extensive. Dinges et al. (1996) explained that a wealth of sleep knowledge is most beneficial when current regulations are incorporated into regulatory and industry scheduling practices. Despite recent attempts to incorporate fatigue research into federal aviation regulations, gaps remain in aspects of the commercial aviation industry (*Flight and Duty Limitations and Rest Requirements*, 2012). Traditionally, aviation fatigue regulations were designed with specific constraints on flight times. Flight time constraints are not sufficient to improve fatigue-related safety within the complex problem set of aviation fatigue (Yildiz et al., 2017). With the general population's increasing use and frequency of the air travel modality, the problem of pilot fatigue also increases (Caldwell, 2004; Lamp et al., 2019; Lee & Kim, 2018). Title 14 C.F.R Part 117 duty time limit

changes have made amendments to industry rules and do not apply to all 14 C.F.R Part 121 air carriers.

Gaps in the Literature

Fatigue was on the 2018-2019 Most Wanted List of Transportation Improvements in every transportation mode (NTSB, 2019); the NTSB evaluates multiple transportation methods, including train, plane, auto, marine, and pipeline. The NTSB's first fatigue aviation-related recommendations occurred in 1972 and suggested flight and duty time limitations for 14 C.F.R Part 135 operators. However, the FAA rescinded and classified this recommendation as unacceptable (Rosekind, 2013), which did not change.

National Aeronautics and Space Administration (NASA) has contributed substantially to fatigue research in aviation. In 1980, NASA-Ames Research Center at Moffett Field, CA, answered a request from Congress by hosting a symposium attended by academia, airlines, and others to determine the extent of fatigue-related aviation problems. The symposium formed the foundational springboard from which a series of studies were later conducted that continued well into the 1990s (Gander et al., 1998). Congressionally funded, comprehensive research was the first large-scale fatigue research into fatigue factors of the long-haul, regional, and corporate/executive pilots.

Other research has been conducted into fatigue in aviation, but the NASA comprehensive series of studies are dated. Despite less recent federally funded research on aviation fatigue, fatigue remains a top concern for the airspace system's safety (NTSB, 2019). Minimal research has been conducted on the improvements and changes to fatigue and rest rules since 14 C.F.R 117 in 2014; no research could be located utilizing multiple relevant journal databases examining fatigue and fatigue factors.

Existing research has helped guide regulations; however, such mandates apply industry-wide and are not specific to an individual's fatigue. Research into individual fatigue factors has primarily been conducted through various physiological monitoring methods (Wilson et al., 2019). However, studies utilizing physiological monitoring primarily focus on the fatigue factors as they occur, rather than the utilization of predictive fatigue factors conducted as a part of this research. Before the 2000s, creating a system where pilots entered their fatigue data before the flight would have been complex for a massive operation and too cumbersome before the widespread use of the internet on cell phones. With the advent of the internet and networked technologies and their mainstream utilization within general society in the late 1990s and early 2000s, individual data entry for fatigue management is a far more practical solution than previously (Bennett, 2000).

Existing research studies primarily use physiological monitoring devices as the primary method of gathering research data. However, physiological monitoring devices are impractical for a pilot to wear regularly outside of research (Wilson et al., 2019). In addition, wires linked to data-gathering devices can be cumbersome, and wearables often use batteries that may not maintain power during prolonged data collection. Some examples of physiological monitoring used in pilot fatigue studies include aviation headsets, video cameras, and heart-related sensors (Wilson et al., 2019). Other data-gathering techniques for fatigue inflight include games and activities conducted and scored throughout a flight (Sieberichs & Kluge, 2018) and video recording (Berberich & Leitner, 2017). Additionally, research using the above data collection methods does not

provide pilots the accurate guidance to identify fatigue before the flight and is instead conducted during flight.

Theoretical Framework

In aviation, the decision-making process is not a dichotomous decision. With every go/no go safety decision, each pilot must weigh all benefits and possible intended consequences. Managing and mitigating fatigue in pilots improves the global airspace system; this goal forms the theoretical framework for this study. The quest for the safe operation of transportation has its roots in the 18th and 19th centuries. To understand the vital role of fatigue factors in accident and incident prevention, it is essential to understand the historical context that led to accident and incident prevention dominoes. Each fatigue factor examined in the dissertation could act as a domino, the basis of Heinrich's domino theory. Accidents can be mitigated by limiting or removing fatigue factors, improving overall aviation safety. It is less likely that anyone's fatigue factor causes an accident but more likely with a series of events—or dominos.

Most safety theories originated in prime factor and machine work around the industrial revolution in the 18th century and the advent of modern factories in the 19th century. Early safety practices used the accident to explain the types of actions that were taken (Dekker, 2019), “An act of divine retribution demanded repentance and prayer; A chance event beyond human control created a need for insurance; An engineering failure suggested engineered solutions” (p. 2).

Fatalities in coal mining were the primary lynchpin for changes in safety. Many coal-mining jobs were extraordinarily hazardous, and growing public concern prompted attention to safety. Andrews (2010) explained:

By the twentieth century, tens of thousands of workers were dying every year on the railroads, factories, and especially in coal mines, including many boys and adolescents. For each laborer killed directly, several were maimed, and several more found their lives shortened by coal dust, lead, and other poisons. (p. 213)

Significant numbers of working-class deaths in factories and coal mines ultimately compelled regulatory bodies to regulate better and inspect working conditions to maintain safety and order, as with the FAA's role today.

In the infancy of safety science, many safety practitioners believed in the theory of *accident proneness*. This concept explained accidents by believing that some individuals were more prone to accidents due to mental status, inattention or preoccupation, or related biological causes. Despite the lack of scientific basis for these theories, they did lead to advancements and improvements in future safety theories because accident proneness was often difficult to prove (Dekker, 2019). Therefore, safety practitioners instead sought to find methods that could be established and had increased scientific merit.

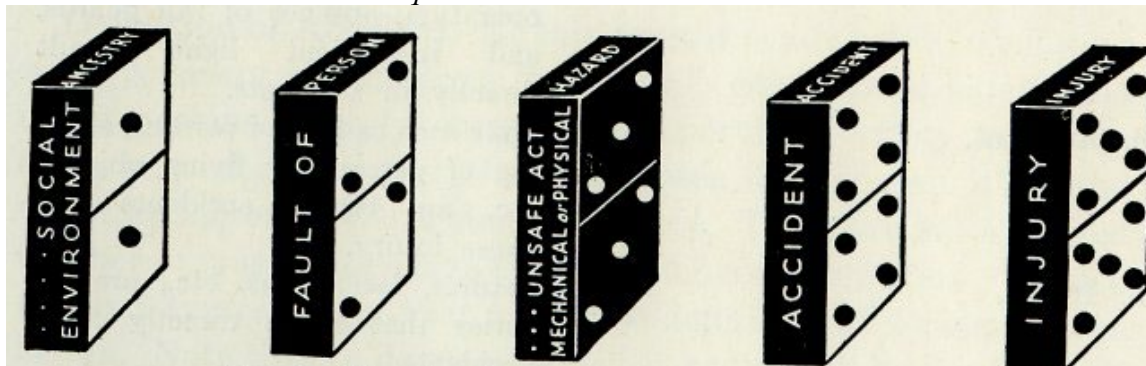
Heinrich's Domino Theory

Heinrich's domino theory, proposed by Herbert W. Heinrich, formed the basis of modern safety theory. Heinrich's domino theory was born out of methodological individualism, a concept that lacked scientific validity. However, it became the theoretical basis for aviation safety concepts, such as Reason's Swiss cheese model (Reason, 1990).

Heinrich's Domino Theory In-Detail. Heinrich's domino theory formed the basis of modern safety theory. While Heinrich did believe in the scientific validity of

accident proneness research, he re-established the idea that accidents and injuries are preventable (Heinrich et al., 1980). As a result, some of Heinrich's findings, such as accident proneness, are no longer relevant. However, due to the industry-wide application of the domino theory's founding concepts in aviation, Heinrich's domino theory is the theoretical basis for this research. Heinrich's principle is that preventable accidents and incidents are the primary reason determining fatigue factors before a flight is essential for aviation safety.

As shown in Figure 1, Heinrich's domino theory demonstrates that accidents can lead to sequential injuries. Accidents are caused when workers commit unsafe acts or direct mechanical or physical hazards in the workplace. Heinrich is often considered one of the founders of safety as a discipline because he suggested that unsafe acts and conditions can be managed. Some management methods proposed by Heinrich's domino theory should include social or organizational support such as training, improving dangerous environmental conditions, and preventing human factors-related errors (Chi & Han, 2013). Standard safety practices seek to manage and minimize safety risks to those involved.

Figure 1*Five Factors in the Accident Sequence*

Note. From “Industrial accident prevention” by H. Heinrich, D. Petersen, and N. Roos, 1980, McGraw Hill. Copyright 1980 by McGraw Hill.

A Sequence of Factors. The first concept, explained by Heinrich (1980), is:

The occurrence of an injury invariably results from a completed sequence of factors – the last one being the accident itself. The accident, in turn, is invariably caused or permitted by the unsafe act of a person and or a mechanical or physical hazard. (p. 21)

The first domino, social environment, and ancestry seem irrelevant at first glance. Heinrich, Petersen, and Roos (1980) explained this as “Recklessness, stubbornness, avariciousness, and other undesirable traits of character may be passed along through inheritance. The environment may develop undesirable traits of character or may interfere with education” (p. 22). This concept of the influence of the environment can also be explained as the concept of nature vs. nurture (Dekker, 2019).

Social environment and ancestry cover modern-day concepts such as safety culture. Conceptually, a just safety culture encourages and sometimes even rewards individuals for providing feedback that improves safety (FAA, 2015). A just safety

culture can provide sufficient incentive to change individual behavior resulting in an inherited characteristic.

The second domino, fault of the person, is described as “Inherited or acquired faults of person, such as recklessness, violent temper, nervousness, excitability, inconsiderateness, ignorance of safe practice, etc., constitute proximate reasons for committing unsafe acts or for the existence of mechanical or physical hazards” (Heinrich et al., 1980, p. 23). While some of these faults are no longer relevant today, the faults of the individual, from a sleep perspective, include sleep medical disorders. Sleep medical disorders are not addressed in this dissertation but are still very important when evaluating quality sleep amongst the general population (Mukherjee et al., 2015). Additionally, fatigue could be attributed to individual attributes such as age in some cases.

The third domino, unsafe act and/or mechanical or physical hazard, is explained as (Heinrich et al., 1980):

Unsafe performance of persons, such as standing under suspended loads, starting machinery without warning, horseplay, and removal of safeguards; and mechanical or physical hazards, such as unguarded gears, unguarded point of operation, absence of rail guards, and insufficient light, result directly in accidents. (p. 23)

Flying fatigued because of scheduling practices fits within this third domino. The research examines what factors can lead to persons' unsafe performance by searching for fatigue factors. Dekker (2019) also noted that this domino included both unsafe acts and unsafe conditions.

The fourth and fifth dominos are accident and injury. The domino chain explains the sequence of preventable injuries. The domino theory describes the injury resulting from an accident and portrays injury as the final domino in a series (Heinrich et al., 1980).

In Heinrich's domino theory, the end of the domino's chain is a failure, either human or mechanical. In modern safety research, human error is seen as more of a domino or item in a sequence that leads to an accident or incident. Using human error as a building block still uses Heinrich's basic conceptual theory that each *domino* is sequential and plays a unique role in the cause of an accident. Three primary problems existed with Heinrich's domino theory in its original form. First, human error can be separated and identified. Second, blaming human error can be primarily political. The blame is placed on the individual, not the process or the system, by blaming human error. Third, human error is not as simple as just a cause. It can play various roles in an accident (Dekker, 2019).

Heinrich's domino theory oversimplified the concept of human error. However, the domino theory's founding idea does not focus on human error being the final step of the process. Instead, Heinrich's domino theory explains that each sequential domino in an accident chain plays a role in leading up to the accident. Stopping one domino could prevent the accident.

Bird's Updated Sequence. As Heinrich's domino theory evolved, pieces with a weak scientific basis were removed. Frank Bird invented an updated version of the domino sequence after reviewing 1.7 million accidents from three hundred companies (Dekker, 2019). The updated chain has many conceptual similarities to Reason's Swiss

cheese model (Reason, 1990). However, Bird's explanation still used the concept that each step in a sequence leading up to the accident plays a role in the accident and subsequent injury. Bird's sequence, instead, involved dominoes that created a sequence that led to an accident as a lack of control (management), primary causes (origins), immediate causes (symptom), accident (contact), and injury-damage (loss) (Dekker, 2019).

Bird's sequence was primarily designed for the insurance industry but can be applied across many industries. It created a method for problem-solving widely used in incident and accident investigation. The *water line* is the line or threshold limit before the loss occurs. The damage could have been prevented by stopping the underlying causes, immediate causes, or incidents until the loss happened. Underlying causes included personal factors and job factors. Direct objectives are poor working conditions or unsafe acts or practices. In a historical context, the waterline is often applied to the image of an iceberg. Underlying causes, immediate causes, and the incident occurred below the waterline. Most preventative factors were beneath the iceberg (George & Douglas, 2007).

Reason's Swiss Cheese Model. Reason's (1990) Swiss cheese model of accident causation is frequently used in aviation to demonstrate the many latent and active failures leading to an accident. Unintended weaknesses or holes in various types of barriers ultimately increase the likelihood of an accident. In the Swiss cheese model, holes can open and close, but an accident may occur when all holes are aligned in preparation for an accident (Perneger, 2005). The Swiss cheese model explains how a cascading series of latent failures, followed by an active failure, leads to a mishap.

The Swiss cheese model has four failures: organizational influences, unsafe supervision, preconditions for dangerous acts, and unsafe acts. Nearly all accidents can be explained by one or more of these failures (Reason, 1990). Despite the frequency and widespread acceptance of the Swiss cheese model, there is some room for interpretation left by Reason. When safety professionals were surveyed about the exact meaning of the model, they disagreed, even amongst themselves, about the precise meaning of Reason's model. Perneger (2005) attributed the many variations in interpretation of Reason's Swiss cheese model to varying backgrounds and applications for its use.

Reason's Swiss cheese model was the basis for the Human Factors Analysis and Classification System (HFACS), as Wiegmann and Shappell (2003) described. The HFACS system provided a framework for aviation safety investigators to manage and identify various human performance failures. HFACS categorizes possible safety factors into four main branches: Organizational Influence, Unsafe Supervision, Preconditions for Unsafe Acts, and Unsafe Acts (Wiegmann & Shappell, 2003).

HFACS is utilized as a method of categorizing accidents. Fatigue-related accidents are further broken down into the Condition of Operators; however, fatigue is not explicitly identified. The Condition of Operators is also broken down into an adverse physiological state. Adverse physiological state includes medical or physiological conditions that can negatively impact performance, including fatigue, hypoxia, and medical illness (Wiegmann & Shappell, 2003). However, HFACS does not explicitly address fatigue as a causal factor.

HFACS is primarily used to group and sort aviation accidents. HFACS is widely used across the aviation industry by U.S. authorities such as the FAA and the NTSB.

HFACS categorization, however, is not without its limits. HFACS focuses on selecting a few specific HFACS categories. Asking those categorizing accidents to limit the number of factors chosen can potentially lead to the under-reporting of fatigue, mainly if a case involves many complex factors. Fatigue is likely the primary cause of only a few accidents and incidents but is an essential contributing factor to many accidents and incidents (Wiegmann & Shappell, 2003).

Dominos and Factors. Fatigue is just one domino in an extensive sequence of dominos leading to an aviation accident or incident. While fatigue can be looked at as individually applying to Heinrich's second and third dominoes or Bird's basic causes, the domino theory can be better utilized in a broad sense. When an accident occurs in aviation, fatigue can be just one piece in a sequence of elements leading up to an accident, but each of the fatigue factors in this present research is combined to represent fatigue as a causal category.

By examining predictive factors of fatigue, Heinrich's domino theory creates the basis necessary to prevent a domino in a very long sequence of events from falling. Identifying fatigue causal factors can help design better tools that help pilots evaluate themselves or other pilots' fatigue more effectively. As a result, increased knowledge of fatigue causal factors reduces the likelihood of fatigue acting as a falling domino. One possible domino in a sequence can be prevented by reducing fatigue—stopping the accident from happening.

Modern Safety Research. Like Heinrich's domino theory, modern safety research searches for the causes of accidents and incidents by carefully examining what occurred before the accident or incident. For example, Chi and Han (2013) reviewed

9,358 construction accidents in the United States. The study authors determined that correlations between accidents and injuries could be identified. By analyzing frequency, Chi and Han (2013) identified significant injury elements, including the type of injury, the parts of the injury, and the severity of the accident. The information gained about possible causes of accidents and incidents was used to avoid causes in Heinrich's domino theory (Chi & Han, 2013), like determining possible causes of fatigue.

Research Model

Heinrich's domino theory is used to derive the fatigue factors in this dissertation. The fatigue factors were chosen from a potential "domino" for a fatigue-related accident. The series of errors in an unsafe environment combined with unsafe behaviors have been previously identified as likely to precede occupational injury. Fatigue, lack of concentration, and annoyance have been previously identified as likely domino items in high-noise environments (Yoon et al., 2016). Yoon et al. (2016) further identified age, sleep hours, and shift hours as influential dominos in traditional high occupational noise settings. Throughout the literature review, the above analysis reviewed fatigue factors in search of the most critical ones likely to impact aviation safety. Fatigue factors identified as influential in aviation fatigue (see Table 1) include scheduling-related factors, including *time awake* (Drongelen et al., 2017; May & Baldwin, 2009; Yildiz et al., 2017), typically scheduled *start time* (Drongelen et al., 2017; May & Baldwin, 2009; Yildiz et al., 2017), *hours of sleep* and *hours on duty* (Drongelen et al., 2017; May & Baldwin, 2009; Yildiz et al., 2017), *stress* (Kirschner, Young, & Fanjoy, 2014; Samel, Wegmann, & Vejvoda, 1997), *sleep quality* (Dai et al., 2018; May & Baldwin, 2009) and *quantity of*

sleep (Kalsi et al., 2018; Lemke et al., 2016; May & Baldwin, 2009), and *age* (Holliday, 1995; Kalsai et al., 2018).

Table 1

Fatigue Factors Literature Support

Fatigue Factors	Literature Support
Time Awake	Drongelen et al., 2017; May & Baldwin, 2009; Yildiz et al., 2017
Start Time	Drongelen et al., 2017; May & Baldwin, 2009; Yildiz et al., 2017
Hours of Sleep	Drongelen et al., 2017; May & Baldwin, 2009; Yildiz et al., 2017
Hours on Duty	Drongelen et al., 2017; May & Baldwin, 2009; Yildiz et al., 2017
Stress	Kirschner et al., 2014; Samel et al., 1997
Sleep Quality	Dai et al., 2018; May & Baldwin, 2009
Sleep Quantity	Kalsi et al., 2018; Lemke et al., 2016; May & Baldwin, 2009
Age	Holliday, 1995; Kalsai et al., 2018

Summary

With a rapidly growing demand for air travel, fatigue and fatigue-related problems have also rapidly expanded (Caldwell, 2004). Along with the expansion of air travel, fatigue regulations have evolved. However, current FAA fatigue regulations only apply to passenger carriers and leave cargo airlines primarily unregulated. Despite being exempt from FAA fatigue regulations, cargo carriers conduct night flights crossing many time zones with more significant circadian rhythm disruptions, resulting in increased detrimental fatigue factors for cargo pilots.

Fatigue management is one component in the conduct of a safe flight. Each domino in the sequence may have detrimental safety consequences when combined with other dominos. The domino concept forms the theoretical base for this dissertation.

Fatigue factors, examined in the dissertation, acting as a domino and, when prevented, can improve aviation safety.

Chapter III: Methodology

This research aims to gain a deeper understanding of fatigue factors in airline pilots. The previous chapter established the academic and theoretical basis for the research methodology. This chapter describes the quantitative methodology, including the research design, population and sample, data collection process, and ethical issues. The seven potential fatigue factors; *time awake, perceived stress, sleep quality, hours of sleep, age, typically scheduled start time, and hours on duty* were identified based on the literature review and previous research (Dai et al., 2018, Drongelen et al., 2017; Holliday, 1995, Kalsi et al., 2018, Kirschner et al., 2014, Lemke et al., 2016, May & Baldwin, 2009; Samel et al., 1997, Yildiz et al., 2017).

Research Method Selection

An electronic survey instrument was used to gather non-experimental quantitative data. A survey method is a superior technique to gather data to encourage open and honest reporting of fatigue in airline pilots because it does not associate the pilot with an employer. The survey tool allows pilots to provide anonymous, open feedback. Multiple regression analysis was used to create a regression equation from survey data in Stage 1, and data analysis was conducted in Stage 2 for model validation.

Access and anonymity in the survey completion process enable collecting data to encourage accurate self-reporting. Online survey research has proved beneficial when discussing sensitive topics due to its anonymity (Cooper et al., 2001). Internet-based data gathering has also previously been shown helpful in challenging to reach groups, including those located in rural locations and of various ages (Hash & Spencer, 2009). Alessi and Martin (2010) also noted that because of the anonymity level in survey

research, research was less likely to be mentally damaging to participants than other forms of research. Finally, the research method described population/sampling, data collection, dissertation design, ethical considerations, reliability, and validity.

Population/Sample

The targeted population for this research was pilots actively flying for passenger carriers under 14 C.F.R Part 121 rules. The accessible population was 14 C.F.R Part 121 passenger airline pilots flying for U.S. carriers. This population was selected because the primary recruitment was derived from locations frequented by pilots from the United States. Foreign carriers are not included due to the wide variability in fatigue-related laws among foreign airlines. Utilizing 14 C.F.R Part 121 pilots employed by a U.S.-based carrier limited generalizability to the U.S.-based airline pilot population. However, this is by design because this study focuses on applying U.S. fatigue regulations. This study sampled active U.S. 14 C.F.R Part 121 passenger airline pilots. This study also utilizes 14 C.F.R Part 121 passenger airline pilots under 14 C.F.R 117 rest rules.

Participants were recruited via specifically chosen social media. Participants were gathered through popular social media outlets for airline pilots, such as Airline Pilot Central and Female Aviators Sticking Together (FAST). Given the importance of anonymity, no single carrier was utilized in the data collection or identified in the results.

Population and Sampling Frame

The population utilized in this dissertation is U.S.-based commercial airline pilots flying for 14 C.F.R Part 121 carriers. The population sampled seeks to find current, qualified airline pilots free of undiagnosed sleep-related illnesses to determine what fatigue factors can be utilized to assess fatigue. In order to gather pilots for the study,

social networks were utilized to attract and gain participants who fit the desired sample parameters.

Additional limits exist by utilizing a population of pilots actively flying for air carriers. Pilots flying for air carriers must hold an Airline Transport Certificate (ATP), be at least 23 years old, and be younger than 65 years old. Pilots maybe 21 years old and hold restricted ATP privileges. The FAA's 2018 *U.S. Civil Airmen Statistics* (FAA, 2019b) estimates the population of active airmen with an ATP to be 162,145. According to 14 C.F.R 121.383 (d), no certificate holder may use any person's services as a pilot on an airplane engaged in operations under Part 121 if that person has reached his or her 65th birthday. The population of ATP certificate holders between the ages of 20 and 64 is 145,147. The number of ATP certificate holders currently engaged in 14 C.F.R 121 airline activities is expected to be significantly less than 145,147 due to pilots not actively flying. These pilots may hold an ATP but do not hold an ATP in airplanes, pilots who hold an ATP but do not fly, and pilots employed in other industries such as business aviation or military operations.

The Bureau of Labor Statistics *Occupational Outlook Handbook* (2019) estimates Airline and Commercial Pilots' population in 2018 to be 124,300. This number includes employed flight engineers and those in other commercial industries such as charter flights, flight instruction, aerial tours, corporate pilots, law enforcement pilots, and agricultural pilots. For this reason, the population of airline pilots carrying passengers is expected to be smaller than the 124,300 identified by the Bureau of Labor.

Sample Size

An *a priori* sample size was determined using G*Power 3.1 to determine the acceptable sample size. Then, the effect size was used to determine the minimum effect. The G*Power 3.1 calculation was used with an effect size of .15. An effect size of .15 was selected because it created a larger sample size to determine statistical significance (Cunningham, 2007). Power (beta) is the chance of accepting a null hypothesis in error and is .8. The alpha level was .05, which requires a larger sample size.

A sample size of 103 pilots was the minimum number of participants needed, but two data sets were gathered. The first data set created a model and regression equation, and the second data set tested the model. Therefore, 206 participants were required. The researcher had a margin of error by gathering a higher sample if some data could not be used.

Sampling Strategy

Convenience sampling is a sampling strategy where the researcher invites groups of people to participate in the study accessible to the researcher (Wenzel, 2017) and is used in this research. For example, convenience sampling has been successfully used to collect airline pilot fatigue-related data (Drongelen et al., 2017; Lee & Kim, 2017).

Social networks were utilized to identify qualified U.S. pilots. Social networks allow a representative sample to be gathered in a timely manner. Social networks also provide a method for pilots to report sensitive information anonymously through the survey. U.S. pilots are listed online; however, the database often does not contain addresses and includes no faster contact methods like email or phone numbers. Social networks allow for the fast and efficient gathering of representative participants. Various

social networks were utilized for data gathering, including Facebook, Airline Pilot Central, and LinkedIn. Using multiple social network streams also maximizes data collection and creates a more representative sample, minimizing bias. Previous researchers have utilized Facebook, a tool planned for use in this dissertation, and found data gathering effective, low cost, and timely (King et al., 2014; Spence et al., 2016). Given the sensitive nature of data related to pilot fatigue, Greive, Witteveen, and Tolan (2014) noted that data collected only via online surveys were more representative, diverse, and of greater quality with greater disclosure of sensitive information. Further, when comparing paper survey data to online survey data, Greive et al. noted that internal reliability with construct relationships was similar online to paper. Social media has also been successfully utilized on aviation safety-related topics (Petitt, 2019).

The sample must be drawn from the targeted pilot population of active passenger airline pilots. To limit responses outside of the desired population of participants, advertising was targeted to those who likely fit within the study criteria. The individuals participating in the survey were U.S. airline pilots flying predominately regularly scheduled 14 C.F.R Part 121 flights under 14 C.F.R Part 117 rest rules. Survey participants only included pilots in Captain and First Officer roles, and Flight Engineers were filtered out.

Data Collection Process

Network Driven Sampling (NDS) was utilized in the data collection process. NDS uses multiple networks, including Facebook, Twitter, LinkedIn, and Airline Pilot Central, to maximize the data collected and create a more representative sample (Petitt, 2019). In this process, potential participants who appeared to fit representative demographics were

encouraged to participate. Participants are not chosen based on their relationships with the researcher (Pettit, 2019), avoiding any concerns resulting from bias from hand-chosen subjects. Additionally, the NDS method is beneficial because of the diversity of multiple data streams from various avenues. Social media networks also provide additional benefits for the conduct of research. Social media allows access to the desired population of pilots beyond what may be known to the researcher. Participants are also protected in that they must ultimately choose to continue the research process and have control over any interaction with the researcher.

Rea and Parker (2014) contend that the ultimate accuracy of a sample depends mainly on how well the sampling frame is constructed. In this case, the sampling frame specifies the location, regulation followed, and type of air carrier. Additionally, participants must be active pilots, hold a first-class medical certificate, and meet the age requirements required for 14 C.F.R Part 121 operations. Finally, Jager et al. (2017) contend that although all convenience samples have less clear generalizability than probability samples, homogeneous convenience samples have clearer generalizability relative to conventional convenience samples. Therefore, the clear sampling frame used in this dissertation aids in generalizability for the conduct of this research.

Design and Procedures

The research followed a correlational design with data gathered through an electronic survey instrument. A survey tool collected demographic, fatigue, and fatigue factor-related data from an airline pilot population. Social media popularly frequented by professional pilots were used, including Airline Pilot Central (www.airlinepilotcentral.com), Curt Lewis' Flight Safety Newsletter (www.fsinfo.com),

and Facebook sharing and alumni distribution lists were used to gather a convenience sample. Participants were asked to register via a link electronically transmitted. To ensure the sample is representative of the target population, participants were screened to determine if they work as a pilot for a U.S.-based passenger airline and hold a current medical, as required by their airline to operate aircraft.

This dissertation research asked pilots to self-report their fatigue using the Fatigue Severity Scale (FSS). Information about fatigue factors (*time awake, perceived stress, sleep quality, hours of sleep, age, hours on duty, and start time*) was gathered utilizing a survey instrument to determine which factors best predict fatigue in airline pilots. In addition to questions related to fatigue predictor factors, necessary demographic information such as type of operation, ratings, and *age* were collected. Participants were also asked if they would like to receive information about the research results.

After collecting 206 or more participants, data were randomly assigned to one of two datasets. Once the dissertation was completed, and the data were analyzed, a regression equation was created with the airline pilots' significant fatigue-related factors. The second data set was used to validate the regression equation and demonstrate a predictive equation for identifying fatigue factors in airline pilots.

Apparatus and Materials

Survey data collected were analyzed using statistical tools. SPSS version 28 (SPSS) was used to conduct the regression equations. SPSS was also used for data preparation and calculation of descriptive statistics.

The survey instrument utilized was delivered utilizing the online platform SurveyMonkey. SurveyMonkey has built-in privacy, data security, and analysis

capability. All data collected were maintained on SurveyMonkey using password protection. Data downloads to the researcher's computer were on a password-protected hard drive.

The survey instrument collected data to be used for determining fatigue association. A copy of the administered survey instrument is included in Appendix B. Response data were then exported from the SurveyMonkey tool into Microsoft Excel for processing. The Microsoft Excel data output from the survey questions was then averaged for the FSS and the PSS and summed for the JSS as a part of the designed survey scoring method for those surveys. Finally, data were randomly assigned to two even groups. Data assigned to the first group was utilized to generate the initial regression equation, while data assigned to the second was to test the regression equation.

Sources of the Data

Web and mobile-based data gathering methods have become increasingly utilized in research for social science-related topics. Data collected via specifically chosen social media allows researchers to gather large amounts of information and aids in producing qualitative techniques (Lazar et al., 2009). Web-based data gathering methods used multiple-choice questions. In addition, participants were asked quantitative questions.

Ethical Consideration

Participants received and acknowledged an informed consent form discussing the purpose of the dissertation, how long survey completion would take, the offer to withdraw for any reason at any time, any potential benefits and risks to the participant, how their privacy was protected, information on where to contact the researcher, and information about the researcher and advisor for the dissertation. Upon agreement,

participants were provided with instructions to complete the survey instrument. The collection tool's original data file was also retained by the collection tool in its original format. Participant names and employers were not collected by the survey tool. Any additional comments were anonymous and de-identified by the researcher if identifying information was included by the participant.

Embry-Riddle Aeronautical University (ERAU) maintains an Institutional Review Board (IRB) for the Protection of Human Subjects in Research. The IRB follows the Department of Health & Human Services' guidance and strives to protect the rights and welfare of participants. The researcher completed the university-established IRB education course. ERAU's policy requires all research involving human subjects to be reviewed and approved through the IRB before beginning research. Because this dissertation does involve the use of human subjects, it was submitted for vetting through the IRB. Data collection could only be carried out upon the approval of the IRB. Based on the dissertation's nature, the dissertation was classified as exempted.

Measurement Instrument

A variety of methods are available to evaluate survey questions. However, previous studies comparing methods have been limited, and results were inconsistent (Yan et al., 2012) in the methods used to evaluate survey questions. A subject matter expert panel was utilized to determine if any changes were required to the survey instrument.

The benefits of a subject matter expert panel review include finding more types and amounts of problems with survey instruments (DeMajo & Landreth, 2004; Presser & Blair, 1994; Willis et al., 1999) and cost-effectiveness of the survey design and

evaluation (Presser & Blair, 1994; Yan et al., 2012). Three experts were used to evaluate the demographics and survey questions. The experts included pilots flying primarily for 14 C.F.R Part 121 passenger carriers. The subject matter experts were asked to assess the survey instrument for clarity, directness, understanding, and context. Experts were also asked to identify any known relationships between the variables. This iterative process continued until all experts agreed on the adequacy of the survey questions.

The survey instrument was used primarily to gather predictive fatigue factors to determine possible leading indicators of fatigue. The predictors of fatigue were used to develop quantitative survey questions based on factors influencing the time of day, a long duration of wakefulness, inadequate sleep, and prolonged work hours. The time of the day was explored by asking subjects about typically scheduled *start times*. The period of wakefulness for pilots was examined by *time awake*. Inadequate sleep was examined with *perceived stress*, *sleep quality*, *hours of sleep*, and *age*. Prolonged work hours were examined with *hours on duty*.

Variables and Scales

There are seven independent variables (IV). The first variable, typically scheduled *start time*, is a nominal variable with three groups, 1700-0559, 0600-0659 and 1300-1659, and 0700-1259. These time groups mirror existing scheduled *start time* blocks used in 14 C.F.R Part 117, with 1700-0559 as the most disruptive *start times* for a sleep schedule and 0700-1259 as the least disruptive *start time* for a sleep schedule (ALPA, 2013). *Time awake* is a continuous variable in minutes.

Perceived stress was measured with the Perceived Stress Scale (PSS). The PSS originated in a 14-item format but was shortened to a 10-item form (Cohen et al., 1983).

The 10-item format, the PSS-10, was used for the dissertation. The PSS-10 asks participants to rate their *perceived stress* on a Likert scale. The scoring of the ten items is averaged, creating a continuous variable. The PSS-10 has been previously studied and determined to be reliable and valid (Kirschner et al., 2014; Roberti et al., 2006).

Participants were asked to evaluate the *sleep quality* they receive on a typical trip by completing the Jenkins Sleep Scale (JSS). The JSS was used to create a continuous variable, with higher scores indicating a lower sleep quality. JSS has been previously used in pilot-related fatigue studies (Drongelen et al., 2014; Drongelen et al., 2017; Reis et al., 2016) and allows a metric with four questions. Participant answers on the JSS questionnaire are totaled for one overall value of sleep quality.

Hours of sleep a night is a continuous variable in minutes. *Age* is a continuous variable in years. *Hours on duty* is a continuous variable in minutes.

The dependent variable (DV) was the level of perceived pilot fatigue. This continuous, observed variable was derived from the FSS. The FSS is a self-reporting questionnaire used to assess fatigue with high sensitivity, reliability, and consistency (Gawron, 2016; Segal et al., 2008). The FSS evaluates the level of perceived fatigue. Clinically significant fatigue is indicated at four or higher (Reis et al., 2016). The questionnaire had nine items, each with a 7-point Likert scale. Scores gathered from the fatigue questionnaire were averaged.

The FSS is frequently utilized in driving-related studies measuring fatigue levels. The FSS is unique because it has been previously used to evaluate fatigue levels for various situations where drivers completed a self-assessment on perceived fatigue (Rizzo

et al., 2019). In addition, the FSS is frequently used in medical-based studies and has been applied to illnesses, *age*, and other medical-related professions.

FSS is frequently known in the medical community as a patient-reported outcome measure (PROM). PROMs are used because they allow researchers to assess both the severity and impact of fatigue, as reported by the participant. Conventional statistical analysis of fatigue does not provide enough information regarding changes in fatigue levels. However, meaningful impact in fatigue changes can be more easily observed using fatigue-related PROMs such as FSS (Rooney et al., 2019).

Data Analysis Approach

A pilot study of twenty pilots was conducted to validate the survey instrument. Before processing data, data were reviewed for completeness. Any incomplete data were removed. Next, participant demographics were gathered. Finally, the process of conducting a multiple linear regression was completed.

Participant Demographics

The dissertation intended to study pilots of United States-based passenger carriers but was not designed to examine any specific operators. Demographic data included pilot experience, typical schedule, and age. Demographic questions consisted of dichotomous and nominal questions. While this group should have a common core of understanding, there is some risk that demographic and survey questions could have different meanings to different individuals. The subject matter expert panel review and re-iteration process limited this problem.

The following demographic data were gathered:

- Age

- Relative Seniority (Bottom 1/3, Middle 1/3, Top 1/3)
- Type of Carrier (Legacy, Major, Ultra Low Cost, Regional)
- Aircraft Size (Wide Body or Narrow Body)
- Type of Flying (Long-Haul or Short-Haul or Both)
- Current Aircraft Type (example: Boeing 737)
- Schedule Status (Line Holder or Reserve)
- Legs in a Typical Day
- History of Sleep Apnea or other Sleep-Related Disease (because of Yes / No)
- Valid First-Class Medical Certificate (Yes /No)

Demographic data contributed to this dissertation for two reasons. First, the data collected helped filter participants who did not meet inclusion criteria. Second, demographic data provided additional information about the background of participants, allowing for better data analysis.

Reliability Assessment Method

Hair et al. (2010) described reliability as the “Extent to which a variable or set of variables is consistent in what it is intended to measure. If multiple measurements are taken, the reliability measures will all be consistent in their values” (p. 2). Reliability refers to the extent a scale produces consistent results regardless of the number of times the dissertation is repeated. Cronbach’s alpha was calculated to evaluate internal consistency and aid in determining reliability.

Validity Assessment Method

Hair et al. (2010) described validity as:

Extent to which a measure or set of measures correctly represents the concept of study – the degree to which it is free from any systematic or nonrandom error.

Validity is concerned with how well the concept is defined by the measure(s). (p. 3)

Validity was tested to prevent type I and type II errors during the statistical process. A type I error occurs when there is no relationship between two variables, but the researcher incorrectly concludes there is. A type II error occurs if the researcher fails to reject the null hypothesis (Laerd, 2019) when it is true.

Laerd et al. (2019) described the measurement error as a measure of how a variable is accurate and consistent. If the DV has a significant measurement error, this will negatively impact data accuracy on the IVs. The researcher's approach to reducing threats to reliability related to measurement error is using summated scales per the validated instructions for each scale. In addition, the dissertation has multiple variables, reducing the risk of over-reliance on any one variable.

Hair et al. (2010) described specification errors as the “inclusion of irrelevant variables or omission of relevant variables from the set of independent variables” (p. 168). The inclusion of irrelevant variables negatively impacts the regression variate. Excluding extraneous variables can bias results and adversely affect the interpretation of the results. Any IVs determined to be unrelated need to be evaluated to determine if and why they should be excluded from calculations (Hair et al., 2010).

Both sample size and generalizability aid in the determination of external validity. Determining statistical power and sample size can impact generalizability. Hair et al. (2019) explained that, in general, a ratio of 5:1 should be the minimum number of

participants for observations. With seven observations, the absolute minimum number of participants is 35. The G*Power calculated, however, indicated that the total number of participants is much larger. Degrees of freedom indicate generalizability and were also calculated to determine the number of participants for the research design. If more participants were available, degrees of freedom were recalculated (Hair et al., 2010).

Regression models were created for the dissertation. In addition, a dual-purposed pilot study was utilized to verify the survey instrument's validity and reliability. During Stage 2 of this analysis, a *t*-test, a correlation between actual and predicted fatigue scores, and a cross-validated R^2 statistical analysis were used to confirm the validity of the created model.

Data Analysis Process/Hypothesis Testing

Multiple regression was the statistical analysis conducted. This correlational design enabled the creation of a model that could be used to reduce the impact of fatigue on the airline industry. While a multiple regression can be utilized to explore relationships, it was utilized for prediction instead. The goal is to create an equation that can predict individuals (Osborne, 2000), in this case, pilots. Multiple linear regressions have also been used to examine fatigue factors such as *age*, gender, perceived physical and mental health, sleep duration, and psychological distress (Kim et al., 2019; Tang et al., 2016). Laerd Statistics (2019) describes multiple regression as an analytical tool used to “predict the value of a variable based on the value of two or more other variables” (p. 1). The dependent variable, perceived pilot fatigue, was the value predicted by the independent variables. Descriptive statistics, including the means, standard deviations, and frequencies, were also calculated.

Multiple regression was also used to determine the overall fit of a model and the contribution of each independent variable to the total variance. The following assumptions exist for the conduct of multiple regression:

1. The DV can be measured on a continuous scale.
2. Data have two or more IVs, which can be continuous or categorical.
3. An independence of observations exists.
4. A linear relationship exists between the DV and each of the IVs.
5. Data exhibit homoscedasticity.
6. Data do not exhibit multicollinearity.
7. No significant outliers, high leverage points, or influential high points.
8. Residual errors are approximately normally distributed.

Multiple regression allows the researcher to determine the model's overall fit (variance).

Multiple regression also enables the researcher to assess the contribution of each variable.

R-squared and adjusted *R*-squared were calculated to determine model fit. *R*-squared is used to measure how well the data fit a regression line. *R*-squared is also known as the coefficient of determination. The *F*-ratio was used to test if the regression model is a good fit for the data (Hair et al., 2019). Finally, an ANOVA was used to determine the overall model's statistical significance.

The next step in the statistical process is determining the value of the variables. For each variable, the regression coefficient, the standard error of the coefficient, the *t* value of the variables, and the collinearity were gathered. The regression and standardized coefficients allow the researcher to determine the change in the dependent variable for each unit of change in the independent variables (Hair et al., 2019). Finally, a

test of the statistical significance of the independent variables was completed. A t value and relative importance were calculated (Laerd Statistics, 2019).

The next set of analyses assesses model fit for Stage 2 data collection. After data analysis for the regression was completed, the model fit was tested by conducting a t -test on the two data sets identified (predicted and actual fatigue DV scores). Again, if a strong model fit can be identified, there was no significant difference between the dependent variable's predicted and actual fatigue scores.

Next, the model fit was tested by conducting a correlation analysis between predicted and actual fatigue. If a statistically significant correlation between the two fatigue scores can be identified, it can be concluded that the model fit is good. This would indicate to the researcher that predicted fatigue scores correlate to actual fatigue scores.

The final step in data analysis is calculating and assessing the cross-validated r -squared. Where R^2 is from the initial fatigue model, n is the sample size (103 pilots), and k is the degrees of freedom, the cross-validated R -squared utilizes Equation 1.

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

A large difference between the two dependent variables, overfitting, can be prevented by performing a cross-validated R -squared. Underfitting a model that does not match the underlying population can also be prevented. Given the same study, a well-fitting model increases the likelihood that the sample can apply to other populations.

Summary

Predictive fatigue factors were evaluated for seven potential factors in 14 C.F.R. 121 passenger airline pilots. The seven potential factors were *time awake*, *perceived stress*, *sleep quality*, *hours of sleep*, *age*, *typically scheduled start time*, and *hours on duty*. Each factor had a pre-determined scale based on research or generally accepted measurements. Demographic data were also gathered to screen participants and supplement survey data.

The dissertation used quantitative applications to a data-gathering survey instrument as the primary research method. A multiple regression analysis was conducted with the data. A model and regression equation was created, and the process was repeated to confirm the model's accuracy and reliability. Descriptive statistics were also gathered to supplement the multiple regression analysis conducted.

Chapter IV: Results

Chapter IV includes the data and statistical analysis on airline pilot fatigue factors discovered during the research. First, the pilot study is discussed. Data were collected and then randomly divided into two groups for use during each stage of the two-stage process. Next, the demographic results are presented. The researcher then created a model used to generate a regression equation. The equation was used to determine which factors were associated with fatigue in airline pilots. The second group of data was then utilized to determine if the equation created during the first stage could be used to predict the data in the second stage.

Pilot Study

A pilot study of 41 potential survey respondents was conducted from August through September 2021. The goal of the pilot study was dual-purposed in that it validated the reliability and validity of the survey instrument. Secondarily, because no survey data changes were made, data could be included in the primary analysis. The survey was administered to a sample of the population for the dissertation study and gathered via NDS discussed in Chapter III.

Expert opinions vary concerning the minimum number of participants statistically necessary within a pilot study. The predetermined sample size is 103 participants ($n = 103$). While the exact number of the final study sample varies based on the number of participants, a recommended pilot study size is approximately 30 to 100 pilot participants (Courtenay, 1978 as cited in Ruel, Wagner, & Gillespie, 2016). Hertzog (2008) instead suggested that samples ranged from 10 to 40 but generally utilized 10% of the entire study as a goal.

Ultimately, the pilot study size of 41 responses was selected because it met the predetermined study minimum of 20 responses for the pilot study. This indicates that of the 41 responses, 48.78% of responses were valid. No major structural changes were made to the survey due to feedback received in the pilot study. However, minor clarification was added to demographics questions concerning types of leave and type of carrier.

As a result of the COVID-19 pandemic occurring simultaneously with the study's data collection, some pilots were going through substantially longer training due to being assigned to an unfamiliar aircraft and were not actively flying. Additionally, a minor clarification was added to the previously validated survey questions informing subjects that Alaska Airlines was intentionally not categorized as a legacy carrier within this survey; the route structure and flying more closely align with a major carrier. Collectively, these clarifications were not expected to impact the previous validation of the questions.

Demographics Results

Because of the chosen regression process, two separate data groups must be examined. The first data group created the regression equation of fatigue factors in airline pilots. The second data group was used to validate the first group's regression equation created by the first group. The total sample size was $N = 273$; demographic information is presented for both groups in the Group 1 section.

Group 1

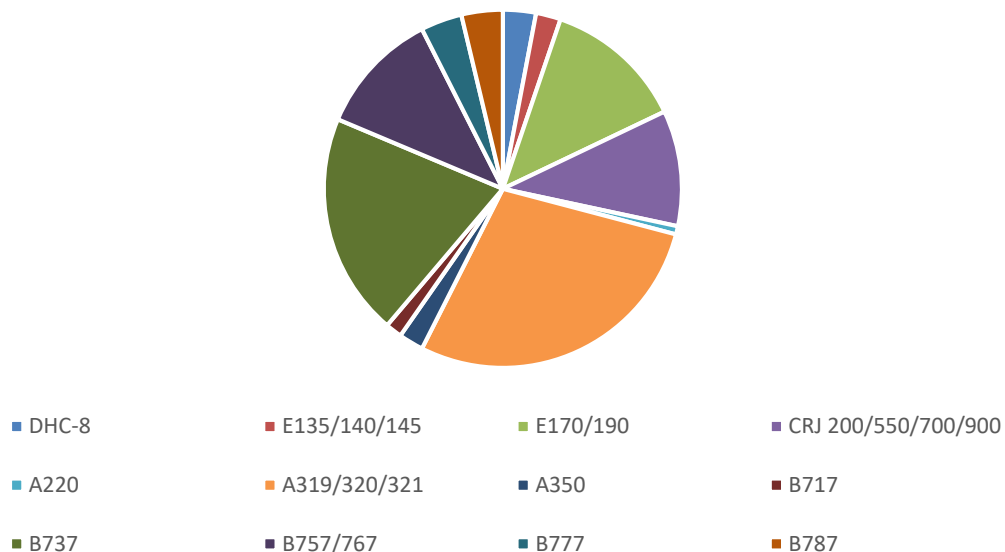
In the first group, the sample size was $n = 136$. Of the 136 participants, 16.18% ($n = 22$) were female. The mean age of the sample was 42.07 ($D = 11.491$). Reported

ethnicity was broken down into the following groups: 89.71% White/Caucasian ($n = 122$), 4.41% Hispanic ($n = 6$), 1.47% Asian/Pacific Islander ($n = 2$), 2.21% Black or African American ($n = 3$), 0% American Indian or Alaskan Native ($n = 0$), 2.21% Multiple Ethnicities ($n = 3$). The mean total flight time listed by participants was 9930.84 ($SD = 6555.43$). Participants' mean 121 total flight time was 7960.68 ($SD = 6311.94$).

Reported type of aircraft were: 79.41% Narrow-Body Passenger ($n = 108$), 15.44% Wide-Body Passenger ($n = 21$), and 5.15% Both Wide and Narrow ($n = 7$). Type of trips listed by participants was: 75.74% Short Haul Flights ($n = 103$), 11.03% Long Haul Flights ($n = 15$), 13.24% Both Long Haul and Short Haul Flights ($n = 18$). There were 86.76% of the pilots who reported flying primarily two crew flights ($n = 118$). Aircraft flown listed by participants was 2.94% DHC-8 ($n = 4$), 2.21% E135/140/145 ($n = 3$), 12.5% E170/190 ($n = 17$), 10.29% CRJ 200/550/700/900 ($n = 14$), 0.74% A220 ($n = 1$), 27.94% A319/320/321 ($n = 38$), 2.21% A350 ($n = 3$), 1.47% B717 ($n = 2$), 19.85% B737 ($n = 27$), 11.03% B757/767 ($n = 15$), 3.68% B777 ($n = 5$), and 3.68% B787 ($n = 5$).

Figure 2

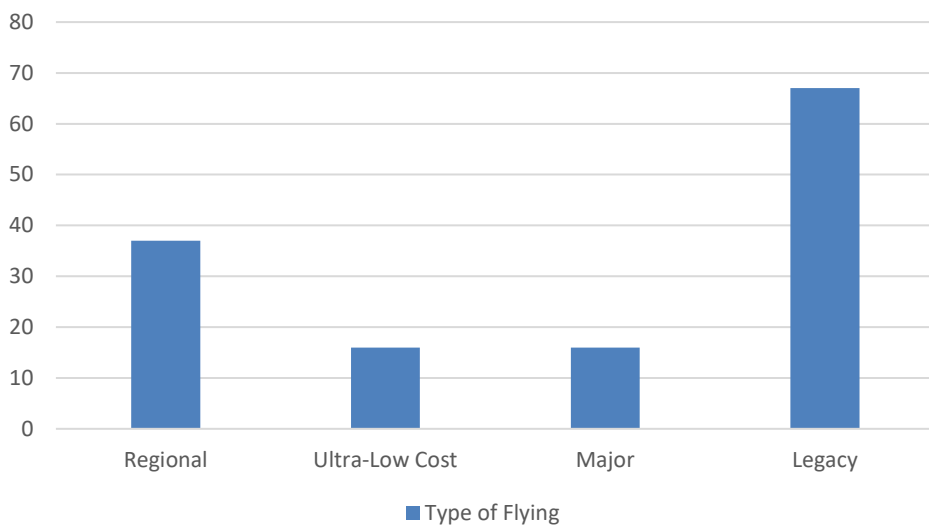
Aircraft Flown by Group 1 Participants



The type of flying listed by participants was 27.21% Regional ($n = 37$), 11.76% Ultra-Low Cost ($n = 16$), 11.76% Major ($n = 16$), and 49.26% Legacy ($n = 67$).

Figure 3

Type of Flying by Group 1 Participants



Among the participants, 20.59% were reserve holders ($n = 28$), 70.59% were line holders ($n = 96$), and 8.82% were both line and reserve holders ($n = 12$). Participants reported a mean of 2.46 legs flown in a typical day ($SD = 1.02$) and a mean of 6.47 hours in the air per day ($SD = 2.83$). A summary of group 1 descriptive statistics is provided in Table 2.

Descriptive statistics were conducted on group 1 predictive fatigue factors. The mean score on the FSS was 3.76 ($SD = 1.14$). The mean number of hours on duty reported was 10.99 ($SD = 3.46$). The mean scheduled start time was aligned with 06:00-06:59 or 13:00-16:59 and accounted for 44.12% ($n = 60$). The mean hours awake before start was 4.17 ($SD = 3.57$). The mean hours of sleep on a typical night during a trip was 7.31 ($SD = 1.78$). The mean JSS score was 6.63 ($SD = 3.38$). The mean PSS score was 1.94 ($SD = 0.30$).

Table 2*Summary of Group 1 Statistics*

Variable		<i>n</i> (%)	<i>M</i>	<i>SD</i>
Age		136	42.07	11.49
Total Flight Time		136	9930.84	6555.43
121 Total Flight Time		136	7960.68	6311.94
Number of Legs Flown in a Day		136	2.46	1.02
Number of Hours in the Air Per Day		136	6.47	2.83
Fatigue Severity Scale		136	3.76	1.14
Hours on Duty		136	10.99	3.46
Hours Awake Before Start		136	4.17	3.57
Hours of Sleep		136	7.31	1.78
Jenkins Sleep Scale		136	6.63	3.38
Perceived Stress Scale		136	1.94	0.30
Gender	Male	114 (83.82)		
	Female	22 (16.18)		
Ethnicity	White	122 (89.71)		
	Hispanic	6 (4.41)		
	Asian/Pacific Islander	2 (1.47)		
	Black/African American	3 (2.21)		
	American Indian or Alaskan Native	0 (0)		
	Multiple	3 (2.21)		
Type of Aircraft	Narrow-Body	108 (79.41)		
	Wide-Body	21 (15.44)		
	Both Wide and Narrow	7 (5.15)		
Type of Trips	Short Haul	103 (75.74)		
	Long Haul	15 (11.03)		
	Both Short Haul and Long Haul	18 (13.24)		
Primarily Crew of 2	Yes	118 (86.76)		
Plane Flown	DHC-8	4 (2.94)		
	E135/140/145	3 (2.21)		
	E170/190	17 (12.5)		
	CRJ 200/550/700/900	14 (10.29)		
	A220	1 (0.74)		
	A319/320/321	38 (27.94)		
	A350	3 (2.21)		
	B717	2 (1.47)		
	B737	27 (19.85)		
	B757/767	15 (11.03)		
	B777	5 (3.68)		
	B787	5 (3.68)		
Type of Flying	Regional	37 (27.21)		
	Ultra Low-Cost	16 (11.76)		
	Major	16 (11.76)		
	Legacy	67 (49.26)		
Type of Schedule	Reserve Holder	28 (20.59)		
	Line Holder	96 (70.59)		
	Both Reserve and Line Holder	12 (8.82)		
Typical Scheduled Start Time	0700-1259	46 (33.82)		
	0600-0659 or 1300-1659	60 (44.12)		
	1700-0559	30 (22.06)		

Group 2

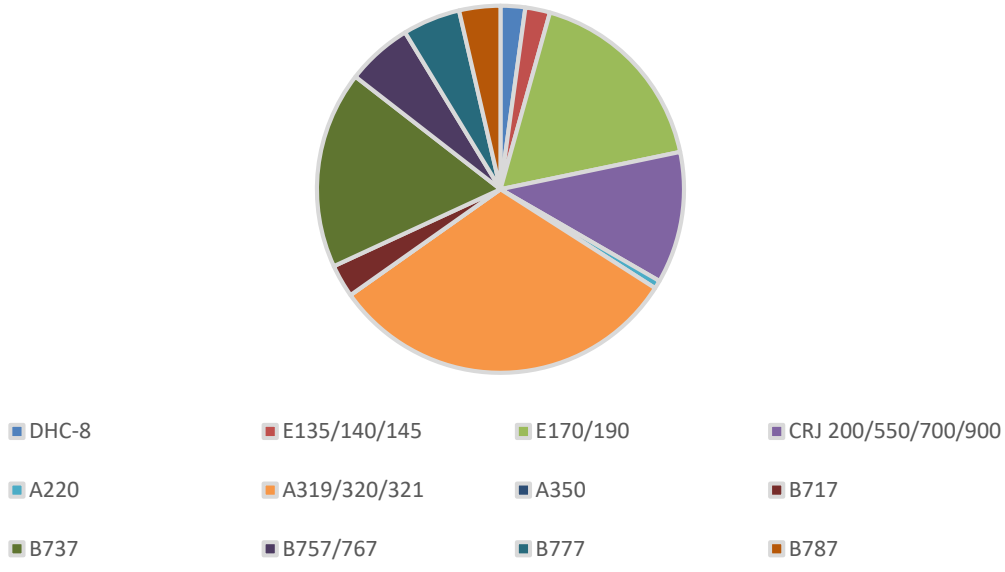
In the second group, the sample size was $n = 135$. Of the 135 participants, 16.30% were ($n = 22$) were female. The mean age of the sample was 41.43 ($SD = 10.31$).

Reported ethnicity was broken down into the following groups: 86.67% White/Caucasian ($n = 117$), 2.96% Hispanic ($n = 4$), 5.93% Asian/Pacific Islander ($n = 8$), 1.48% Black or African American ($n = 2$), 0.74% American Indian or Alaskan Native ($n = 1$), 2.22% Multiple Ethnicities ($n = 3$). The mean total flight time listed by participants was 9021.26 ($SD = 6203.90$). Participants' mean 121 total flight time was 6733.48 ($SD = 5810.77$).

Reported type of aircraft were: 87.41% Narrow-Body Passenger ($n = 118$), 9.23% Wide-Body Passenger ($n = 13$), and 2.22% Both Wide and Narrow ($n = 3$). Type of trips listed by participants was: 85.19% Short Haul Flights ($n = 115$), 8.15% Long Haul Flights ($n = 11$), 6.67% Both Long Haul and Short Haul Flights ($n = 9$). There were 88.89% of the pilots reported flying primarily two crew flights ($n = 120$). Aircraft flown listed by participants was 2.22% DHC-8 ($n = 3$), 2.22% E135/140/145 ($n = 3$), 17.78% E170/190 ($n = 24$), 11.85% CRJ 200/550/700/900 ($n = 16$), 0.74% A220 ($n = 1$), 31.85% A319/320/321 ($n = 43$), 0% A350 ($n = 0$), 2.96% B717 ($n = 4$), 17.78% B737 ($n = 24$), 5.93% B757/767 ($n = 8$), 5.19% B777 ($n = 7$), and 5.19% B787 ($n = 7$).

Figure 4

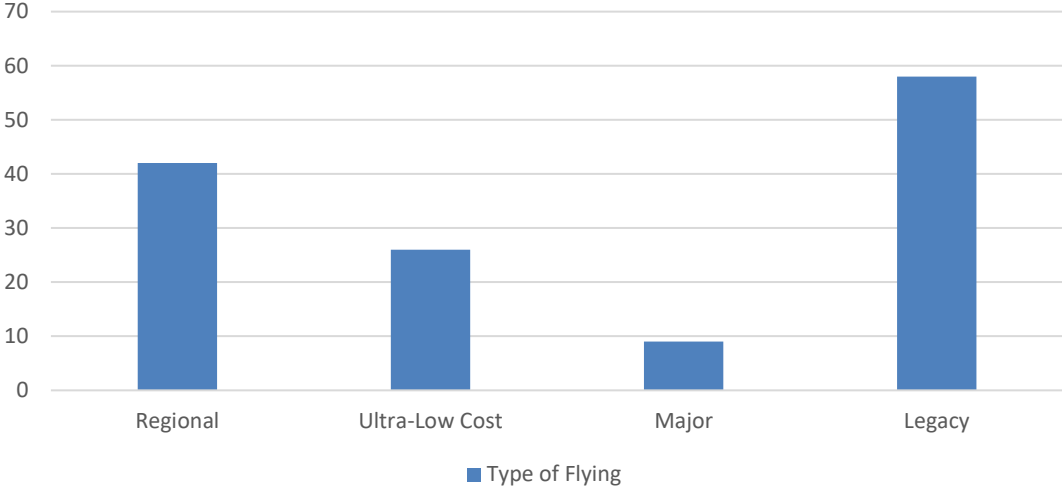
Aircraft Flown By Group 2 Participants



Note. Type of flying listed by participants was 31.11% Regional ($n = 42$), 19.26% Ultra-Low Cost ($n = 26$), 6.67% Major ($n = 9$), and 42.96% Legacy ($n = 58$).

Figure 5

Aircraft Flown By Group 2 Participants



Among the participants, 24.45% were reserve holders ($n = 33$), 66.67% were line holders ($n = 90$), and 8.89% were both line and reserve holders ($n = 12$). Participants reported a mean of 2.70 legs flown in a typical day ($SD = 1.25$) and a mean of 6.27 hours in the air per day ($SD = 2.84$). A summary of group 2 descriptive statistics is provided in Table 3.

Table 3*Summary of Group 2 Demographic Statistics*

Variable		<i>n</i> (%)	<i>M</i>	<i>SD</i>
Age		135	41.43	10.31
Total Flight Time		135	9021.26	6203.90
121 Total Flight Time		135	6733.48	5810.77
Number of Legs Flown in a Day		135	2.70	1.25
Number of Hours in the Air Per Day		135	6.27	2.84
FSS		135	3.85	1.12
Hours on Duty		135	10.58	2.15
Hours Awake Before Start		135	3.70	2.52
Hours of Sleep		135	7.18	1.42
JSS		135	6.67	3.259
PSS		135	1.95	0.30
Gender	Male	113 (83.70)		
	Female	22 (16.30)		
Ethnicity	White	117 (86.67)		
	Hispanic	4 (2.96)		
	Asian/Pacific Islander	8 (5.93)		
	Black or African American	2 (1.48)		
	American Indian or Alaskan Native	1 (0.74)		
	Multiple	3 (2.22)		
Type of Aircraft	Narrow-Body	118 (87.41)		
	Wide-Body	13 (9.23)		
	Both Wide and Narrow	3 (2.22)		
Type of Trips	Short Haul	115 (85.19)		
	Long Haul	11 (8.15)		
	Both Short Haul and Long Haul	9 (6.67)		
Primarily Crew of 2	Yes	120 (88.89)		
Plane Flown	DHC-8	3 (2.22)		
	E135/140/145	3 (2.22)		
	E170/190	24 (17.78)		
	CRJ 200/550/700/900	16 (11.85)		
	A220	1 (0.74)		
	A319/320/321	43 (31.85)		
	A350	0 (0)		
	B717	4 (2.96)		
	B737	24 (17.78)		
	B757/767	8 (5.93)		
	B777	7 (5.19)		
	B787	7 (5.19)		
Type of Flying	Regional	42 (31.11)		
	Ultra Low-Cost	26 (19.26)		
	Major	9 (6.67)		
	Legacy	58 (42.96)		
Type of Schedule	Reserve Holder	33 (24.45)		
	Line Holder	90 (66.67)		
	Both Reserve and Line Holder	12 (8.89)		
Typical Scheduled Start Time	0700-1259	40 (29.62)		
	0600-0659 or 1300-1659	67 (49.62)		
	1700-0559	28 (20.74)		

Note. FSS = Fatigue Severity Scale, JSS = Jenkins Sleep Scale, PSS = Perceived Stress Scale

Internal Consistency and Reliability

All scales utilized in the research were previously validated; however, the PSS and FSS allowed for a Cronbach's alpha reliability test. The PSS and FSS scales use averaged questions to evaluate stress (PSS) and fatigue (FSS), while the remaining questions do not utilize averaged values. The Cronbach's alpha is commonly used to measure internal consistency when multiple Likert scales are averaged for the same value (Laerd, 2019). The results of a Cronbach's alpha should fall between the range of .65 and .84 (Cortina, 1993) and are used to measure the internal consistency of the individual questions on a scale. The Cronbach's alpha was calculated during Stage 1 and Stage 2 for JSS and summarized in Table 4.

Table 4

Summary of Group 1 and Group 2 Cronbach's Alpha

Variable	Group 1 Cronbach	Group 2 Cronbach
PSS	.311	.061
FSS	.848	.846

Note. PSS = Perceived Stress Scale, FSS = Fatigue Severity Scale

A review of the Cronbach's alpha if the item was deleted indicated a slight improvement with the removal of Item 4 for group 1 ($\alpha = .335$) and group 2 ($\alpha = .282$), Item 5 for group 1 ($\alpha = .426$) and group 2 ($\alpha = .264$), and Item 7 for group 1 ($\alpha = .409$) and group 2 ($\alpha = .285$). Despite a low Cronbach's alpha, the researcher opted to continue utilizing the PSS scale as designed because the scale was previously validated. The Cronbach's alpha for FSS was within range of desired value.

Assumptions

It is essential to confirm that assumptions are met when conducting a multiple regression analysis, as this reflects the accuracy of the analysis conducted. As discussed in Chapter III, there are eight assumptions when conducting a multiple regression analysis:

1. The DV should be measured on a continuous scale.
2. Have two or more IVs, which can be continuous or categorical.
3. Have independence of observations.
4. There is a linear relationship between the DV and each of the IVs.
5. Data has homoscedasticity, which means the data along the line of best fit remains similar throughout the line.
6. Data does not show multicollinearity, which would indicate there is no or minimal correlation between two predictor variables.
7. There are no significant outliers, high leverage points, or influential high points.
8. Residual errors are approximately normally distributed.

The first two assumptions are met by the design of the study. The third assumption, independence of observations, is designed to test if adjacent observations are correlated (Laerd Statistics, 2019); therefore, a Durbin-Watson test was conducted. Field (2013, p.311) described a resulting value of more than one but less than three as ideal to ensure the independence of observations, while a value of approximately 2.0 generally indicates no correlation between residuals or complete independence (Laerd, 2019).

As shown in Table 5, the Durbin-Watson result was 1.914, indicating that assumption 3 was met for group 1 data. Therefore, the best model identified is displayed below in Table 5, Model 1.

Table 5

Model Summary with Durbin-Watson Test

Model	<i>R</i>	<i>R</i> ²	Adjusted <i>R</i> ²	Durbin-Watson
1 ^{ab}	.419	.176	.157	1.914

a. Predictors: (Constant) Age, JSS, Hours on Duty

b. Dependent Variable: FSS

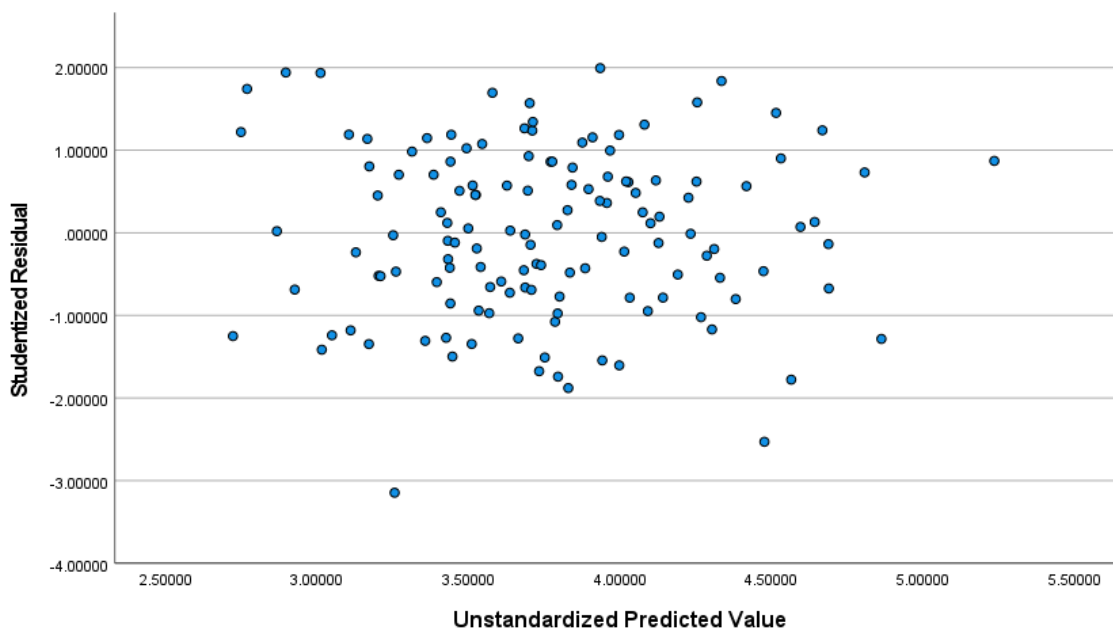
Note. JSS = Jenkins Sleep Scale, FSS = Fatigue Severity Scale.

The fourth assumption of a multiple regression analysis requires a linear relationship between the dependent variable and each independent variable. A scatterplot was utilized to establish a linear relationship between the dependent and independent variables.

As shown in Figure 6, the scatterplot forms a horizontal band, indicating that the relationship between dependent and independent variables is likely to be linear. As shown in Appendix D, partial regression plots were utilized to establish if a linear relationship exists between the dependent variable and each independent variable. A visual review of the partial regression plots indicates that the data passes the assumption of linearity, satisfying assumption 4. Therefore, a visual inspection is a method recommended by Laerd (2019) for this analysis.

Figure 6

Plot of Studentized Residual by Unstandardized Predicted Value



The fifth assumption of a multiple regression analysis requires homoscedasticity of residuals. This assumption is met when residuals are equal for all values of the predicted variables. There was homoscedasticity, as assessed by visual inspection of a plot of studentized residuals versus unstandardized predicted values. Homoscedasticity of residuals indicates that the standard deviation of the errors is similar. As shown in Figure 6, the plotted values do not appear to become wider at higher or lower values. Therefore, assumption 5 is assessed to be met.

The sixth assumption of a multiple regression analysis requires that data must not show multicollinearity. Multicollinearity occurs when two or more independent variables are highly correlated (Laerd Statistics, 2019). Identifying multicollinearity is a two-stage process, an inspection of correlation coefficients and Tolerance/VIF values. As shown in

Table 6, none of the independent variables had correlation coefficients greater than .7, indicating that data lacked multicollinearity.

Table 6

Summary of Correlations Between Variables

	FSS	Age	Hours on Duty	Hours Awake Before Start	Hours of Sleep	JSS	PSS	0600- 0659 hr & 1300- 1659 hr	1700- 0559 hr
FSS	1.000	-.148	.205	-.010	-.206	.341	.199	-.004	.008
Age	-.148	1.000	.085	.196	.163	-.060	-.164	-.217	.088
Hours on Duty	.205	.085	1.000	.089	.115	.024	.145	-.105	.185
Hours Awake Before Start	-.010	.196	.089	1.000	.353	-.030	.048	-.284	.552
Hours of Sleep	-.206	.163	.115	.353	1.000	-.325	-.109	-.232	.233
JSS	.341	-.060	.024	-.030	-.325	1.000	.212	.004	.052
PSS	.199	-.164	.145	.048	-.109	.212	1.000	-.022	.049
0600- 0659 hr & 1300- 1659 hr	-.004	-.217	-.105	-.284	-.232	.004	-.022	1.000	-.541
1700- 0559 hr	.008	.088	.185	.552	.233	.052	.049	-.541	1.000

Note. FSS = Fatigue Severity Scale, JSS = Jenkins Sleep Scale, PSS = Perceived Stress Scale.

Next, VIF/Tolerance scores were analyzed. A collinearity problem could exist if the Tolerance value is less than 0.1 – which is a VIF of greater than 10. In this data set, the lowest value was .989. VIF scores ranged between 1.005 and 1.011, below the point

of concern at ten. As shown in Table 7, the data analysis indicated that collinearity was not an issue with this data set. Next, Homoscedasticity was examined using the residuals vs. the predicted values. The residuals and predicted values are shown in Figure 6.

Homoscedasticity exists when no significant increase or decrease in the spread is seen on the scatter plot. Data did not appear to have significant outlying values from a visual inspection. Therefore, the larger than required sample size and a lack of multicollinearity are assessed as satisfactorily meeting assumption 6.

Table 7

Summary of Collinearity Statistics

Model	Tolerance	VIF
Age	.989	1.011
Hours on Duty	.992	1.008
JSS	.995	1.005

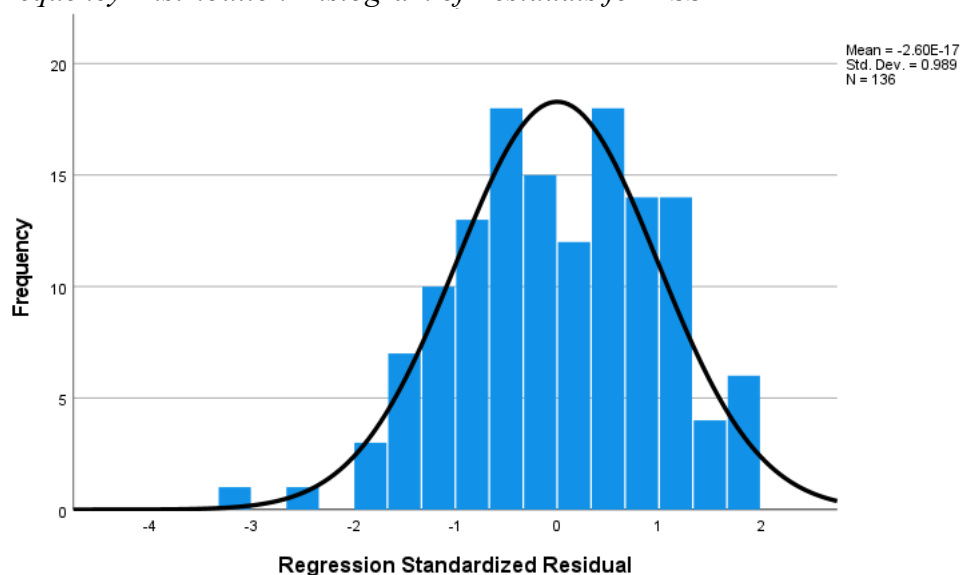
Note. JSS = Jenkins Sleep Scale

For the seventh assumption of the multiple regression analysis, there should be no significant outliers, high leverage points, or highly influential data points. A large number of participants were recruited for the research. The survey item design did not allow responses to be significantly outside norms. In addition, fatigue is very individual, so variations in fatigue are normal and expected. Based on these two issues, it is not expected that significant outliers are possible. An additional inspection of Cook's Distance (Cook's $D = .009$), a metric used to estimate the influence of outliers, did not reveal compelling cases. Based on these tests, assumption 7 is assessed to be satisfied.

The eighth and final assumption of a multiple regression analysis requires residual errors are approximately normally distributed, as described by Laerd (2019). Distribution was tested with a histogram superimposing a normal curve and a normal probability plot (p-p plot). Figure 7 shows the frequency distribution histogram of residuals. This curve was not perfectly normally distributed; however, the residuals were sufficiently normally distributed. Laerd (2019) described that an approximate visual inspection is adequate for assessing normal distribution. The normal p-p plot of regression standardized residuals is shown in Figure 8 also indicates that although the residuals were not perfectly aligned, they were close to the normal diagonal line. Therefore, data were normally distributed, satisfying assumption 8.

Figure 7

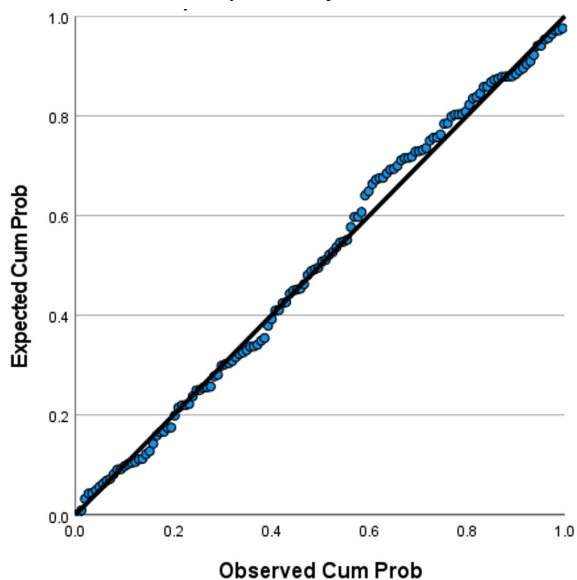
Frequency Distribution Histogram of Residuals for FSS



Note. FSS = Fatigue Severity Scale

Figure 8

Normal Probability Plot of Standardized Residual of FSS



Note. FSS = Fatigue Severity Scale

Each of the eight assumptions for a multiple regression was satisfied. The assumptions are necessary to ensure a valid study and confirm that the correct statistical process is completed. While some assumptions were not perfectly satisfied, deviations were only minor and are not expected to influence the study's statistical analysis or conclusions. The following section outlines the results of the multiple regression analysis.

Multiple Regression Analysis

Multiple regression analysis was conducted utilizing three main steps. First, model fit was used to determine if the model fits the data. Second, the regression model coefficients were verified and confirmed using a correlation. Finally, SPSS was utilized to make predictions of the dependent variable based on the values of the independent variable.

Stage 1

The goal of Stage 1 was to collect a sample and create a regression equation of predictive fatigue factors. Linear regression was conducted with the group 1 data set for this stage. Additionally, a backward stepwise regression was utilized to eliminate statistically insignificant fatigue factors and account for the categorical variable, *Scheduled Start Time*. The best model identified three statistically significant fatigue factors: *Age*, *Hours on Duty*, and *JSS* (Sleep Quality). Equation 2 shows the regression formula informed by the analysis.

$$Y = 2.88 + (-.014X_1) + (.069X_2) + (.110X_3) \quad (2)$$

To create the regression model, coefficients from group 1 data (Table 8 – Model 1) identified statistically significant predictor values.

Table 8

Coefficients

Model		Unstandardized <i>B</i>	Coefficients Std. Error	Standardized Coefficients Beta	Sig.
1 ^a	Constant	2.881	.469		.000
	Age	-.014	.008	-.146	.069
	Hours on Duty	.069	.026	.210	.009
	JSS	.110	.027	.327	.000

Note. JSS = Jenkins Sleep Scale. ^a Predictors: (Constant), Age, Hours on Duty, JSS.

In the regression equation, *Y* is the predicted fatigue score, and *X*₁, *X*₂, and *X*₃ are Age, Hours on Duty, and JSS, respectively. The data analysis revealed an *R*² for the overall model was .176 (17.6%) with an adjusted *R*² of .157 (15.7%) and an *R*² Change of -.012,

indicating the model fit with a medium-size effect according to Cohen (1988), as shown in Table 5. Cohen (1988) considers an r-square value of .12 or below to indicate a low effect size, a value between .13 to .25 as a medium effect size, and a value of .26 or above as a high effect size. In addition, Age, Hours on Duty, and JSS were all found to predict Y better than the mean, $F(3,135) = 9.388, p < .00001$, as displayed in Table 9. Based on the results shown in Table 9, all predictors other than Age, Hours on Duty, and JSS are constant.

Table 9

ANOVA Model

Model		Sum of Squares	df	Mean Square	<i>F</i>	Sig.
1 ^a	Regression	30.863	3	10.288	9.388	.000011
	Residual	144.641	132	1.096		
	Total	175.503	135			

Note. JSS = Jenkins Sleep Scale. ^a Predictors: (Constant), Age, Hours on Duty, JSS.

Stage 2

The goal in the second stage was to test the regression equation created in Stage 1. To validate the findings from Stage 1, a predictive model for fatigue factors in airline pilots was developed and tested. A separate independent sample of the data collected was used to develop predicted data and test the regression equation created in Stage 1. Group 2 data included 135 participants for Stage 2 model testing. The regression equation from Stage 1 was used with the second data set to obtain a predictive fatigue factor score. After the predictive fatigue factors score was created, a *t*-test, a correlation between actual and predicted fatigue scores, and a cross-validated R^2 statistical analysis were conducted.

The first test performed to compare the predicted and actual fatigue scores is a *t*-test. Actual vs. Predicted fatigue scores were also graphed as identified in Figure 9. As shown in Table 10, the result of the *t*-test was not statistically significant, indicating that the actual FSS does not differ from the predicted FSS.

Table 10

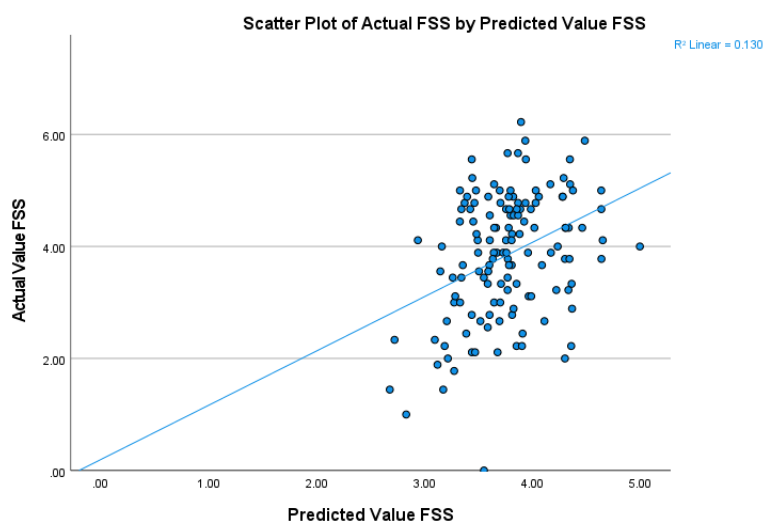
T-Test of Actual and Predicted Scores of Fatigue

		Levene's Test for Equality of Variances	Sig.	<i>t</i>	df	Sig.	T-test for Equality of Means		95% CI	
		<i>F</i>					Mean Difference	Std. Error Difference	Lower	Upper
FSS	Equal Variances Assumed	91.67	.00	.802	268	.42	-.08	.10	-.12	.28

Note. CI = confidence interval; FSS = Fatigue Severity Scale.

Figure 9

Scatter Plot of Actual FSS by Predicted Value FSS



Note. FSS = Fatigue Severity Scale.

Next, a correlation was conducted between actual and predicted fatigue scores to determine if the two data sets (actual and predicted fatigue) were significantly correlated. The results of the correlation analysis are displayed in Table 11.

Table 11

Correlational Analysis Between Actual and Predicted Fatigue Scores

		Actual	Predicted
Actual	Pearson	1	.36
	Sig.		.00
	<i>N</i>	135	135
Predicted	Pearson	.36	1
	Sig.	.00	
	<i>N</i>	135	135

The results of the correlation analysis indicated a strong positive correlation between actual and predicted fatigue scores $r(135) = .36, p < .001$. Combined with the t -test result, this significant correlation suggests that the actual and predicted scores are significantly related. In addition, the correlation further validates the regression equation created in Stage 1. Finally, a cross-validated R^2 was used to test for model validation. Equation 2 calculates the estimated squared cross-validity coefficient:

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

where N = sample size, k = number of predictors, and R^2 = observed squared multiple correlations (Field, 2013, p.312).

For Stage 2, Equation 3 is the formula used to calculate the cross-validity coefficient.

$$.131 = 1 - \left(\frac{134-1}{134}\right)\left(\frac{134+3+1}{134-3-1}\right)(1 - .176) \quad (3)$$

where $N = 134$, $k = 3$, and $R^2 = .176$.

The cross-validity coefficient is $R_{cv}^2 = .131$, indicating a medium fit of the model (Field, 2013; Cohen, 1988), as the cross-validity coefficient is similar to the original R^2 obtained for the model in Stage 1. Equation 4 shows the final regression formula created because of the analysis.

$$\text{Predicted FSS} = 2.88 + -.014(\text{Age}) + .069(\text{Hours on Duty}) + .110(\text{JSS}) \quad (4)$$

Summary

A model was created and then validated in the above analysis to predict fatigue (FSS) in commercial passenger-carrying airline pilots. The research was comprised of two separate stages. Stage 1 was used to create a regression equation, and Stage 2 performed a series of analyses to build a model. Stage 1 indicated three significant predictor variables and explained 17.6% (15.7% adjusted) of the variance in the model created. The three predictor variables were *age*, *hours on duty*, and *JSS*. Stage 2 demonstrated by utilizing a *t*-test, correlation, and cross-validated R^2 that the model has good predictive qualities. Chapter V provides additional discussion on the statistical analysis conducted in this chapter. It also discusses the theoretical and practical contributions of this research and offers additional recommendations for the target population and future research.

Chapter V: Discussion, Conclusions, and Recommendations

This research intended to gain a deeper understanding of fatigue factors in airline pilots. The previous chapter conveyed the results of the statistical analysis. This chapter discusses the statistical analysis process and the predictor variables, discusses theoretical and practical contributions, finding limitations, and recommendations for the target population and future research. The research explored the possible predictors of perceived pilot fatigue in passenger-carrying airline pilots, including perceived stress, sleep quality, hours of sleep, age, typically scheduled start time, and hours on duty.

Discussion

The previous chapter established the quantitative data analysis, including the descriptive statistics, population, sample, and statistical calculations. In addition, actual demographic data were gathered and are published in Table 2 and Table 3. Values in the demographics table, such as mean, standard deviation, and percentages, appeared to be generally consistent with the aviation community and anticipated airline pilot target participant population (FAA, 2019b). Therefore, it is possible that the social media networking utilized to gather participants may have resulted in a younger population of participants. However, the average age of airline pilots across the industry is unknown (FAA, 2019b), making it difficult to determine if a younger group participated compared to what is reflective of the industry.

There were 271 fully completed and qualified responses to the research; therefore, 206 participants were required to complete the study. Each set of data was used to create the equation model. Then, data from the equation model was compared to actual data. The first stage of the study identified factors that could predict fatigue and created a

model; a model was created to predict values when applied to a second data set. *Age*, *Hours on Duty*, and *Sleep Quality* (JSS) proved sufficient to create a model equation.

The second stage of the research study attempted to compare the model created in the first stage to its data set. Using this type of calculation, the data in the second set was used to compare predicted values created with the equation during the first stage to the data in the second stage. T-tests, correlation, and cross-validation were conducted in the second stage. The model tested the difference between the actual fatigue factors scores and the predictive fatigue factors score. The model was a good fit for the second data set tested and was statistically significant.

Significant Predictor Variables

The analysis identified that *age*, *hours on duty*, and *sleep quality* were statistically significant predictors of fatigue within the identified population. Utilizing the unstandardized B coefficients, two noteworthy items can be derived about *age*. First, *Age* is a negative predictor (*Standardized B* = -.146). This result indicates that as *age* increases, *fatigue* (FSS) decreases. *Age* had the smallest effect on fatigue relative to the other factors.

Age had the smallest effect size on fatigue relative to the other factors. This relationship between *age* and FSS seems counterintuitive; however, a possible explanation is that older pilots tend to be more senior. Senior pilots have been at an airline longer; therefore, a more senior pilot may fly, hold regular schedules, and receive more rest.

Next, *hours on duty* were a significant predictor (*Standardized B* = .210) for perceived fatigue. It has been previously identified that accident rates increase with

increases in duty time (Goode, 2003). Caldwell (2012) attributed increased fatigue and decreased alertness levels to excessive duty periods. Continuous duty overnights, where a pilot remains on duty overnight, are likely to be especially detrimental to fatigue (Sallinen et al., 2017; Cabon et al., 2003; Co et al., 1999) due to the extended duty period over a time in which is typically a window of circadian low.

Finally, *sleep quality* (JSS) had the most significant influence (*Standardized B* = .327) on the equation and *fatigue* (FSS) as a result. A higher score on the JSS indicated a lower sleep quality. Research comparing fatigue levels and reported sleep quality in pilots flying internationally noted a correlation between perceived fatigue and sleep quality (Dai et al., 2018). Cabon et al. (2003) identified the unique challenges in sleep quality for long-haul crews utilizing poorly designed crew rest facilities and noted the connection between sleep quality and fatigue.

Challenges in getting adequate sleep and rest facilities also extend to the hotels utilized by flight crews which have additional challenges such as noise and comfort. In a study examining *sleep quality* in truck drivers, researchers indicated that sleep quality appeared to negatively impact the concentration of drivers (Lemke et al., 2016). Sleep quality had the most significant impact on perceived fatigue in the airline pilots studied. While sleep quantity is addressed by 14 C.F.R 117, *sleep quality* on pilot overnight stops is not addressed. Sleep quality is likely not addressed in 14 C.F.R 117 due to the complexity of determining a quality overnight hotel location. The research identified predictor variables of *age*, *hours on duty*, and *sleep quality* (JSS). It created a valid regression equation that can be used to determine factors associated with fatigue in airline pilots who primarily carry passengers.

Non-Significant Predictor Variables

The analysis conducted sought to determine which factors may be able to predict fatigue accurately. Four predictor variables studied were not significant predictors of fatigue in passenger-carrying airline pilots: *time awake*, *perceived stress*, *hours of sleep*, and *typically scheduled start time*. Because the above predictor variables were not significant, they were not utilized in model creation.

Time awake was identified in the literature review as contributing to fatigue in airline pilots (Drongelen et al., 2017). However, in a research study examining PVT tests and cognitive fatigue in flight, *time awake* was not identified as having a significant effect on fatigue (Granger et al., 2016). In addition, 14 C.F.R 117 provides some limitations on report times and duty requirements that may have positively impacted *time awake*. Therefore, although it seems likely that *time awake* influences fatigue, the study did not identify it as a significant predictor variable.

Perceived stress was also identified as a non-significant predictor variable. Higher stress levels were identified on flights associated with more fatigue (Samel et al., 1997). However, stress-related health problems such as high blood pressure and mental health are screened during the FAA medical certification process. Although no current studies could be located, the medical certificate process may lead to a population of pilots well prepared to deal with the stresses of everyday life and limit its influence on their perceived fatigue.

Despite possible connections between *hours of sleep* and perceived fatigue, the research did not find *hours of sleep* to be a significant predictor of perceived fatigue. One possible reason for this is that the long-haul flights included in this research often include

the use of intermittent sleep on board. Another possibility is that micro-sleep could be occurring regularly on the flight deck but was not accounted for in the research (Colino, 2018). *Hours of sleep*, like *time awake*, also has scheduling limitations which could have made these predictors less problematic.

Finally, *typically scheduled start time* was not a significant predictor of fatigue in airline pilots. Typically scheduled start time was aligned with the categories used by 14 C.F.R 117. In the study, 79% of pilots ($N = 271$) identified a daytime scheduled start time as typical for the previous month. Daytime scheduled start times are less disruptive to the window of circadian low and can result in less fatigue. If there were more participants with very late start times, like those typical of cargo pilots, the results for this predictor variable might have been different.

Conclusions

Theoretical Contributions

Safety decision-making in the airline industry is not a dichotomous decision. Safely operating a flight involves weighing the implications of fatigue and other possible hazards such as maintenance issues, weather, and other external issues. Heinrich's domino theory was used to derive the fatigue factors in this dissertation. The significant predictor variables, *age*, *hours on duty*, and *sleep quality* form a potential "domino" for a fatigue-related accident.

Heinrich's domino theory suggests that accidents can be mitigated by limiting or removing the dominos. Heinrich's theory stresses that it is less likely that anyone factor causes an accident; instead, a combination of several factors or "dominos" increases the likelihood of an accident. Some concepts associated with Heinrich's domino theory are

not accurate today, such as the concept of accident proneness (Dekker, 2019). The traditional model identifies a series of pre-determined dominos. The third domino, unsafe acts and/or mechanical or physical hazards, is where fatigue-related risks are addressed in the original model. However, modern interpretations such as Bird's updated sequence and Reason's Swiss cheese model use the concept that a sequence of events or "dominos" leading up to an accident plays a role in the accident (Reason, 1990) rather than specific pre-determined dominos.

Applying this concept of a sequence of events to the regression equation, any one of the predictive fatigue factors included in the equation is not likely to cause an accident by itself. However, safety could be improved by analyzing airline pilots prior to flight for age, hours on duty, and sleep quality as a group. Significantly, these factors form the theoretical basis for continued study on U.S.-based airline pilots flying primarily passengers. While some of these factors have been studied, these factors have not previously been studied in the same way by creating a model with this population. Additionally, previous studies have not typically occurred on U.S.-based passenger-carrying pilots.

The principal concept of Heinrich's domino theory that accidents and incidents are preventable by reducing and managing unsafe acts and conditions remains true. A regression model is a tool for reducing and managing identified fatigue conditions. Increased knowledge of predictive fatigue factors gained from the research may reduce the likelihood of fatigue acting as a falling domino.

Practical Contributions

Aviation safety, particularly the risks associated with increased fatigue levels, remains an essential topic amongst regulatory authorities (FAA, NTSB), airlines and aviation providers, pilots and others in the aviation industry, and researchers. Since 2016, the NTSB has updated its “Most Wanted List.” While fatigue stops short of being specifically addressed, it has direct ties to many of the cross-disciplinary desired improvements (NTSB, 2021).

Risks associated with fatigued, passenger-carrying pilots within commercial airlines are more complex than some aviation concerns because a multi-faceted approach to its resolution is necessary. Minimizing fatigue is not a straightforward regulatory change. Instead, it requires improvements and changes to a complex scheduling software, union contracts, and norms and practices of the industry as a whole. Addressing fatigue also includes changes to the behavior of individuals, cultural change, and addressing any stigmas or financial penalties involved in a pilot notifying the airline of their fatigue.

Despite an exhaustive literature review, no other aviation-related fatigue research was discovered utilizing this study’s methods to predict fatigue and infer conclusions. This research created a model that other researchers can utilize. Other researchers have successfully addressed factors in aviation through different methods (Gregory et al., 2020; Wilson et al., 2020). Additional research should examine ties between the identified fatigue factors and airline pilots. This present research is a starting point for future researchers and those interested in improving fatigue. The complexities of fatigue have resulted in a 17.6% variance in the model. This finding will need to be studied further to understand the model's reliability. This challenge highlights the importance of

further research, study, and emphasis on fatigue, specifically fatigue factors. Many factors that influence fatigue are under-reported, under-discussed, and under-researched. Additionally, publishing this research adds to existing discussions about fatigue in airline pilots.

The research was generalizable to represent airline pilots who fly under 14 C.F.R 117 rules. Despite different air carrier fatigue policies and limitations, the study is generalizable to other airline pilots who carry passengers primarily. Limiting the population sought to remove confounding variables that could negatively impact the data. Because of the role of airlines in the United States, it is expected that data on this group of pilots could aid in improving safety.

This method, if generalized, may be helpful to the aviation industry because it can be used in advance of a scheduled flight and does not require a wearable biometric device. This research could be a starting point for future aviation fatigue research studies conducted similarly. In addition, the fatigue factors identified within this study can also be used as a starting point for subsequent aviation fatigue research seeking to understand other types of airline pilots, such as cargo pilots.

Many aviation accidents involve pilot fatigue (NTSB, 2016). This problem is especially true on flights with more extensive, longer duty times (Goode, 2003). Therefore, reducing fatigue remains essential for improving safety (NTSB, 2019; 2021).

Lastly, 14 C.F.R Part 117 is already eight years old. It was a starting point but still left many gaps, including fatigue regulations for 14 C.F.R Part 135, 14 C.F.R Part 91K, and 14 C.F.R Part 121 Cargo carriers. Nevertheless, this research provides an essential base for regulators looking to fund future research projects tied to regulatory changes.

Limitations of the Findings

This study asked pilots to look back on their previous month of flying when thinking about their answers to fatigue-related questions. It is possible that this window was too wide for participants to respond accurately due to memory lapses. If a more extensive, easier to access pilot population was available, this window could be narrowed.

The research did not address variables outside of the identified predictive fatigue factors. Unreported or underreported health issues may have existed in the target population studied. Homelife and what a pilot chooses to do during their off time or time on overnights can have a profound but challenging to measure the effect on fatigue. Many aspects of company operation could not be directly accounted for, such as maintenance, scheduling, and weather-related delays, because they were beyond the scope of the study and vary at each airline. It is also possible that other factors related to fatigue have a more significant influence than the predictive fatigue factors identified.

Perceived fatigue, stress, and sleep quality are subject to perception, which is not necessarily reality. In this study, pilot participants were relied upon to report conditions accurately and honestly. However, participants had no repercussion if they did not report accurately, and researchers have minimal cues to identify data that is not reported accurately or honestly. Despite all the protections in place for research participants, it is possible that some participants still feared negative consequences for accurately reporting sub-optimal conditions. Participants' fears could have resulted in participants reporting inaccurately or not starting the survey.

This research could not avoid several limitations due to financial and time constraints. A researcher could improve outreach with additional funding by visiting conferences and airshows and increasing participants. It is possible that increasing the time the study was open to further distance from COVID-19 may have increased study participants. Many pilots were training to regain currency after extended or were off on extended leave when the research was conducted. Despite the challenges of COVID-19, the study gathered more participants than was required. Because significant results were still obtained, more participants may not have substantially affected the study's outcome.

This research study also utilized a convenience sample. Unfortunately, convenience samples can over-represent some groups while under-representing others and are subject to researcher bias. Nonetheless, this research attempted to overcome these issues by surveying as many qualified applicants as possible and utilizing a wide variety of social networks instead of those just regularly utilized by the researcher.

Recommendations

The first recommendations are directed towards professional pilots, the target population. The second set of recommendations explicitly informs future research methodology related to similar studies. Next, areas to expand fatigue research are identified. Finally, future study participants and groups are also identified, making the research generalizable to a larger population beyond U.S. airline pilots who primarily fly passengers.

Recommendations for Professional Pilots

The aviation community is interested in fatigue research. Increased research data may improve safety regulation. In particular, many who contacted the researcher wanted

to understand why the scope was limited to 14 C.F.R Part 121 Pilots. Pilots outside the airlines complained of being forgotten by regulations primarily focused on passenger carriers. One pilot complained of complex circadian rhythm problems which interfere with their health and relationships.

While cargo and business jet operators were not a part of the target population, they are often grouped in statistics with their airline pilot counterparts (FAA, 2019b). Additionally, both groups of pilots have similarities due to job requirements, including the minimum age to earn an ATP Certificate and the need to remain medically fit enough to maintain an FAA medical certificate. Fatigued but overlooked professional aviators can advocate through their unions, where applicable, or through their management. Another possible avenue for regulatory fatigue improvement is contacting elected representatives who could potentially influence regulations and manage FAA funding.

Airline pilots flying primarily passengers covered under this study still have fatigue and benefit from continued research and regulatory improvements. Advisory Circular (AC) 120-103A outlines the content of an FRMS; however, this advisory circular is not legally binding. Passenger airlines are not mandated to have an FRMS, and if they do, they do not necessarily have to include the topics covered in AC 120-103A. Pay protection for fatigue-related occurrences is contractually negotiated and sometimes not always granted because it is often at the discretion of pilot management. There are competing priorities with any contractually negotiated benefit. However, the most challenging hurdle these pilots must overcome is long-held corporate culture and stigma from peers and management concerning fatigue and fatigue-related sick calls.

While some airlines likely have not adapted 120-103A or have only partially implemented it, some have made significant improvements and successfully negotiated fatigue leave pay protection. For these pilots, change can be made by participating in union, company, and legislative aviation-related opportunities to advocate for improved fatigue programs, much like other professional aviators.

Recommendations for Future Research Methodology

Utilizing an equation model to predict fatigue allows aviation research to predict fatigue before entering the air. While several other studies have examined fatigue in aviation, it has nearly always been through various physiological monitoring devices (Berberich & Leitner, 2017; Wilson et al., 2019). Wearable devices create additional challenges due to being cumbersome and unable to determine fatigue until after a pilot is already in the air. With that in mind, this type of fatigue survey tool could regulatory mandates on fatigue, improve aviation safety, and reduce airline fatigue-related inefficiencies.

Gathering participants for this research proved to be more challenging than expected due to many pilots on long-term leave or training due to extended leaves caused by the COVID-19 pandemic. Increasing the number of participants could improve the statistical significance of the study and may have potentially altered the variance represented in the model. A shorter survey with fewer fatigue factors examined may have resulted in more participants and more care and dedication spent on responses. Some of the fatigue factors in this study could have been measured differently, impacting the study results.

Recommendations for Future Research

With a larger body of participants, survey refinements, and further research into what factors may be predictive, this type of survey could prove valuable as a fatigue tool. However, additional research should be conducted across other groups of professional pilots. A need for further research amongst other pilot groups is especially true of 14 C.F.R Part 121 Cargo pilots who fly demanding schedules that are disruptive to the natural circadian rhythm. These disruptions may result in heightened impacts of debilitating fatigue (Gander et al., 2016; Gander et al., 2015) and accompanying negative health impacts (Mukherjee et al., 2015).

The fatigue factors identified in this study could be studied via an alternative methodology. For example, structural equation modeling could be utilized with minor changes now that fatigue factors could be selected without being exploratory. Another alternative is Partial Least Square (PLS) modeling. However, PLS modeling does not address model fit and the regression equation or structural equation modeling conducted in this research.

Concern for fatigue in aviation is not unique to the United States. This study could have been expanded to cover foreign airline pilots with additional time and more resources. Expanding the study to foreign pilots would have also increased the number of eligible airline pilot participants, as there are many more pilots globally than in the United States alone. In addition, because aviation is global, improving air space safety abroad would also impact U.S.-based air carriers. However, due to limitations on finishing this study in a reasonable amount of time and the number of possible confounding variables associated with researching foreign pilots with various backgrounds, the addition of foreign pilots was not feasible for this study.

Finally, several regulatory changes were made in 2014 due to 14 C.F.R 117. However, no research was identified during the literature review process evaluating the overall effectiveness of these changes. While 14 C.F.R 117 had a general goal of reducing the risks associated with fatigue, the specific changes were not always rooted in research. Extensive government fatigue research studies were conducted between 20 to 30 years ago and are now dated (Avers et al., 2011).

Summary

Conclusions from the statistical analysis presented in Chapter IV were discussed. First, the significant predictor variables, *age*, *hours on duty*, and *sleep quality*, were explained and discussed. Non-significant predictor variables were also further examined because they did not return significant results. Next, the theoretical contributions linked to Heinrich's domino theory and practical contributions to the aviation industry were explored. Study limitations were discussed. Finally, future recommendations for professional pilots and researchers were provided.

References

- Akerstedt, T. (2000). Consensus statement: Fatigue and accidents in transportation operations. *Journal of Sleep Research*, 9(4), 295. <https://doi.org/10.146/j.1365-2869.2000.00228>
- Akhtar, M. J., & Utne, I. B. (2014). Human fatigue's effect on the risk of maritime groundings – A Bayesian network modeling approach. *Safety Science*, 62, 427. <https://doi.org/10.1016/j.ssci.2013.10.002>
- Aircraft Owners and Pilots Association. (2017). *Career pilot: What is reserve?* <http://www.aopa.org>
- Airline Pilots Association. (2013). *Guide to Part 117 flight time limitations and rest requirements*. <http://www.alpa.org>
- Alessi, E., & Martin, J. (2010) Conducting an internet-based survey: Benefits, pitfalls, and lessons learned. *Social Work Research*, 34(2), 122-128.
- American Psychological Association. (2020). *Dictionary*. <https://www.dictionairy.apa.org>
- Andrews, T. G. (2010) *Killing for coal: America's deadliest labor war*. Harvard University Press.
- Avers, K., & Johnson, W. B. (2011). A review of federal aviation administration fatigue research: Transitioning scientific results to the aviation industry. *Aviation Psychology and Applied Human Factors*, 1(2), 87-98. <https://doi.org/10.1027/2192-0923/a000016>
- Bal, E., Arslan, O., & Tavacioglu, L. (2015). Prioritization of the causal factors of fatigue in seafarers and measurement of fatigue with the application of the lactate test. *Safety Science*, 72, 46-54. <https://doi.org/10.1016/j.ssci.2014.08.003>
- Basner, M., & Dinges, D. (2011). Maximizing sensitivity of the psychomotor vigilance test (PVT) to sleep loss. *Sleep*, 34(5), 581-591. <https://doi.org/10.1093/sleep/34.5.581>
- Bennett, S. A. (2018). Pilot workload and fatigue on short-haul routes: An evaluation supported by instantaneous self-assessment and ethnography. *Journal of Risk Research*, 21(5), 645-677. <https://doi.org/10.1080/13669877.2016.1235603>
- Berberich, J., & Leitner, R. (2017). The look of tiredness: Evaluation of pilot fatigue based on video recordings. *Aviation Psychology and Applied Human Factors*, 7(2), 86-94. <https://doi.org/10.1027/2192-0923/a000122>

- Bureau of Labor Statistics. (2019). *Occupational outlook handbook*.
<https://www.bls.gov/ooh/transportation-and-material-moving/airline-and-commercial-pilots.htm>
- Cabon, P., Bourgeois-Bougrine, S., Mollard, R., Coblenz, A., & Speyer, J. (2003). Electronic pilot-activity monitor: A countermeasure against fatigue on long-haul flights. *Aviation, Space, and Environmental Medicine*, 74(6), 679-682.
- Caldwell, J. A. (2004). Fatigue in aviation. *Travel Medicine and Infection Disease*, 3(2), 85-96, <https://doi.org/10.1016/j.tmaid.2004.07.008>
- Caldwell, J. A. (2012). Crew schedules, sleep deprivation, and aviation performance. *Fatigue Science*, 21(2), 85-89, <https://doi.org/10.1177/09637214111435842>
- Case Analysis and Reporting Online*. (2021). National Transportation Safety Board. <https://data.ntsb.gov/carol-main-public/basic-search>.
- Chi, S., & Han, S. (2013). Analyses of systems theory for construction accident prevention with specific reference to OSHA accident reports. *International Journal of Project Management*, 31(7), 1027-1041. <https://doi.org/10.1016/j.ijproman.2012.12.004>
- Co, E., Gregory, K., Johnson, M., & Rosekind, M. (1999). Crew factors in flight operations xi: A survey of fatigue factors in regional airline operations. *NASA/TM-1999-208799*.
- Coalition of Airline Pilots Associations. (2019). *Cargo carve-out*. <https://www.capapilots.org/legislative-issues/cargo-carve-out/>
- Cohen, S., Kamarck, T., & Mermelstein, R. (1983). A global measure of perceived stress. *Journal of Health and Social Behavior*, 24(4), 385-396. <https://doi.org/10.23072/2136404>
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2 ed.). Psychology Press.
- Cohen, S. (2015). Scales. <https://www.cmu.edu/dietrich/psychology/stress-immunity-disease-lab/index.html>
- Colino, S. (2018). The bizarre phenomenon of microsleep. U.S. News & World Report Health. <https://health.usnews.com/wellness/mind/articles/2018-05-16/the-bizarre-phenomenon-of-microsleep>
- Cooper, A., Scherer, C., & Mathy, R. (2001). Overcoming methodological concerns in an investigation of online sexual activities. *CyberPsychology and Behavior*, 4, 437-447.

- Cortina, J. M. (1993) What is coefficient alpha: An examination of theory and applications? *Journal of Applied Psychology*, 78, 98-104, <https://dx.doi.org/10.1037/0021-9010.78.1.98>
- Cunningham, J. (2007). Power, effect and sample size using GPower: practical issues for researchers and members of research ethics committees. *Evidence Based Midwifery*, 5(4), 132-136.
- Dai, J., Luo, M., Hu, W., Ma, J., & Wen, Z. (2018). Developing a fatigue questionnaire for Chinese civil aviation pilots. *International Journal of Occupational Safety and Ergonomics: JOSE*, 1-9. <https://doi.org/10.1080/10803548.2018.1456796>
- Darwent, D., Dawson, D., Paterson, J. L., Roach, G. D., & Ferguson, S. A. (2015). Managing fatigue: It really is about sleep. *Accident Analysis and Prevention*, 82, 20-26. <https://doi.org/10.1016/j.aap.2015.05.009>
- Dawson, D., Cleggett, C., Thompson, K., & Thomas, M. J. W. (2017). Fatigue proofing: The role of protective behaviors in mediating fatigue-related risk in a defense aviation environment. *Accident Analysis and Prevention*, 99(Pt B), 465-468. <https://doi.org/10.1016/j.aap.2015.10.011>
- Deboer, T. (2018). Sleep homeostasis and the circadian clock: Do the circadian pacemaker and the sleep homeostat influence each other's functioning? *Neurobiology of Sleep and Circadian Rhythms*, 5, 68-77. <https://doi.org/10.1016/j.nbscr.2018.02.003>
- Dekker, S. (2019). *Foundations of safety science: A century of understanding accidents and disasters*. Taylor & Francis, CRC Press.
- Department of Defense (2011). *DoD Accident/mishap/identification classification, reporting guide, and CSSO list*. https://www.dema.mil/Portals/31/Documents/Policy/8210-1c/A17_DoD_Accident_Mishap_Classification_Tool_and_CSSO_List_Jan_2017_2.pdf
- Dinges, D., Graeber, R., Rosekind, M., Samel, A., & Wiegmann, H. (1996). Principles and guidelines for duty and rest scheduling in commercial aviation. *NASA Technical Memorandum 110404*. <https://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/19990063635.pdf>
- Drongelen, A., Boot, C. R. L., Hlobil, H., Smid, T., & van der Beek, Allard J. (2017). Risk factors for fatigue among airline pilots. *International Archives of Occupational and Environmental Health*, 90(1), 39-47. <https://doi.org/10.1007/s00420-016-1170-2>

- Drongelen, A., Boot, C., Hlobil, H., Twisk, J., Smid, T., & van der Beek, A. (2014). Evaluation of an mHealth intervention aiming to improve health-related behavior and sleep and reduce fatigue among airline pilots. *Scandinavian Journal of Work, Environment & Health*, 40(6), 557-568. <https://doi.org/10.5271/sjweh.3447>
- Federal Aviation Administration. (2012). AC117-3. *Fitness for duty*. https://www.faa.gov/documentLibrary/media/Advisory_Circular/AC_117-3.pdf
- Federal Aviation Administration. (2013). AC120-103A. *Fatigue risk management systems for aviation safety*. https://www.faa.gov/documentLibrary/media/Advisory_Circular/AC_120-103A.pdf
- Federal Aviation Administration. (2015). *A EUROCONTROL-FAA action plan 15 white paper*. <https://www.skybrary.aero/bookshelf/books/3224.pdf>
- Federal Aviation Administration. (2019a). *Guide for aviation medical examiners*. https://www.faa.gov/about/office_org/headquarters_offices/avs/offices/aam/ame/guide/media/guide.pdf
- Federal Aviation Administration. (2019b). *U.S. civil airmen statistics*. <http://www.faa.gov>
- Federal Aviation Administration. (2020). *Technical areas of research*. Retrieved from <http://www.faa.gov>
- Flight and Duty Limitations and Rest Requirements, January 4, 2012 (to be codified at 14 C.F.R. pt. 117)
- Farquhar, M. (2017). Are aviation industry fatigue risk management strategies needed in healthcare? A reply. *Anesthesia*, 72(11), 1419-1420. <https://doi.org/10.1111/anae.14101>
- Field, A. (2013). *Discovering statistics using IBM SPSS Statistics*. Sage.
- Gander, P., Graeber, R., Connell, L., Gregory, K., Miller, D., & Rosekind, M. (1998). Flight crew fatigue 1: Objectives and methods. *Aviation, Space, and Environmental Medicine*. 69(9), B1-B7.
- Gander, P., Mulrine, H. M., Van Den Berg, M. J., Wu, L., Smith, A., Signal, L., & Mangie, J. (2016). Does the circadian clock drift when pilots fly multiple transpacific flights with 1- to 2-day layovers? *Chronobiology International*, 33(8), 982-994. <https://doi.org/10.1080/07420528.2016.1189430>
- Gander, P. H., Mulrine, H. M., Van Den Berg, M. J., Smith, A. A., Signal, T. L., Wu, L. J., & Belenky, G. (2015). Effects of sleep/wake history and circadian phase on

- proposed pilot fatigue safety performance indicators. *Journal of Sleep Research*, 24(1), 110-119. <https://doi.org/10.1111/jsr.12197>
- Garrison, P. (2010). Aftermath: The mystery of Colgan 3407. *Flying*. <https://www.flyingmag.com/safety/accident-investigations/aftermath-mystery-colgan-3407/>
- Gawron, V. J. (2016). Overview of self-reported measures of fatigue. *The International Journal of Aviation Psychology*, 26(3-4), 120-131. <https://doi.org/10.1080/10508414.2017.1329627>
- Goode, J. H. (2003). Are pilots at risk of accidents due to fatigue? *Journal of Safety Research*, 34(3), 309-313. [https://doi.org/10.1016/S0022-4375\(03\)00033-1](https://doi.org/10.1016/S0022-4375(03)00033-1)
- Gregory, K., Hobbs, A., Parke, B., Bathhurst, N., Pradhan, S., & Flynn-Evans, E. (2020). An evaluation of fatigue factors in maritime pilot work scheduling. *Chronobiology International*, 37(9-10), 1495-1501. <https://doi.org/10.1080/07420528.2020.1817932>
- Hair, J. F., Black, W. C., Babin, B. J., and Anderson, R. E. (2010). *Multivariate data analysis* (7th Edition). Pearson Prentice Hall.
- Hash, K., & Spencer, S. (2009). "You've got subjects": The promise of the internet in research with lesbian, gay, bisexual, and transgender populations. In W. Meezan & J. I. Martin (Eds.), *Handbook of research with gay, lesbian, bisexual, and transgender populations* (pp. 238-258). Routledge.
- Heinrich, H., Petersen, D., & Roos, N. (1980). *Industrial accident prevention*. McGraw Hill.
- Hellhammer, D, Stone, A., Hellhammer, J., & Broderick, J. (2010). Measuring stress. *Encyclopedia of behavioral neuroscience*, 2, 186-191. Elsevier.
- Hertzog, M. A. (2008). Considerations in determining sample size for pilot studies. *Research in Nursing & Health*, 31(2), 180-191. <https://doi.org/10.1002/nur.20247>
- Hobbs, A., Williamson, A., & Van Dongen, H. (2010). A circadian rhythm in skill-based errors in aviation maintenance. *Chronobiology International*, 27(6), 1304-1316. <https://doi.org/10.3109/07420528.2010.484890>
- Holliday, R. (1995). *Understanding aging*. Cambridge University Press
- International Ergonomics Association (2020). *What is ergonomics?* <https://iea.cc/what-is-ergonomics>

- Jager, J., Ptnick, D., & Bornstein, M. (2017). More than just convenient: The scientific merits of homogeneous convenience samples. *Monographs of the Society for Research in Child Development*, 82(2), 13-30. <https://doi.org/10.1111/mono.12296>
- Jenkins, C. D., Stanton, B., Niemcryk, S., & Rose, R. (1988). A scale for the estimation of sleep problems in clinical research. *Journal of Clinical Epidemiology*, 41(4), 313-321. [https://doi.org/10.1016/0895-4356\(88\)90138-2](https://doi.org/10.1016/0895-4356(88)90138-2)
- Kalsi, J., Tervo, T., Bachour, A., & Partinen, M. (2018). Sleep versus non-sleep-related fatal road accidents. *Sleep Medicine*, 51, 148-152. <https://doi.org/10.1016/j.sleep.2018.04.017>
- King, D. B., O'Rourke, N., & Delongis, A. (2014). Social media recruitment and online data collection: A beginner's guide and best practices for accessing low-prevalence and hard-to-reach populations. *Canadian Psychology*, 55(4), 240-249. <https://doi.org/10.1037/a0038087>
- Kim, S. J., Kim, S., Jeon, S., Leary, E., Barwick, F., & Mignot, E. (2019). Factors associated with fatigue in patients with insomnia. *Journal of Psychiatric Research*, 117, 24-30. <https://doi.org/10.1016/j.jpsychires.2019.06.021>
- Kirschner, J., Young, J., & Fanjoy, R. (2014). Stress and coping as a function of experience level in collegiate flight students. *Journal of Aviation Technology and Engineering*, 3(2), 14-19.
- Laerd Statistics (2019). *Multiple regression analysis using SPSS statistics*. <https://statistics.laerd.com/spss-tutorials/friedman-test-using-spss-statistics.php>
- Lamp, A., Gregory, K., Cook, M., Smith, R. S., Rasmussen, I., Gage, N., Belenky, G. (2019). Time of day effects on sleep, fatigue, and sleepiness inflight, layover, and post-flight in short and long-haul commercial aviation routes. *Sleep*, 42(Supplement 1), A82-A82. <https://doi.org/10.1093/sleep/zsz067.200>
- Lavrakas, P. J. (2012). *Encyclopedia of survey research methods*. Sage.
- Lazar, D., Petland, A., Adamic, L., Aral, S., Barabasi, A., Brewer, D., Nicholas, C., Contractor, N., Fowler, J., Gutmann, M., Jebara, T., King, G., Macy, M., Roy, D., & Van Alstyne, M. (2009). Computational social science. *Science*, 323, 5915, 721-723.
- Lee, S., & Kim, J. K. (2018). Factors contributing to the risk of airline pilot fatigue. *Journal of Air Transport Management*, 67, 197-207. <https://doi.org/10.1016/j.jairtraman.2017.12.009>

- Lemke, M. K., Apostolopoulos, Y., Hege, A., Sönmez, S., & Wideman, L. (2016). Understanding the role of sleep quality and sleep duration in commercial driving safety. *Accident Analysis and Prevention*, 97, 79-86.
<https://doi.org/10.1016/j.aap.2016.08.024>
- Lindbergh, C. A. (1953). *The Spirit of St. Louis*. C. Scribner's Sons.
- Maquet, P. (2001). The role of sleep in learning and memory. *Science*, 294, 1048-1052.
<https://doi.org/10.1126/science.1062856>
- Marcus, J. H., & Rosekind, M. R. (2017). Fatigue in transportation: NTSB investigations and safety recommendations. *Injury Prevention*, 23(4), 232.
<https://doi.org/10.1136/injuryprev-2015-041791>
- May, J. F., & Baldwin, C. L. (2009). Driver fatigue: The importance of identifying causal factors of fatigue when considering detection and countermeasure technologies. *Transportation Research Part F: Psychology and Behavior*, 12(3), 218-224.
<https://doi.org/10.1016/j.trf.2008.11.005>
- Morris, M. B., Wiedbusch, M. D., & Gunzelmann, G. (2018). Fatigue incident antecedents, consequences, and aviation operational risk management resources. *Aerospace Medicine and Human Performance*, 89(8), 708-716.
<https://doi.org/10.3357/AMHP.5019.2018>
- Mukherjee, S., Patel, S. R., Kales, S. N., Ayas, N. T., Strohl, K. P., & Gozal, D. American Thoracic Society ad hoc Committee on Healthy Sleep. (2015). An official American thoracic society statement: The importance of healthy sleep. Recommendations and future priorities. *American Journal of Respiratory and Critical Care Medicine*, 191(12), 1450-1458.
<https://doi.org/10.1164/rccm.201504-0767ST>
- National Aeronautics and Space Administration. (1999). *An analysis of Part 121/135 duty schedule-related fatigue incidents*. Prepared for the Deputy Associate Administrator for Regulation and Certification, Federal Aviation Administration.
- National Institute of General Medical Sciences. (2020). *Circadian Rhythms*.
<http://www.nigms.nih.gov>
- National Transportation Safety Board. (2010). *Aircraft accident report: Loss of control on approach Colgan Air, Inc. operating as Continental Connection Flight 3407*.
<http://www.nts.gov>
- National Transportation Safety Board. (2014). *Aircraft accident report: Crash during a nighttime nonprecision instrument approach to landing UPS Flight 1354*.
<http://www.nts.gov>

- National Transportation Safety Board. (2016). *Reduce fatigue-related accidents*. <https://www.nts.gov/safety/mwl/Pages/mwl1-2016.aspx>
- National Transportation Safety Board. (2019). *2019-2020 Most wanted list of transportation improvements*. <http://www.nts.gov>
- National Transportation Safety Board. (2021). *2021-2022 Most wanted list of transportation improvements*. <http://www.nts.gov>
- Osborne, J. (2000). Prediction in multiple regression. *Practical Assessment, Research, and Evaluation*, 7(2), 1-7. <https://doi.org/10.7257/7j20-gg86>
- Tang, F. T., Li, R., & Huang, S. (2016). The association between job-related psychosocial factors and prolonged fatigue among industrial employees in Taiwan. *PLOS One*, 11(3). <https://doi.org/10.1371/journal.pone.0150429>
- Perneger, T. V. (2005). The Swiss cheese model of safety incidents: Are there holes in the metaphor? *BMC Health Services Research*, 5(1), 71-71. <https://doi.org/10.1186/1472-6963-5-71>
- Pettit, K. K. (2019). *Safety culture, training, understanding, aviation passion: The impact on manual flight and operational performance* (Doctoral proposal). <http://commons.erau.edu>
- Presser, S., & Blair, J. (1994). Survey pretesting: Do different methods produce different results? *Sociological Methodology*, 24, 73-104.
- Quintana, D., & Heathers, J. (2014). Considerations in the assessment of heart rate variability in biobehavioral research. *Frontiers in Psychology*, 5, 805. <https://doi.org/10.3389/fpsyg.2014.00805>
- Rea, L., & Parker, A. (2014). *Designing and conducting survey research: A comprehensive guide*. Jossey-Bass.
- Reason, J. (1990). *Human error*. Cambridge University Press
- Reis, C., Mestre, C., & Canhão, H. (2013). Prevalence of fatigue in a group of airline pilots. *Aviation, Space, and Environmental Medicine*, 84(8), 828-833. <https://doi.org/10.3357/ASEM.3548.2013>
- Reis, C., Mestre, C., Canhão, H., Gradwell, D., & Paiva, T. (2016). Sleep complaints and fatigue of airline pilots. *Sleep Science*, 9(2), 73-77. <https://doi.org/10.1016/j.slsci.2016.05.003>
- Reifman, J. (2004). Alternative methods for modeling fatigue and performance. *Aviation, Space, and Environmental Medicine*, 75(Supplement 1), A173-A180.

- Rizzo, D., Lavigne, G., Creti, L., Baltzan, M., Rompré, P., Bailes, S., Fichten, C., & Libman, E. (2019). The role of fatigue and sleepiness in drivers with obstructive sleep apnea. *Transportation Research Part F: Psychology and Behaviour*, *62*, 796-804. <https://doi.org/10.1016/j.trf.2019.03.011>
- Roberti, J., Harrington, L., & Storch, E. (2006). Further psychometric support for the 10-Item version of the perceived stress scale. *Journal of College Counseling*, *9*(2), 135-147. <https://doi.org/10.1002/j.2161-1882.2006.tb00100.x>
- Rooney, S., McFadyen, D. A., Wood, D. L., Moffat, D. F., & Paul, P. (2019). Minimally important difference of the fatigue severity scale and modified fatigue impact scale in people with multiple sclerosis. *Multiple Sclerosis and Related Disorders*, *35*, 158-163. <https://doi.org/10.1016/j.msard.2019.07.028>
- Rosekind, M. (2013). Good sleep and safe travels: NTSB safety recommendations on fatigue. *Sleep Review*, *14*(5), 16.
- Rosekind, M., Gregory, K., & Mallis, M. (2006). Alertness management in aviation operations: Enhancing performance and sleep. *Aviation, Space, and Environment Medicine*, *77*(12), 1256-1265.
- Rudari, L., Sperlak, L., Geske, R., Jones, G., & Johnson, M. (2014). The sustainability of FAR Part 117: Flight and duty limitation and rest requirements for flight crewmembers. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *58*(1), 1969-1973. <https://doi.org/10.1177/1541931214581411>
- Ruel, E., Wagner, W., & Gillespie, B. (2016). *Practice of survey research: Theory and applications*. Sage.
- Sallinen, M., Sihvola, M., Puttonen, S., Ketola, K., Tuori, A., Härmä, M., & Åkerstedt, T. (2017). Sleep, alertness, and alertness management among commercial airline pilots on short-haul and long-haul flights. *Accident Analysis and Prevention*, *98*, 320-329. <https://doi.org/10.1016/j.aap.2016.10.029>
- Samel, A., Wegmann, H., & Vejvoda, M. (1997). Aircrew fatigue in long-haul operations. *Accident Analysis and Prevention*, *29*(4), 439-452. [https://doi.org/10.1016/S0001-4575\(97\)00023-7](https://doi.org/10.1016/S0001-4575(97)00023-7)
- Sieberichs, S., & Kluge, A. (2018). Effects of in-flight countermeasures to mitigate fatigue risks in aviation. *Aviation Psychology and Applied Human Factors*, *8*(2), 86-92. <https://doi.org/10.1027/2192-0923/a000143>
- Smith, B., & Phillips, B. A. (2011). Truckers drive their own assessment for obstructive sleep apnea: A collaborative approach to online self-assessment for obstructive

- sleep apnea. *Journal of Clinical Sleep Medicine*, 7(3), 241-245.
<https://doi.org/10.5664/JCSM.1060>
- Spence, P. R., Lachlan, K. A., & Rainear, A. M. (2016). Social media and crisis research: Data collection and directions. *Computers in Human Behavior*, 54, 667-672.
<https://doi.org/10.1016/j.chb.2015.08.045>
- The State of Airline Safety: Federal Oversight of Commercial Aviation, Senate, 115th Cong. 4 (2019) (Testimony of the Honorable Robert L. Sumwalt, III).
- Stutts, J., Wilkins, J., Osberg, J. S., & Vaughn, B. (2003). Drivers risk factors for sleep-related crashes. *Accident Analysis & Prevention*, 35(3), 321-331.
[https://doi.org/10.1016/S0001-4575\(02\)00007-6](https://doi.org/10.1016/S0001-4575(02)00007-6)
- Taneja, N. (2007). Fatigue in aviation: A survey of the awareness and attitudes of Indian air force pilots. *The International Journal of Aviation Psychology*, 17(3), 275-284.
<https://doi.org/10.1080/10508410701343466>
- Taylor, K. (2014). Sleeping on the job – A critical analysis of the FAA’s cargo carve-out under F.A.R. 117 and the simple solution that no one is talking about. *Journal of Air Law and Commerce*, 79(2), 401-437.
- Van Den Berg, M., Signal, T., & Gander, P. (2020). Fatigue risk management for cabin crew: The importance of company support and sufficient rest for work-life balance – a qualitative study. *Industrial Health*, 58(1), 2-14.
<https://doi.org/10.2486/indhealth.2018-0233>
- Weiland, M., Nesthus, T., Compatore, C., Popkin, S., Mangie, J., Thomas, L. C., & Flynn-Evans, E. (2013). Aviation fatigue: Issues in developing fatigue risk management systems. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 57(1), 1-5. <https://doi.org/10.1177/1541931213571001>
- Wenzel, A. (2017). *The SAGE encyclopedia of abnormal and clinical psychology*. Sage Publications.
- Wiegmann, D., & Shappell, S. A human error approach to aviation accident analysis: The human factors analysis and classification system (1st ed.). Ashgate.
<https://doi.org/10.4324/9781315263878>
- Willis, G. B., Schechter, S., & Whitaker, K. (1999). *A comparison of cognitive, interviewing, expert review, and behavior coding: What do they tell us?* In proceedings of the section on survey research methods, Alexandria, VA: American Statistical Association, 28-37.
- Wilson, N., Guragain, B., Verma, A., Archer, L., & Tavakolian, K. (2019). Blending human and machine: Feasibility of measuring fatigue through the aviation

headset. *Human Factors: The Journal of the Human Factors and Ergonomics Society*. <https://doi.org/10.1177/0018720819849783>

- Wu, L. J., Gander, P. H., van den Berg, M., & Signal, T. L. (2018). Equivalence testing as a tool for fatigue risk management in aviation. *Aerospace Medicine and Human Performance*, *89*(4), 383-388. <https://doi.org/10.3357/AMHP.4790.2018>
- Yan, T., Kreuter, F., & Tourangeau, R. (2012). Evaluating survey questions: A comparison of methods. *Journal of Official Statistics*, *28*(4), 503-529.
- Yildiz, B. C., Gzara, F., & Elhedhli, S. (2017). Airline crew pairing with fatigue: Modeling and analysis. *Transportation Research Part C*, *74*, 99-112. <https://doi.org/10.1016/j.trc.2016.11.002>
- Zaslona, J., O'Keeffe, K., Signal, T., & Gander, P. (2018). Shared responsibility for managing fatigue: Hearing the pilots. *PloS One*, *13*(5), e0195530-e0195530. <https://doi.org/10.1371/journal.pone.0195530>

Appendix A

Permission to Conduct Research

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

Principal Investigator: Heidi Kim

Other Investigators: Dr. David Esser

Role: Faculty Campus: Daytona Beach College: Arts & Sciences

Project Title: A Prediction Model for Passenger Airline Pilot Perceived Fatigue

Review Board Use Only

Initial Reviewer: Teri Gabriel Date: 07/20/2021 Approval #: 22-005

Determination: Exempt

Dr. Beth Blickensderfer

IRB Chair Signature: Elizabeth L. Blickensderfer

Digitally signed by Elizabeth L.
Blickensderfer
Date: 2021.07.20 13:52:28 -0400

07/20/2021

Brief Description:

The purpose of the proposed research will be to determine factors that influence fatigue in commercial airline pilots. Participants will be asked to complete a survey via SurveyMonkey.

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.)

Appendix B

Data Collection Device

<https://www.surveymonkey.com/r/KRBHK2M>

Airline Pilot Perceived Fatigue Survey

1. Informed Consent

INFORMED CONSENT FORM

A PREDICTION MODEL FOR AIRLINE PILOT PERCEIVED FATIGUE

Purpose of this Research: I am asking you to take part in a research project for the purpose of ascertaining perceived airline pilot fatigue to improve aviation safety. During this study, you will be asked to complete a brief online survey about your fatigue and information about your typical flights. The completion of the survey will take approximately twenty minutes.

Eligibility: To be in this study, you must be a U.S. based pilot flying commercially primarily under Part 121 rules with Part 117 rest rules. You must have a current 1st class medical certificate. You may also not have any untreated or unreported sleep disorders.

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 benefits to you as a participant, your assistance in this research will help improve knowledge about fatigue in aviation and possibly improve the safety of current fatigue related practices.

Confidentiality of records: Your individual information will be protected in all data resulting from this study. Your responses to this survey will be anonymous. No personal information will be collected other than basic demographic descriptors. The online survey system will not save IP address or any other identifying information. In order to protect the anonymity of your responses, I will keep your responses in a password-protected file on a password-protected computer. No one other than the researcher 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: There is no compensation offered for taking part in this study.

Contact: If you have any questions or would like additional information about this study, please contact Heidi Kim, kleincd8@my.erau.edu, or the faculty member overseeing this project, Dr. D. Esser, david.esser@erau.edu. For any concerns or questions as a participant in this research, contact the Institutional Review Board (IRB) at 386-226-7179 or via email teri.gabriel@erau.edu.

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

CONSENT. By checking AGREE below, I certify that I am a resident of the U.S., am a U.S. based pilot flying commercially primarily under Part 121 rules with Part 117 rest rules, have a current 1st class medical certificate, and do not have any untreated or unreported sleep disorders. I understand the information on this form, and voluntarily agree to participate in the study.

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

Please print a copy of this form for your records. A copy of this form can also be requested from Heidi Kim,

1. Do you agree to participate? 0

Agree

Disagree

Airline Pilot Perceived Fatigue Survey

2. Demographic Data

* 2. In the last month, were you on (for more than one week) :

- an extended leave
- voluntary leave
- training (such as new hire or new airplane)
- furlough

0

Yes

No

* 3. Did you fly for a U.S. based 14 CFR Part 121 air carrier that primarily flies passengers during the previous month? 0

Yes

No

* 4. Do you have a current 1st Class Medical Certificate? 0

Yes

No

* 5. How old are you? (in years) 0

21

65

6. What is your gender? 0

Female

Male

7. Which race/ethnicity best describes you? (Please choose only one.) 0

American Indian or Alaskan Native

Asian / Pacific Islander

Black or African American

Hispanic

White / Caucasian

Multiple ethnicity / Other (please specify)

* 8. What is your Total Flight Time? (Whole Number)

* 9. What is your Total Part 121 Flight Time? (Whole Number)

* 10. What category best describes your type of flying?

- Wide-Body Passenger (777, 787, A330, 767)
- Narrow-Body Passenger (A320, CRJ, B737, 757)
- Both Wide and Narrow
- Other

* 11. What type of flying best describes what you typically fly?

- Long Haul Flights (typically 1 flight in a 24 hour period, longer turn-around times, maximum flight time of 9 hours or more)
- Short Haul Flights (typically 2 or more flights in a 24 hour period, shorter turn-around times, maximum flight time of less than 9 hours)
- Both Long Haul and Short Haul Flights

* 12. Do you fly primarily single crew (2 people) U.S. domestic flying (including Canada, Mexico, Central America, Caribbean, Hawaii)?

- Yes
- No

* 13. What is your current aircraft type? (If more than one, select primary aircraft)

Other (please specify)

* 14. What type of carrier best describes your flying?

Note: While Alaska is a Legacy carrier, they have been grouped in the Major category in order to best characterize the correct type of flying they do. This is for research purposes only.

- Legacy (Delta/American/United/Hawaiian)
- Major (Alaska/JetBlue/Southwest)
- Ultra-Low Cost (Allegiant/Frontier/Spirit/Sun Country)
- Regional (Endeavor/Envoy/PSA/Republic/Skywest/horizon/CommutAir)

Other (please specify)

* 15. Do you have a history of untreated or unreported sleep apnea and/or other sleep-related diseases?

- Yes
- No

* 16. In the last month of flying, were you a Line Holder or Reserve Holder? (choose the best answer)

- Line Holder
- Reserve Holder
- Combination of Line and Reserve Holder

* 17. How many legs of flying do you do in a typical day? (Choose the best answer)



Airline Pilot Perceived Fatigue Survey

3. Fatigue-Related Questions

When completing this survey, please answer the questions based on the last month of scheduled flying with your best estimate on what a typical trip is.

* 18. How many hours do you typically spend in the air on a typical trip day?  

* 19. How many hours do you typically spend on duty during a typical trip day?  

* 20. What is your typical scheduled start time?  

17:00-05:59

06:00-06:59 or 13:00-16:59

07:00-12:59

* 21. How long are you typically awake before starting your flights for a typical day? (in Hours)  

* 22. How long are you typically awake when you finish flying a typical trip - in a 24 hour period? (in Hours)  

* 23. How many hours of sleep do you receive per layover on a typical trip - in a 24 hour period? (in Hours)  

* 24. How many hours of duty-free time do you receive per layover on a typical trip - in a 24 hour period? (in Hours)  

Airline Pilot Perceived Fatigue Survey

4. Jenkins Sleep Questionnaire

* 25. How many days in the past 30 days did you:  0

	Not At All	1-3 Days	4-7 Days	8-14 Days	15-21 Days	22-30 Days
Have trouble falling asleep?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Wake up several times per night but did not have trouble falling asleep again?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Wake up one or more times per night (including waking far too early) and have trouble falling asleep again?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Wake up after your usual amount of sleep feeling tired or worn out?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

From “A scale for the estimation of sleep problems in clinical research,” by C. D.

Jenkins, B. Stanton, S. Niemcryk, and R. Rose, 1988, *Journal of Clinical Epidemiology*, 41(4), p. 313-321. CC BY-NC-ND.

Airline Pilot Perceived Fatigue Survey

5. Perceived Stress Scale

The questions in this scale ask you about your feelings and thoughts during the last month. In each case, please indicate with a check how often you felt or thought a certain way.

* 26. Perceived Stress Scale  

	0 - Never	1 - Almost Never	2 - Sometimes	3 - Fairly Often	4 - Very Often
In the last month, how often have you been upset because of something that happened unexpectedly?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
In the last month, how often have you felt that you were unable to control the important things in your life?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
In the last month, how often have you felt nervous and "stressed"?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
In the last month, how often have you felt confident about your ability to handle your personal problems?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
In the last month, how often have you felt that things were going your way?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
In the last month, how often have you found that you could not cope with all the things that you had to do?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
In the last month, how often have you been able to control irritations in your life?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
In the last month, how often have you felt that you were on top of things?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
In the last month, how often have you been angered because of things that were outside of your control?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
In the last month, how often have you felt difficulties were piling up so high that you could not overcome them?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Permission granted from Cohen, S. (2015). Scales.

<https://www.cmu.edu/dietrich/psychology/stress-immunity-disease-lab/index.html>

Airline Pilot Perceived Fatigue Survey

6. Fatigue Severity Scale

Choose a number from 1 to 7 that indicates your degree of agreement with each statement where 1 indicates strongly disagree and 7, strongly disagree.

* 27. Fatigue Severity Scale 0


	1 (Strongly Disagree)	2	3	4	5	6	7 (Strongly Agree)
My motivation is lower when I am fatigued.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Exercise brings on my fatigue.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I am easily fatigued.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Fatigue interferes with my physical functioning.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Fatigue causes frequent problems for me.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My fatigue prevents sustained physical functioning.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Fatigue interferes with carrying out certain duties and responsibilities.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Fatigue is among my three most disabling symptoms.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Fatigue interferes with my work, family, or social life.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

From “The fatigue Severity Scale: Application to patients with multiple sclerosis and systemic lupus erythematosus,” by L. B. Krupp, N. G. LaRocca, J. Muir-Nash, A. D. Steinberg, 1989, *Archives of Neurology*, 46(10), p. 1121-1123. CC BY-NC-ND.

Airline Pilot Perceived Fatigue Survey

7. Thank You

Thank you for your participation! If you are interested in receiving a study update at completion please provide your contact information below. If not, leave it blank.

28. What is your email address? (optional)  0

Email Address:

Appendix C

Subject Matter Experts

Robin Kim, Alaskan Airlines

Education

Embry-Riddle Aeronautical University – Daytona Beach
Bachelor of Science in Aeronautical Science
Minor in Business Administration and Air Traffic Management

Career

2017 - Present, Alaska Airlines, First Officer
2011 - 2017, ExpressJet Airlines, First Officer and Line Oriented Safety Audit (LOSA) Observer
2016 - 2017, Airline Pilots Association (ALPA), Airport Safety Liaison (ASL) Newark Liberty International Airport

Flight Information

Certificates and Ratings:
Airline Transport Pilot – Airplane Multiengine Land
Commercial Privileges – Airplane Single-Engine Land
Certified Flight Instructor – Airplane Single-Engine and Multiengine, Instrument Airplane
Ground Instructor – Advanced and Instrument
Aircraft Dispatcher

Type Ratings:

B-737
A-320
EMB-145

Total Flight Hours:

4,678

Rachel Lindvig, American Airlines**Education**

Embry-Riddle Aeronautical University – Worldwide
Master of Science in Aeronautics
Major: Aviation Education and Safety Science

University of North Dakota – Grand Forks
Bachelor of Science in Aeronautics
Major: Aviation Education and Safety Science

Career

2018 - Present, American Airlines, First Officer
2010 - 2018, Envoy/American Eagle, Captain and Line Check Airman
2008 - 2009, Mesaba Airlines, First Officer
2007 – 2008, UND Aerospace, Flight Instructor
2006 – 2006, American Airlines, Flight Operations Intern

Flight Information

Certificates and Ratings:

Airline Transport Pilot – Airplane Multiengine Land
Commercial Privileges – Airplane Single-Engine Land and Sea
Certified Flight Instructor – Airplane Single-Engine and Multiengine, Instrument
Airplane

Type Ratings:

CL-65
A-320
EMB-145
DC-3 (SIC Only)
SF-340 (SIC Only)

Total Flight Hours:
7,500

Jason Fox, United Airlines**Education**

Embry-Riddle Aeronautical University – Daytona Beach
Bachelor of Science in Aeronautical Science
Minor in Air Traffic Management

Career

2020 - Present, United Airlines, First Officer
2013 – 2020, ExpressJet Airlines, First Officer, EPIC Ambassador, ALPA National Education Committee Volunteer, District Advocacy Volunteer, Pilot to Pilot Program Volunteer, Chairman of the Family Awareness Committee, Secretary/Treasurer for ExpressJet LEC-177 Newark
2011 – 2013, Embry Riddle Aeronautical University, Flight Instructor

Flight Information

Certificates and Ratings:

Airline Transport Pilot – Airplane Multiengine Land
Commercial Privileges – Airplane Single-Engine Land
Certified Flight Instructor – Airplane Single-Engine, Instrument Airplane

Type Ratings:

EMB-145

Total Flight Hours:

4500

Appendix D

