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## Examining Unstable Approach Predictors Using Flight Data Monitoring Information

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# **Examining Unstable Approach Predictors Using Flight Data Monitoring Information**

David Alan Carroll

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

Embry-Riddle Aeronautical University

Daytona Beach, Florida

October 2020

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Information**

David Alan Carroll

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



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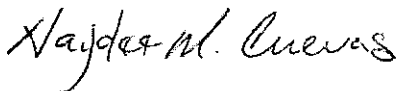
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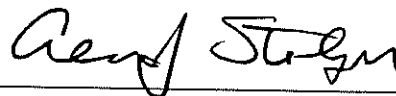
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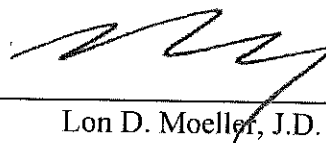
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## Abstract

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Title: Examining Unstable Approach Predictors Using Flight Data Monitoring Information

Institution: Embry-Riddle Aeronautical University

Degree: Doctor of Philosophy in Aviation

Year: 2020

The approach and landing phase of flight is statistically the most dangerous part of flying. While it only accounts for 4% of flight time, it represents 49% of commercial jet mishaps. One key to mitigating the risks involved in this flight segment is the stabilized approach. A stabilized approach requires meeting rigorous standards for many flight parameters as the aircraft nears landing. Exceeding any of these parameters results in an unstable approach (UA). The energy management (EM) accomplished by the flight crew, represented by the EM variables in the study, influences the execution of a stabilized approach.

While EM is a critical element of executing a stabilized approach, there appears to be a lack of studies that identify specific EM variables that contribute to UA probability. Additionally, several possible moderating variables (MVs) may affect the probability of a UA. Fortunately, modern jet transport aircraft have Flight Data Monitoring (FDM) systems that capture a wealth of information that enable the analysis of these EM variables. This study used FDM data to answer the questions about what influence a set of EM variables has on the probability of a UA event. The analysis also determined what impact a set of possible MVs, not directly related to EM, has on these EM variables influence.

The analysis used logistic regression (LR) to investigate FDM information. The LR provided estimations of odds ratios for each of the variables and the interaction factors for the MVs. These statistics defined a model to evaluate the influences of the EM and MVs, providing answers to the research questions posed. The results determined the model was a good fit to the data but had poor discrimination. The model supported three of the original seven EM hypotheses and none of the 28 MV hypotheses.

The study identified three specific EM variables that significantly influenced the probability of a UA event. Of the MVs, only one significant influence was revealed but was opposite that hypothesized. Identifying the EM variables, and examining their impacts, shows their importance in preventing UAs. Further, the results help prevent future UAs by informing the design of training programs. Additionally, the current effort fills gaps in the current body of knowledge, as there appears to be a lack of studies in the areas investigated.

A gap in the body of knowledge filled by investigating an area of limited research and the results provide practical application in the analysis of EM-related events. Aviation safety practitioners now have additional information to identify trend issues that may lead to the increased probability of a UA event. Finally, this study was one of very few granted access to actual operational FDM information by an air carrier. The data were crucial in evaluating the proposed model against real-world flight operations, comparing theory to reality. Without access to such closely held information, the research for this dissertation would not have been possible.

## **Dedication**

I dedicate this effort to my Lord and Savior, Jesus Christ, whose leading brought me to and through this monumental undertaking. And to my wife, Jacki, for without her support and confidence, I would not have been able to sustain the effort needed to reach this goal.

## **Acknowledgements**

The results of the research conducted for this study provide information valuable to a larger research project. This larger project is a collaboration between Embry-Riddle Aeronautical University (ERAU) and an unidentified airline participating in the project, referred to in this effort as the Participating Airline (PA). The relevant project between ERAU and the PA is the Energy Management (EM)/Flight Data Monitoring (FDM) project. While the results inform the larger EM/FDM project, this dissertation was conducted independently from the larger project.

I want to thank the PA for the unique opportunity of conducting this study using actual operational FDM information. In addition, the support received from SAFRAN in providing software, training, and support in the use of the Analysis Ground Station system was crucial to the success of the analysis. Without the incredible support of these two organizations, the study would not have been possible.

I would like to thank my late parents, Lee and Pat Carroll, for instilling in me the work ethic needed to complete such a monumental task. They taught by example the dedication and focus needed to overcome monumental obstacles. I wish they were here to witness the completion of this effort.

Most importantly, I want to thank my long-suffering wife, Jacki, who has taken care of me and many of life's details while I have labored through this process. Without your love, understanding, encouragement, and patience, I would not have achieved this goal. Your sacrifices have been noticed and deeply appreciated. Now we can move forward together in doing the things we've been missing during this project. I love you!



## Table of Contents

	Page
Signature Page .....	ii
Abstract.....	iii
Dedication.....	v
Acknowledgements.....	vi
List of Tables .....	xi
List of Figures.....	xiii
Chapter I: Introduction.....	1
Statement of the Problem.....	7
Purpose Statement.....	8
Significance of the Study .....	9
Research Questions.....	10
Delimitations.....	16
Limitations and Assumptions .....	17
Summary .....	19
Definitions of Terms .....	20
List of Acronyms .....	24
Chapter II    Review of the Relevant Literature.....	27
Unstable Approaches .....	27
Moderating Factors .....	29
Flight Data Monitoring .....	33
Aircraft Energy Management .....	38

	Gaps in the Literature.....	46
	Theoretical Framework.....	46
	Research Model .....	47
	Hypotheses and Support .....	48
	Summary .....	56
Chapter III	Methodology .....	59
	Research Method Selection.....	59
	Population/Sample .....	60
	Sampling Frame and Strategy.....	60
	Data Collection Process .....	61
	Design and Procedures.....	62
	Apparatus and Materials .....	63
	Sources of the Data .....	63
	Ethical Consideration.....	64
	Measurement Instrument .....	64
	Variables and Scales .....	65
	Data Analysis Approach .....	74
	Participant Demographics.....	74
	Reliability Assessment Method .....	75
	Validity Assessment Method .....	76
	Data Analysis Process/Hypothesis Testing.....	77
	Summary .....	88

Chapter IV	Results.....	89
	Demographics Results .....	89
	Descriptive Statistics.....	91
	Energy Management Variables.....	91
	Moderating Variables.....	97
	Testing of Assumptions .....	100
	Model Development.....	108
	Reliability and Validity Testing Results.....	111
	Reliability Testing.....	111
	Validity Testing .....	112
	Hypothesis Testing Results.....	114
	Energy Management Hypothesis Testing .....	115
	Moderating Variable Influence Hypothesis Testing .....	118
	Summary .....	128
Chapter V	Discussion, Conclusions, and Recommendations .....	132
	Discussion .....	132
	Energy Management Related Hypotheses .....	132
	Energy Management Related Hypotheses .....	140
	Conclusions.....	146
	Theoretical Contributions .....	147
	Practical Contributions.....	147
	Limitations of the Findings.....	149
	Recommendations.....	151

Recommendations for the Airlines in the Region.....	151
Recommendations for Future Research .....	152
References.....	155
Appendices.....	162
A    Permission to Conduct Research.....	162
B    Tables .....	165

## List of Tables

Table	Page
1 RQ2 Hypothesis Identification Matrix .....	16
2 Unstable Approach Indicators .....	66
3 Late Start Value Assignment.....	68
4 Energy Management Variables in the FDM Dataset.....	71
5 Moderating Variables .....	72
6 Guidance for Evaluating AUC in ROC Analysis .....	85
7 Corporate Demographics of Major Air Carriers Operating in the Market.....	90
8 Categorical Energy Management Variable Descriptive Statistics .....	92
9 Continuous Energy Management Variable Descriptive Statistics .....	93
10 Moderating Variable Descriptive Statistics.....	98
11 Calculated Minimum Sample Sizes .....	103
12 Assessment of Linearity .....	105
13 Summary of Tolerance and VIF Values.....	106
14 Collinearity Diagnostics .....	107
15 Summary of Critical Test Results .....	108
16 Summary of Procedure Differences .....	110
17 Summary of Training and Assessment Classification Error Rates .....	112
18 Area Under the Curve.....	114
19 Forced Entry Model.....	115
20 Summary of Interactions .....	120
21 Lighting * Flap Dist Interaction .....	122

22	Lighting * Speed Brake Interaction.....	123
23	Duration * High Speed Interaction.....	125
24	Hypothesis Testing Results Matrix .....	130

## List of Figures

Figure		Page
1	Percentage of Accidents by Phase of Flight.....	2
2	Stabilized Approach Concept.....	3
3	Proposed Model of the System.....	48
4	Notional Flight Data Acquisition System .....	62
5	Landing Gear Extension Histograms .....	95
6	lap Extension Histograms.....	97
7	Receiver Operating Characteristic.....	113
8	Model of the System after Hypothesis Testing .....	131

## Chapter I: Introduction

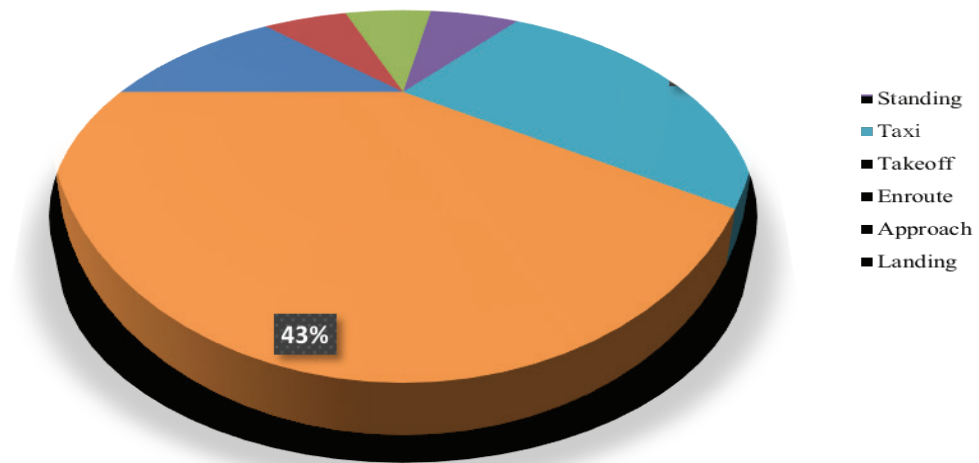
Commercial aviation is an extremely safe mode of transportation. Over the 58 years from 1959 through 2017, the worldwide commercial jet fleet flew 1,453 million flight hours during 772 million flights. During this period, there were 1,989 commercial aviation accidents worldwide, of which 626 resulted in fatalities, yielding an accident rate of  $1.37 \times 10^{-6}$  accidents, with  $4.31 \times 10^{-7}$  fatal accidents, per flight hour. For the ten years from 2008-2017, the numbers are about 544 million flight hours, 387 accidents, and 55 with fatalities. The rate for the 2008-2017 period is  $7.11 \times 10^{-7}$  accidents, with  $1.01 \times 10^{-7}$  fatal accidents, per flight hour (Boeing, 2018). These statistics illustrate a significant increase in aviation safety.

The approach and landing phase of flight is statistically the most dangerous part of flying. The 2014 International Civil Aviation Organization (ICAO) Safety Report shows that, for the air carrier accidents in 2013, 61% occurred in the approach and landing phases of flight, as depicted in Figure 1. During approach and landing, the pilot flying must bring the aircraft down from cruising altitude to touchdown at a specific point on the ground, in the appropriate configuration, within a narrow range of airspeed and vertical velocity, and in a flight attitude that ensures a smooth transition from air to ground. Digression from desired parameters in any of these areas increases the risk of a mishap; the more considerable the digression, the higher the risk.



## Figure 1

### *Percentage of Accidents by Phase of Flight*



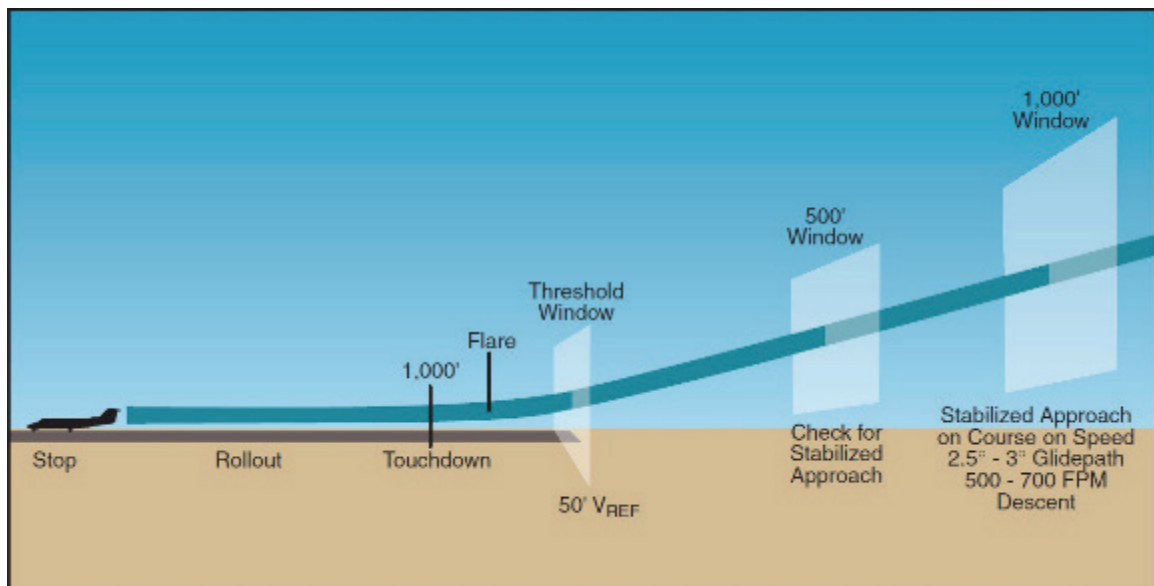
*Note.* Adapted from “2014 Safety Report,” by International Civil Aviation Organization (ICAO), 2014, p. 13.

To mitigate these risks, pilots utilize the concept of the stabilized approach. This concept evolved with the advent of jet-powered airliners in the 1950s and ‘60s. Pilots discovered that newer technology jet transport aircraft, with lower drag coefficients allowing for higher speed, did not slow as readily as piston and turboprop aircraft, nor did the engines respond as quickly when pilots reacted to low-speed situations (Charles, 2000). Advisory Circular (AC) 91-79A states that at no later than 1000 feet above touchdown in Instrument Meteorological Conditions (IMC) or 500 feet above touchdown in Visual Meteorological Conditions (VMC), the pilot flying should have the aircraft

established on the correct final approach course and glidepath, at the appropriate airspeed and vertical velocity, and in the correct configuration (Federal Aviation Administration [FAA], 2018c). Figure 2 provides a depiction of the stabilized approach concept. The pilot monitoring (PM) calls out deviations, which the pilot flying (PF) must acknowledge with positive corrections initiated. Significant deviations result in an unstable approach (UA), requiring abandoning the approach and bringing the aircraft back around for another approach attempt (Albright, 2014).

## Figure 2

### *Stabilized Approach Concept*



*Note.* Adapted from “Air Traffic Procedures Bulletin, 2019-1,” by FAA, 2019, p. 2.

The flight crew strives to prevent these deviations by careful control of the airspeed and altitude, along with other approach parameters, to control the aircraft’s energy state. An aircraft’s energy state in flight consists of three components: potential,

kinetic, and chemical. The potential energy is the aircraft's altitude above the ground, kinetic energy is the aircraft's airspeed, and chemical energy is the fuel onboard the aircraft (Merkt, 2013). In level, constant airspeed flight, the potential and kinetic energy states are stable, while burning fuel to create enough thrust to overcome drag decreases the chemical energy level. Changing aircraft configuration, such as retracting or extending the landing gear, can change the amount of drag resulting in a change in the fuel burn rate. The fuel's chemical energy may also increase either the kinetic energy by increasing the airspeed, the potential energy by increasing the altitude, or both simultaneously.

Further, the flight crew can interchange energy between potential and kinetic forms. Allowing the aircraft to slow in a climb converts some kinetic energy into potential energy. Likewise, if the aircraft accelerates in a descent, some potential energy is converted into kinetic energy. In aviation, the term *energy management* (EM) refers to control of the three energy states. As described by Airbus, EM is “. . . continuously controlling each parameter: airspeed, thrust, configuration and flight path, and in transiently trading one parameter for another” (Airbus, 2005, p. 2). Flight crews perform EM by maintaining the altitude and airspeed within the desired parameters, and controlling the rates of change of both.

Establishing the aircraft on the correct final approach course and glidepath, at the appropriate airspeed and vertical velocity, and in the correct configuration, results in the aircraft being at a particular energy level. Too little energy results in landing difficulties such as excessive sink rate, which may generate a hard landing, or landing with an excessive pitch attitude, which may result in a tailstrike (Airbus, 2005; Veillette, 2016).

Too much energy may also result in landing difficulties. The aircraft may float, producing a long touchdown, which reduces the runway available to decelerate to taxi speed. A touchdown with excessive speed can result in excessive braking, leading to brake overheating, brake fires, and blown tires. If there is insufficient runway remaining to decelerate, the aircraft may depart the runway into or beyond the overrun (Veillette, 2016). It is incumbent on the flight crew to properly manage the aircraft's energy state to execute a safe approach and landing.

Proper EM is the key to setting up and executing a stabilized approach, beginning at the initial descent from cruising altitude. For example, as the aircraft begins the initial descent from cruise altitude, it usually starts from a stable airspeed and altitude cruise. If the pilot changes the flight path from level flight to descent without changing the thrust or configuration, the aircraft will accelerate. The configuration must be changed to increase drag, or thrust reduced, to maintain a stable airspeed. If the new descending flight path is steep enough, the reduction of thrust to idle may not prevent acceleration. In such a case, a configuration change that would increase drag, such as extending spoilers, would also be required to maintain airspeed. During the descent from cruise altitude, the crew should be striving to arrive at the final approach fix (FAF) at the desired configuration, altitude, and airspeed (Veillette, 2016). Early awareness that the aircraft is higher than desired allows the PF to correct the energy state by slowing earlier to compensate for the additional descent needed. Too much airspeed may require an earlier configuration to increase drag and, therefore, deceleration. As noted by Airbus (2005), "decelerating on a 3-degree glide path in clean configuration usually is not possible" (p.

3). The earlier any deviations from the desired energy state are detected, the more EM options are available to the aircrew.

Other factors have the potential to influence the flight crew's EM. "A high level of mental workload is associated with an increased risk of pilot operational errors" (Zhang et al., 2019, p. 829). Improper EM is considered a type of operational error.

Environmental factors, such as conducting the approach during day or night lighting conditions, may influence EM via changes in pilot performance (Zhang et al., 2019).

Flightcrew-related factors, such as the experience of the pilot flying the approach or continuously high pilot task loading, may also impact pilot performance, and thus EM (Keller et al., 2019; Wanyan et al., 2018; Zhang et al., 2019). Additional factors, such as whether the approach is hand-flown by the pilot or accomplished on autopilot, may have an impact on EM as well (Mouloua et al., 2019). During flight, the Flight Data Monitoring (FDM) system is continuously recording EM variables.

Flight Data Monitoring systems make it possible to review the EM practices of the flight crew and their success in controlling the energy state of the aircraft throughout the flight. The terms FDM and Flight Operational Quality Assurance (FOQA) are often used interchangeably; this study used FDM for consistency. These systems record hundreds, even thousands, of parameters at rates up to 32 hertz and at very high fidelity (SAFRAN, 2012). Ground analysis of these data allows for the creation of even more data calculated from recorded information. Through the analysis of FDM information, it may be possible to learn if EM practices exhibited during the descent and approach phases of flight can indicate the probability of a UA event occurrence.

The current literature regarding EM appeared to mostly focus on three primary areas: continuous descent operations (CDO), prevention of loss of control incidents, and energy awareness aids for pilots. Continuous descent operations involve minimizing or eliminating level-flight segments during the descent phase of flight. The intent of CDO is to minimize fuel consumption, emissions, and noise (Prats et al., 2014). Studies in the area of preventing loss of control focus on maintaining sufficient energy to safely maneuver the aircraft at all times (Merkt, 2013). Additionally, studies have been conducted over the years to examine ways to use the technology available at the time to provide pilots with some form of indicator in the cockpit to provide a visual representation of the energy state of the aircraft (Baker, 2017; Noyes, 2007; Zagalsky, 1973). Thus, the current literature in the field of aircraft EM has focused on efficiency, safety, and situational awareness, but lacked a focus on the relationships between EM, potential moderating variables (MVs), and UA events.

### **Statement of the Problem**

The most critical phase of flight is the final approach and landing phase. Although it accounts for only 4% of the flight time, it is where 49% of commercial jet mishaps historically occur (Boeing, 2018). One of the keys to improving the safety of the final approach and landing phase of flight is to utilize the stabilized approach concept (FAA, 2018c). Many variables impact the accomplishment of a stabilized approach, some of which are captured directly via FDM. Post-flight analysis of the FDM information may reveal others. Thus, the flight parameters that are indicators of EM practices can be found or derived from the FDM information.

Since EM is a critical component of a stabilized approach, poor control of EM variables will likely increase the probability of UAs. The EM variables related to UAs had not been identified through a statistical study of the FDM information available. If a specific relationship can be identified between an EM variable and the probability of a UA event, the EM variable can be considered a UA predictor. Unfortunately, current practices in the airline industry only tabulate UAs that have occurred and do not proactively address any such predictor EM variables. The current literature appeared to lack studies investigating possible relationships between EM variables and UA events. Additional detail on the current literature is provided in Chapter II.

Non-EM variables, such as environmental conditions or flight crew related factors, may exert an influence on the predicting EM variables. Like the EM variables, the FDM system may capture some of these variables. Others may require calculation from the FDM information. Still others may be found outside of the FDM system altogether. These MVs may either increase or decrease the effect a predicting EM variable has on a UA event's probability. Identifying these MVs and their effects provide further clarity on the relationships between EM and UA events. The review of current literature on the possible influences these MVs might have on EM as related to UAs revealed an apparent lack of such studies. Again, the literature review in Chapter II provides additional detail.

### **Purpose Statement**

The intent of this study was to utilize statistical analysis to identify relationships between the EM variables found in FDM information and the probability of the

occurrence of a UA for a particular flight. In addition, the study sought to identify possible relationships between MVs and the EM variables that influence UAs.

### **Significance of the Study**

The study seeks to identify the relationships between certain flight variables and UA events using FDM information. The analysis herein should lead to an improved understanding of the EM predictors of UA events, and the influence of possible MVs. The outcome of the study should make valuable contributions, both practical and theoretical.

The practical contributions of this effort are in the area of aviation safety. By identifying the relationships between EM variables and UA events, safety practitioners have new information to investigate UA events. The results also provide those tasked with developing training programs for flight crews with information to create focused training modules identifying critical EM variables. Increased awareness of these EM issues enables pilots to be more vigilant at the key EM points, to prevent errors. Increased awareness may also help pilots recognize sooner when a critical EM problem has begun, facilitating quicker corrective actions. With this enhanced knowledge, flight crews are better equipped to avoid the EM errors that have a high probability of leading to a UA, thus increasing flight safety.

In addition to its practical contributions, the study provides theoretical contributions to the body of knowledge by exploring areas that appeared neglected in the current literature. A review of the current literature appeared to reveal a lack of significant research of aircraft EM variables concerning UAs. The current literature also seemed to lack significant investigation into the possible impact any MVs may have on



how these predicting EM variables affect the occurrence of UAs. Identifying the EM variables and possible MVs that influence the probability of a UA event is the first step in filling these research gaps. The study also identified significant areas for further research to expand further the body of knowledge in this area.

### **Research Questions**

The genesis of the current study was examining how the EM variables influence the occurrence of UA events. The flight crew executes the descent from cruise flight through the approach and landing following generally accepted rules-of-thumb and standard operating procedures. How well the flight crew performs the descent and approach is recorded by the FDM system, which allows for analysis of the EM variables selected. Three of the EM variables, late start of descent, high speed below 10,000 feet, and use of spoilers on descent, cover the descent phase. The remaining four, distance to the destination at landing gear extension, airspeed at landing gear extension, distance to the destination at flap extension, and airspeed at flap extension, address the approach phase. The overall question of the impacts these EM variables exert on UA probability was broken down into seven hypotheses, each related to an element of the descent and approach reflected in an EM variable.

The review of the literature regarding the EM variables and UA events revealed other non-EM factors that impact UA events, as well as other approach and landing phase events. Four of those non-EM factors, lighting, experience (by proxy of who is flying), duration of flight, and automation use, are identifiable within the FDM information. It was postulated that these non-EM factors might exert a moderating influence on the EM variables, leading to the expansion of the study to include a second research question on

how these four factors, now the MVs, may moderate the influence of the EM variables. Since each relationship between EM and MV pair is likely to be different, this resulted in an additional 28 hypotheses related to the MVs. The research questions and associated hypotheses are presented below.

**1. Research Question (RQ) 1: What are the impacts of EM variables on the occurrence of UAs?**

Hypothesis (H) 1a<sub>1</sub>: A longer delay in the start of descent is associated with an increase in the probability of having a UA.

H1b<sub>1</sub>: High-speed below 10,000 feet is associated with an increase in the probability of having a UA.

H1c<sub>1</sub>: Higher airspeed at gear extension is associated with an increase in the probability of having a UA.

H1d<sub>1</sub>: A shorter distance to destination at gear extension is associated with an increase in the probability of having a UA.

H1e<sub>1</sub>: Higher airspeed at flap extension is associated with an increase in the probability of having a UA.

H1f<sub>1</sub>: A shorter distance to destination at flap extension is associated with an increase in the probability of having a UA.

H1g<sub>1</sub>: Using spoilers on descent is associated with an increase in the probability of having a UA.

**2. RQ2: How do MVs moderate the effects of EM variables on the occurrence of UAs?**

H2aa<sub>1</sub>: A longer delay in the start of descent, when moderated by reduced lighting, is associated with a further increase in the probability of having a UA.

H2ba<sub>1</sub>: High-speed below 10,000 feet, when moderated by reduced lighting, is associated with a further increase in the probability of having a UA.

H2ca<sub>1</sub>: Higher airspeed at gear extension, when moderated by reduced lighting, is associated with a further increase in the probability of having a UA.

H2da<sub>1</sub>: A shorter distance to destination at gear extension, when moderated by reduced lighting, is associated with a further increase in the probability of having a UA.

H2ea<sub>1</sub>: Higher airspeed at flap extension, when moderated by reduced lighting, is associated with a further increase in the probability of having a UA.

H2fa<sub>1</sub>: A shorter distance to destination at flap extension, when moderated by reduced lighting, is associated with a further increase in the probability of having a UA.

H2ga<sub>1</sub>: Using spoilers on descent, when moderated by reduced lighting, is associated with a further increase in the probability of having a UA.

H2ab<sub>1</sub>: A longer delay in the start of descent, when moderated by pilot inexperience, is associated with a further increase in the probability of having a UA.

H2bb<sub>1</sub>: High-speed below 10,000 feet, when moderated by pilot inexperience, is associated with a further increase in the probability of having a UA.

H2cb<sub>1</sub>: Higher airspeed at gear extension, when moderated by pilot inexperience, is associated with a further increase in the probability of having a UA.

H2db<sub>1</sub>: A shorter distance to destination at gear extension, when moderated by pilot inexperience, is associated with a further increase in the probability of having a UA.

H2eb<sub>1</sub>: Higher airspeed at flap extension, when moderated by pilot inexperience, is associated with a further increase in the probability of having a UA.

H2fb<sub>1</sub>: A shorter distance to destination at flap extension, when moderated by pilot inexperience, is associated with a further increase in the probability of having a UA.

H2gb<sub>1</sub>: Using spoilers on descent, when moderated by pilot inexperience, is associated with a further increase in the probability of having a UA.

H2ac<sub>1</sub>: A longer delay in the start of descent, when moderated by decreased duration, is associated with a further increase in the probability of having a UA.

H2bc<sub>1</sub>: High-speed below 10,000 feet, when moderated by decreased duration, is associated with a further increase in the probability of having a UA.

H2cc<sub>1</sub>: Higher airspeed at gear extension, when moderated by decreased duration, is associated with a further increase in the probability of having a UA.

H2dc<sub>1</sub>: A shorter distance to destination at gear extension, when moderated by decreased duration, is associated with a further increase in the probability of having a UA.

H2ec<sub>1</sub>: Higher airspeed at flap extension, when moderated by decreased duration, is associated with a further increase in the probability of having a UA.

H2fc<sub>1</sub>: A shorter distance to destination at flap extension, when moderated by decreased duration, is associated with a further increase in the probability of having a UA.

H2gc<sub>1</sub>: Using spoilers on descent, when moderated by decreased duration, is associated with a further increase in the probability of having a UA.

H2ad<sub>1</sub>: A longer delay in the start of descent, when moderated by non-automated flight, is associated with a further increase in the probability of having a UA.

H2bd<sub>1</sub>: High-speed below 10,000 feet, when moderated by non-automated flight, is associated with a further increase in the probability of having a UA.

H2cd<sub>1</sub>: Higher airspeed at gear extension, when moderated by non-automated flight, is associated with a further increase in the probability of having a UA.

H2dd<sub>1</sub>: A shorter distance to destination at gear extension, when moderated by non-automated flight, is associated with a further increase in the probability of having a UA.

H2ed<sub>1</sub>: Higher airspeed at flap extension, when moderated by non-automated flight, is associated with a further increase in the probability of having a UA.

H2fd<sub>1</sub>: A shorter distance to destination at flap extension, when moderated by non-automated flight, is associated with a further increase in the probability of having a UA.

H2gd<sub>1</sub>: Using spoilers on descent, when moderated by non-automated flight, is associated with a further increase in the probability of having a UA.

The number of EM variables and MVs mandates a large number of hypotheses. Due to the complexity and number of hypotheses for RQ2, a hypothesis identification matrix is provided in Table 1.

**Table 1***RQ2 Hypothesis Identification Matrix*

EM Variables	Moderating Variables			
	Lighting	Experience	Duration	Automation
Late Start	2aa	2ab	2ac	2ad
High Speed	2ba	2bb	2bc	2bd
Gear Speed	2ca	2cb	2cc	2cd
Gear Dist	2da	2db	2dc	2dd
Flap Speed	2ea	2eb	2ec	2ed
Flap Dist	2fa	2fb	2fc	2fd
Speed Brake	2ga	2gb	2gc	2gd

*Note.* Dist = Distance.

**Delimitations**

While the study's investigative approach applies to all phases of flight, the data analysis will be limited to identifying relationships between UAs and EM variables, and possible MVs only. Since approach and landing phase mishaps are the most common, addressing this area has the highest potential to positively impact aviation safety (International Civil Aviation Organization, 2014). Analysis of the variables in multiple phases of flight would substantially increase the time required to process the FDM information. Only the flight phases from the initiation of the descent from cruise to the final approach have a substantial effect on UAs. Therefore, while the approach may help identify other such deficiencies in other phases of flight, the inclusion of flight phases outside those indicated would have added little, if anything, to the investigation.

The present study focused on the relationships between identifiable EM variables and UAs, and the impact of possible MVs on that relationship. While there may be other non-EM variables that influence UAs, such variables were not relevant to this

investigation. These non-EM variables were also not captured by the FDM system.

Further, the inclusion of various other possible predictors of UAs could distort the studied variables' effects. The study excluded the examination of UA predictors that were not related to EM and the MVs to avoid such potential distortion.

The FDM dataset was limited to the 20 months provided by the PA. This dataset included all flights where the airborne systems captured valid FDM data between April 1st, 2016, to November 30th, 2017. Any impacts on the occurrences of UAs related to changes to operational procedures or regulations taking effect after November 30th, 2017, are not reflected in the data.

### **Limitations and Assumptions**

Only one airline participated in the larger EM/FDM project, limiting the sample to a single airline. Concerning the results, the significance lies in the analysis process itself, rather than the dataset. While the dataset was crucial to the study, the analysis process is of greater importance. The analysis successfully identified several EM variable predictors of UAs within the sample dataset; the resulting analysis process should be repeatable with any other airline's FDM information. Additionally, the analysis process may apply to other issues for which FDM information is available and other phases of flight.

It was assumed that similar jet transport aircraft are affected by the same EM variables and MVs in the same or very similar fashion. Aerodynamic principles of large, swept-wing commercial jet airplanes are similar among all manufacturers (Carbaugh et al., 1998). The fleet of aircraft used by the PA consisted of single-aisle, twin-engine turbojet transport aircraft seating between approximately 100 and 200 passengers and



maximum takeoff weights between 120,000 and 210,000 pounds. Energy management characteristics within this class of aircraft will vary little among models or manufacturers. Therefore, the results of this study should be generalizable across similar jet fleets.

It is common among jet air carriers that promotions to Captain are seniority-based. Pilots are hired as First Officers (FOs) and gain experience operating the carrier's aircraft, company Standard Operating Procedures (SOPs), and destinations under a Captain's supervision. The most senior FOs usually fill vacant Captain positions through a seniority bidding process. Therefore, Captains will likely have more experience in the PA's aircraft and SOPs. The Captain will likely also have more experience operating into the PA's destinations. Thus, it was assumed that Captains have more experience than FOs.

Since the dataset was constrained to a single airline, this limitation may introduce biases related to the airline's culture, the airline's training program, and the culture of the ethnographic region from which the majority of pilots within the population originate. Fortunately, the PA's operating standards, procedures, and training comply with ICAO standards. Compliance with ICAO recommendations provides standardized regulations internationally. While there may be some procedural differences between airlines, the results should be applicable to any airline operating the same type aircraft within the same regulatory structure. Nations that are ICAO member states agree to establish a regulatory environment for air carrier operations and training, as well as air navigation standards, that conform to ICAO standards and recommended practices. Aircrew training is addressed in ICAO document 9868, *Procedures for Air Navigation Services: Training* (ICAO, 2015). It was assumed that all airlines operating from ICAO member states

comply with very similar operations standards and practices. It was also assumed that all such airlines are using similar training programs. Thus, the PA's operating practices, standards, and training programs were very similar to many other airlines operating worldwide. This commonality with many other airlines significantly assists in the generalizability of the study across differing pilot groups.

The assumptions above, that the effects of EM variables and MVs are similar across similar jet transport fleets and that operating standards, practices, and training are similar across pilot groups and airlines, homogenizing global airline industry operations, are foundational to the study. The findings of this study should be generalizable to other airlines operating under ICAO rules within their aircraft fleets that are similar to the type used in this study. The fleet of aircraft used by the PA consists of single-aisle, twin-engine turbojet transport aircraft seating between approximately 100 and 200 passengers and maximum takeoff weights between 120,000 and 210,000 pounds. Energy management characteristics within this class of aircraft will vary little among models or manufacturers. And ICAO-compliance provides standardized regulations internationally. There may be some procedural differences between airlines, but the results should be applicable to any airline operating the same type aircraft within the same regulatory structure. Therefore, while this effort's specific outcomes are limited to the PA, the process should be generalizable to other airlines.

### **Summary**

The approach and landing phase of flight is identified as having the most considerable risk of an accident. The concept of the stabilized approach seeks to minimize variation from the ideal approach parameters to reduce this risk. Proper

execution of a stabilized approach requires sound EM practices. Other variables may exist that influence EM. Exceeding the allowable variation results in a UA, which increases the risk of an accident. Analysis of FDM information may help identify relationships between EM, the possible MVs, and UAs.

The following chapters examine the current literature in these areas and identify gaps in the literature. The study is explained, including the research methods selected, the population and sampling scheme, and the process of collecting and analyzing the data. The results are presented, along with conclusions and recommendations that arose from the research.

### **Definitions of Terms**

14 CFR Part 121	Part 121 within Title 14 of the Code of Federal Regulations which contains the operating requirements for domestic, flag, and supplemental air carrier operations (FAA, 2020).
Analysis Ground Station	Software suite used to review, interpret, and analyze FDM information downloaded from the aircraft.
Energy Management	The control and exchange of altitude, airspeed, thrust, and drag to establish the aircraft in the desired energy state.
Flag Operations	Any U.S. air carrier operations, utilizing turbojet aircraft with nine or more passenger seats or a payload capacity of more than 7,500 pounds, that originate within the U.S. or its territories or possessions to a

point outside the U.S. or its territories or possessions, or from within the 48 contiguous states to a point outside the contiguous 48 states, or originate and terminate at points outside the U.S. (FAA, 2011).

Flap Dist	This continuous variable captures the distance from the point where the flap lever is selected to any position beyond the up position to the point of landing.
Flap Speed	This continuous variable captures the airspeed when the flap lever is selected to any position beyond the up position.
Flight Data Monitoring	A system that records vast amounts of data during flight for later review and analysis, predominately for maintenance and safety functions.
Flight Data Recorder	The device onboard the aircraft that records the FDM information for both routine analysis and accident investigation.
Gatekeeper	The person(s) having the resources to link FDM data to crewmembers (FAA, 2004).
Gear Dist	This continuous variable captures the distance from the point where the landing gear handle is selected to the down position to the point of landing.

Gear Speed	This continuous variable captures the airspeed when the landing gear handle is selected to the down position.
High Speed	This categorical variable captures events where the aircraft airspeed exceeds 250 KIAS below 10,000 feet. This variable is coded with a value of 1.0 above 250 KIAS.
International Civil Aviation Organization	A body of the United Nations working with 193 member States to develop and implement international aviation standards.
Late Start	This categorical variable captures events where the descent from cruise altitude begins at 95% of the distance calculated by the equation $\text{Distance} = \text{Altitude}/1000 * 3.$
Moderation	The effect when a “second independent variable changes the form of the relationship between another independent variable and the dependent variable” (Hair et al., 2010, p. 180).
Multicollinearity	“Correlation among three or more independent variables (Hair et al., 2010, p. 165).
Pilot Flying	The flight crew member responsible for actual control of the aircraft during flight.

Pilot Monitoring	The flight crew member responsible for monitoring navigation, communications, and systems, as well as the action of the Pilot Flying, in flight.
Runway Excursion	An aircraft unintentionally leaving the runway surface, either by running off the side or end, on takeoff or landing.
Speed Brake	This categorical variable captures whether the spoilers were extended during the descent from cruise altitude to landing. This variable is coded 0.0 if the spoilers are not used, and 1.0 if they are.
Spoilers	A flight control that significantly decreases lift on a section of the wing, while simultaneously increasing drag, allowing the pilot to increase descent rate and/or decrease airspeed rapidly when activated. Also known as Speed Brake.
Stabilized Approach	An approach to landing where, at no later than 1000 feet above touchdown in Instrument Meteorological Conditions (IMC) or 500 feet above touchdown in Visual Meteorological Conditions (VMC), the pilot flying has the aircraft established on the correct final approach course and glidepath, at the appropriate airspeed and vertical velocity, and in the correct configuration (FAA, 2018c).

Supplemental Operations	Any U.S. air carrier operations where the carrier and the customer, or the customer's representative, specifically negotiate departure time and location, and arrival location (FAA, 2011).
Tailstrike	When the aft fuselage of an aircraft impacts the ground during landing.
Unstable Approach	An approach to landing that has not met stabilized approach criteria. For the categorical variable <i>Unstable Approach</i> , a UA occurred and is identified by the FDM system with a value of 1.0.

### List of Acronyms

AC	Advisory Circular
ACS	Airman Certification Standards
AGS	Analysis Ground Station
ATC	Air Traffic Control
ATP	Airline Transport Pilot
AUC	Area Under the Curve
CATS	Crew Activity Tracking System
CDO	Continuous Descent Operations
CFIT	Controlled Flight into Terrain
CFR	Code of Federal Regulations
DM	Data Mining

DV	Dependent Variable
EM	Energy Management
ERAU	Embry-Riddle Aeronautical University
EUROCAE	European Organization for Civil Aviation Equipment
FAA	Federal Aviation Administration
FAF	Final Approach Fix
FDAU	Flight Data Acquisition Unit
FDM	Flight Data Monitoring
FDR	Flight Data Recorder
GPS	Global Positioning System
HL	Hosmer and Lemeshow
ICAO	International Civil Aviation Organization
IFR	Instrument Flight Rules
ILS	Instrument Landing System
IMC	Instrument Meteorological Conditions
IRB	Institutional Review Board
IV	Independent Variable
LOC	Localizer Landing System
LR	Logistic Regression
MPS	Minimum Performance Standards
MV	Moderating Variable
NM	Nautical Miles
PA	Participating Airline



PAC	Percentage Accuracy in Classification
PF	Pilot Flying
PM	Pilot Monitoring
QAR	Quick Access Recorder
ROC	Receiver Operating Characteristic
SA	Situational Awareness
SAW	Stabilized Approach Window
TDZE	Touchdown Zone Elevation
TSO	Technical Standards Order
UA	Unstable approach
VFR	Visual Flight Rules
VIF	Variance Inflation Factor
VMC	Visual Meteorological Conditions
VOR	Very High-Frequency Omni-directional Range

## **Chapter II: Review of the Relevant Literature**

The current literature related to the study covered several important topics. This chapter explores the relevant literature concerning aircraft EM, UAs, and FDM. The following review reveals the research gaps in these principal areas. The variables of interest and the research model are presented as well as the justifications for the hypotheses.

### **Unstable Approaches**

During takeoff, the aircraft is climbing away from the ground at the highest allowable thrust setting, rapidly accelerating through the critical slow-speed regime. The takeoff phase of flight, representing only 2% of flight time, experiences infrequent mishaps. Only 12% of the fatal accidents in worldwide commercial jet operations occurred in this flight phase in the decade from 2008 to 2017 (Boeing, 2018). However, during approach and landing, the aircraft is descending toward the ground and operating in the slow-speed regime.

The final approach and landing represent just 4% of flight time but account for nearly half (49%) of the fatal accidents in worldwide commercial jet operations in the decade from 2008-2017 (Boeing, 2018). The disproportionate frequency of fatal accidents in the approach and landing flight phases led to a renewed emphasis on adhering to stabilized approach criteria (Slatter, 1997). The FAA states in AC 91-79A that “a stabilized approach is the safest profile, and it is one of the most critical elements to ensure a safe approach to a landing operation” (FAA, 2018c, p. A1-3). Striving to maintain stabilized approach criteria reduces deviations from desired parameters.

According to the Flight Safety Foundation, focusing to maintain stabilized approach criteria provides other benefits as well. By focusing on flying a stabilized approach, the flight crew will also benefit from increased horizontal awareness, vertical awareness, airspeed awareness, and energy-condition awareness (Flight Safety Foundation [FSF], 2009b). By working diligently to maintain the proper ground track, the flight crew will have increased awareness of the aircraft's horizontal position along the final approach course and any deviations and trends. Striving to maintain the proper glidepath allows the crew better awareness of the aircraft's vertical position and the descent rate, deviations, and trends. By concentrating on maintaining the proper airspeed, the crew will maintain better awareness of current airspeed, margin to the minimum safe speed, deviations from the desired speed, and any trends. Increased energy-condition awareness is gained from observing the thrust setting required to maintain the stabilized approach criteria and noting deviations from the norm (FSF, 2009b). From this, it is evident that there are significant safety benefits from striving to maintain stabilized approach criteria.

Various sources contain guidance on criteria that defines a stabilized approach. Advisory Circular 91-79A contains the FAA guidance regarding stabilized approaches. This document describes a stabilized approach window (SAW) at 1000' above the runway touchdown zone elevation (TDZE) in IMC, or 500' above TDZE in VMC (FAA, 2018c). The aircraft should be configured for landing, in trim, on-course (+/- 1 dot of localizer deviation), on-glidepath (+/- 1 dot of glideslope deviation), and at the appropriate airspeed (+5/-0 of computed reference speed) with a descent rate appropriate for the groundspeed (FAA, 2018c). A maximum descent rate of 1000 feet per minute is a

common standard for jet operations (George, 2007). The Flight Safety Foundation's Approach and Landing Accident Reduction task force published stabilized approach criteria in their ALAR Briefing Note 4.1, which substantially matches the FAA's criteria with additional guidance for unique procedures and abnormal conditions (FSF, 2009a). Having met the stabilized approach criteria at the window, the pilot must remain vigilant.

[I]t's essential to maintain such tight tolerances all the way to touchdown. Strict adherence to such stabilized approach [standard operating procedures] minimizes the probability of a landing accident. Indeed, when [Business & Commercial Aviation magazine] reviewed two decades of NTSB turbine aircraft approach and landing accident and incident reports, we found one or more lapses in stabilized approach discipline were factors in virtually every mishap, except for a scant few events involving mechanical failures. (George, 2007, p. 4)

The PA for this study has established stabilized approach criteria that do not differentiate between instrument or visual conditions. All flights are to use a SAW of 1000 feet above field elevation. The PA also specified that the aircraft is to be in the landing configuration with the thrust set to maintain airspeed. The pilots are also to have all briefings and checklists completed before reaching the SAW (*Flight crew operations manual*, 2017).

### ***Moderating Factors***

The flight crew has numerous tasks to accomplish in preparation for the approach and landing while maintaining proper EM, making the descent from cruise altitude to landing a high workload phase of flight (Schvaneveldt et al., 2001). There are possible MVs, factors that may influence the flight crew's ability to maintain proper EM while completing the required tasks. Various studies have touched on some of these variables,

including whether the approach is accomplished during day or night, the experience of the PF, the duration of the flight (contributing to increased workload), and whether the approach is hand-flown or coupled to the autopilot.

**Lighting.** As day transitions through twilight into night, the loss of ambient lighting restricts visibility. During night approaches, many perceptual cues pilots use to determine spatial position with reference to the ground are unavailable. Also, cockpit instruments and approach documents can be more challenging to read, leading to EM errors. In a study by Kelly and Efthymiou (2019) that analyzed controlled flight into terrain (CFIT) mishaps, visibility issues were a factor in 94% of the accidents. In a CFIT mishap, the flight crew has failed to maintain altitude awareness, whereas a UA is often attributed to a loss of energy awareness. The referenced work did not differentiate among different potential visibility restrictions. Instead, night conditions, weather, and other restrictions to vision were considered together regarding CFIT accidents. The study did note that “[i]t became a critical factor when weather, haze, or darkness restricted the vision of the flight crew to a point where normal duties were effected” (Kelly & Efthymiou, 2019, p. 162). Generally, the lighting conditions of day, twilight, or night impact the flight during a substantial part of the descent through to the approach. While the FDM system of the PA captured whether the approach and landing were conducted in day or night conditions, weather conditions were not.

**Experience.** The experience level of the PF may also influence EM concerning UAs. A more experienced pilot is expected to have better judgment and a better ability to assess the aircraft's energy state than a less experienced pilot (Zhang et al., 2019). Contrarily, a study by Todd and Thomas (2012) investigated the impact of pilot

experience on the execution of stabilized approaches. Their work found “. . . no statistically significant difference between the performance of Captains and First Officers against the stabilized approach criteria used . . .” in their analysis (Todd & Thomas, 2012). The FDM system in the study indicates which pilot (Captain or FO) was flying the approach but did not provide specifics regarding that pilot’s experience.

**Duration.** Duration impacts all pilots' performance regardless of their experience, interfering with mental acuity and decision making. For shorter duration flights, the required tasks for flight (start, taxi, takeoff, climb, cruise, descent, approach, and landing) occur quickly with limited breaks in the activity. Additionally, these shorter flights allow limited time for planning the descent and approach phase. The lack of breaks in activity results in increased mental workload, which is “associated with decreased accuracy rate of detecting abnormal information and longer reaction time” (Wanyan et al., 2018, p. 5). The portion of the flight from beginning the descent from cruise through parking at the gate at the end of the flight is a noted high-workload environment (Bennett, 2019). Short-duration flights, therefore, with the inherently limited time under higher workloads to plan the descent phase, may impact pilot decision making, resulting in poor EM decisions, potentially leading to a UA.

**Automation.** Jet transport aircraft are equipped with sophisticated auto-flight systems capable of much greater precision than the human pilot. These systems follow the programmed route of flight and are also capable of following a vertical profile. The vertical profile is the desired climb and descent schedule. Some are capable of flying the aircraft throughout the approach, landing, and even the after-landing rollout. In many aircraft, the auto-flight system includes auto-throttles which can maintain the selected

airspeed (and thus, energy level), which may even be supplied by the system. Adequately monitored, the auto-flight system can relieve the flight crew of a significant amount of workload.

Regardless of whether the system includes auto-throttles, the flight crew is responsible for ensuring that the aircraft is at the appropriate energy level at all times. When flight crews become over-reliant on the auto-flight systems, they may lose awareness of the energy state. While their paper was specific to CFIT, Kelly and Efthymiou (2019) note the risk of over-reliance on automation:

[Situational awareness (SA)] is essentially a pilot's ability to retain an accurate mental model, in three-dimensional space of the aircraft's position, altitude, speed, and prediction of the aircraft's future path, etc. Loss of SA can occur due to poor workload management, conflicting information, weather conditions, lack of aircraft systems knowledge, and inadequate planning. An increased reliance on automation is also viewed as a major contributing factor. Aircraft automation exists to aid flight crew in conducting a safer flight. Complacency and a lack of vigilance, when system monitoring is required, can result in a loss of SA with devastating consequences. This complacency can be attributed to the human operators over dependence on an aircraft's automated systems. (p. 156)

The loss of situational awareness discussed above includes losing energy awareness. Proper EM depends upon proper energy awareness. Moreover, pilots heavily reliant on the auto-flight system to maintain the energy state may have difficulty with EM when hand-flying during the descent and approach.

With the emphasis placed on stabilized approaches by regulators and operators, there are few UAs. A 2006 Boeing study of 5,609 approaches found that only 245 were UAs, or just 4.4% (Graeber, 2006). While approximately 4% of approaches are unstable, this 4% accounts for 40% of approach and landing accidents (Veillette, 2016). The errors are often EM problems and occur on both the high and low sides of the desired parameters. According to an analysis by Airbus:

Approximately 70% of rushed approaches and UAs involve incorrect management of the aircraft energy level, resulting in an excess or deficit of energy, as follows:

- Being slow and/or low on approach: 40% of events
- Being fast and/or high on approach: 30% of events. (Airbus, 2005, p. 2)

These statistics point to the likelihood that flight crews are having difficulties evaluating the aircraft energy state, controlling the energy state, or both. Such problems are often cited as a causal factor regarding UAs (Airbus, 2005). In 1997, Continental Airlines added EM as part of their recurrent training program. In their 2000 Line Oriented Safety Audit, Continental observed a reduction in UAs of 70% over the previous four years (Wagener & Ison, 2014). Such training, however, is not universal, nor is it mandatory.

### **Flight Data Monitoring**

Advances in flight data recorder (FDR) technology made FDM possible. Flight data recorders are as old as aviation itself. Two of aviation's most historic flights included the use of such recorders.

Wilbur and Orville Wright's historic first flight was documented by the first flight data recorder. This rudimentary device recorded propeller rotation, distance



traveled through the air, and flight duration. Charles Lindbergh's airplane the *Spirit of St. Louis* was also fitted with a flight-recording device. Lindbergh's recorder was [more] sophisticated, employing a barograph that marked changes in barometric pressure or altitude on a rotating paper cylinder. (Grossi, 1999, p. 7)

The earliest FDRs used in airliners utilized a metal foil tape. As this tape moved at a constant rate, styli marked the foil to indicate basic aircraft parameters of heading, airspeed, altitude, and vertical acceleration with the time recorded by the advancement of the foil. Such recorders were mandated in the U.S. by the Civil Aeronautics Authority in 1957 (Grossi, 1999). They were required to be crash protected to facilitate accident investigation efforts. Requirements for FDRs remained unchanged until 1972 when digital technology enabled the recording of many more parameters, and magnetic tape replaced foil. This allowed the requirements to increase to include recording "pitch and roll attitude, thrust for each engine, flap position, flight control input or control surface position, lateral acceleration, pitch trim, and thrust reverser position for each engine, but only for aircraft certificated after 1969" (Grossi, 1999, p. 2). These requirements remained until the late 1980s with the introduction of solid-state FDRs."

The next significant technological advancement in FDR technology, solid-state memory, increased reliability and crash and fire survivability. It also allowed for increased storage capacity, as much as four times that of tape-based FDRs (Grossi, 1999). These advances also allowed for changes in FDR requirements in 1987 and 1988, including increasing the number of recorded parameters in older aircraft. The parameters for those aircraft certificated before 1969 were increased to include "pitch and roll attitude, longitudinal acceleration, the thrust of each engine, and control column or pitch

control surface position” (Grossi, 1999, p. 3). Requirements were updated once again in 1997 that mandated:

- transport airplanes type certificated before October 1, 1969, and manufactured before October 11, 1991, to record as a minimum the first 18 to 22 parameters listed in the rule by August 18, 2001;
- transport airplanes manufactured after October 11, 1991, and before August 18, 2001, to record as a minimum the first 34 parameters listed in the rule by August 18, 2001;
- transport airplanes manufactured after August 18, 2000, must record as a minimum the first 57 FDR parameter listed in the rule;
- transport airplanes manufactured after August 18, 2002, must record as a minimum all 88 FDR parameters listed in the rule. Transport airplanes manufactured after August 18, 2002, must record as a minimum all 88 FDR parameters listed in the rule. (Grossi, 1999, p. 3)

The complete list of digital FDR systems parameters is found in Appendix E to 14 CFR Part 125, included in Table B2. To convert the various analog inputs from sensors throughout the aircraft into digital values that the FDR can record, the system often employs a flight data acquisition unit (FDAU) (FAA, 2004).

Modern aircraft now include numerous digital systems. Digital control units now manage the engines, the pilot's instrument panels are predominately digital displays, and radio systems are now digital as well. Digital buses interconnect all these systems, which allows the FDAU to collect vast amounts of information by monitoring the data bus. Now

it is possible to record the information on the pilot's displays and the raw input from the sensors (Grossi, 1999).

Another benefit coming from the advent of digital recording systems was the Quick Access Recorder (QAR). These devices record information provided by the FDAU but, unlike the FDRs, are not required to be crash survivable. QARs can record thousands of parameters; many more than required for the FDR to record. QARs enable the airline to access the recorded information accessing the FDR (Grossi, 1999). Airlines can then conduct a detailed analysis of the recorded data for various maintenance and operations purposes using the appropriate software (SAFRAN, 2012). This activity is known as FDM.

Airlines use FDM information to monitor the aircraft's condition, identify any exceedances beyond aircraft limitations, and various safety issues. The analysis software rapidly sorts through the voluminous data and can identify data that indicates a need to perform maintenance on the aircraft. Some parameters, while still within normal operating limits, may indicate a trend that requires further investigation. Oil pressure fluctuations or a trend of slightly decreasing oil pressure may indicate a need to inspect or change an engine. Another issue might be an increase in the average fuel burn for a particular aircraft. Exceedances that previously required the aircrew to notice and write up for maintenance are now automatically identified. An indication of a flap overspeed may necessitate an inspection of the flaps. Alternatively, perhaps a hard landing is recorded, indicating a need to inspect the landing gear and airframe. The analysis software can identify singular events and identify trends for a single aircraft or across the

entire fleet. The information that FDM can provide to maintenance is vital to a proactive maintenance department.

The analysis software can also identify operational issues to help enhance safety. The FDM can provide information on compliance with regulations and SOPs. One example could be the required use of heavy automatic braking at a particular airfield due to a short runway. The FDM system in modern transport category aircraft can record the autobraking system's settings and whether or not it was armed. If the airline finds that too many pilots are not following the procedure, the airline can publish a safety memo reminding the pilots of the necessity to comply with SOPs. The ability of FDM to identify and track safety issues is invaluable.

The review of the literature found numerous studies investigating various uses of FDM information. Studies varied from papers on how various data mining (DM) techniques can be applied to FDM information to analyzing fuel flow data within FDM information to predict fuel consumption, to methods of enhancing current FDM analysis by tracking pilot actions. A selection of these studies are discussed below. However, these studies did not investigate the use of FDM information for the identification of relationships between poor EM practices and UA events.

A study by Zhao, Li, and Wang (2017) examined the application of DM techniques to FDM information. Their work looked at how to apply various analysis techniques and described some of the problems that arise when applied to FDM information. One such problem is the dynamic nature of FDM information. They highlight the need to consider "...the spatial and temporal nature of flight data prior to assigning DM techniques" (Zhao et al., 2017, p. 397). The data within FDM is not the

same as a spreadsheet of responses to a survey, but rather slices of time and space concerning an aircraft in flight.

Stolzer and Halford (2007) conducted an investigation of the use of FDM information evaluated methods of predicting fuel consumption by applying DM techniques to engine fuel flow data, calibrated airspeed, gross weight, and altitude. By applying several techniques, the researchers found that two methods of analysis provided excellent results over analysis by multiple regression methods (Stolzer & Halford, 2007). One goal of the research by Stolzer and Halford was to develop a tool that would enable airlines to identify aircraft experiencing fuel burn rates well outside the expected.

A study by Callantine (2001) examined the possibility of expanding the capabilities of FDM to infer aircrew intent. The Crew Activity Tracking System (CATS) envisioned within the paper compared aircrew actions against a model of activity that is considered correct, to include acceptable alternative actions. The analysis showed that CATS would identify both commission and omission errors and identify errors that do not create a detectable deviation from standard procedures (Callantine, 2001).

### **Aircraft Energy Management**

The topic of aircraft EM has been around since the earliest years of aviation. The military fighter pilot community has long taught about EM with respect to air-to-air combat (Shaw, 1985). Indeed, in its most rudimentary forms of airspeed and altitude, EM is mentioned in a book on World War I aviation published in 1918 (Molter, 1918). Having an energy edge over the adversary is one of the critical elements in maintaining the tactical advantage necessary to win, or at least survive, the fight. In U.S. civilian

aviation, teaching or evaluating EM was not an area required during the certification process until the most recent updates to the Airman Certification Standards (ACS).

As of June 2019, the ACS specifically identify EM as an area of emphasis. The new ACS establishes a requirement that the “applicant demonstrates understanding of [a] stabilized approach, to include energy management concepts” (FAA, 2018a, p. 21; 2018b, pp. 15-16; 2018d, p. 21; 2019, p. 21). These new standards apply to all new pilot certificate applicants, as well as new instrument rating applicants. The ACS for Private and Commercial pilot ratings offer little additional information explaining stabilized approaches. The ACS for the instrument rating, however, explains that “[a] stabilized approach is characterized by a constant angle, constant rate of descent approach profile ending near the touchdown point, where the landing maneuver begins” (FAA, 2018b, p. A-16). The ACS for the Airline Transport Pilot certification goes further, stating:

A stabilized approach is one in which the pilot establishes and maintains a constant angle glide path towards a predetermined point on the landing surface. It is based on the pilot’s judgment of certain visual clues and depends on the maintenance of a constant final descent airspeed and configuration. (FAA, 2019, p. A-24)

While these explanations provide some additional information describing a stabilized approach, they lack the specificity found in AC 91-79A. Most notably, the ACS descriptions lack any emphasis on EM.

While EM has not been an area of emphasis in civil aviation as a whole, EM is extensively taught in two subsets: gliders and aerobatics. In gliders, EM is exceptionally critical. Once launched from the winch, auto, or tow plane, the only source of added

energy is “. . . solely from natural forces, such as thermals and ridge waves” (FAA, 2013, pp. 1-4). The glider pilot must manage the aircraft's energy to remain aloft for the desired time and arrive at a landing point with sufficient energy to complete the necessary maneuvers for landing. For the aerobatic pilot, the “. . . conscious exchange of airspeed for altitude and back again is energy management and is a fundamental concept of performing aerobatic sequences” (Szurovy & Goulian, 1997, p. 20). In the airline industry, EM has primarily focused on the quest for fuel efficiency (Merkt, 2013). According to the Bureau of Transportation Statistics, in 2015, U.S. air carriers spent nearly 15% of all operating expenses for fuel (Bureau of Transportation Statistics, 2016). This is an increase from 10% reported in 2000, making it a critical metric within the airline industry (Stolzer, 2002). While fuel efficiency is essential, EM has a critical safety element as well. In all cases, operating the aircraft in a manner such that there is sufficient energy for the pilot to maintain control is critical. The top three causes of fatalities in commercial aviation, loss of control – in flight, runway excursions, and controlled flight into terrain, all have poor EM as a common element (Merkt, 2013).

The total energy of an aircraft consists of three elements: chemical, potential, and kinetic (Merkt, 2013). The chemical energy is the fuel that the engine(s) convert into thrust. The energy attributable to the aircraft's height above the ground, or altitude, is potential energy. Kinetic energy is the energy of its motion through the air or airspeed. The equations for these two forms of energy are expressed by Equations 1 and 2 (Merkt, 2013).

$$E_P = m \cdot g \cdot h \tag{1}$$

$$E_K = (m \cdot V^2)/2 \tag{2}$$

where:

$E_P$  = Potential energy

$E_K$  = Kinetic Energy

$G$  = Acceleration of gravity

$H$  = Height

$M$  = Mass

$V$  = Velocity

Total energy at any given moment is the sum of the instantaneous potential and kinetic energies per unit of weight. Adding the two equations together gives the total energy equation expressed in Equation 3 (Merkt, 2013).

$$E_T = mgh + mV^2/2g \quad (3)$$

where:

$E_T$  = Total energy per unit of weight

$G$  = Acceleration of gravity

$H$  = Height (or Altitude)

$M$  = Mass

$V$  = Velocity

Converting chemical energy in the fuel into thrust works to overcome drag. Energy is lost due to drag. Many sources of drag affect an aircraft in flight.

The total drag of an airplane is composed of the drags of individual components and forces caused by interference between these components. The drag of an airplane configuration must include the various drags due to lift, form, friction, interference, leakage, etc. (Hurt, 1965, pp. 1-17)



Drag produced by the creation of lift is known as induced drag and is greatest at high airfoil angles of attack associated with slow speeds and aggressive maneuvering (Hurt, 1965). As airspeed increases, induced drag decreases with the inverse of the square of the airspeed. Skin friction and unbalanced pressure distribution resulting from the aircraft moving through the air creates parasitic drag (Hurt, 1965). Parasitic drag increases with the square of the airspeed and includes all drag components not associated with the creation of lift. Total drag is the sum of the induced and parasitic drag.

Extended landing gear and flaps can increase drag dramatically, and configuration changes that increase drag require an increase in thrust to maintain airspeed and altitude (Hurt, 1965). Management of drag through configuration is just one part of overall EM. “Controlling the aircraft energy level consists in continuously controlling each parameter: airspeed, thrust, configuration and flight path, and in transiently trading one parameter for another” (Airbus, 2005, p. 2). These four parameters are interrelated such that a change to one will produce a change in one or more of the other three.

Flightpath, specifically the vertical flightpath, is one of the parameters involved in EM. To maintain altitude and airspeed requires enough thrust to counterbalance the total drag. To accelerate in level flight or climbing, or to climb at a constant airspeed requires additional thrust. A steep climb may result in a loss of airspeed even in a clean, low drag configuration with maximum thrust selected. A constant speed descent requires less thrust than level flight. A steep descent may result in acceleration even in a high drag configuration with idle thrust. This characteristic is especially prevalent in the latest aircraft designs that have had significant attention given to reducing drag to increase fuel efficiency and speed.

As aircraft manufacturers have continuously strived to make their aircraft more efficient through drag reduction, EM requires more significant attention. Manufacturers advise flight crews to monitor the aircraft's energy state continuously. Airbus advises that "throughout the entire flight a next target should be defined, in order to stay ahead of the aircraft at all times" (Airbus, 2006, p. 4). Targets include such parameters as altitudes, airspeeds, configurations, thrust settings, as well as combinations of these and others. Preparing for the descent phase of the flight in advance allows the flight crew to identify appropriate targets and fly the aircraft to meet the identified targets. The risk is that, should appropriate targets be missed for any reason, it often makes it more difficult, if not impossible, to achieve subsequent targets. "The key to avoiding such cascading problems is timely planning and preparation for the descent during the low workload cruise phase of flight" (Veillette, 2016, p. 2). This EM planning is key to a smoothly executed descent.

Energy management is also an essential element in stabilized approaches. As the aircraft approaches the airport for landing, the crew will have slowed and descended. The crew will intercept a normal glidepath, usually a three-degree descent, as they configure the aircraft for landing. According to the Flight Safety Foundation, typical deceleration rates are:

For level flight

- 10 to 15 knots per nautical mile with gear up and approach flaps
- 20 to 30 knots per nautical mile during gear and landing flap extension

For descent on a three-degree glidepath

- 10 to 20 knots per nautical mile with landing gear and approach flaps during extension of landing flaps

- deceleration not possible in a clean configuration (FSF, 2009c)

An aircraft intercepting the glideslope with only slats extended typically requires 1000 feet of altitude and three miles to establish the landing configuration (FSF, 2009c).

Arrival at the stabilized approach target altitude, appropriately configured, on-speed and on glidepath requires the careful management of the energy state of the aircraft.

The current literature in EM had a focus on three primary areas: continuous descent operations (CDO), prevention of loss of control incidents, and energy awareness aids for pilots. Each of these study areas can be applied to the approach and landing phase but are also applicable to other phases as well. While these studies may involve the approach and landing phase of flight, they have not provided significant attention to the prevention of UAs.

Continuous descent operations involve minimizing or eliminating level-flight segments during the descent phase of flight. The intent of CDO is to minimize fuel consumption, emissions, and noise (Prats et al., 2014). The concept involves determining the point along the route of flight when the descent for landing can be commenced and then proceed without the need for an increase in thrust. “Ideally, a CDO consists in a full engine-idle descent, from the cruise altitude to the interception of the instrument landing system (ILS) glide slope” (Prats et al., 2014, p. 2). While CDOs are not necessarily incompatible with stabilized approaches, the EM focus is on keeping the power as low as possible throughout the descent.

Another EM topic receiving attention in the literature is the prevention of loss of control. These studies focused on maintaining sufficient energy to safely maneuver the aircraft at all times (Merkt, 2013). This is a critical element in ensuring the safety of

flight. Loss of control accidents accounted for over 49% of onboard commercial aviation fatalities worldwide for the decade 2008 to 2017 (Boeing, 2018). These studies do apply to the concept of stabilized approaches in that it is impossible to execute a stabilized approach with loss of control. Having the necessary energy to remain in control, however, does not guarantee a stabilized approach.

To assist pilots in the task of EM, studies have been conducted over the years to examine ways to use the technology available at the time to provide pilots with some form of indicator in the cockpit to provide a visual representation of the energy state of the aircraft (Baker, 2017; Noyes, 2007; Zagalsky, 1973). Advances in processing and display technology have allowed for the development of highly intuitive displays of aircraft energy state. Zagalsky (1973) presents an electro-mechanical cockpit display with pointers that indicate the calculated current energy state and the current energy rate of change. It is an attempt to distill tabular and graphic information into a display that provides *in-flight cues* to help the pilot manage the energy state (Zagalsky, 1973, p. 2). With the advent of the digital cockpit, energy management displays became able to provide not only current state information, but also predictive energy state information for the near future and computer determined ideal energy state. The display evaluated in Noyes' (2007) study used a vertical tape-style display to present this information, allowing a pilot to determine the current and desired energy states, and the trend of the change of these values. A decade later, the OZ display studied by Baker (2017) presents the pilot with even more EM information. As stated by Baker:

The OZ concept display provides intuitive energy management information and may mitigate LOC-I by displaying an airplane's current power setting in relation

to its minimum allowable speed (stall), its maximum lift (lift/drag), and its maximum allowable speed (structural limits). (2017, p. 35)

These studies examined ways of helping pilots understand their current energy state by providing a visual indication in the cockpit. They lacked, however, other aspects inherent in maintaining a stabilized approach, such as vertical and lateral path control. Thus, the current literature in the field of aircraft EM focused on efficiency, safety, and energy awareness, but lacked a focus on the specifics of possible relationships between poor EM practices and UA events.

### **Gaps in the Literature**

The review of the current literature identified gaps in the current body of knowledge. In the area of EM and UAs, current literature focused on the reduction of fuel consumption, emissions, and noise, as well as the prevention of loss of control, but lacks research on EM and the occurrence of UAs. The literature also appeared to lack studies that examine how the various potential MVs might affect EM. While there are some studies that addressed the direct impact these MVs exert on UAs, there was an apparent lack of studies examining the influence of these variables on EM. A summary table of the review of the current literature can be found in Table B1 of Appendix B.

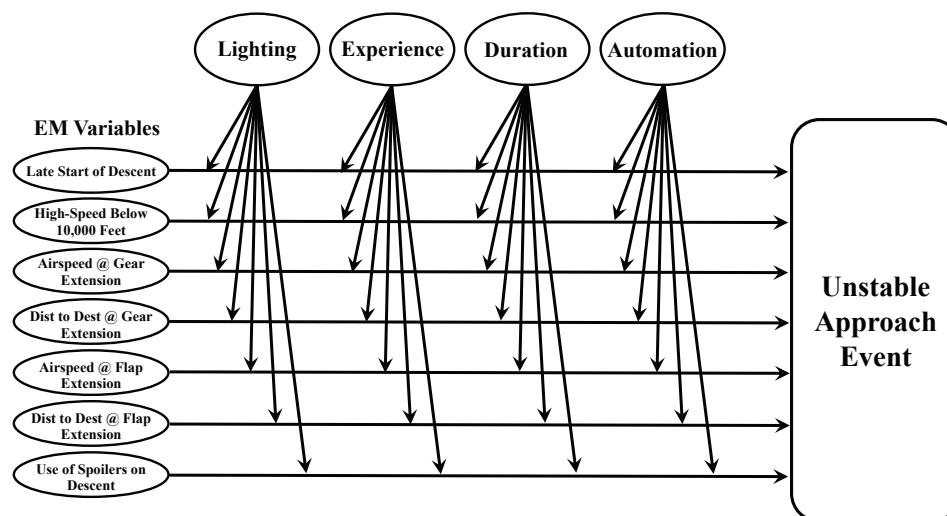
### **Theoretical Framework**

The literature review informed the theoretical model to be used in this research. The model, shown in Figure 3, was used to predict the probability of whether a UA event will occur based on the EM and MV inputs related to a particular flight. The model shows the various EM variables hypothesized to predict UA probability. The MVs are shown moderating each of the EM variables' impact. As each of the MVs shifts from

favorable conditions toward unfavorable conditions, it was expected that their influence on the relationship between the EM variables and UA probability would result in an increase in UA probability. It should be noted that this model is theoretical. The study sought to confirm each of the hypothesized relationships. However, after the conclusion of the analysis, it became apparent there are different relationships among the variables in the model. It may also be found that there are other variables not included in this model that predict the probability of a UA event.

### ***Research Model***

The model in Figure 3 shows the seven IVs influencing the probability of a UA event. Each of the MVs is shown moderating the IVs, possibly increasing or decreasing an IV's influence on UA probability. Note that the model is not showing influences that the MVs might exert on UA probability directly. The model only includes variables that are supported by both the review of the literature and the data available in the FDM dataset.

**Figure 3***Proposed Model of the System*

*Note.* Horizontal lines from EM variables to UA Event indicate direct effects. Line from MVs to direct effects lines indicate moderation effects.

### ***Hypotheses and Support***

Due to the large number of variables in the model, there are many hypotheses in the study. Each of the variables exerts its own influence on the probability of a UA event. The literature review informed the development of the theories regarding the relationships between the IV and the probability of UAs, as well as the moderating influence of the MVs on the IVs. The section that follows discusses each of the variables and the hypotheses related to their influence in the model.

**Hypotheses for Direct EM Variable Influence.** The model in Figure 3 shows the hypothesized relationships between the seven EM variables and the probability of a

UA event. The EM variables have direct relationships with this probability, as indicated. The hypotheses for each of these EM variables follows.

H1a<sub>1</sub>: *A longer delay in the start of descent is associated with an increase in the probability of having a UA.* Delaying the start of the descent in a jet airliner very far past the point computed by three times the altitude above the destination can provide EM problems for the flight crew as described in various technical articles (Airbus, 2006; FSF, 2009b). This distance provides roughly a three-degree descent angle. Above this angle, it is difficult to keep the airspeed within aircraft or legal limits. Therefore, it was hypothesized that delaying the start of the descent from cruise altitude will be a predictor or an increased probability of a UA event.

H1b<sub>1</sub>: *High-speed below 10,000 feet is associated with an increase in the probability of having a UA.* Passing 10,000 feet on the descent usually requires an airspeed of 250 KIAS or less. Exceeding 250 KIAS can represent an EM problem, as simultaneously continuing the descent and decelerating may not be possible (Airbus, 2006). Stopping the descent to slow increases the angle required to meet descent profile requirements, exacerbating the problem. Thus, it was hypothesized that high speed (above 250 KIAS) below 10,000 feet will be a predictor or an increased probability of a UA event.

H1c<sub>1</sub>: *Higher airspeed at gear extension is associated with an increase in the probability of having a UA.* If the PF decides that the landing gear needs to be extended at a high airspeed, it may be indicative of an EM problem. Extending the landing gear increases drag substantially, which can help decelerate the aircraft. The landing gear is normally extended as the aircraft approaches the final descent for landing, with airspeed



close to the stabilized approach requirement. Extension at higher airspeeds may be an indicator that airspeed is too high for a stabilized approach. Therefore, it was hypothesized that higher airspeeds at gear extension are a predictor of an increased probability of a UA event.

H1d<sub>1</sub>: *A shorter distance to destination at gear extension is associated with an increase in the probability of having a UA.* If the PF decides that the landing gear extension needs to be delayed until closer to the destination, it may be indicative of an EM problem. The landing gear should only be extended below the associated limiting speed. If speed is excessive approaching the stabilized approach point, the PF may need to delay landing gear extension. Delayed extension until closer to the destination may be an indicator that airspeed is too high for gear extension and, subsequently, for a stabilized approach. Therefore, it was hypothesized that higher airspeeds at gear extension are a predictor of an increased probability of a UA event.

H1e<sub>1</sub>: *Higher airspeed at flap extension is associated with an increase in the probability of having a UA.* If the PF decides that the flaps need to be extended at a high airspeed, it may be indicative of an EM problem. Extending the flaps increases drag but to a much lesser degree than the landing gear. Nevertheless, extending the flaps may help decelerate the aircraft. The flaps are normally extended as the aircraft approaches the final decent for landing, with airspeed somewhat below flap limit speeds. Extension at higher airspeeds may be an indicator that airspeed is too high for a stabilized approach. Therefore, it was hypothesized that higher airspeeds at flap extension are a predictor of an increased probability of a UA event.

H1f<sub>1</sub>: *A shorter distance to destination at flap extension is associated with an increase in the probability of having a UA.* If the PF decides that flap extension needs to be delayed until closer to the destination, it may be indicative of an EM problem. Like the landing gear, the flaps should only be extended below the associated limiting speed. If speed is excessive approaching the stabilized approach point, the PF may need to delay flap extension. Delayed extension until closer to the destination may be an indicator that airspeed is too high for flap extension and, subsequently, for a stabilized approach. Therefore, it was hypothesized that higher airspeeds at flap extension are a predictor of an increased probability of a UA event.

H1g<sub>1</sub>: *Using spoilers on descent is associated with an increase in the probability of having a UA.* Spoilers are used to increase the descent rate while preventing or limiting an increase in airspeed. If the PF decides that spoilers are needed during the descent, it may be indicative of an EM problem. If the EM problem is of sufficient magnitude, the use of spoilers may be insufficient to correct the problem and prevent a UA event. Because the use of spoilers on the descent indicates a desire to correct an excessive energy situation, it was hypothesized that such use is a predictor of an increased probability of a UA event.

**Hypotheses for MV Moderating Influence.** The hypotheses regarding the MVs involve how they influence the IVs as predictors of a UA event. In each case of an MV, the moderation was measured as the MV transitions from a favorable condition to an unfavorable one. To avoid excessive repetition, each of the MVs will be discussed in general, followed by a discussion of the hypothesized moderating effect in each hypothesis.

**Lighting.** The *MV Lighting* captures the ambient lighting conditions of day, twilight, and night. As ambient lighting transitions from day (0.0) to twilight (1.0) into night (2.0), visual cues are reduced, which may present an increased workload for the flight crew (Zhang et al., 2019). This increase in workload may allow the more subtle cues of deteriorating EM to be missed, contributing to further EM complications. Further, reductions in visibility were identified as a factor in 94% of CFIT accidents, highlighting the impact of decreasing visibility (Kelly & Efthymiou, 2019). Overall, it was hypothesized that reductions in ambient lighting, indicated by increasing values of the *MV Lighting*, moderate the IVs in a way that increases the probability of a UA event. The associated hypotheses for the *MV Lighting* were:

H2aa<sub>1</sub>: A longer delay in the start of descent, when moderated by reduced lighting, is associated with a further increase in the probability of having a UA.

H2ba<sub>1</sub>: High-speed below 10,000 feet, when moderated by reduced lighting, is associated with a further increase in the probability of having a UA.

H2ca<sub>1</sub>: Higher airspeed at gear extension, when moderated by reduced lighting, is associated with a further increase in the probability of having a UA.

H2da<sub>1</sub>: A shorter distance to destination at gear extension, when moderated by reduced lighting, is associated with a further increase in the probability of having a UA.

H2ea<sub>1</sub>: Higher airspeed at flap extension, when moderated by reduced lighting, is associated with a further increase in the probability of having a UA.

H 2fa<sub>1</sub>: A shorter distance to destination at flap extension, when moderated by reduced lighting, is associated with a further increase in the probability of having a UA.

H2ga<sub>1</sub>: Using spoilers on descent, when moderated by reduced lighting, is associated with a further increase in the probability of having a UA.

**Experience.** The MV *Experience* captures which crew member is the PF, the Captain or the FO. *Experience* is coded 0.0 when the Captain is the PF, and 1.0 when the FO is the PF. In general, the Captain is the more experienced member of the flight crew and is considered the expert in the cockpit. Thus, the FO should, in similar situations and conditions, have a higher overall workload (Zhang et al., 2019). This higher workload is expected to translate into greater difficulty in maintaining proper EM. Therefore, it was hypothesized that, when the FO is the PF, indicated by increased values of the MV *Experience*, IVs are moderated such that there is an increase in the probability of a UA event. Associated hypotheses for the MV *Experience* were:

H2ab<sub>1</sub>: A longer delay in the start of descent, when moderated by pilot inexperience, is associated with a further increase in the probability of having a UA.

H2bb<sub>1</sub>: High-speed below 10,000 feet, when moderated by pilot inexperience, is associated with a further increase in the probability of having a UA.

H2cb<sub>1</sub>: Higher airspeed at gear extension, when moderated by pilot inexperience, is associated with a further increase in the probability of having a UA.

H2db<sub>1</sub>: A shorter distance to destination at gear extension, when moderated by pilot inexperience, is associated with a further increase in the probability of having a UA.

H2eb<sub>1</sub>: Higher airspeed at flap extension, when moderated by pilot inexperience, is associated with a further increase in the probability of having a UA.

H2fb<sub>1</sub>: A shorter distance to destination at flap extension, when moderated by pilot inexperience, is associated with a further increase in the probability of having a UA.

H2gb<sub>1</sub>: Using spoilers on descent, when moderated by pilot inexperience, is associated with a further increase in the probability of having a UA.

***Duration.*** The MV *Duration* captures the duration of the flight. As previously shown, flights of shorter durations tend to compress all of the processes involved in conducting a flight. This results in a continuous high-workload environment, which increases the chances of pilot errors (Wanyan et al., 2018). Further, compression of the cruise phase allows limited time to plan the descent phase. For this reason, the study coded the MV *Duration* with the values of 1.0 for flight durations in the bottom quartile and 0.0 for those above the bottom quartile. It is hypothesized that the IVs are moderated such that as the value of the MV *Duration* increases, the probability of a UA event increases. The hypotheses associated with the MV *Duration* were:

H2ac<sub>1</sub>: A longer delay in the start of descent, when moderated by decreased duration, is associated with a further increase in the probability of having a UA.

H2bc<sub>1</sub>: High-speed below 10,000 feet, when moderated by decreased duration, is associated with a further increase in the probability of having a UA.

H2cc<sub>1</sub>: Higher airspeed at gear extension, when moderated by decreased duration, is associated with a further increase in the probability of having a UA.

H2dc<sub>1</sub>: A shorter distance to destination at gear extension, when moderated by decreased duration, is associated with a further increase in the probability of having a UA.

H2ec<sub>1</sub>: Higher airspeed at flap extension, when moderated by decreased duration, is associated with a further increase in the probability of having a UA.

H2fc<sub>1</sub>: A shorter distance to destination at flap extension, when moderated by decreased duration, is associated with a further increase in the probability of having a UA.

H2gc<sub>1</sub>: Using spoilers on descent, when moderated by decreased duration, is associated with a further increase in the probability of having a UA.

***Automation.*** The MV *Automation* captures the use of the autopilot in the approach phase. *Automation* is coded as 0.0 when the autopilot is used for the approach and 1.0 when the approach is manually flown. The autopilot, when properly used, relieves the PF of a significant amount of task execution, allowing the PF to allocate more mental resources to EM efforts. However, reliance on automation in the cockpit has been identified as a source of degraded ability to efficiently execute the cognitive skills necessary to safely fly the aircraft and perform EM (Casner et al., 2014). Modern airliners are highly automated, and it is expected that pilots will use it when it is available. Therefore, it is hypothesized that, as *Automation* moves from an autopilot approach to a manually flown approach, the IVs are moderated such that the probability of a UA event increases. The hypotheses associated with the MV *Automation* were:

H2ad<sub>1</sub>: A longer delay in the start of descent, when moderated by non-automated flight, is associated with a further increase in the probability of having a UA.

H2bd<sub>1</sub>: High-speed below 10,000 feet, when moderated by non-automated flight, is associated with a further increase in the probability of having a UA.

H2cd<sub>1</sub>: Higher airspeed at gear extension, when moderated by non-automated flight, is associated with a further increase in the probability of having a UA.

H2dd<sub>1</sub>: A shorter distance to destination at gear extension, when moderated by non-automated flight, is associated with a further increase in the probability of having a UA.

H2ed<sub>1</sub>: Higher airspeed at flap extension, when moderated by non-automated flight, is associated with a further increase in the probability of having a UA.

H2fd<sub>1</sub>: A shorter distance to destination at flap extension, when moderated by non-automated flight, is associated with a further increase in the probability of having a UA.

H2gd<sub>1</sub>: Using spoilers on descent, when moderated by non-automated flight, is associated with a further increase in the probability of having a UA.

### **Summary**

The current literature showed that the approach and landing is statistically the most dangerous phase of flight (Boeing, 2018). While compromising a small percentage of the overall flight time, it accounts for nearly half of all commercial jet accidents. The literature also identified the stabilized approach as an effective way to mitigate the dangers (FAA, 2018c). By meeting the stabilized approach criteria, pilots minimize deviations from the desired flight path and other critical parameters. Failure to maintain strict adherence to stabilized approach criteria results in a UA event. The FDM system not only identifies UA events but also captures the EM variables involved.

The current literature included numerous studies related to the use of FDM information. These studies included ways to apply DM techniques to the tremendous volumes of information that FDM produces, ways to identify operational outliers such as anomalous fuel burns, and methods of tracking aircrew actions for comparison against

standards. The literature, however, seemed to lack studies that investigate the use of FDM information to identify any specific relationships between EM variables and UA events.

To consistently meet the stabilized approach criteria and thereby avoid a UA event, pilots must practice effective EM in the descent and approach phases of flight. Current literature also showed that, while it is certainly not a new concept in aviation, EM has not been considered a high priority topic, with the notable exceptions of gliders, aerobatics, and fighter combat maneuvering. Some studies focused on efficiency and noise reduction by analyzing the physics of the descent and seeking to optimize such by using the force of gravity to power CDOs (Prats et al., 2014). Other studies focused on the need to ensure there is always sufficient energy available to maneuver the aircraft safely, thus avoiding a loss of control mishap (Merkt, 2013). Another area within the literature over the years has been some focus on how to assist the flight crew with EM by attempting to design a cockpit instrument to display the current and future energy states, as well as the rate of change of the energy status (Baker, 2017; Noyes, 2007; Zagalsky, 1973). While there are numerous texts regarding the physics of EM, and some on the application of those physics to aircraft in flight, there appeared to be a lack of studies on how specific EM practices during descent and approach predict the probability of a UA event.

The study examined how the seven IVs may be able to predict an increased probability of a UA. In addition, the study examined the influence of several MVs on the IVs. As there appear to be limited studies in this area, the current effort begins to fill an important gap in the literature. Significant relationships were found that may be practical in improving training and safety protocols in the area of EM and UAs. Identifying these



relationships should produce valuable insight into reducing the probability of the occurrences of UAs.

### **Chapter III: Methodology**

The literature review revealed that FDM information contains a wealth of data collected at a high rate and high fidelity. This information enables analysis of aircraft performance and maintenance related trends and identifies and verifies possible safety-related events that occur during flight. One area that was lacking was using FDM information to identify EM errors, specifically those related to UA events. The FDM information provided such insights and helped identify several other variables' impacts on these relationships.

This chapter discusses the selected research method, the population and how the sample was chosen, sources of the data and the collection system, the variables in the study, and the statistical techniques used in the analysis. Additionally, the software used to extract and compute the desired variables and statistical analysis of the variables is discussed. This research strived to identify EM variables related to UA events and identify the impacts that a selection of MVs may have on those EM variables. Predictive statistical techniques, specifically logistic regression (LR), were used to conduct this analysis.

#### **Research Method Selection**

The research method is quantitative analysis using the PA's FDM information to investigate the relationships various EM errors may have on the occurrence of UA events. Since the dependent variable (DV), the occurrence or not of a UA event, is dichotomous, the statistical analysis selected was an LR. The FDM system provided quantitative data, with continuous or categorical data for the IVs and dichotomous categorical data for the DV. "When you have a categorical DV and one or more IVs" it is suggested that the

quantitative technique of LR is appropriate (Vogt et al., 2014, p. 307). The LR technique “. . . attempts to predict the probability that an observation falls into one of two categories of a dichotomous [DV] based on one or more independent variables [IVs] that can be either continuous or categorical” (Laerd Statistics, 2019, p. 1). Additionally, the LR assessed the impacts of a selection of MVs on the EM/UA relationships.

### **Population/Sample**

The study population was all commercial jet airline approaches flown by the major air carriers in the PA's geographic region in which the aircraft type was a single-aisle, twin-engine turbojet transport aircraft seating between approximately 100 and 200 passengers and maximum takeoff weights between 120,000 and 210,000 pounds.

Worldwide, the commercial jet fleet completed 30.1 million flights in 2017 (Boeing, 2018). For major air carrier commercial jet operations in the region, roughly 830,000 total approaches were flown (*2017 Aviation sector data analysis*, 2018). These flights were accomplished in a diverse fleet of aircraft, day and night, in a wide range of weather conditions. EM played a crucial role in whether these flights ended with a stabilized approach and landing. For perspective, this requires an average of over 2270 approaches per day, 94 approaches per hour, or about 1.5 approaches every minute. The study population was those approaches flown in aircraft similar to those operated by the PA.

### ***Sampling Frame and Strategy***

The sample consisted of commercial flights performed by the PA from December 1st, 2016, through November 30th, 2017. The sample timeframe was selected as it included one full year of flights with no overlap. Limiting the sample to a one-year timeframe prevented having certain months overrepresented in any seasonal or otherwise

cyclical patterns that may influence UAs that the FDM information cannot identify.

During the sample period, the PA flew approximately 250,000 commercial flights. Other flights flown for training, maintenance, repositioning, or other non-commercial reasons were excluded. As a percentage, the PA accomplished just over 30% of the commercial flights in the region. The 312,087 flights operated by the PA are a convenience sample, as only the PA agreed to allow access to actual FDM information from flight operations. Non-commercial flights contained in this convenience sample were removed before accomplishing the analysis.

The approaches in the population are all from carriers subject to operations standards and training program requirements that were compliant with ICAO standards and recommendations. Further, the majority (67%) of the aircraft operated by the air carriers in the region are similar to those operated by the PA (*2017 Aviation sector data analysis*, 2018). As such, the sample should be representative of the overall population.

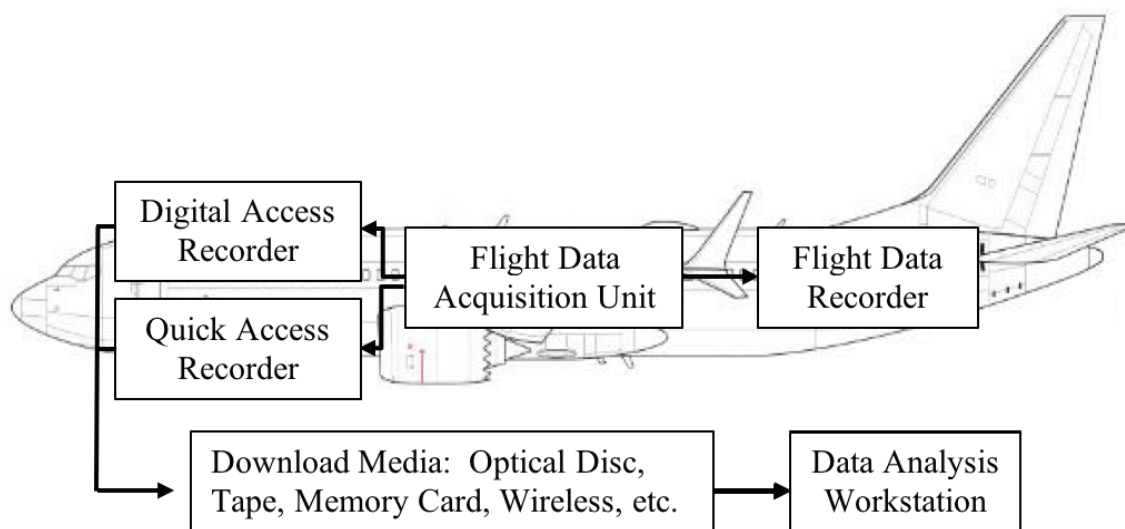
### **Data Collection Process**

The data for the study are archival. The EM data were contained within or computed from the archived FDM information provided by the PA. The raw data were recorded continuously during flight and downloaded for analysis. The aircraft captured and recorded hundreds to thousands of pieces of information during the aircraft's operation at rates ranging from once every four seconds to 32 times per second. Sensors fed raw readings of the various parameters to the Flight Data Acquisition Unit (FDAU). The FDAU converted the raw information into digital data and passed the digital information to the various recorders installed in the aircraft. The FDAU records data to include the information required by regulation for a crash survivable Flight Data

Recorder (FDR), as well as operation and maintenance data retrieved and archived for use in safety and performance analysis (Grossi, 1999). Figure 4 provides a basic depiction of a notional system.

**Figure 4**

*Notional Flight Data Acquisition System*



*Note.* Adapted from “Analysis Ground Station User Manual,” by SAFRAN, 2012.

The Analysis Ground Station (AGS) software developed by SAFRAN identified and processed data related to UAs. Calculation of critical EM data points related to the descent from altitude to the stabilized approach target altitude helped identify relationships between EM errors and UAs.

### ***Design and Procedures***

This archival study was an analysis of FDM information provided by the PA. The PA continuously collects FDM information on all flights. These data include non-

commercial flights conducted for training, maintenance, and logistical reasons. Data recorded were regularly retrieved from the onboard Quick Access Recorder and transferred to the PA's AGS database. For this effort, the FDM information for flights conducted from April 1st, 2016, to November 30th, 2017, was encrypted and copied to an external hard drive for transfer.

### ***Apparatus and Materials***

In order to be usable for the study, the password-protected FDM information received from the PA was decrypted and transferred to an AGS database installed on an Apple iMac with an Intel Core i5 processor running at 3.8 gigahertz and 64 gigabytes of random access memory. Installed on the iMac was the necessary software to process and analyze the FDM dataset. The FDM data were directly accessed using the AGS software, and statistical analysis was accomplished using SPSS® version 26. All the data remained password-protected to ensure confidentiality.

### ***Sources of the Data***

Data for the study came from or were calculated from the FDM data provided by the PA. The dataset included all flights during which the airborne systems captured valid FDM information between April 1st, 2016, to November 30th, 2017. The sample was limited to the period from December 1st, 2016, to November 30th, 2017, to limit any effects from seasonal weather patterns. Also, flights not involving commercial operations were removed from the dataset. Additional parameters, such as the distance from the destination when the descent from cruise altitude begins, were computed from data within AGS. The data were exported into SPSS® version 26 to conduct the LR statistical analysis.

## **Ethical Consideration**

A critical aspect of FDM information is that the confidentiality of the flight crew is critical. Confidentiality helps ensure that flight crew members can share information about mistakes without fear of retribution and is vital in facilitating the sharing of this vital safety information with national authorities and the industry (FAA, 2004). While the FDM information from the PA was de-identified of any specific flight crew member identification, the flight and date information remains. The actual flight number and date are not both present in any data included in this paper to maintain flight crew confidentiality. Further, to maintain the PA's confidentiality, flight numbers, departure locations, and destination locations will not be presented together in any data.

Any research at ERAU that involves human subjects is required to undergo review by the university Institutional Review Board (IRB). In the case of this effort, human subjects were not directly involved. However, archival data generated by the flight crews' actions and requiring confidentiality were analyzed. To ensure that ethical principles regarding such research, and applicable to the study, are identified and followed, application for research approval was submitted to the ERAU IRB. The IRB review determined that the study was exempt from further IRB review. Documentation of the IRB Exempt Determination can be found in Appendix A.

## **Measurement Instrument**

The FDM system records volumes of data on every flight. The individual parameters are in many forms. Discrete parameters have precise values, such as up or down on the landing gear selector handle (SAFRAN, 2012). Other parameters are derived from sensor inputs with conversion calculations made within the FDAU. These

calculations can be as simple as a multiplying factor or a linear equation or a complex polynomial (SAFRAN, 2012). The FDM system also records alphanumeric information such as the date, the identifier of the airports of departure and arrival, and the designator of the runways used (SAFRAN, 2012). The data were analyzed using the AGS software to identify UAs and examine their relationship to EM errors.

### *Variables and Scales*

The PA programmed AGS such that exceeding specific parameters at or below the stabilized approach safety altitude of 1,000 feet above the landing altitude flags events. The closer to the ground that these events occur, the higher Severity Class the event is categorized. Events categorized as Severity Class 1 occur between 1,000 feet and more than 750 feet. Events categorized as Severity Class 2 occur between 750 feet and above 500. Events categorized as Severity Class 3 occur at 500 feet or less. These events identify violations of the stabilized approach criteria established by the PA and thus are indicative of UA events. A UA is flagged based on the number and severity of these events:

- A single Severity Class 3 event alone flags a UA Severity Class 1
- A single Severity Class 3 and any Severity Class 2 events flag a UA Severity Class 2
- Two or more Severity Class 3 events flags a UA Severity Class 3

A summary of these UA indicating events is provided in Table 2.



**Table 2***Unstable Approach Indicators*

Event	Description
Hi-Speed on Approach	Exceeding the reference approach speed by 25 knots for 5 seconds or more
Hi Descent Rate on Approach	Exceeding 1,200 feet per minute descent rate for 5 seconds or more
N1 Low on Approach	Engine power below 35% N1 for 5 seconds or more
Late Landing Configuration	Flaps not established at 40 degrees and still in motion signifying that the landing configuration was not established

*Note.* Adapted from “Analysis Ground Station User Manual,” by SAFRAN, 2012, p. 16.

The PA uses the level of severity in evaluating the UA event under its Safety Management System. For this study, however, the UA flag is considered a binary variable; either a UA occurred, or it did not. While the PA uses thresholds for differing Severity Classes, the occurrence of a UA itself is binary. The DV in the analysis was whether a UA occurred during the flight.

**Variables of Interest.** The variables of interest are indicators of possible EM errors during the descent from cruise altitude to touchdown, including the distance to the destination at the start of the descent, airspeed below 10,000 feet, airspeed at landing gear extension, distance to the destination at landing gear extension, airspeed at flap extension, distance to the destination at flap extension, and use of spoilers during the descent. Each of these variables represents an EM element that may indicate a poor understanding of EM by the flight crew. These variables are the IVs for the study.

The first IV, *Late Start*, is the distance to the destination of initiating the descent from cruise flight. This categorical variable was computed within AGS. Groundspeed is reported every second in nautical miles per hour. The reported groundspeed divided by 3,600 gives the distance traveled in that second. Computation began when AGS reported a change from cruise to descent, terminating at touchdown. The sum of these individual distances provided the distance traveled from beginning the descent until touchdown.

A conventional computation of when to initiate the descent is an easily remembered formula of three times the cruise altitude above the destination elevation in thousands of feet. This technique can be expressed by Equation 4 (Ison, 2006).

$$Dist = \frac{Alt}{1000} \cdot 3 \quad (4)$$

where:

*Dist* = Distance from touchdown to begin decent in nautical miles

*Alt* = Altitude to lose

To compute the values of *Late Start*, the actual descent distance was divided by the expected descent distance from Equation 4 to arrive at a percentage of the expected distance. Values of the IV *Late Start* were assigned, as indicated in Table 3.

**Table 3***Late Start Value Assignment*

Percentage of Estimated Distance (ED)	Value of <i>Late Start</i>
Actual Distance $\geq$ 95% ED	0.0
95% ED > Actual Distance $\geq$ 85% ED	1.0
85% ED > Actual Distance $\geq$ 75% ED	2.0
75% ED > Actual Distance	3.0

*Note.* Estimated Distance is computed using Equation 4.

It is also common to add ten miles to this calculation to slow the aircraft (Ison, 2006). The distance to the destination at which the descent begins impacts EM. If the descent begins too soon and uses standard descent techniques (pitch and power settings producing a predictable descent rate), the aircraft will end up low on energy by being below the desired descent profile. This early descent would require either adjusting the descent rate if recognized early or a level-flight segment at a lower altitude. Conversely, if the descent begins late, standard descent techniques result in the aircraft having too much altitude or an increased descent rate, which reduces the pilots' ability to slow the aircraft in preparation for the approach and landing. The Flight Safety Foundation recommends additional checkpoints in the descent of 9,000 feet above the landing elevation at 30 nautical miles from the destination and 3,000 feet above the landing elevation at 15 nautical miles from the destination (2009a). Delaying the descent long enough may result in the pilots unable to reach the approach altitude and slow the aircraft in time to conduct a safe approach, leading to a UA.

Delaying the descent from cruise is one possible cause for the second IV: high speed below 10,000 feet. This categorical variable, *High Speed*, was captured in-flight by

the FDM system, reporting the maximum airspeed above 250 Knots, as well as setting the event flags programmed by the PA, if appropriate. Other causes can be unintentional, such as forgetting to slow during the descent, or intentional, such as attempting to arrive at the destination prior to the arrival of a storm. Failing to use spoilers, if necessary, while attempting to increase the descent rate can also lead to high speeds. While regulations are part of the reason for slowing the aircraft, usually to a maximum of 250 knots below 10,000 feet, another reason is EM. Keeping the speed down to 250 knots or less simplifies the transition to the approach and landing phase as there is less energy to dissipate in order to configure the aircraft for the approach. A standard limitation for airline aircraft is the landing gear extension, and flight with the landing gear down is limited to a maximum of 250 knots. By limiting speed to 250 knots or less, the landing gear extension can occur at any time as required to assist EM during this transition.

Extending the landing gear adds a significant amount of drag to the aircraft. While spoilers can assist with additional drag, many aircraft have restrictions on deploying spoilers in conjunction with the flaps, making the spoilers of limited use in slowing for landing (FSF, 2009c). The third IV, airspeed at landing gear extension, was a significant variable in that it helped indicate whether the pilot flying was aware of the speed, should a UA occur due to high speed. The continuous variable *Gear Speed* was captured by recording the airspeed at the moment the landing gear handle was selected to the down position. A delay of landing gear extension below the maximum extension speed, followed by an approach resulting in a UA due to high speed, may indicate that the pilot failed to understand the landing gear's ability to help slow the aircraft.

The continuous variable *Gear Dist* was the fourth IV and was calculated in the same manner as noted for *Late Start* beginning at the point when the landing gear handle was selected to the down position. Most jet transport aircraft exhibit a consistent deceleration with the landing gear extended and descending on a three-degree glidepath (FSF, 2009c). If the landing gear extension is delayed to a point closer to the destination, followed by an approach resulting in a UA due to high speed, it may indicate that the pilot failed to understand the landing gear's ability to help with EM.

Flaps also provide additional drag that can be used by the pilots to aid in EM. Both the airspeed at flap extension and the distance from the destination at flap extension are of interest because these data points can provide insight into the pilots' energy awareness. The continuous variable *Flap Speed*, the fifth IV, was captured by recording the airspeed at the moment the flap lever was moved to any position beyond the up position. The continuous variable *Flap Dist*, the sixth IV, was calculated in the same manner as noted for *Late Start* but beginning at the moment the flap lever was moved to any position beyond the up position. The use of flaps, however, can be much more complicated. The flaps on jet transport aircraft typically have numerous different settings with differing maximum extension speeds associated with each position. If utilized early enough, speed permitting, the additional drag from the flaps may be enough to prevent a UA from high airspeed. Conversely, poor EM during the descent may result in the speed exceeding flap extension limitations, which may cause a UA based on not being correctly configured at the stabilized approach altitude.

The spoilers can also indicate poor EM during the descent. If the aircraft is above the descent profile or at a higher speed than desired, spoilers may help manage the

aircraft's energy state. Extending the spoilers reduces lift and increases drag, allowing the pilot to increase the descent rate while holding airspeed steady or decreasing airspeed with a constant descent rate or level. The seventh IV, Speed Brake, was a categorical variable that was 0.0 if spoilers were not used during the descent through landing phases of flight, and 1.0 if spoilers were used. If the aircraft experienced a UA because the approach and landing phase was entered with too much energy, and spoilers were not used during the descent, it may be an indicator that the pilots did not understand the spoilers' use as an EM tool. Table 4 provides a listing of the variables of interest.

**Table 4**

*Energy Management Variables in the FDM Dataset*

Variable	Description	Scale
<i>Unstable Approach</i>	The Dependent Variable. Indicates a UA event has occurred.	Dichotomous
<i>Late Start</i>	Indicates the distance to destination at the start of the descent from cruise altitude.	Categorical
<i>High Speed</i>	Indicates whether the criteria for High Speed Below 10,000 feet MSL event has been met and the relative severity of the event if it occurred.	Categorical
<i>Gear Speed</i>	Captures the Calibrated Airspeed at landing gear extension.	Continuous
<i>Gear Dist</i>	Captures the distance to the point of landing at landing gear extension.	Continuous
<i>Flap Speed</i>	Captures the Calibrated Airspeed at initial flaps extension.	Continuous
<i>Flap Dist</i>	Captures the distance to the point of landing at initial flaps extension.	Continuous
<i>Speed Brake</i>	Indicates spoiler deployment during the descent from cruise altitude.	Categorical/ Dichotomous

*Note.* Dist = Distance; Dest = Destination.

**Moderating Variables.** As described in the literature review, other variables, while not EM in nature, may interact with the EM variables resulting in an influence on UAs. Lighting may impact the aircrew's visual acuity both inside and outside the cockpit. The more light, the better the aircrew can see to execute the approach. The pilot with more experience should be more proficient and skilled at executing the descent and approach. If the duration is shorter, it may decrease the precision with which the aircrew executes the descent and approach. The autopilot is much more precise at controlling the aircraft; therefore, it is expected that automation will reduce UAs. These MVs may influence the occurrence of UAs. Therefore, the study assessed the impact their inclusion had on the model. Table 5 summarizes these possible MVs.

**Table 5**

*Moderating Variables*

Variable	Description	Scale
<i>Lighting</i>	Indicates whether the approach was accomplished during daylight, twilight (dusk/dawn), or night conditions.	Categorical
<i>Experience</i>	Indicates whether the Captain (Experienced) or FO (Inexperienced) accomplished the approach.	Categorical/ Dichotomous
<i>Duration</i>	Indicates the duration of the flight with the premise that a short flight increases task loading, increasing pilot EM errors.	Categorical/ Dichotomous
<i>Automation</i>	Indicates approach accomplishment via the autopilot (0.0) or manually flown by the PF (1.0).	Categorical/ Dichotomous

*Note.* Duration = 1.0 indicates flights with a duration in the bottom quartile.

**Confounding Variables.** There may have been confounding variables. Some situations may force the pilots into a situation that would appear to be a poor EM practice but was not of their choosing. One such situation would be Air Traffic Control (ATC) directions that prevent the aircrew from beginning the descent from cruise until later than desired. Another such situation would be ATC abnormally stopping the descent in progress, such as might be caused by interfering traffic. Another potentially confounding variable is aircrew deviations to avoid weather during the descent to landing phase. Such deviations might significantly delay the normal descent, resulting in a much steeper than normal descent. A steeper descent reduces the options the aircrew must slow the aircraft in preparation for the approach and landing. None of these potentially confounding variables are, unfortunately, captured by the FDM system. The FDM system does not store weather radar displays nor radio communications. Moreover, while the system does record the aircraft ground track, the reason for any deviation from the typical flight path is not. The researcher evaluated the cases to see if there was a pattern for a particular flight, aircraft, or airfield that might indicate something external to the aircrews' EM practices was influencing a UA's occurrence.

While there may have been variables external to the flight crew's EM practices that seek to confound the study, these are not highly common occurrences. As such, these events will help increase the flight crew's awareness of the abnormality of the situation. This awareness should assist the flight crew in making timely corrections to the EM problems that are being forced upon them. Therefore, the impact of these confounding variables, unless identified as a particular pattern (which can then be controlled), was expected to be non-significant.



While various potentially confounding variables may influence UA events' occurrence, the EM portion of the analysis focused on the possible relationships between EM errors and UA events. As mentioned in the delimitations, the inclusion of various other possible predictors of UAs could potentially distort the effects of the EM variables. The analysis excluded the examination of UA predictors that are not related to EM practices to avoid such potential distortion.

The research model captures the seven postulated EM variables and the interactions of the four identified interaction variables. This created a somewhat complicated model, and thus a large number of hypothesis in the study. A graphic representation of this model is provided in Figure 3.

### **Data Analysis Approach**

The study sought to predict UAs by evaluating the relationships of selected EM variables with the probability of a UA event and the influence of selected MVs on those relationships. The study extracted or computed the required variables from the FDM information provided by the PA. Since the DV was dichotomous, using LR as the data analysis approach was suggested (Laerd Statistics, 2019). “Logistic Regression is a specialized form of regression that is formulated to predict and explain a binary (two-group) categorical variable . . .” providing “. . . coefficients indicating the relative impact of each predictor variable” (Hair et al., 2010, p. 317). The LR analysis approach followed the process as outlined in Laerd Statistics *Binomial Logistic Regression* (2019).

### ***Participant Demographics***

The PA operates internationally in a geographic region it shares with other comparably sized airlines. The demographic information for the air carriers serving the

PA's region was evaluated to assess how the size, fleet, and operations of the regions other air carriers compare to those of the PA. In addition, ICAO membership among nations from which these air carriers operate was identified. Member nations of ICAO are expected to establish compliant rules and standards for aviation within their jurisdiction. Thus, this demographic was critical to verify whether these air carriers were likely to have similar operating standards and procedures. The results should be generalizable to the air carriers operating in the same geographic region, drawing pilots from the same ethno-geographic and cultural area, and operating with similar standards.

### ***Reliability Assessment Method***

Reliability assessment of the FDM data consists of both the reliability of the data collection process and the analysis's reliability. As explained below, the collection of FDM data is exceptionally reliable and accurate. The dataset was split by random selection into two subsets, a training set and an assessment set, to test the reliability of the LR model. If the prediction error rate for the assessment set is similar to the prediction error rate of the training set, then the model is presumed to be reliable (Rana et al., 2010).

**FDM System Reliability.** FDM systems can precisely record thousands of parameters for analysis at high sampling rates. The FAA reminds air carriers to examine FDM data to ensure that it is reasonable and consistent (FAA, 2004). Since air carriers use FDM data to evaluate aircraft and operations efficiency, it is incumbent on the carrier to ensure that the FDM data is as accurate as possible. Marketing materials report mechanical/electrical reliability of FDR/FDAU devices as high as 50,000 hours Mean Time Between Failure (L3, 2018). The design of FDR/FDAU devices must meet stringent standards to achieve certification. The FAA's minimum performance standards

(MPS) for flight data recorders, found in Technical Standards Order (TSO)-124A, state that FDRs must meet the MPS found in the European Organization for Civil Aviation Equipment standard ED-112A. The MPSs specify the required external dimensions, the physical testing requirements for crash survivability, and the required performance (European Organization for Civil Aviation Equipment, 2013). The performance specifications require the bit error rate to be no more than one error in  $10^5$  bits, and, when using data compression, the word error may not exceed one error in  $10^5$  words. Since the systems that acquire and record the data must meet stringent certification standards, the FDM data is, therefore, considered reliable.

Assessment of the LR analysis reliability was accomplished through examination of the prediction error rates across datasets. When the results can be interpreted consistently in differing situations, the model is reliable (Field, 2018). Therefore, the reliability testing for the LR analysis was assessed by comparing different datasets for consistent results in the prediction error rate.

### ***Validity Assessment Method***

Validity assessment of the FDM data consists of an examination of the data collected as well as the validity of the analysis. The validity of the data collected, that it is an accurate measure of the desired parameters, is subject to strict regulations. To assess the validity of the LR data analysis, it is suggested that a comparison of the Hosmer and Lemeshow (HL) goodness of fit test and the Receiver Operating Characteristic (ROC) curve assessment be conducted using a dataset different from that used to define the model (Bewick et al., 2005). Using separate testing and hold-out datasets aligns with this suggestion.

**FDM System Validity.** The FDM system records a multitude of parameters at a rate of at least one hertz. The system is designed to accurately record the data for safety and efficiency analysis and meet the regulatory requirements to capture the necessary data. These requirements are specified for digital flight data recording systems in Appendix E of 14 CFR Part 125 (FAA, 2017). This appendix provides a list of the minimum parameters that the system must capture, the minimum range of values, the sensors' accuracy providing the input, and the sample interval required. Values provided can be discrete, such as indicating the status of a control, system, or switch (FAA, 2017). These values could be simply on/off or up/down, or there may be several discrete indicators, such as which navigation source, such as VOR/GPS/ILS/LOC, is in use at the given moment. The minimum required by regulation is shown in Table B2 of Appendix B. Since an approved flight recorder system must meet these stringent requirements, and such an approved system generates the FDM data utilized by this study, the FDM data is, therefore, considered valid.

### ***Data Analysis Process/Hypothesis Testing***

The data analysis process began with an examination of the FDM information in AGS. This analysis determined what information was already available in the dataset, and what information needed computation. Once identified, these additional variables required appropriate procedures to be written within AGS to perform the necessary computations. With the procedures written, the raw data files were processed to generate new variables. After processing, specific selected parameters and variables were extracted in a snapshot of each flight and exported in a comma-separated value (.csv) format for importation into Microsoft® Excel® and SPSS®, one file per month. The

exported files were imported into Excel® to examine the information for missing data and apparent erroneous data and extreme outliers. These cases were scrutinized and, if appropriate, removed from the dataset. Then the monthly files were consolidated into a single file containing the entire year of FDM information. This single file was exported in the .csv format and imported into SPSS® to conduct the statistical analysis.

As previously mentioned, the statistical analysis process, based on a dichotomous DV, was an LR. Hair et al. (2010) explain, “[l]ogistic regression is the preferred method for two-group (binary) dependent variables due to its robustness, ease of interpretation, and diagnostics” (p. 333). This technique seeks to determine the probability of an observation belonging to one of the two categories of the DV. In the case of this study, the observations were the flights within the FDM dataset, and the two categories of the DV were whether a UA event occurred or it did not. In order to accomplish the LR, seven assumptions must be met. These assumptions are:

- one DV, which must be dichotomous,
- one or more IVs that are either nominal or continuous,
- independence of observations, and categories of DV and all nominal IVs mutually exclusive and collectively exhaustive,
- a minimum of 15 cases per IV,
- a linear relationship between continuous IVs and the logit transformation of the DV,
- no multicollinearity, and
- no “significant outliers, high leverage or highly influential points.” (Laerd Statistics, 2019, pp. 3-5)

Each of these assumptions is addressed below.

*One DV, which must be dichotomous.* The only DV for the study, *UA Event*, indicated whether or not a UA event occurred. If a UA event occurred, then the value of *UA Event* was 1; otherwise, it was 0. Thus, the single DV is dichotomous, and this assumption was met.

*One or more IVs that are either nominal or continuous.* The study had seven IVs. Four of the IVs were continuous, and one was nominal. The remaining two IVs were ordinal. It is noted, however, that an ordinal IV may be used in an LR if treated as either nominal or continuous. Therefore, the ordinal IVs *Late Start* and *High Speed* were treated as nominal. With these adjustments, the assumption of one or more IVs that are either nominal or continuous was met.

*Independence of observations and categories of DV and all nominal IVs mutually exclusive and collectively exhaustive.* Each observation was from a different flight, conducted under the specific conditions of a particular date and time. Thus, even if the flight had the same crew operating the same flight number in the same aircraft, the totality of that observation's conditions is unique to that specific approach event, ensuring the independence of observations. Further, for the DV and all nominal IVs, the categories encompass all the possibilities for the respective variables. In each case, the observation can only exist in a single category of the respective variable. As such, the conditions of the assumption of independence of observations were met.

*Minimum of 15 cases per IV.* There were seven IVs in the study, with an additional four MVs, for a total of 11. A minimum of 165 cases is required to meet this assumption. With the size of the FDM data, this assumption is easily met. However,

selecting too large a sample for analysis could result in statistical significance of a variable that is irrelevant in practice (Hair et al., 2010). Further, it is suggested that each category of the DV should have at least 10 observations. UAs historically occur at a rate of 4% (Veillette, 2016). Therefore, the minimum sample for the LR would be 250 cases for 10 UA observations in the DV. When the PA's actual UA rate was calculated, this minimum sample was adjusted to achieve 10 UA observations, as suggested.

An examination of the data assessed these first four assumptions. More advanced analysis was required to assess the remaining three assumptions. The paragraphs that follow describe the process using SPSS® to assess linearity, multicollinearity, and outliers.

*Linear relationship between continuous IVs and the logit transformation of the DV.* The Box-Tidwell test is suggested to test for a linear relationship between the continuous IVs and the logit transformation of the DV (Laerd Statistics, 2019). In SPSS®, this was done by conducting the LR including the interaction of each continuous IV with its log (Field, 2018). Reviewing the *Variables in the Equation* table produced by SPSS® revealed the significance levels determined for the interaction variables. Tabachnick and Fidell (2014) recommend applying a Bonferroni correction using the total number of terms in this model, including the interaction terms and the constant, to adjust the level at which significance is accepted (As cited in Laerd Statistics, 2019). Any significant interaction has violated the assumption of linearity.

Any identified issues of non-linearity can potentially be remedied. A transformation of the IV will be attempted to see if linearity can be established. Should the transformation of a continuous variable fail to establish linearity, there are two

alternatives. One alternative is to transform the continuous variable into ordinal categories and treat it as nominal (Laerd Statistics, 2019). The other alternative is to eliminate the offending variable from the model. Thus, the assumption of a linear relationship between the continuous IVs and the DV's logit transformation can be met.

*No multicollinearity.* Once linearity has been established, it must be determined if any multicollinearity exists in the model. Multicollinearity is when two or more IVs have a strong correlation. While SPSS® lacks a dedicated function to detect multicollinearity in logistic regression, it is recommended to use the linear regression process using the DV and IVs from the regression model (Field, 2018). The linear regression process in SPSS® will provide tolerance and variance inflation factor (VIF) statistics to assess if multicollinearity exists among the IVs. Any VIF greater than 10 (Myers, 1990, as cited in Field, 2018) and tolerance values less than 0.1 (Menard, 1995, as cited in Field, 2018) indicate a multicollinearity problem.

Field (2018) recommends two possible solutions in the event multicollinearity exists. One suggestion is to conduct a principal component analysis, using the component scores to represent the offending IVs. Another suggestion, which Field considers the “safest (although unsatisfactory) remedy is to acknowledge the unreliability of the model” (2018, p. 669).

*No significant outliers, high leverage, or highly influential points.* Points such as these have a significant adverse effect on the regression analysis, reducing the prediction's accuracy and statistical significance (Laerd Statistics, 2019). The SPSS® software package provides a diagnostic that helps identify cases that poorly fit the model by flagging cases where the standardized residual exceeds  $\pm 2$ . Scrutinization of these



cases will determine why the standardized residual was so large and if elimination from the analysis is warranted. Alternatively, a transformation of the offending variable may resolve the issue. With this analysis accomplished, the assumption of no significant outliers is met.

**Binomial Logistic Regression.** With the data thoroughly examined, outliers dealt with, and assumptions met, initiation of the LR can commence. The LR attempts to predict the logit of the DV with the model in Equation 5 (Laerd Statistics, 2019).

$$\text{logit}(Y) = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + \dots + b_nX_n + e \quad (5)$$

where:

Y = the dependent variable

$b_0$  = the sample intercept

$b_1$  = the sample slope for  $X_1$

$b_n$  = the sample slope for  $X_n$

e = the sample residuals

During the analysis process, SPSS® will first compute the value of the constant  $b_0$  by estimating the model with no IVs included, otherwise known as the *null model*. The steps that follow depend on what type of approach to the regression is selected: hierarchical or empirical.

In a hierarchical regression, the researcher determines which IVs to add to the model and what sequence — thus allowing the researcher to let the theory of the study drive the design of the model. In a forward stepwise regression, IVs are added to the model, one at a time, starting with the IV that is the best predictor of the available IVs. Additional IVs are added to the model until the improvement of fit of the model becomes

statistically insignificant ( $p > 0.05$ ). Conversely, in a backward stepwise regression, the first model includes all of the IVs, removing the IV that contributes the least to the fit of the model until only those IVs that are statistically significant remain in the model.

Due to the model's complexity, with seven IVs and four MVs, the study conducted both forward and backward stepwise regressions. This approach may help to overcome the limitations of the forward and backward stepwise regressions on their own. In forward stepwise regression, the algorithm may fail to include a variable that becomes significant only after becoming part of the model. In backward stepwise regression, removal of a significant variable may occur due to its significance being suppressed by another variable in the model. A comparison of the results of the forward and backward approaches informed any necessary modifications to the model in an attempt to achieve a model that is the best fit. The HL goodness of fit test, where statistical significance shows a poorly fitting model, provides an assessment of the model's goodness of fit.

With a well fit model, the next assessment to be made was how well the model explains the variance in the DV. The Model Summary table produced by SPSS® provided several choices in making this assessment. The Cox and Snell  $R^2$  and the Nagelkerke  $R^2$  values provide a pseudo- $R^2$  that attempts to approximate  $R^2$  for the logistic regression. A problem with the Cox and Snell  $R^2$  is that it has an upper bound of less than 1. The Nagelkerke  $R^2$  value is a modification of the Cox and Snell  $R^2$  that corrects this issue.

Several measures can be used to examine how well the model predicts the DV based on the IVs. These measures compare the model's predictions to the actual outcome from the data, as shown in the *Classification Tables* produced by SPSS®. These

measurements are the percentage accuracy in classification (PAC), sensitivity, selectivity, positive predictive value, and negative predictive value (Laerd Statistics, 2019). The PAC is the overall percentage of cases that were correctly predicted, matching the actual occurrence. Sensitivity is the percentage of cases where a UA occurred that the model correctly predicted a UA would occur. On the other hand, selectivity is the percentage of cases where a UA did not occur, and the model correctly predicted that a UA would not occur. The positive predictive value is the percentage of cases correctly predicted to have UAs relative to the number of cases where a UA was predicted. Finally, the study's negative predictive value is the percentage of cases correctly predicted that a UA would not occur relative to the number of cases where a UA was not predicted. These five measures provided an assessment of how well the model predicted the outcome of the occurrence of a UA given the EM variables.

The ROC curve provided a further assessment of how well the model discriminates. While the model was initially generated by using a cutoff of 50% or higher probability of occurrence to predict that a UA would occur, the ROC curve evaluates all possible cutoff points. Increasing the cutoff point results in a lower likelihood of classification of a case as having a UA occur, thus a higher likelihood of classification of a case as not having a UA (Laerd Statistics, 2019). The ROC plot shows sensitivity versus 1 minus specificity (Hilbe, 2009). In SPSS®, the ROC plot consists of a line from the origin to (1,1) that represents a model that has no discrimination, and a line that represents the discrimination of the model throughout the range of cutoffs from 0.0 to 1.0. As described by Pepe:

For any chosen threshold value [of the cutoff point]  $c$ , one can define a dichotomous test by the positivity criterion  $X \geq c$ , and calculate the associated error rates. A plot of 1 minus the false-negative rate (or true positive rate) versus the false-positive rate for all possible choices [of the cutoff threshold] is the ROC curve for  $X$ . (2000, p. 308)

The farther the model line is above the reference line, the more discriminating the model. The difference between the two lines can be evaluated by computing the area under the curve (AUC) for the model line. The AUC of the reference line is 0.5; therefore, the more that the AUC for the model exceeds 0.5 represents increasing levels of discrimination of the model. Hosmer Jr. et al. (2013) provide a useful guide for evaluating the level of discrimination concerning the AUC, summarized in Table 6.

**Table 6**

*Guidance for Evaluating AUC in ROC Analysis*

Area Under the Curve (AUC)	Discrimination Ability
0.5	No Discrimination
$0.5 < \text{AUC} < 0.7$	Poor Discrimination
$0.7 \leq \text{AUC} < 0.8$	Acceptable Discrimination
$0.8 \leq \text{AUC} < 0.9$	Excellent Discrimination
$0.9 \leq \text{AUC}$	Outstanding Discrimination

*Note.* Adapted from Hosmer Jr. et al. (2013).

A final assessment of the basic model was made by examining the *Variables in the Equation* table produced by SPSS®. This table lists all of the variables in the model and provides several informative statistics for each. The b coefficients from Equation 5 indicate how much the log-odds change per unit change in the variable when all the other

variables are fixed. The  $Exp(B)$  values show the odds ratio (how much the odds change for each unit increase) for each IV. The significance of each IV in the model indicates whether the IV added to the model significantly. Finally, the table provides the 95% CI for each  $Exp(B)$ . If the value of 1.0 falls within the CI of an IV, it is an indication that an increase in the specific IV could produce either an increase or decrease in the odds ratio. Each of these measures helps in assessing the basic model.

Once the basic model was assessed, the impact of each MV was evaluated. This evaluation involved adding each interaction to the model, one at a time, assessing how it changed the b coefficient of the associated IV, as well as the overall fit and prediction power of the model.

**Hypothesis Testing.** To test the various hypotheses, the SPSS® output of the appropriate LR was evaluated. First, it was determined if the variable in question makes a significant contribution to the model. Significance can be determined by checking the Sig. column in the *Variables in the Equation* table. Since the hypotheses are directional, the value can be halved to determine significance. A value in this column of  $p < 0.05$  indicates that the variable made a statistically significant contribution to the model. Once significance has been confirmed, the value in the *B* column is examined. *B* is the change in the log-odds for each unit change in the IV when all of the other variables are constant (Laerd Statistics, 2019). *B* is also the slope of the variable in Equation 5. If this value is a positive number, it indicates that the log-odds increase for increases in the IV. A negative value indicates that the log-odds decrease for increases in the IV. Next, the  $Exp(B)$  value should be examined.  $Exp(B)$  indicates the odds ratio for the variable. The odds ratio shows how much the odds for the DV change for each unit change of the IV. If  $Exp(B)$  is

greater than 1.0, it indicates that the log-odds increase for increases in the IV.  $Exp(B)$  less than 1.0 indicates that the log-odds decrease for increases in the IV (Laerd Statistics, 2019). Finally, the 95% CI for the IV should be examined. If the CI spans 1.0, the odds ratio could either decrease or increase per unit increment of the IV, making the contribution of the IV indeterminate.

The process outlined above was applied to each hypothesis within each RQ. If the variable makes a significant contribution to the model, the  $B$  and  $Exp(B)$  will indicate the contribution that the variable makes. If the variable does not make a significant contribution to the model, then the null hypothesis with respect to that variable cannot be rejected.

To test hypotheses for the MVs, the basic model is modified by adding the MV of interest and calculating the LR to provide new  $B$  and  $Exp(B)$  values for the IVs with the added MV. Next, the interacting variable between the MV and each of the IVs in the basic model is added in turn. The LR is recomputed, and the significance of the interaction variable is evaluated. If the interaction variable is significant ( $p < 0.05$ ), the  $Exp(B)$  value for the interaction variable are assessed. Here,  $Exp(B)$  indicates the odds ratio for the interaction variable. The odds ratio shows how much the odds for the DV change for each unit change of the interaction variable. If  $Exp(B)$  is greater than 1.0, it indicates that the log-odds increase for increases in the interaction variable.  $Exp(B)$  less than 1.0 indicates that the log-odds decrease for increases in the interaction variable (Laerd Statistics, 2019). Comparing the  $Exp(B)$  value for the interaction variable with the  $Exp(B)$  value for the IV alone reveals how the MV moderates the effect of the IV. The hypothesis testing process above was repeated for each IV and MV interaction.

## Summary

This was a study of archival FDM data. The PA's FDM system collected these data during more than 300,000 flights. The raw data were processed using AGS software to limit the data to only commercial flights. Training or maintenance flights may include intentional violations of the stabilized approach criteria based on the particular objectives of the flight. Since the objectives of these flights are unknown, it is impossible to separate EM driven UAs from those occurring due to other factors. Thus, removing these non-commercial flights from the sample eliminates the potentially confounding data. In addition, some additional variables not customarily captured by the FDM system will be calculated within the AGS program. The dataset will be randomly split into two sets, one to build the model and another to test for validity and reliability. Next, a statistical analysis of the FDM information using SPSS® will perform an LR. The result of this process will be a model of how the IVs affect the probability of a UA event. The sensitivity and selectivity of the model should be better than 50%, and the ROC AUC should be much better than 0.5. The model will be used to test the hypotheses for each of the EM variables, as well as the effects of the potential MVs using the test dataset to compare model outcomes.

## Chapter IV: Results

This chapter provides details of the analysis of the data. The demographics of the population are presented along with how they contribute to the generalizability of the research. Descriptive statistics are provided for each of the variables, both EM and MV. The reliability and validity testing results are presented, and their impacts on the analysis are explained. Next, the results of the testing for each of the hypotheses are presented. Finally, a summary of the analysis is provided.

### Demographics Results

The study population is all commercial jet airline approaches flown by the air carriers in the geographic region of the PA. Air carriers in the region flew approximately 830,000 approaches in 2017 (*2017 Aviation sector data analysis*, 2018). These flights were accomplished in a diverse fleet of aircraft, day and night, in a wide range of weather conditions. While the aircraft and conditions, and the air carrier operating the flight, may differ, there are several aspects common across this population.

Numerous commonalities aid in the generalizability of the study. The population comes from a region where all the national aviation authorities are members of ICAO. Thus, the aviation rules across the region are fairly universal. There are no unique operating regulations that impact the analysis. Additionally, all the commercial jet carriers in the region operate in accordance with ICAO-compliant standards, providing uniformity of training and operations standards, further aiding generalizability.

Another aid to generalizability is that the flight crew members are most likely drawn from the people within the region, providing uniformity of the flight crews' ethnogeographic culture. Cultural differences could influence attitudes and norms that might



have influenced the sample. The sample consists of commercial flights performed by the PA from December 1st, 2016, through November 30th, 2017. The demographic data for the air carriers in the region are provided in Table 7.

**Table 7**

*Corporate Demographics of Major Air Carriers Operating in the Market*

	Participating Airline	Airline A	Airline B	Airline C
Pilots (PIC and SIC)	1,000+	1,500+	1,900+	600+
Fleet Size	100+	100+	140+	50+
Percentage of Fleet Type Similar to PA	100	10	80	95
Passengers Carried (millions)	30+	20+	30+	10+
Cargo Carried (tons)	100+	50+	230+	70+
Total Flights	251,000	256,000	226,000	87,000
Percentage of Region's Flights	30	31	27	10
ICAO Membership of Airline's Nation	Yes	Yes	Yes	Yes

*Note.* Pilot count, fleet size, and fleet type data current as of December 31st, 2017. Other information reflects operations for the year 2017. Identification of airlines masked to maintain the confidentiality of the PA. Adapted from (*2017 Aviation sector data analysis*, 2018) and (International Civil Aviation Organization, 2020).

As Table 7 shows, of the four major air carriers in the region, three are similar in fleet size, the number of pilots, and operations conducted. All four operate similar aircraft types within their fleet, constituting differing percentages of their total fleet from 10% to 100%. The similarity of these carriers from which the population of approaches is derived aids in the study's generalizability.

## **Descriptive Statistics**

The analysis included categorical and continuous variables in the EM variables, while the MVs were all categorical. The original dataset was cleaned of cases with obviously erroneous values, such as airspeeds reported below the minimum flight speed or zero values for altitude or airspeed for the aircraft in flight. Cases with missing data for the EM variables were also removed from the dataset. Destination airports with high percentages of UAs were analyzed. In all cases, the airport had a meager number of arrivals, resulting in a single or very few approaches with a UA driving a very high UA rate. None of these cases were deemed problematic and remained in the dataset. The descriptive statistics below are derived from the resultant cleaned dataset.

### ***Energy Management Variables***

The EM variables consisted of four categorical variables (including the DV) and four continuous variables. Of the categorical variables, three are binary, and one consists of four categories. The binary variables are Unstable Approach (the DV), High Speed, and Speed Brake. Late Start consisted of four categories, as described in Table 3 above. The descriptive statistics for the categorical variables are presented in Table 8.

**Table 8***Categorical Energy Management Variable Descriptive Statistics*

	Value	Frequency	Percent	Cumulative Percent
Unstable Approach (DV)	0 (Stabilized)	207,969	98.6	98.6
	1 (Unstable)	3,026	1.4	100.0
	Total	210,995	100.0	
<i>Late Start</i>	0 ( $AD \geq 95\%ED$ )	210,367	99.7	99.7
	1 ( $95\% > AD \geq 85\%$ )	583	0.3	100.0
	2 ( $85\% > AD \geq 75\%$ )	44	0.0	100.0
	3 ( $75\%ED > AD$ )	1	0.0	100.0
	Total	210,995	100.0	
<i>High Speed</i>	0 ( $KIAS \leq 250$ )	158,604	75.2	75.2
	1 ( $KIAS > 250$ )	52,391	24.8	100.0
	Total	210,995	100.0	
<i>Speed Brake</i>	0 (Not Used)	56,565	26.8	26.8
	1 (Used)	154,430	73.2	100.0
	Total	210,995	100.0	

*Note.* AD = Actual Distance of start of descent; ED = Estimated Distance of start of descent as calculated in Equation 3; KIAS = Knots Indicated Airspeed.

As previously stated, a 2006 Boeing study found 4.4% of approaches resulting in UAs (Graeber, 2006). Table 8 clearly shows that UAs are very rare events for the PA, with an occurrence rate in the dataset of only 1.4%. Beginning the descent phase late (at less than 95% of the distance computed using Equation 3) is even rarer, with only 0.3% of the cases in the dataset identified as such. Conversely, high speed on the descent was much more common, occurring on nearly 25% of the cases. However, the use of spoilers was widespread in the dataset, with over 73% of cases indicating such an occurrence.

Along with the categorical variables above, there were four continuous EM variables. These variables captured the airspeed and distance to the destination at the extension of the landing gear and flaps. The descriptive statistics for the continuous EM variables are presented in Table 9.

**Table 9**

*Continuous Energy Management Variable Descriptive Statistics*

	Min	Max	Mean	Std. Deviation	Skewness	Kurtosis
Gear Speed	106.50	365.50	179.06	23.54	1.40	2.90
Gear Dist	0.25	49.57	8.59	3.17	2.42	9.61
Flap Speed	117.00	327.50	222.75	17.43	0.48	-0.19
Flap Dist	2.57	79.62	16.80	4.60	1.97	8.41

*Note.* Dist. to Dest. = Distance to Destination; For all variables, N = 210995.

The landing gear and flaps must be extended such that the aircraft is appropriately configured at the SAW to meet the stabilized approach criteria. The FAA's Instrument Flying Handbook (2016) states that the Outer Marker (OM) for an instrument approach will be located four to seven miles from the airport and indicates the location of the final approach fix. The PA's SOPs direct that, in general, the landing gear and flaps are extended not later than three miles before the OM or seven miles from the runway threshold, whichever occurs first (*Flight crew operations manual*, 2017). The SAW of 1000 feet AGL, along a 3<sup>0</sup> glidepath, corresponds to roughly 3 miles from the runway threshold. Therefore, the landing gear and flaps are ordinarily extended 4-5 miles prior to the SAW.

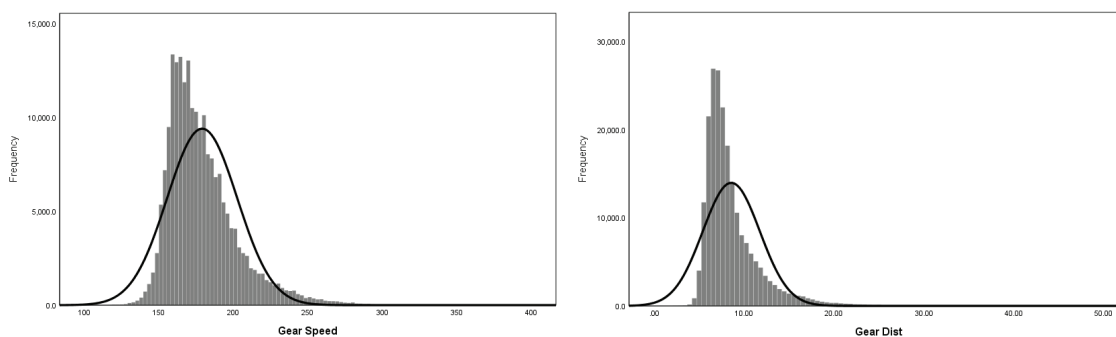
Assuming the OM is 5 miles from the threshold, the PA targets an airspeed of 150 KIAS at the FAF with the landing gear extended allowing the aircraft to decelerate while descending on the glideslope to a nominal 130 KIAS  $V_{Ref}$ . Values of *Gear Speed* had a mean of 179.06 KIAS (SD = 23.54), which closely corresponded to the recommended airspeed when extending the landing gear at 3 miles before the OM. Additionally, a kurtosis of 2.90 indicates that *Gear Speed* values were more concentrated near the mean than the extremes. A skewness value of 1.40 showed that the tail above the mean was more extensive than the tail below. There were values of *Gear Speed* that were above the 270 KIAS limiting airspeed for gear extension on the PA's aircraft. A review of the data did not reveal an error in the data collection system, nor did the number and interval for these extreme values indicate that these cases would be considered outliers. The descriptive statistics for *Gear Speed* indicate that, overall, flight crew did very well following the SOP guidance.

*Gear extension*, per the PA's SOP, should occur at 3 NM prior to the OM, which corresponds to a value of 8 for *Gear Dist*. Again, flight crew did well in following SOP guidance. The mean for *Gear Dist* was 8.59 NM (SD = 3.17). A kurtosis of 9.61 indicates that values of *Gear Dist* are highly concentrated near the mean with relatively few values in the extreme. A skewness value of 2.42 indicates many more values in the curve tail above the mean than the curve tail below. There is no specification limiting the distance at which the landing gear may be lowered. The SOPs do, however, require the aircraft to be fully configured by the SAW. There are values of *Gear Dist* that indicate that the landing gear handle was selected to Down even after passing the SAW. The SAW distance is 1.76 SDs below the mean, indicating that these occurrences are rare. As with

airspeed, a review of the distance data for landing gear extension did not reveal an error in the data collection system, and the number and interval for these extreme values do not indicate that these would be considered outliers. The graph on the left in Figure 5 depicts the distribution of *Gear Speed*, while the graph on the right depicts that of *Gear Dist*.

**Figure 5**

### Landing Gear Extension Histograms



*Note.* Histograms produced by SPSS®.

The flaps on the PA's aircraft have various limiting speeds, with a decreasing maximum speed as the amount of flaps employed increases. As such, the flaps require an additional measure of awareness during employment to ensure the flaps are not extended at an airspeed above the limit for the amount selected. The maximum speed for any flap employment is 250 KIAS for the PA's aircraft. The values of *Flap Speed* ( $M = 222.75$ ,  $SD = 17.43$ ) showed that most flap employments fell within the restriction. The limiting speed of 250 KIAS was 1.56 SD above the mean. The kurtosis of -0.19 indicated that *Flap Speed* exhibited a distribution slightly flatter than a normal distribution. The skewness value of 0.48 indicated more values in the curve tail above the mean than in the

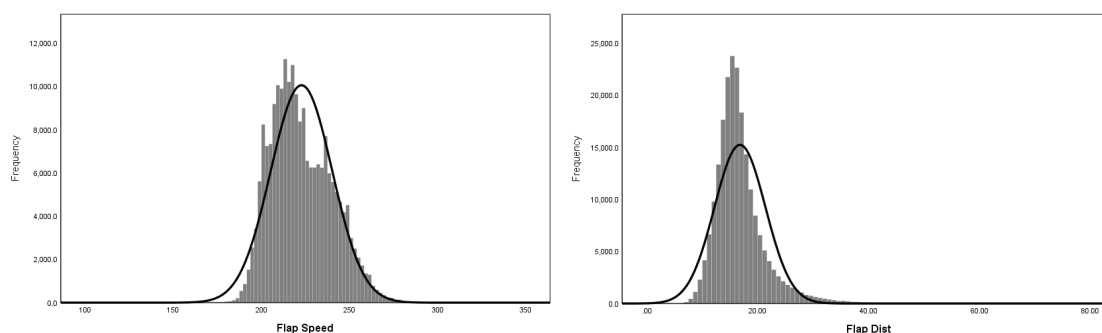
curve tail below. Like *Gear Speed*, there were values of *Flap Speed* that were above the 250 KIAS limiting airspeed for flap extension on the PA's aircraft. Again, a review of the data did not reveal an error in the data collection system, and the number and interval for these extreme values of *Flap Speed* did not indicate consideration of these cases as outliers.

The other variable recorded at flap extension is the distance to landing. *Flap Dist* captured the distance flown to landing from the moment of flaps selection to any position beyond the full up position. The mean for *Flap Dist* was 16.80 NM (SD = 4.80). Much like for landing gear extension, the kurtosis for flap extension was 8.41, indicating the values are highly concentrated close to the mean. While there is no published maximum distance from landing at which flaps may be extended, There is an admonition in the PA's SOPs to "monitor distance to the OM in order not to establish FLAP 05 configuration too early" (*Flight crew operations manual*, 2017). Again, the PA's SOPs require the aircraft to be fully configured by the SAW. There are values of *Flap Dist* that indicate flap deployment at points beyond the SAW. The SAW distance is 3.1 SDs below the mean, indicating that these occurrences are very rare. However, there were many more cases where flaps were selected down much earlier, some as many as 13 SD above the mean. As with the other continuous EM variables, a review of the distance data for flap extension did not reveal an error in the data collection system, and the number and interval for these extreme values did not indicate that these would be considered outliers. A possible explanation for the extreme values for *Flap Dist* may be the extension of flaps in a holding pattern during the approach phase. Such an event would cause the computation of distance to the destination to begin while the aircraft was in holding. Such

an occurrence would have added significantly to the distance reported for *Flap Dist* for the associated case. The graph on the left in Figure 6 depicts the distribution of *Flap Speed*, while the graph on the right depicts that of *Flap Dist*.

**Figure 6**

*Flap Extension Histograms*



*Note.* Histograms produced by SPSS®.

***Moderating Variables***

The four MVs capture factors that may moderate the EM variables influence on the probability of a UA event. While Lighting, Experience, and Automation were extracted from the FDM information, Duration was computed by examining the reported flight durations and flagging the bottom quartile to designate short (less than 52 minutes duration) and long (52 minutes or longer duration). The descriptive statistics for the MVs are presented in Table 10.



**Table 10***Moderating Variable Descriptive Statistics*

	Value	Frequency	Percent	Cumulative Percent
<i>Lighting</i>	1 (Day)	123,464	58.5	58.5
	2 (Twilight)	18,682	8.9	67.4
	3 (Night)	68,849	32.6	100.0
	Total	210,995	100.0	
<i>Experience</i>	1 (Captain)	89,491	42.4	42.4
	2 (First Officer)	121,504	57.6	100.0
	Total	210,995	100.0	
<i>Duration</i>	0 (Longer Flight)	158,819	75.3	75.3
	1 (Short Flight)	52,176	24.7	100.0
	Total	210,995	100.0	
<i>Automation</i>	0 (Autopilot)	205,934	97.6	97.6
	1 (Manual)	5,061	2.4	100.0
	Total	210,995	100.0	

*Note.* Short Flight = Bottom Quartile.

The FDM system determined the value of the MV *Lighting* by comparing the time of landing with the sunrise/sunset tables for the destination airfield. Dusk and dawn were combined into the single value of twilight. Twilight is the period before sunrise and after sunset, during which “there is natural light provided by the upper atmosphere, which does receive direct sunlight and reflects part of it toward the Earth’s surface” (FAA, 2020, p. 10-2-8). To narrow this definition even further, the FAA provides the following definition:

Civil twilight is defined to begin in the morning, and to end in the evening when the center of the Sun is geometrically 6 degrees below the horizon. This is the limit at which twilight illumination is sufficient, under good weather conditions, for terrestrial objects to be clearly distinguished. (FAA, 2020, p. 10-2-8)

In the middle latitudes, civil twilight periods in the morning and evening are approximately 30 minutes. This limited period is roughly 4.2% of the day. Thus, the limited number of landings identified as occurring in twilight lighting conditions, 8.9%, is understandable. Additionally, most airlines operate fewer flights during the overnight hours. Thus, the value of 32.6% of approach and landings occurring in night lighting conditions is also understandable.

The MV *Experience* was determined by which pilot was controlling the autopilot/flight director system. The FDM system records which cockpit side is controlling the autopilot/flight director system during the approach. The PA's SOPs direct control selection to the side of the PF. It is usual for air carrier flight crews to alternate the PF/PM duties on each leg, allowing less experienced pilots (usually the FO) to gain experience while also allowing more experienced pilots (usually the Captain) to maintain proficiency. To help FOs gain experience, the Captain may permit the FO to operate as the PF on additional legs. This may explain why Captains were recorded as making 42.4% of landings, while FOs were recorded as making 57.6%. Along with pilot experience, the duration of the flight impacts pilot performance.

The MV *Duration* was computed within SPSS® using the recorded time from liftoff to touchdown in hours, minutes, and seconds (hh:mm:ss). This value was first converted into decimal hours (H.h), then SPSS® was used to establish the quartiles. The

bottom quartile was designated as short flights (flagged with a value of 1), with all other flights designated as long flights (flagged with a value of 0). Those flights with durations exactly at the breaking point between the quartiles were designated as longer flights. Thus, the short flights accounted for 24.7 % of the flights. The increased overall task loading during shorter duration flights decreases pilot performance (Wanyan et al., 2018).

The autopilot helps in reducing pilot task loading. The MV *Automation* captured autopilot use for the approach. The FDM system does not just record which cockpit side controls the autopilot/flight director system; it also records whether the autopilot was engaged and flying the aircraft during the approach. The FDM system indicates a disengaged autopilot with a value of 0 and an engaged autopilot with a value of 1. These values were recoded 0 for an engaged autopilot and 1 for manually flown with the autopilot disengaged for the study. The MV *Automation* indicates that 97.6% of the approaches executed by the PA had the autopilot engaged. Before a model employing the EM variables and MVs described above could be developed, LR's assumptions had to be validated.

### **Testing of Assumptions**

Before any analysis of the data could be accomplished, the assumptions for the LR needed testing. These assumptions were extensively described in the Data analysis process/hypothesis testing section in Chapter III. For LR, the seven assumptions are:

- one DV, which must be dichotomous,
- one or more IVs that are either nominal or continuous,
- independence of observations, and categories of DV and all nominal IVs mutually exclusive and collectively exhaustive,

- a minimum of 15 cases per IV,
- a linear relationship between continuous IVs and the logit transformation of the DV,
- no multicollinearity, and
- no “significant outliers, high leverage or highly influential points.” (Laerd Statistics, 2019, pp. 3-5)

Each of the seven assumptions was validated, as discussed below.

There must be a single DV, which is dichotomous. The single DV for the study, UA Event, consists of values of 0 for cases where a UA did not occur, and 1 for cases where a UA did occur. The assumption of a single, dichotomous DV was met.

There must be one or more IVs that are either nominal or continuous. There are seven IVs and four MVs. Three of the IVs and all four MVs were nominal, and the remaining four IVs were continuous. The assumption that there must be one or more IVs that are either nominal or continuous was met.

Observations must be independent, and categories of DV and all nominal IVs mutually exclusive and collectively exhaustive. The dataset was cleaned of duplicate cases. These cases were identified by comparing flight dates, destinations, landing times, durations, and aircraft identification, ensuring each case was a separate, independent observation of a specific approach event. The values for each variable can only exist in one category for that variable in each case. There are no possible values for any variable other than those found in the set for each case present in the set. Thus, the assumption of independence of observations and exclusivity of variables was met.

There must be a minimum of 15 cases per IV. The previous discussion indicated that, with an industry average of 4% UAs, there needed to be a minimum of 250 cases to satisfy the suggested minimum of 10 instances of each category of the DV. Equation 6 was used to calculate the number of cases to meet the minimum of 10 events for each variable.

$$S_m = Em / \left(\frac{X}{N}\right) \quad (6)$$

where:

$S_m$  = Minimum sample size

$E_m$  = Minimum number of events

$X$  = Number of cases in which a UA occurred, and the variable is flagged

$N$  = Total number of cases

Using Equation 6, the minimum sample size associated with each of the categorical variables, both EM and MV, was calculated. For the MV Lighting, only the category with the fewest occurrences was calculated. The results of the calculations are presented in Table 11.

**Table 11***Calculated Minimum Sample Sizes*

	UA Occurrences	Percentage of UAs	Percentage of Total	Minimum Sample Size
Late Start	24	0.79%	0.01%	87,915
High Speed	845	27.92%	0.40%	2,497
Speed Brake	2,058	68.01%	0.98%	1,025
Lighting (Twilight)	201	6.64%	0.10%	10,497
Experience	2,311	76.37%	1.10%	913
Duration	2,355	77.83%	1.12%	896
Automation	204	6.74%	0.10%	10,343

*Note.* N = 210995; Minimum sample size calculated using Equation 6.

The variables with very low occurrence rates require a very large sample size.

*Late Start*, the variable that occurs the fewest times in UA events, demands a minimum sample size of nearly 88,000. The next two variables least frequently occurring in a UA event, *Lighting (Twilight)* and *Automation*, each drive minimum sample sizes of just under 10,500. Hair et al. (2010) caution that very large sample sizes result in giving statistical significance to any difference regardless of relevance. Therefore, the seldom occurring variable *Late Start* was subjected to additional review to reduce the possibility of inflated statistical significance.

The LR indicated that *Late Start* alone was non-significant ( $p = 0.094$ ). When all the EM variables were included in the model, *Late Start* was still non-significant ( $p = 0.172$ ). Since *Late Start* occurred at such a low rate, the Firth LR was used to verify this variable's significance. The Firth LR is a method of computing the LR that seeks to minimize the bias introduced by small group size. In the study's case, the small sample was the 24 cases of UA when *Late Start* was non-zero. Even with the bias correction,

*Late Start* failed to be significant. The results of the Firth LR confirmed that *Late Start* was a non-significant variable both alone ( $p = 0.189$ ) and when part of the basic model ( $p = 0.205$ ). Due to the very low occurrence rate, and the lack of significance in the LR models, it was decided to exclude *Late Start* from minimum sample size considerations. Multiple random subsets were extracted from the training dataset with crosstab analysis accomplished to select training and assessment sets that came closest to fulfilling the 10-instance suggestion on the remaining variables. With a sample size of 10,500, the assumption of 15 cases per IV was met.

There must be a linear relationship between continuous IVs and the logit transformation of the DV. The linear relationship between the continuous variables and the logit of the dependent variable was assessed via the Box-Tidwell (1962) procedure. The LR was accomplished, including the interaction between each continuous IV and its log and assessing the significance of the interaction. A Bonferroni correction was applied using all twelve terms in the model resulting in statistical significance acceptance when  $p < .00417$  (Tabachnick & Fidell, 2014). Based on this assessment, all continuous independent variables were linearly related to the logit of the dependent variable. The results of this analysis are provided in Table 12.

**Table 12***Assessment of Linearity.*

	B	S.E.	Wald	df	Sig.	Exp(B)
Step 1 <sup>a</sup> Late Start(1)	-17.132	7,163.691	.000	1	.998	.000
High Speed(1)	.058	.194	.088	1	.766	1.059
Gear Speed	.104	.218	.227	1	.633	1.109
Gear Dist	-.756	.290	6.771	1	.009	.470
Flap Speed	-.494	.607	.662	1	.416	.610
Flap Dist	-.017	.297	.003	1	.954	.983
Speed Brake(1)	-.090	.189	.228	1	.633	.914
Gear Speed by Ln_GearSpeed	-.014	.035	.162	1	.687	.986
Gear Dist by Ln_GearDist	.186	.081	5.254	1	.022	1.205
Flap Speed by Ln_FlapSpeed	.079	.094	.706	1	.401	1.082
Flap Dist by Ln_FlapDist	.000	.074	.000	1	1.000	1.000
Constant	7.826	21.645	.131	1	.718	2,504.986

*Note.* a. Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Gear Speed \* Ln\_Gear Speed, Gear Dist \* Ln\_Gear Dist, Flap Speed \* Ln\_Flap Speed, Flap Dist \* Ln\_Flap Dist.

There must be no multicollinearity. To assess for multicollinearity, the linear regression process was conducted using the DV and IVs from the model as recommended by Field (2018). The linear regression process provides statistics for tolerance and VIF. In assessing tolerance, values less than 0.1 indicate potential multicollinearity problems (Menard, 1995, as cited in Field, 2018). The model's tolerance values were all well above 0.1, indicating that there are no multicollinearity issues. The other statistic provided is the VIF, which indicate problems when values exceed 10 (Meys, 1990, as cited in Field, 2018). The study model's VIF values were all much less than 10, further indicating that



there are no multicollinearity issues. The tolerance and VIF values for the model are provided in Table 13.

**Table 13**

Summary of Tolerance and VIF Values

Model		Collinearity Statistics	
		Tolerance	VIF
1	Late Start	.996	1.004
	High Speed	.972	1.028
	Gear Speed	.430	2.325
	Gear Dist	.493	2.028
	Flap Speed	.796	1.256
	Flap Dist	.793	1.261
	Speed Brake	.943	1.060

*Note.* Dependent Variable: Unstable Approach.

The linear regression process in SPSS® also produces a table of collinearity diagnostics. Variables sharing high proportions of variance on the same small eigenvalue indicates problems (Field, 2018). The review of the collinearity diagnostics table indicated that there were no significant problems within the model. While this process reveals which variables may be problematic, it does not provide a simple resolution. Elimination of any variable removes potentially valuable information from the model. An examination of the collinearity diagnostics table shows that none of the variables in the model have high levels of variance proportion on the same small eigenvalue. It was determined that there was no multicollinearity since no variables shared high variability on the same eigenvalue. This determination was bolstered by the tolerance values all well

above 0.1, and all VIF values well below 10. The assumption of no multicollinearity in the model was deemed met. The collinearity diagnostics table is provided in Table 14.

**Table 14**

*Collinearity Diagnostics*

Dim.	Eigen.	Cond. Index	Variance Proportions							
			(Const.)	Late Start	High Speed	Gear Speed	Gear Dist	Flap Speed	Flap Dist	Speed Brake
1	5.893	1.000	.00	.00	.01	.00	.00	.00	.00	.01
2	.999	2.429	.00	.98	.01	.00	.00	.00	.00	.00
3	.719	2.862	.00	.01	.94	.00	.00	.00	.00	.00
4	.229	5.077	.00	.00	.00	.00	.00	.00	.01	.95
5	.097	7.775	.00	.00	.00	.00	.45	.00	.12	.00
6	.055	10.391	.01	.00	.04	.02	.09	.01	.60	.00
7	.005	34.080	.20	.00	.00	.96	.45	.10	.27	.00
8	.003	44.636	.79	.00	.00	.02	.00	.89	.00	.03

*Note.* Dependent Variable: Unstable Approach; Dim. = Dimension; Eigen. = Eigenvalue; Cond. = Condition; Const. = Constant.

There must be no significant outliers, high leverage, or highly influential points. The dataset was thoroughly examined for suspect data. Cases, where there appeared to be any type of error in the FDM system's recording of the data, were eliminated. These cases included those with missing values for the variables of interest. Cases with extreme values were analyzed, eliminating those with outlier data. In the continuous IVs, extreme values followed a trend that did not indicate these values were outliers. The number and interval of these extreme values indicated that no single case was of high leverage of

highly influential on its own. Therefore, the assumption of no significant outliers, high leverage, or highly influential points was met.

### Model Development

With the assumptions associated with LR met, the model was created in SPSS®. Forced entry, forward stepwise, and backward stepwise models were compared to determine the best overall model. The Forced Entry and Backward Stepwise procedures both resulted in a model with three significant variables, while the Forward Stepwise procedure produced a model with only two significant variables. A discussion of each of the models is below, and complete SPSS® results for each model are provided in Appendix B. A summary of the critical results of the Omnibus Tests of Model Coefficients, Model Summary, and HL Test is provided in Table 15.

**Table 15**

*Summary of Critical Test Results*

	Forced Entry	Stepwise	
		Forward	Backward
Omnibus Test Sig.	<0.001	<0.001	<0.001
Model Summary $-2LL$	1453.75	1463.647	1455.378
Nagelkerke $R^2$	0.024	0.017	0.023
Hosmer and Lemeshow $\chi^2$	13.033	2.593	15.265
Hosmer and Lemeshow Sig	0.111	0.957	0.054

*Note.* Sig. = Significance,  $-2LL$  = -2 Log-Likelihood; See Appendix B, Tables B3 and B4 for full details.

The Omnibus Tests of Model Coefficients for the three models were all  $p < 0.001$ , indicating that all the models were statistically significant at  $p < 0.05$ . Likewise, all three

models had a -2 Log-Likelihood very close to 1460. The Nagelkerke  $R^2$  values for all three models indicate that they all explain very little of the variability in the DV. The Forced Entry and Backward Stepwise models explain just 2.3% of the variance, and the Forward Stepwise model only 1.7%. While the  $R^2$  values are small, the models only include EM variables, which are a small portion of the factors influencing UA occurrence. Many other factors are not modeled, including but not limited to weather, winds, aircraft malfunctions, and ATC. Thus, a small  $R^2$  was expected. Finally, the HL Test for significance exceeds 0.05 for all three models, indicating that none of the models would be considered a poor fit. Moreover, with a chi-square value of 2.593 and a significance of nearly 1.0, the HL test seemed to indicate that the Forward Stepwise model was the best fit to the data.

Due to the extreme difference in group sizes between UA and non-UA events, the default classification cutoff of 0.5 was not appropriate. All three models placed all cases into the Stabilized Approach group (*Unstable Approach* = 0) with the default classification cutoff of 0.5, therefore all the UA cases were misclassified as stabilized. The cutoff value was adjusted to account for the prior probabilities of UA versus non-UA events. Hair et al. (2010) provide the formula for determining the cutoff value in Equation 7.

$$Z_{CS} = \frac{N_A Z_B + N_B Z_A}{N_A + N_B} \quad (7)$$

where:

$Z_{CS}$  = calculated cutoff value between groups

$N_A$  = number of observations in group A

$N_B$  = number of observations in group B

$Z_A$  = centroid for group A

$Z_B$  = centroid for group B

Group A, UA events, had 140 observations with a mean predicted probability of 0.01713.

Group B, non-UA events, had 10,360 observations with a mean predicted probability of 0.1328. Entering these values into Equation 7 yields a  $Z_{CS}$  of 0.017.

With the classification cutoff adjusted to the calculated value of 0.017, the Forced Entry, Forward Stepwise, and Backward Stepwise procedures were accomplished. A review of the classification tables resulting from the three procedures determined which model provided the best results. The resultant classification tables are provided in Appendix B. A summary of the classification table results is provided in Table 16.

**Table 16**

*Summary of Procedure Differences*

Procedure	PAC	Sensitivity	Selectivity	Positive PV	Negative PV
Forced	76.2	42.1	76.7	2.39	98.99
Forward	77.4	35.0	78.0	2.11	98.89
Backward	76.8	42.1	77.6	2.44	99.00

*Note.* PAC = Percentage Accuracy in Classification; PV = Predictive Value; See Appendix B, Tables B3 and B4 for full details.

The classification results for the three procedures were very similar, with minor variations. All three produced moderate PAC around 77%. In addition, all three procedures resulted in very high negative predictive values near 99%, showing excellent identification of non-UA events. However, they also all resulted in low sensitivity (less than 50%) and a very low positive predictive value of about 2.5%, indicating poor

identification of actual UA events. With very little difference among the models concerning classification performance, and since hypothesis testing required that all the EM variables be present in the model, the Forced Entry model was selected for reliability, validity, and hypothesis testing.

### **Reliability and Validity Testing Results**

Having selected the Forced Entry model for testing the many hypotheses, confirmation of reliability and validity was accomplished using the assessment dataset. To generate the two datasets, 50% of the sample of 210,995 cases were randomly selected in SPSS®. First, the selected cases were copied into a new file as the training set. Then, the unselected cases were copied into a file as the assessment dataset. This process ensured that they were two separate sets, rather than just two sets randomly selected from the same dataset. Otherwise, numerous individual cases would likely appear in both datasets, negatively influencing the reliability and validity testing results.

#### ***Reliability Testing***

For reliability testing of the model, the dataset was split by random selection into a training set and an assessment set. A random sample of 10,500 cases selected from the training set produced the sample to generate the model. A sample of 10,500 cases, the same as the sample size used to generate the model, was randomly extracted from the assessment set and used to determine the model's reliability. The SPSS® Scoring Wizard function generated predicted probabilities for the assessment sample cases using the same variable coefficients as in the training model. A crosstabs analysis generated the same classification table as would be produced in the LR procedure. If the prediction error rate for the assessment set is similar to the training set's prediction error rate, then the model

is presumed to be reliable (Rana et al., 2010). A review of the results revealed that the assessment set's prediction error rate was indeed similar to that of the training set. Thus, the model was determined to be reliable. A summary of the comparison between the training and assessment sets' classification tables is provided in Table 17.

**Table 17**

*Comparison of Training and Assessment Classification Error Rates.*

	PAC	Sensitivity	Selectivity	Positive PV	Negative PV
Training	76.2	36.9	76.9	2.38	98.99
Assessment	76.9	40.0	77.5	2.59	98.85

*Note.* PAC = Percentage Accuracy in Classification; PV = Predictive Value.

### ***Validity Testing***

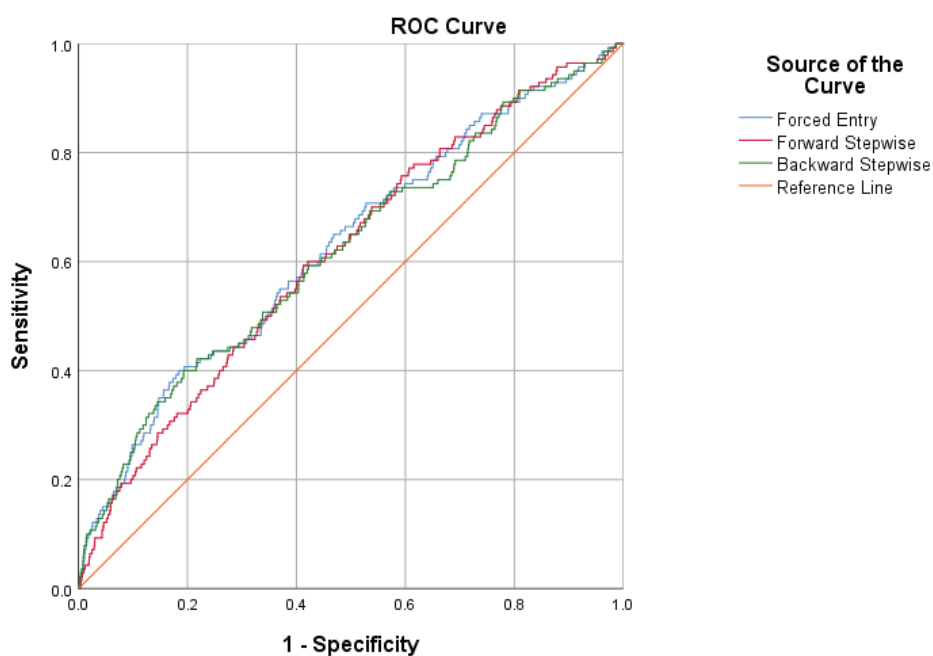
The test of model validity used two measures. The HL goodness of fit test is computed by SPSS® during the LR procedure. The ROC was computed after the final model was determined. Both measures indicate that the model exhibits poor discrimination in predicting UA events.

The HL goodness of fit test provides a measure that verifies if the model is a good fit with the data. If the HL significance value indicates statistical significance ( $p < 0.05$ ), the model is not a good fit. These values are in Table 16 above. For the Forward Stepwise model, the HL test of significance had a value of 0.957, or nearly 1.0, which, combined with the HL chi-squared value for this model of 2.593, indicated a fairly good fit to the data. All three models produced HL significance values above  $p = 0.05$ ; thus, all were presumed to fit the data, thus aiding in validity.

Another measure of the validity of the LR model is the AUC value from the ROC. The ROC generated by SPSS® provided the AUC for the three models. Based on the AUCs, none of the three models provide much discrimination. The best AUC achieved was 0.626 for the Force Entry model; with Referencing Table 6 in Chapter III, AUC values between 0.5 and 0.7 indicate poor discrimination. The results of the ROC computation are provided in Figure 7 and Table 18.

**Figure 7**

*Receiver Operating Characteristic*



*Note.* Receiver Operating Characteristic Curve produced by SPSS®.



**Table 18***Area Under the Curve*

Test Result Variable(s)	Area	Std. Error <sup>a</sup>	Asymptotic Sig. <sup>b</sup>	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
Forced Entry	0.627	0.025	0.000	0.578	0.676
Forward Stepwise	0.614	0.024	0.000	0.567	0.661
Backward Stepwise	0.619	0.026	0.000	0.569	0.669

*Note.* Std. = Standard; Sig. = Significance; a. Under the nonparametric assumption; b. Null hypothesis: true area = 0.5.

Based on the HL goodness of fit test results and the AUC, the three models were determined to be marginally valid. The HL significance indicated that the models were a marginal fit, while the AUC indicated that the model provided poor discrimination. As noted above, there are many factors outside of EM that may influence UAs. Therefore, a model with poor discrimination and marginal fit is understandable, but not desirable.

### **Hypothesis Testing Results**

With the model defined and the reliability and validity confirmed, each of the hypotheses was tested using the model's variable coefficients. For the EM variables, the coefficients were taken directly from the model. The MVs, however, required the addition of the interaction between the appropriate EM variable and the MV to the model, with results providing coefficients for analysis. The basic Forced Entry model was used to provide coefficients for all the EM variables. For the full SPSS® analysis results for the Forced Entry Model, see Appendix B, Table B3. The table of variables in the Forced Entry model is in Table 19.

**Table 19***Forced Entry Model*

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
Step 1 <sup>a</sup>	Late Start(1)	.16.908	7301.899	.000	1	.998	.000	.000	.
	High Speed(1)	.064	.193	.109	1	.741	1.066	.730	1.557
	<b>Gear Speed</b>	<b>.015</b>	<b>.005</b>	<b>8.065</b>	<b>1</b>	<b>.005</b>	<b>1.015</b>	<b>1.005</b>	<b>1.026</b>
	<b>Gear Dist</b>	<b>-.108</b>	<b>.043</b>	<b>6.277</b>	<b>1</b>	<b>.012</b>	<b>.898</b>	<b>.826</b>	<b>.977</b>
	<b>Flap Speed</b>	<b>.016</b>	<b>.005</b>	<b>9.020</b>	<b>1</b>	<b>.003</b>	<b>1.016</b>	<b>1.006</b>	<b>1.027</b>
	Flap Dist	-.013	.022	.342	1	.559	.987	.945	1.031
	Speed Brake(1)	-.094	.188	.252	1	.616	.910	.629	1.315
	Constant	-9.541	1.167	66.825	1	.000	.000		

*Note.* a. Variable(s) entered on step 1: High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake.

***Energy Management Variable Hypothesis Testing***

The first step to test the hypotheses related to the EM variables was to review the variables' significance. If the variable was significant ( $p < 0.05$ ), it was a significant contributor to the model, with confirmation by examining the Wald statistic. The Wald statistic indicates how much the variable contributed to the model. The second step in assessing the variable was to evaluate the  $Exp(B)$  value. This  $Exp(B)$  value indicates the change in the probability of the DV per unit change in the associated IV. The  $Exp(B)$  value indicates the direction of the change, with values above 1.0 indicating an increase in the probability and values below 1.0 indicating a decrease. An  $Exp(B)$  value of 1.0 indicates that there is no effect. The third step is evaluating the 95% confidence interval

(CI) for  $Exp(B)$ . If the 95% CI spans the value 1.0, the variable's effect is ambiguous since, within the 95% CI, the effect could be positive, negative, or no effect at all. If the variable was insignificant ( $p > 0.05$ ) or the 95% CI includes the value of 1.0, then the associated hypothesis was not supported. The testing of the hypotheses associated with each of the EM variables follows.

H1a<sub>1</sub>: A longer delay in the start of the descent is associated with an increase in the probability of having a UA. Early data analysis revealed that the EM variable *Late Start* had an extremely low occurrence rate, producing a considerable sample size requirement that would amplify the significance of other variables. In the sample size of 10,500, some random samples would have an occurrence of *Late Start*, while other samples would not. Even with large sample sizes, *Late Start's* coefficient failed to be significant, and the 95% Confidence Interval (CI) included the value of 1.0. If the CI includes the value 1.0, the direction of the effect of the variable is ambiguous. Thus, the hypothesis was not supported.

H1b<sub>1</sub>: High-speed below 10,000 feet is associated with an increase in the probability of having a UA. The EM variable *High Speed* was not significant in the model (Wald = 0.92,  $p = 0.762$ ,  $Exp(B) = 1.060$ , 95% CI: 0.726-1.026). The significance is greater than  $p = 0.05$ , and the 95% CI also includes the value 1.0. Hypothesis H1b<sub>1</sub> was not supported.

H1c<sub>1</sub>: Higher airspeed at gear extension is associated with an increase in the probability of having a UA. *Gear Speed* was significant in the model (Wald = 8.061,  $p = 0.005$ , 95% CI: 1.005-1.549). The Wald statistic of 8.061 indicates that *Gear Speed* contributed significantly to the model. The  $Exp(B)$  value of 1.015 reveals a positive

relationship in which every unit increase in *Gear Speed*, the probability of a UA event increases by a factor of 1.015. Put another way, a one-knot increase in *Gear Speed* increases the probability of a UA event by 1.50%. Therefore, hypothesis H1c<sub>1</sub> was supported.

H1d<sub>1</sub>: A shorter distance to the destination at gear extension is associated with an increase in the probability of having a UA. Like the airspeed at gear extension, *Gear Dist* was significant (Wald = 6.360,  $p = 0.012$ ,  $Exp(B) = 0.898$ , 95% CI: 0.825-0.976). The Wald statistic of 6.360 shows that *Gear Dist* was a significant contributor to the model, though not as much as *Gear Speed*. The  $Exp(B)$  value of 0.898 indicates a negative relationship such that for each unit increase in *Gear Dist*, the probability of a UA event decreases by a factor of 0.898. Since this hypothesis is related to decreases in *Gear Dist*, dividing 1.0 by 0.898 yields the appropriate factor of 1.114. This factor increases probability of a UA per unit decrease in *Gear Dist* by 11.4%, resulting in support of the hypothesis.

H1e<sub>1</sub>: Higher airspeed at flap extension is associated with an increase in the probability of having a UA. *Flap Speed* was also significant in the model. Again, the Wald statistic of 9.029 indicates that *Flap Speed* contributed significantly to the model. The  $Exp(B)$  value of 1.016 indicates a positive relationship with the DV. For each unit increase in Flap Speed, a UA event's probability increases by a factor of 1.016. This gives an increase in the probability of a UA per unit increase in *Flap Speed* of 1.6%.

Hypothesis H1e was supported.

H1f<sub>1</sub>: A shorter distance to the destination at flap extension is associated with an increase in the probability of having a UA. *Flap Dist* was not significant in the model

(Wald = 0.330,  $p = 0.566$ ,  $Exp(B) = 0.987$ , 95% CI: 0.946-1.031). Unlike the other continuous EM variables, *Flap Dist* contributed little to the model, as indicated by the Wald statistic value of 0.330. Further, the 95% CI included the value 1.0 making the effect of *Flap Dist* ambiguous. For these reasons, the hypothesis for H1f was not supported.

H1g<sub>1</sub>: Using spoilers on descent is associated with an increase in the probability of having a UA. Another variable not significant in the model was *Speed Brake* (Wald = 0.264,  $p = 0.607$ ,  $Exp(B) = 0.908$ , 95% CI: 0.946-1.313). The Wald statistic shows little contribution to the model. Inclusion of 1.0 in the 95% CI makes the effect of *Speed Brake* ambiguous. Thus, the hypothesis was not supported.

After testing the hypotheses associated with the EM variables, the possible influences of the MVs were investigated. Even though an EM variable might not have been significant in the basic model, an MV's influence may have altered the EM variable's contribution to the model. The testing of MV influence is reported below.

### ***Moderating Variable Influence Hypothesis Testing***

Testing of the hypotheses related to the influence of the MVs was a more involved process. Each MV had to be added to the model in turn to produce a new baseline. Then, each interaction was added in turn to evaluate the interaction between the EM variables and the MV of interest. If the interaction variable was significant ( $p < 0.05$ ), then the EM variable was checked for significance. If the EM variable is also significant, then the interaction odds ratio can be determined by adding the B values for the EM variable and the interaction variable, and exponentiating the sum. Due to the

large number of SPSS® outputs required in this process, the tables are provided in Appendix B, Table B5. A summary of the interactions is provided in Table 20.

**Table 20***Summary of Interactions*

	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
					Lower	Upper
Lighting * Late Start	.000	2	1.000			
Lighting * High Speed	.318	2	.853			
Lighting * Gear Speed	1.116	2	.572			
Lighting * Gear Dist	.365	2	.833			
Lighting * Flap Speed	.735	2	.692			
<b>Lighting * Flap Dist</b>	<b>7.095</b>	<b>2</b>	<b>.029</b>			
<b>Lighting * Speed Brake</b>	<b>13.359</b>	<b>2</b>	<b>.001</b>			
Experience(1) by Late Start(1)	.000	1	1.000	.462	.000	
Experience(1) by High Speed(1)	1.074	1	.300	.642	.277	1.485
Experience(1) by Gear Speed	.388	1	.533	1.007	.986	1.027
Experience(1) by Gear Dist	.097	1	.756	.978	.853	1.123
Experience(1) by Flap Speed	.000	1	.995	1.000	.959	1.043
Experience(1) by Flap Dist	.174	1	.677	1.020	.930	1.119
Experience(1) by Speed Brake(1)	.456	1	.499	.599	.135	2.652
Duration by Late Start(1)	.000	1	1.000	.900	.000	.
<b>Duration by High Speed(1)</b>	<b>4.408</b>	<b>1</b>	<b>.036</b>	<b>2.519</b>	<b>1.063</b>	<b>5.968</b>
Duration by Gear Speed	.383	1	.536	.995	.980	1.010
Duration by Gear Dist	.183	1	.669	.970	.841	1.117
Duration by Flap Speed	.236	1	.627	1.006	.983	1.028
Duration by Flap Dist	.125	1	.724	1.017	.925	1.119
Duration by Speed Brake(1)	.578	1	.447	.716	.303	1.694
Automation(1) by Late Start(1)	.000	1	1.000	.243	.000	.
Automation(1) by High Speed(1)	.163	1	.686	.743	.176	3.136
Automation(1) by Gear Speed	.064	1	.800	1.003	.981	1.026
Automation(1) by Gear Dist	2.076	1	.150	.771	.541	1.098
Automation(1) by Flap Speed	.248	1	.618	.990	.954	1.029
<b>Automation(1) by Flap Dist</b>	<b>2.923</b>	<b>1</b>	<b>.087</b>	<b>.846</b>	<b>.699</b>	<b>1.025</b>
Automation(1) by Speed Brake(1)	1.645	1	.200	2.889	.571	14.612

*Note.* Significant ( $p < 0.05$ ) interactions highlighted in bold. All hypotheses are directional, so the single-tailed significance is determined by taking half the  $p$ -value.

Details explained in specific hypothesis results, where necessary.

H2aa<sub>1</sub>: A longer delay in the start of the descent, when moderated by reduced lighting, is associated with a further increase in the probability of having a UA. The interaction variable, *Lighting \* Late Start*, was not significant ( $p = 1.000$ ). Therefore, the hypothesis was not supported.

H2ba<sub>1</sub>: High-speed below 10,000 feet, when moderated by reduced lighting, is associated with a further increase in the probability of having a UA. The interaction variable, *Lighting \* High Speed*, was not significant ( $p = 0.853$ ). Thus, the hypothesis H2ba<sub>1</sub> was not supported.

H2ca<sub>1</sub>: Higher airspeed at gear extension, when moderated by reduced lighting, is associated with a further increase in the probability of having a UA. The interaction variable, *Lighting \* Gear Speed*, was not significant ( $p = 0.572$ ), resulting in a failure to support the hypothesis.

H2da<sub>1</sub>: A shorter distance to the destination at gear extension, when moderated by reduced lighting, is associated with a further increase in the probability of having a UA. The interaction variable, *Gear Dist \* Lighting*, was not significant ( $p = 0.833$ ). The hypothesis H2da<sub>1</sub> was not supported.

H2ea<sub>1</sub>: Higher airspeed at flap extension, when moderated by reduced lighting, is associated with a further increase in the probability of having a UA. The interaction variable, *Flap Speed \* Lighting*, was not significant ( $p = 0.692$ ), producing a lack of support for the hypothesis.

H2fa<sub>1</sub>: A shorter distance to the destination at flap extension, when moderated by reduced lighting, is associated with a further increase in the probability of having a UA.



The interaction variable, *Flap Dist \* Lighting*, was significant ( $Wald = 7.095$ ,  $df = 2$ ,  $p = 0.029$ ) in the interaction model. Likewise, *Flap Dist* was also significant ( $B = -0.062$ ,  $Wald = 3.997$ ,  $df = 1$ ,  $p = 0.046$ ,  $Exp(B) = 0.940$ ). The twilight values of *Flap Dist \* Lighting(1)* were not significant ( $p = 0.057$ ), but night *Flap Dist \* Lighting(2)* was significant ( $B = 0.012$ ,  $Wald = 6.282$ ,  $p = 0.012$ ,  $Exp(B) = 1.107$ ). While the computation of this interaction's effect is possible, note that that the interaction effect is in the opposite direction of the EM variable effect. The negative B value and the  $Exp(B)$  below 1 for *Flap Dist* indicate a decrease in the probability of a UA event as *Flap Dist* increases. The study was interested in the effect as *Flap Dist* decreases. Inverting both will still result in effects in opposite directions, indicating that decreasing *Flap Dist* influenced by the decreased lighting of night decreases a UA event's probability. This influence is in the opposite direction of the hypothesis, which is therefore not supported. Table 21 provides additional details from the SPSS® output for the *Lighting \* Flap Dist* interaction.

**Table 21**

*Lighting \* Flap Dist Interaction*

	B	df	Sig.	Exp(B)	95 % C.I. for EXP(B)	
					Lower	Upper
Flap Dist * Lighting		2	.029			
Flap Dist by Lighting(1)	.089	1	.057	1.093	.997	1.197
Flap Dist by Lighting(2)	.101	1	.012	1.107	1.022	1.198
Flap Dist	-.062	1	.046	.940	.885	.999

*Note.* Full details for this interaction are found in Appendix B, Table B5.

H2ga<sub>1</sub>: Using spoilers on the descent, when moderated by reduced lighting, is associated with a further increase in the probability of having a UA. The interaction

variable, *Speed Brake \* Lighting*, was significant (Wald = 13.359,  $df = 2$ ,  $p = 0.001$ ).

However, *Speed Brake* was not significant ( $p = 0.278$ ) in the interaction model.

Therefore, hypothesis H2ga<sub>1</sub> was not supported. Additional details from the SPSS® output for the *Speed Brake \* Lighting* interaction are provided in Table 22.

**Table 22**

*Lighting \* Speed Brake Interaction*

	B	df	Sig.	Exp(B)	95 % C.I. for EXP(B)	
					Lower	Upper
Speed Brake * Lighting		2	.001			
Speed Brake(1) by Lighting(1)	1.134	1	.294	3.109	.374	25.842
Speed Brake(1) by Lighting(2)	1.383	1	.001	.251	.111	.567
Speed Brake	.271	1	.278	1.311	.803	2.193

*Note.* Full details for this interaction are found in Appendix B, Table B5.

H2ab<sub>1</sub>: A longer delay in the start of the descent, when moderated by pilot inexperience, is associated with a further increase in the probability of having a UA. The interaction variable, *Experience \* Late Start*, was not significant ( $p = 1.000$ ). Thus, the results did not support the hypothesis.

H2bb<sub>1</sub>: High-speed below 10,000 feet, when moderated by pilot inexperience, is associated with a further increase in the probability of having a UA. The interaction variable, *Experience \* High Speed*, was not significant ( $p = 0.300$ ). This hypothesis could not be supported.

H2cb<sub>1</sub>: Higher airspeed at gear extension, when moderated by pilot inexperience, is associated with a further increase in the probability of having a UA. The interaction

variable, *Experience \* Gear Speed*, was not significant ( $p = 0.533$ ). Therefore, hypothesis H2cb<sub>1</sub> was not supported.

H2db<sub>1</sub>: A shorter distance to the destination at gear extension, when moderated by pilot inexperience, is associated with a further increase in the probability of having a UA. The interaction variable, *Experience \* Gear Dist*, was not significant ( $p = 0.756$ ). As a result, the hypothesis was not supported.

H2eb<sub>1</sub>: Higher airspeed at flap extension, when moderated by pilot inexperience, is associated with a further increase in the probability of having a UA. The interaction variable, *Experience \* Flap Speed*, was not significant ( $p = 0.995$ ). Therefore, hypothesis H2eb<sub>1</sub> was not supported.

H2fb<sub>1</sub>: A shorter distance to the destination at flap extension, when moderated by pilot inexperience, is associated with a further increase in the probability of having a UA. The interaction variable, *Experience \* Flap Dist*, was not significant ( $p = 0.677$ ), resulting in a failure to support the hypothesis.

H2gb<sub>1</sub>: Using spoilers on the descent, when moderated by pilot inexperience, is associated with a further increase in the probability of having a UA. The interaction variable, *Experience \* Speed Brake*, was not significant ( $p = 0.499$ ). Thus, hypothesis H2gb<sub>1</sub> was not supported.

H2ac<sub>1</sub>: A longer delay in the start of the descent, when moderated by decreased duration, is associated with a further increase in the probability of having a UA. The interaction variable, *Duration \* Late Start*, was not significant ( $p = 1.000$ ). Hypothesis H2ac<sub>1</sub> was not supported.

H2bc<sub>1</sub>: High-speed below 10,000 feet, when moderated by decreased duration, is associated with a further increase in the probability of having a UA. The interaction variable, *Duration \* High Speed*, was significant ( $p = 0.036$ ). However, in the interaction model, *High Speed* was not significant ( $p = 0.493$ ). Therefore, the hypothesis was not supported. Additional details from the SPSS® output for the *Duration \* High Speed* interaction are provided in Table 23.

**Table 23**

*Duration \* High Speed Interaction*

	B	df	Sig.	Exp(B)	95 % C.I. for EXP(B)	
					Lower	Upper
Duration by High Speed	.924	1	.036	2.519	1.063	5.968
High Speed	-.159	1	.493	.853	.542	1.343

*Note.* Full details for this interaction are found in Appendix B, Table B5.

H2cc<sub>1</sub>: Higher airspeed at gear extension, when moderated by decreased duration, is associated with a further increase in the probability of having a UA. The interaction variable, *Duration \* Gear Speed*, was not significant ( $p = 0.536$ ). Thus, the hypothesis H2cc<sub>1</sub> was not supported.

H2dc<sub>1</sub>: A shorter distance to the destination at gear extension, when moderated by decreased duration, is associated with a further increase in the probability of having a UA. The interaction variable, *Duration \* Gear Dist*, was not significant ( $p = 0.669$ ), producing a failure to support the hypothesis.

H2ec<sub>1</sub>: Higher airspeed at flap extension, when moderated by decreased duration, is associated with a further increase in the probability of having a UA. The interaction variable, *Duration \* Flap Speed*, was not significant ( $p = 0.627$ ). As a result, the hypothesis was not supported.

H2fc<sub>1</sub>: A shorter distance to the destination at flap extension, when moderated by decreased duration, is associated with a further increase in the probability of having a UA. The interaction variable, *Flap Dist \* Duration*, was not significant ( $p = 0.724$ ). Therefore, hypothesis H2fc<sub>1</sub> was not supported.

H2gc<sub>1</sub>: Using spoilers on the descent, when moderated by decreased duration, is associated with a further increase in the probability of having a UA. The interaction variable, *Duration \* Speed Brake*, was not significant ( $p = 0.447$ ), producing a failure to support hypothesis H2gc<sub>1</sub>.

H2ad<sub>1</sub>: A longer delay in the start of the descent, when moderated by non-automated flight, is associated with a further increase in the probability of having a UA. The interaction variable, *Automation \* Late Start*, was not significant ( $p = 1.000$ ). Therefore, the hypothesis was not supported.

H2bd<sub>1</sub>: High-speed below 10,000 feet, when moderated by non-automated flight, is associated with a further increase in the probability of having a UA. The interaction variable, *Automation \* High Speed*, was not significant ( $p = 0.686$ ). Hypothesis H2bd<sub>1</sub> was not supported.

H2cd<sub>1</sub>: Higher airspeed at gear extension, when moderated by non-automated flight, is associated with a further increase in the probability of having a UA. The

interaction variable, *Automation \* Gear Speed*, was not significant ( $p = 0.800$ ). Thus, the hypothesis was not supported.

H2dd<sub>1</sub>: A shorter distance to the destination at gear extension, when moderated by non-automated flight, is associated with a further increase in the probability of having a UA. *Automation \* Gear Dist*, was not significant ( $p = 0.150$ ). The results failed to support the hypothesis.

H2ed<sub>1</sub>: Higher airspeed at flap extension, when moderated by non-automated flight, is associated with a further increase in the probability of having a UA. The interaction variable, *Automation \* Flap Speed*, was not significant ( $p = 0.618$ ). Therefore, hypothesis H2ed<sub>1</sub> was not supported.

H2fd<sub>1</sub>: A shorter distance to the destination at flap extension, when moderated by non-automated flight, is associated with a further increase in the probability of having a UA. The two-tailed significance of the interaction variable, *Automation \* Flap Dist*, was  $p = 0.087$ . Since the hypothesis is directional, the  $p$ -value can be cut in half, resulting in  $p = 0.044$ , which is significant. However, *Flap Dist* was not significant in the interaction model ( $p = 0.853$ ). The results failed to support hypothesis H2fd<sub>1</sub>.

H2gd<sub>1</sub>: Using spoilers on the descent, when moderated by non-automated flight, is associated with a further increase in the probability of having a UA. The interaction variable, *Speed Brake \* Automation*, was not significant ( $p = 0.200$ ) in the interaction model. Therefore, the hypothesis was not supported.

Four of the interaction-related hypotheses showed significance in the interaction models. However, either the EM variable in the interaction was not significant or the

interaction resulted in a change in UA probability opposite that hypothesized. Therefore, even though the interactions were significant, the MV hypotheses were not supported.

### **Summary**

The initial examination of the dataset revealed an EM variable that exhibited a minuscule occurrence. *Late Start* occurred in the entire dataset only 628 times in all 210,995 cases or just 0.30% of all cases. Among 3,026 UA events, *Late Start* occurred just 24 times or just 0.79%. To meet the recommendation of 10 instances of the DV for UA events required a sample size of 87,915, which would have created inappropriate significance levels to the model's other variables. Even with the very large sample size required, *Late Start* failed to be significant in any analysis. To avoid influencing the analysis of the other variables, *Late Start* was discounted when determining the sample size. A sample size of 10,500 was considered appropriate to meet the assumptions for the LR.

The seven LR assumptions were all tested and considered met. Next, the model's reliability and validity were assessed by applying the coefficients defined by the testing dataset to the assessment dataset. The classification error rates produced with the assessment set were very close to those generated by the training set (Table 18), thus verifying reliability. The HL goodness of fit test, in which significance ( $p < 0.05$ ) indicates a poor fit with the data, assessed validity. The HL significance for the Forced Entry model of  $p = 0.126$  indicated a reasonable fit. However, the other assessment of validity, the ROC AUC (Figure 7 and Table 19), produced a value of 0.626. Values for the AUC between 0.5 and 0.7 indicate poor discrimination by the model. Due to an

assessment of poor discrimination, the results of the study should be approached cautiously.

The results of the hypothesis testing related to the EM variables yielded three hypotheses that were supported: those related to the variables *Gear Speed*, *Gear Dist*, and *Flap Speed*. All three were in relation to continuous EM variables. For those hypotheses not supported, all were due to a lack of significance of the variable in the model. There were no instances among the EM variables where the variable was significant, but the effect's direction was the opposite of that in the alternative hypothesis.

Hypothesis testing for the MV revealed four statistically significant interactions. All interactions tested for the MV *Experience* resulted in a lack of significance and did not support the related hypotheses. For the MV *Lighting*, the interactions with *Flap Dist* ( $p = 0.029$ ) and *Speed Brake* ( $p = 0.001$ ) were significant. *Flap Dist* was also significant ( $p = 0.46$ ) in the interaction model, but the interaction's influence was in the opposite direction of the hypothesis. *Speed Brake* was not significant ( $p = 0.278$ ) in the interaction model. Similarly, the MV *Duration* interacting with *High Speed* was significant ( $p = 0.036$ ), but *High Speed* was not significant ( $p = 0.278$ ) in the interaction model. Finally, *Automation's* interaction with *Flap Dist* was significant ( $p = 0.087$ ) by taking half to obtain the one-tailed significance ( $p = 0.044$ ). Nevertheless, *Flap Dist* was not significant ( $p = 0.853$ ) in the interaction model. Therefore, all of the hypotheses related to the interactions with the MVs were not supported. A summary of the results of hypothesis testing is provided in Table 24.

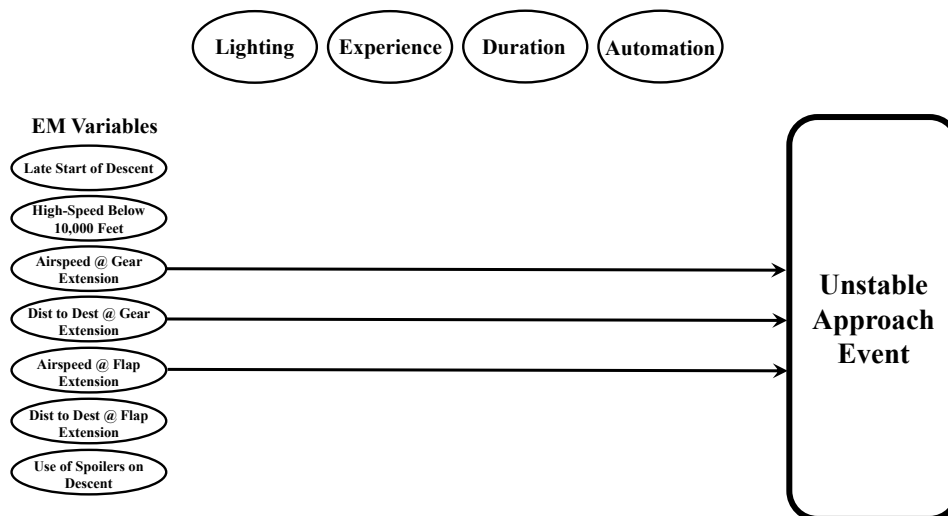


**Table 24***Hypotheses Testing Results Matrix*

EM Variables	Basic Model	Moderating Variables			
		<i>Lighting</i>	<i>Experience</i>	<i>Duration</i>	<i>Automation</i>
<i>Late Start</i>	1a: Not Supported	2aa: Not Supported	2ab: Not Supported	2ac: Not Supported	2ad: Not Supported
<i>High Speed</i>	1b: Not Supported	2ba: Not Supported	2bb: Not Supported	2bc: Not Supported	2bd: Not Supported
<i>Gear Speed</i>	<b>1c: Supported</b>	2ca: Not Supported	2cb: Not Supported	2cc: Not Supported	2cd: Not Supported
<i>Gear Dist</i>	<b>1d: Supported</b>	2da: Not Supported	2db: Not Supported	2dc: Not Supported	2dd: Not Supported
<i>Flap Speed</i>	<b>1e: Supported</b>	2ea: Not Supported	2eb: Not Supported	2ec: Not Supported	2ed: Not Supported
<i>Flap Dist</i>	1f: Not Supported	2fa: Not Supported	2fb: Not Supported	2fc: Not Supported	2fd: Not Supported
<i>Speed Brake</i>	1g: Not Supported	2ga: Not Supported	2gb: Not Supported	2gc: Not Supported	2gd: Not Supported

*Note.* Derived from SPSS® output tables in Appendix B, Tables B3, and B5.

The model of the system was revised to reflect the results of the hypothesis testing. Removal of the hypothesized direct influences of *Late Start*, *High Speed*, *Flap Dist*, and *Speed Brake* reflect the findings of non-support in the analysis. Additionally, the hypothesized moderating influences of *Lighting*, *Experience*, *Duration*, and *Automation* were all removed due to the findings of non-support. With the non-supported influences removed, only the direct influences of *Gear Speed*, *Gear Dist*, and *Flap Speed* remained in the model. The revised model is shown in Figure 8.

**Figure 8***Model of the System after Hypothesis Testing*

*Note.* Hypothesis testing supported three of the hypotheses.

With the hypothesis testing completed and the model revised to reflect the findings therein, examining the results remains. Chapter V discusses the hypothesis testing results for each of the EM variables. Also addressed are the results of the interactions for each of the MVs. Finally, conclusions are drawn, and recommendations provided with respect to the results of this study.

## **Chapter V: Discussion, Conclusions, and Recommendations**

As stated in Chapter I, the purpose of this research effort was to identify relationships between the EM variables found in FDM information and the probability of a UA's occurrence for a particular flight using statistical analysis. The study also sought to identify relationships between MVs and the EM variables that influence UAs. As this was an archival analysis, variables needed to be extracted or computed from the FDM information. The EM variables selected represented a number of the critical points of reference used by pilots in planning and executing the descent and approach phases of flight. Likewise, MVs selection came from identifiable conditions in the FDM information that the literature indicated might impact pilot EM performance sufficiently to influence the probability of a UA event. Data analysis was accomplished using the LR process within SPSS®. Results for the EM variables indicated that three of the seven hypotheses were supported (H1c, H1d, H1e) in the basic model. The analysis did not support any of the 28 hypotheses related to the MVs. This chapter discusses the model results, offers conclusions, and provides recommendations for additional research.

### **Discussion**

The study examined the key reference points used by the flight crew to estimate the energy state during the descent and approach phases to identify how EM variables may influence the UA event's probability. These points of reference allow the flight crew to plan correct points for various actions, and in some cases to also make corrections during the execution. In the following sections, each hypothesis' results are discussed, along with proposed explanations for such results.

### ***Energy Management Related Hypotheses***

There were seven hypotheses related to EM variables, three categorical related to the descent phase (*Late Start*, *High Speed*, and *Speed Brake*), and four continuous related to the approach phase (*Gear Speed*, *Gear Dist*, *Flap Speed*, and *Flap Dist*). Of these, *Gear Speed*, *Gear Dist*, and *Flap Speed* saw their hypotheses supported.

**Hypothesis 1a.** The EM variable *Late Start* was selected because the initiation of the descent is the first EM key point in the descent and approach phases. In theory, delaying the start of the descent sufficiently would result in a higher than desired EM state which the flight crew would find challenging in returning to the desired EM state. Out of the 210,995 cases in the overall dataset, there were only 628 occurrences, or 0.3%, of *Late Start*. Of these, only 24 were associated with a UA event or 0.01%. Possible causes for this low occurrence rate may be proactive requests to begin the descent by the flight crew or ATC direction to initiate the descent. Either scenario is plausible, but the dataset lacks any information to confirm either possibility. Sample size requirements necessary to include *Late Start* in the model (nearly 90,000) would adversely bias the results for the other variables in the model. Even in exploratory analyses, which inflated the occurrence of *Late Start* by removing 75% of the cases where *Late Start* = 0, still resulted in a lack of significance. For these reasons, *Late Start* was removed from consideration when determining the sample size. In the sample of 10,500 cases, there were only 29 instances of *Late Start*, and only one related to a UA. The meager occurrence of *Late Start* was likely the reason for measures related to *Late Start* being non-significant.

Late initiation of the descent was selected as an IV since it would seem to create a situation with compounding EM problems that would increase a UA event's probability.

In practice, for the PA, it is an event even rarer than UAs. From nominal cruising altitudes of around 30,000 feet, the flight crew has nearly 100 miles to make EM corrections for this error. A more focused study would be necessary to determine why late initiation of the descent is so uncommon. Concerning UAs, however, late initiation of the descent was not found to be a significant predictor.

**Hypothesis 1b.** *High Speed* identified the occurrence of an airspeed exceeding 250 KIAS below and altitude of 10,000 feet. This is a requirement in most IACO-compliant national aviation regulations and is also a requirement within the PA's SOPs. The EM ramifications of exceeding this limitation are difficulty in slowing the aircraft appropriately to configure the aircraft and to execute the approach and landing, leading to an increased probability of a UA event. The FDM information only records the occurrence, without indication of whether the exceedance was accidental or intentional. During the descent, if idle power is selected, descent rate and airspeed have a direct relationship. Increasing the descent rate results in a commensurate increase in airspeed. Since a late initiation of the descent is a rare event, instances of High Speed are likely due to loss of altitude awareness approaching 10,000 feet in the descent and failing to slow to 250 KIAS, or an intentional attempt to correct an excessively high altitude state by increasing the descent rate above that achieved with maximum drag available while maintaining 250 KIAS. *High Speed* was associated with UA events 845 times or 27.92% and in 0.40% of all cases. However, *High Speed* was non-significant ( $p = 0.762$ ) in the model, thus failing to support the hypothesis.

During a normal descent, the aircraft should pass through 10,000 feet approximately 33 miles from the destination (as computed using Equation 4). The flight

crew now had less time and distance to correct for any EM errors than at the initiation of the descent. As such, the expectation was that the excessive energy involved in this high-speed state would be more challenging to manage, increasing UA probability. The data show, however, that this hypothesis was not supported. One plausible explanation is the flight crew intentionally exceeding speed to correct an excessive altitude condition while in a high drag configuration, expecting to correct the high-speed condition with drag after resolving the altitude problem. Additional study is needed to determine if this is the case. Overall, however, exceeding 250 KIAS below 10,000 feet was not a predictor of UA probability.

**Hypothesis 1c.** Due to its high drag, the landing gear are very effective in helping to slow the aircraft once the airspeed is below the maximum extension speed. Thus, the landing gear is a valuable and effective EM tool as the aircraft transitions into the approach phase of flight. Extending the landing gear at higher airspeeds was theorized as an indication of an attempt to control an excessive energy state. Thus, it would create a positive relationship between *Gear Speed* and UAs in which, as the airspeed at gear extension increased, so would the probability of a UA event.

Additionally, a significant number of landing gear extensions occurred well above the limiting speed for the PA's aircraft. *Gear Speed* exhibited a fairly narrow dispersion about the mean, but with a fairly extensive positive tail ( $Mean = 179.06$ ,  $SD = 23.54$ ,  $Min. = 106.50$ ,  $Max. = 365.50$ ,  $Skewness = 1.40$ ,  $Kurtosis = 2.90$ ). A review of the extreme positive tail cases did not reveal any obvious errors in the dataset that would indicate a possible anomaly in the collection system. The analysis retained these cases due to the reliability and validity of the FDM collection system. *Gear Speed* was found to

be very significant in the model with a significant contribution ( $p = 0.005$ , Wald = 8.065,  $Exp(B) = 1.015$ ). For each unit of increase in *Gear Speed*, the odds of a UA event increased by 1.50%, indicating this hypothesis is supported.

The PA's SOPs indicate a target of 150 KIAS at the FAF, with a recommendation to extend the landing gear and flaps three miles before the FAF. Since the PA's aircraft slow approximately 10 KIAS per mile with the gear extended during the approach, the SOPs expect an airspeed at the configuration point of about 180 KIAS, which is very close to the mean *Gear Speed* of 179.06 KIAS. Flight crews extending the landing gear above 180 KIAS may be attempting to correct an excessive energy state. Thus, higher values for *Gear Speed* were expected to predict an increased probability of a UA event. The analysis supported this expectation. This finding's significance is that aircrew that consistently finds the need to configure at speeds above the recommended 180 KIAS are at a higher risk of experiencing a UA event.

**Hypothesis 1d.** The distance from the destination of landing gear extension also provides energy state information. According to the PA's SOPs, the landing gear's extension should occur at approximately 8 miles from the destination. Delaying beyond the 8-mile point was theorized to likely be due to excessive energy in the form of airspeed. This would create a negative relationship in which, as the distance from the destination at gear extension decreased, the probability of a UA event would increase. As with *Gear Speed*, *Gear Dist* displayed a fairly narrow dispersion but with an extensive positive tail ( $Mean = 8.59$ ,  $SD = 3.17$ ,  $Min. = 0.25$ ,  $Max. = 49.57$ ,  $Skewness = 2.42$ ,  $Kurtosis = 9.61$ ). Again, a review of the cases in the extreme positive tail did not reveal any obvious errors in the dataset that would indicate a possible anomaly in the collection

system. The analysis retained these cases due to the reliability and validity of the FDM collection system. A potential explanation for the more extreme values of *Gear Dist* is the initiation of configuring the aircraft by extension of the gear but, before extending the flaps, aborting the approach. In this case, the AGS programming would not indicate a go-around; thus, the *Gear Dist* computation would not reset, and the data snapshot used to build the dataset would not identify the anomaly. The values of interest, however, are those at the lower end of the scale. *Gear Dist* was also found to be very significant in the model with a significant contribution ( $p = 0.012$ , Wald = 6.227,  $Exp(B) = 0.898$ ). For each unit of decrease in *Gear Dist*, the odds of a UA event increased by 1.11%, supporting the hypothesis.

The mean for *Gear Dist* was 8.59, just outside the eight miles provided in the PA's SOPs. A flight crew with an excessive energy problem during the approach phase would commonly configure earlier to allow the added drag from the landing gear to assist in deceleration. Delaying configuration beyond the SOP standard was expected to be due to aircraft limitations. Delayed configuration would combine the EM issues of too much speed with insufficient drag to assist in slowing, resulting in an increase in UA probability. The analysis seemed to agree, as the probability of a UA increased as *Gear Dist* decreased. A flight crew that consistently delays landing gear extension inside of the distance specified in the SOPs has a more significant potential for a UA event.

**Hypothesis 1e.** Flap extension speed is another possible indication of energy state. Like the landing gear, flaps also increase drag, but to a lesser extent. In theory, flap extension at higher speeds indicates an excess energy state, increasing the UA event probability. The PA's SOPs call for initiating flap extension during the early portion of



the approach. A review of the descriptive statistics for *Flap Speed* ( $Mean = 222.75$ ,  $SD = 17.43$ ,  $Min. = 117$ ,  $Max. = 327.50$ ,  $Skewness = 0.48$ ,  $Kurtosis = -0.19$ ) revealed that the limiting speed for flap extension is 1.56 SD above the mean. In the vast majority of cases, *Flap Speed* is within the limitation. Further, the kurtosis statistic for *Flap Speed* indicates that distribution is slightly flatter than normal. Once again, a review of extreme cases revealed no anomalies with the FDM system. *Flap Speed* was significant in the model ( $p = 0.003$ ,  $Wald = 9.020$ ,  $Exp(B) = 1.016$ ). For each 1 knot increase in *Flap Speed*, the odds of a UA event increased by 1.6%, supporting the hypothesis.

Since flap extension increases drag, but less than the landing gear, it is probable that the flight crew would begin with flap extension to manage an excessive energy situation on approach. The landing gear is an all-at-once drag increase, while the flaps can add drag incrementally. In theory, the greater the EM problem, the sooner (faster airspeed) that flap extension would be used to correct the excessive energy. The analysis appears to agree with this assessment, as increases in *Flap Speed* increases the probability of a UA event. Consistently high flap extension speeds create a higher risk of a UA.

**Hypothesis 1f.** Another indication of the energy state is the distance to the destination at flap extension. Delayed flap extension may indicate a problem of excess airspeed. Values of *Flap Dist* ( $Mean = 16.80$ ,  $SD = 4.60$ ,  $Min. = 2.57$ ,  $Max = 79.62$ ,  $Skewness = 1.97$ ,  $Kurtosis = 8.41$ ) are clustered close the mean, as indicated by the  $SD$  of 4.6 and the kurtosis of 8.41. While there is no maximum flap extension distance, the PA's SOPs caution not to configure too early. An investigation of extreme values within *Flap Dist*, like previous variables, revealed no problems with the FDM system.

Regarding these large values of *Flap Dist*, there is a highly probable cause for these values. If the aircraft were to begin flap extension while in, or then subsequently assigned, holding the additional flown miles while in holding would continue to increase *Flap Dist*. These high values are likely the result of such a situation. *Flap Dist* was non-significant ( $p = 0.566$ ) in the model, and the hypothesis was not supported.

The distance from the destination of the initial flap extension has minimal restriction. In theory, excess energy in the way of airspeed would delay initial flap extension, indicating an increase in UA probability. However, the lack of significance of *Flap Dist* in the model shows this to be incorrect. Final landing flap selection was not considered as this occurs very close to the stabilized approach point. Delaying flap selection at this point in and of itself would directly cause a UA. Upon reviewing the results, the distance when a different flap position selection occurs may be a better indicator of UA probability. However, the current study found that decreasing distance when flaps are initially extended (*Flap Dist*) did not predict an increase in UA probability.

**Hypothesis 1g.** The spoilers, also known as speed brakes, assist in EM by reducing lift while increasing drag. In the descent phase, spoilers can slow the aircraft, increase the rate of descent without increasing airspeed, or to a limited extent, do both simultaneously. In the approach phase, as the aircraft is slowed and configured, spoilers become less effective and, in some aircraft, are not allowed to be used after flaps extension. *Speed Brake* captured the use of spoilers during the descent and approach phases of flight. Common descent profiles can be flown without the use of spoilers, which reserves their use for situations where an EM problem has developed, and

management of excess energy (altitude, speed, or both) is required. In theory, using the speed brakes may indicate an EM problem that would lead to an increase in UA probability. However, *Speed Brake* was not significant ( $p = 0.607$ ) in the model. This lack of significance may indicate that the proactive use of the spoilers was a useful EM tool for the flights studied. However, with *Speed Brake* non-significant, the hypothesis was not supported.

Since the speed brakes are specifically an EM tool designed to help reduce the energy state, the use of that tool might indicate excessive energy such that a UA would result. Indeed, speed brakes use occurred during the descent and approach phases of flight in over 68% of flights where a UA occurred. However, the model found this to be non-significant. Non-significance might be due to the flight crew making good use of this EM tool attempting to correct an excessive energy state. The analysis found that speed brake use is not a predictor of UA events.

### ***Moderating Variable Related Hypotheses***

There were 28 hypotheses associated with the interactions of the EM variables with the MVs. In all 28 interaction models, the hypothesis lacked support. In 24 interaction models, the interaction variable was not significant ( $p > 0.05$ ). In three interaction models, the interaction variable was significant ( $p < 0.05$ ), but the associated EM variable was not. In the remaining interaction model, the influence was in the opposite direction of the hypothesis. The influences of the MVs are discussed in general, with the four specific interactions discussed in greater detail.

**Hypotheses Related to Lighting (H2aa, H2ba, H2ca, H2da, H2ea, H2fa, H2ga).** The MV *Lighting* was extracted from the FDM information. The AGS system

compares the reported landing time against the sunrise/sunset tables for the destination airport. The system assigned values of 1 for dawn, 2 for day, 3 for dusk, and 4 for night. For the analysis, day was assigned a value of 1 as the best case for lighting conditions. Dawn and dusk were assigned a value of 2 as the next case in degrading lighting, and night was assigned a value of 3 as the worst case in lighting conditions. The study theorized that as the lighting conditions went from day to night, best to worst, the moderating effects of the lighting condition on the EM variables would increase the probability of a UA event. This theory was supported by research identifying visibility as a factor in 94% of CFIT accidents, in which altitude awareness was lost rather than energy state awareness (Kelly & Efthymiou, 2019).

For the EM variables *Late Start*, *High Speed*, *Gear Speed*, *Gear Dist*, and *Flap Speed*, the interaction variables were non-significant ( $p > 0.05$ ). The interaction variable of *Lighting \* Flap Dist* was significant, as was *Flap Dist* in this interaction model, indicating a significant effect. However, the effect of the interaction was in the opposite direction of the hypothesis. In night lighting conditions, the moderating effect of *Lighting* on *Flap Dist* was to reduce, rather than increase, UA event probability. This is a surprising result, since the expectation was that restricted visibility due to reduced lighting would create an increase in difficulty in EM.

Another surprising result was the interaction between *Lighting* and the EM variable *Speed Brake*. The interaction variable *Lighting \* Speed Brake* was significant, but the EM variable *Speed Brake* was not in this interaction model. Like the interaction between *Lighting* and *Flap Dist*, the direction of this significant interaction was opposite of the hypothesis. These interesting interactions may be the result of flight crew being

more EM aware and more vigilant in adhering to approach procedures due to decreased ability to detect obstacles as well as reduced depth perception. Both of these interactions should be examined more closely in future research.

Exterior environmental lighting was included in the visibility conditions in the study by Kelly and Efthymiou (2019). The current effort was unable to extract the visibility on approach. However, it was able to determine lighting conditions from the capture of dawn, day, dusk, or night in the FDM information. This analysis expected that, as the environmental lighting decreased, the loss of external visual cues would increase the difficulty in maintaining proper EM. The model, however, refutes this expectation. A probable explanation for this result is good flight crew discipline in using internal cues for EM. The flight crew was making EM decisions based more on aircraft instrument indications rather than on external visual cues. The only statistically significant moderation produced as *Lighting* got worse was to reduce the probability of a UA. Overall, *Lighting's* only moderating effect was the opposite of that hypothesized.

**Hypotheses Related to Experience (H2ab, H2bb, H2cb, H2db, H2eb, H2fb, H2gb).** The MV *Experience* was determined by which side of the cockpit was in control of the flight director/autopilot, as reported by the FDM system. If the left side was in control, the assumption was the Captain was the PF, and Experience was coded as 0. If the right side was in control, Experience was coded 1, indicating the FO was the PF. The assumption was that the Captain would be the more experienced crew member, and thus more capable of managing energy. Therefore, if the FO was the PF, it was theorized that EM would not be as precise, thus increasing the probability of a UA event. However, the analysis found Experience non-significance ( $p > 0.05$ ) in all interaction models. The non-

significance may be due to the slightly higher percentage of flights where the FO was the PF (57.6% versus 42.4% for Captains), providing FOs with slightly higher proficiency resulting in offsetting for the lack of experience. This result supports the research of Todd and Thomas (2012) that did not find a difference between Captains and FOs regarding stabilized approach performance criteria.

Zhang et al. (2019) suggested that Captains, with more experience, would be more proficient in dealing with EM problems that might arise during a flight. However, the results failed to support the hypothesis. Flight crew members for airlines are subject to high performance standards in both initial and recurrent training. The standards are the same for both Captains and FOs, regardless of experience. Thus, both should be capable of similar performance in the execution of the descent and approach. The data indicate that this is likely, as *Experience* did not provide any significant moderating effects.

**Hypotheses Related to Duration (H2ac, H2bc, H2cc, H2dc, H2ec, H2fc, H2gc).** The MV *Duration* required conversion to a binary categorical value from a continuous value reported by the FDM system. The system reported flight duration in an hours, minutes, and seconds format with no delimitation between the values (i.e., hh:mm:ss). The original hh:mm:ss format was first converted into a decimal hours format (i.e., H.h), and then descriptive statistics were computed to find the bottom quartile of durations. Cases in the bottom quartile were coded 1 in the MV *Duration* to indicate the shorter flights, reflecting the theory that shorter flights have a higher task loading with minimal opportunities for breaks. Without breaks, mental workload increases, resulting in a decreased ability to detect errors and increased reaction time (Wanyan et al., 2018). Due to the issues associated with shorter duration flights, the expectation was that the

*MV Duration* was expected to influence EM such that UA probability would increase. *Duration's* influence was non-significant ( $p > 0.05$ ) in all the interaction models, except for the model of interaction with *High Speed*. The interaction variable *Duration \* High Speed* was significant and in the direction of the hypothesis. While *High Speed* was not significant in the interaction model, nevertheless, the significance of the interaction variable does indicate that there is an influence in this interaction that suggests future research into this relationship.

For these reasons, all of the hypotheses related to *MV Duration* were not supported.

A potential cause for this outcome may be the PA's flight crew scheduling process. Scheduling short-duration flights early in a crew member's workday may mitigate the identified issues. However, with de-identified data, confirming this possibility is not possible. While previous studies (Wanyan et al., 2018) indicated that flight crew performance suffers from the high task loading of shorter duration flights, *Duration* provided no statistically significant moderating effects in the interaction model.

**Hypotheses Related to Automation (H2ad, H2bd, H2cd, H2dd, H2ed, H2fd, H2gd).** The coding of the *MV Automation* was the inverse of the FDM systems report of whether the autopilot was engaged. Thus, if the autopilot was engaged, *Automation* was coded 0 and coded 1 if the autopilot was not engaged (indicating a hand-flown approach). The autopilot was engaged in over 97% of the data's approaches, indicating a potential for over-reliance on automation. Kelly and Efthymiou (1986) identified overreliance on automation as a major contributor to complacency, lack of vigilance, and loss of SA. While the PA's SOPs assume the use of the autopilot for the approach, manual flying for

proficiency is allowed, leaving the final decision to the PF. Based on the very high percentage noted for autopilot executed approaches, the expectation was that, for approaches flown manually, the moderation effects of *Automation* would influence the EM variables such as to produce an increase in the probability of a UA event. The potential for both overreliance on automation and a reduction in basic proficiency could contribute to such a result. However, only one of the interaction models yielded a significant interaction. The interaction *Automation \* Flap Dist* was significant (single-tailed  $p = 0.044$ ), and acted in the direction of the hypothesis. However, *Flap Dist* was not significant ( $p = 0.835$ ) in the interaction model, resulting in a failure to support the hypothesis. This significant interaction bears further exploration in future research. In all other associated interaction models, the influence of *Automation* was non-significant ( $p > 0.05$ ).

Automation in the cockpit has both benefits and detriments. The automation is capable of flying the aircraft with greater precision than human pilots can. With auto-throttles, the system can even manage the energy state with little assistance from the pilots. However, Kelly and Efthymiou (2019) identified excessive reliance on automation as leading to decreases in pilot proficiency. The PA's SOPs specify that the procedures assume full use of automation, while not prohibiting manual flight for proficiency (*Flight crew operations manual*, 2017). With most approaches in the dataset flown using the autopilot, it was an expectation that the resultant moderating effects of *Automation* would manifest a decrease in proficiency. What the analysis revealed, however, was that *Automation* provided no significant moderating effects in the interaction model.



**Moderating Variable Interactions of Interest.** While none of the MV interactions resulted in support of the related hypotheses, the four interactions that were statistically significant were interesting. The two interactions related to *Lighting* indicated an influence opposite of the hypotheses, while the interactions related to *Duration* and *Automation* indicated an influence in the direction of the hypotheses. As noted, each of these results should be further investigated to gain better insights into their effects on UA probability in future research.

### **Conclusions**

The analysis identified the relationships between certain flight variables and UA events using FDM information. The results lead to an improved understanding of the EM predictors of UA events and the influence of possible MVs. The outcomes of the study make valuable contributions, both practical and theoretical.

Many factors influence UA probability, of which EM is just a subset. In examining EM's influence on UAs, remember that EM is a continuously fluid process. Multiple methods are available to the flight crew to alter the energy state of the aircraft. As the results of this study highlight, EM errors during the descent and approach process do not always result in a UA event. The investigation into the influences of the MVs indicates that even when there are other factors that, on the surface, would seem to increase the probability of a UA occurring, the data indicate that those factors have no significant impact on UAs. The results identified three EM factors that were significant concerning UA occurrence and thus provide a focus for further investigation. More importantly, the current study validated the idea that FDM information can identify

descent and approach EM variables that affect UA probability. As noted previously, this methodology should apply to other flight phases and target issues.

The data indicate that, overall, the PA's flight crews were disciplined in their adherence to the SOPs regarding the descent through landing phases of flight. This discipline was evident by the low rate of UAs identified in the FDM information. The thresholds used in this analysis were more sensitive in identifying UAs than the analysis used operationally by the PA. Nonetheless, the results revealed a 1.4% UA rate for the PA, far below the 4.4% rate for the industry overall (Graeber, 2006).

### ***Theoretical Contributions***

The study validated that the LR process can produce a model that effectively predicts UA probability based on EM variables in the descent and approach phase of flight. As there appeared to be a lack of studies in the area in the literature, this initial investigation lays the foundation for filling this gap, providing insights for academia and industry. This effort was unique because it utilized actual operational FDM information from an airline, thus representing a significant contribution to the body of knowledge.

Additionally, the current work examined how non-energy related MVs might alter the influence EM variables have in predicting UAs, which also expanded knowledge due to an apparent lack of such studies in the literature. This investigation is an initial step into a more holistic approach in aviation data analysis by including moderating factors. While the study revealed no significant moderating influence from the MVs examined, expansion of this type of analysis is needed to understand the influence of these additional variables in how EM predicts UAs and other EM related events.

### ***Practical Contributions***

The primary area of practical contributions of the study is safety. The safety realm is both proactive and reactive. Proactive safety activities seek to prevent undesired events such as UAs. The results provide safety practitioners with new information to screen FDM information. The FDM system can identify trends in these variables so that safety personnel can inform flight crews across the system of trends that may lead to increased instances of UAs.

Further, armed with these results, airline training departments can fine-tune training programs to specifically address the EM-specific issues identified. By increasing awareness of these critical EM issues, pilots can be more vigilant for these errors. While the improvements to initial and recurrent training programs will enhance flight crew awareness regarding EM's impact on UA occurrences, it is also possible to provide immediate training for pilots exhibiting problems with EM.

The results enable emergent training by leveraging the FDM analysis system. By referencing the key UA predictors, FDM information can identify flights where a UA did not occur but was more likely (i.e. UA close calls). If allowed, the FDM system can even identify specific flight crew members exhibiting trends of the EM errors that predict UAs, even if a UA did not occur. The identified flight crew could be provided with focused training addressing the specific errors being made by the crew member immediately on identification. Such dedicated training should assist in reducing exhibited EM error trends, preventing future UAs.

When prevention has failed, safety investigations seek to identify what went wrong. With the additional information provided by the results of this study, safety practitioners investigating UA events will have a better understanding of the relationship

between these EM variables and UAs, which may enable quicker resolutions to investigations or more focused findings. Additionally, focused findings provide improved feedback to the training programs to facilitate improvements.

### **Limitations of the Findings**

The study has four limitations. First, the analysis was limited to the data from a single airline. The fact that the PA's policies, procedures, and training were in accordance with ICAO standards aids in generalization. Likewise, the nations where the PA operates have ICAO-compliant regulations, further aiding in generalization. However, cultural differences in the ethno-geographic region do limit the generalizability of the findings. Fortunately, the study can be replicated with other carriers and in other ethno-geographic areas. The necessary data can be extracted or computed from the carrier's FDM system. Following the methodology described in Chapter III, the data analysis should provide results specific to that carrier.

The second limitation pertains to aircraft. The PA operates a fleet of aircraft consisting of various single-aisle, twin-engine jet transport aircraft. This fleet has the characteristics of seating between approximately 100 and 200 passengers and maximum takeoff weights between 120,000 and 210,000 pounds. The findings are thus limited to operators of aircraft that closely match those characteristics. However, the similar performance and flight characteristics of typical transport category aircraft aid in generalizability across other aircraft fleets outside this characteristic set. Again, replication of this effort is possible with FDM information from another aircraft type. Using the methodology described in Chapter III, applied to the appropriate FDM information from another aircraft type, the analysis would provide results specific to

other aircraft types. Such an analysis would identify differences arising from significantly different aircraft performance, such as deceleration rates and gear or flap extension limitations.

Third, this effort examined data from a specific, one-year timeframe, and thus influenced by the regulations, training, and standards extant at that time. Since these influences are subject to change, generalization is limited outside of the period covered by the study. However, replication of the analysis can easily update the results to accommodate any significant changes in these areas.

Fourth, the findings are limited due to the limitations of the model. While many variables influence UAs, this investigation only examined a handful of EM variables available in the archival data. Since the scope of the study was limited to how the EM variables influence the probability of a UA event, the influence of non-EM factors was not relevant. The lack of moderation by the four MVs in this study suggests that the potential confounding variables have little impact on how the EM variables influence UAs. Due to the focus on the EM variables, the model only accounted for a small portion of the variability in the data.

Additionally, the model's low sensitivity results in some UA events being missed, resulting in Type II error. Given the rarity of UA events and the focus on only the selected EM predictors, the model's low discrimination is understandable. While the current model provides a baseline from which to approach EM influences on UAs, refinement of the model through additional research is desirable, as addressed in the recommendations.

## **Recommendations**

Moving forward, several recommendations arise. There are practical recommendations that are focused on how the airline industry can benefit from the results. There are also recommendations for further research using the current study as a springboard to expand the body of knowledge further.

### ***Recommendations for the Airlines in the Region***

There are three recommendations for the airline industry. The recommendations provided focus on the airlines in the region of operations of the PA. Note, however, that all airlines could potentially benefit from taking them under consideration.

The first recommendation is that the airline industry conducts similar studies using their FDM information. Since the data in the sample drives the model, different samples will yield somewhat different models. Factors such as culture, training, standards, and many others influence FDM information. Thus, each airline should have a unique model reflecting its characteristics. Using its unique model, each airline should tailor training and safety programs to address the critical EM areas identified.

The second recommendation is that the airline industry and the pilot groups work together to facilitate just-in-time training. Use the FDM system to identify pilots exhibiting trends of EM errors that increase the probability of a UA event and provide immediate supplemental EM training. While maintaining pilot anonymity, the FDM system could match such a pilot to a specific EM training module to immediately address the issue rather than waiting for the next training cycle.

The third recommendation is that the airline industry increases academia's ability to access de-identified FDM information. Access to comprehensive operational data was

vital to the current study. However, timely access to current data would allow the academic community to address today's problems rather than those of several years ago. Cooperation between academia and airlines will significantly benefit both.

### ***Recommendations for Future Research***

There are four recommendations for future research. Follow-on investigations are necessary to validate the results of the current effort. Further exploration of the interactions that were statistically significant, while not supporting the hypotheses of this study, may produce better insights. Another area for additional research is investigating if the methodology would enable prediction of UA severity. Finally, studies are needed to expand the methodology to other flight phases and EM problems.

The data limited the current study. While some computation was available to generate additional EM variables, the current analysis was constrained to the archival data. A follow-up effort would allow for the capture of data explicitly designed for the study. Following the overall methodology in Chapter III with enhanced data collection would help validate this effort's results. Additionally, refining the data may help increase the discrimination of the model. A specific recommendation would be to refine the variable capturing the distance from the destination of flap deployment to a specific setting typically selected closer to the FAF. This change would help eliminate the possibility of capturing holding distances in the data. Better data will yield a better model, and refining the model for EM influences on UAs should enhance safety.

For the interactions that produced statistical significance, focused research may bring clarity. Those related to Lighting were surprising in that they were contrary to the related hypotheses. A closer look is needed to understand the dynamics that yield a

decrease in UA probability with an increase in the level of difficulty. The interaction between *Lighting* and *Flap Dist* should be of particular interest, as both the interaction and EM variables were significant in the interaction model. The only reason it did not support the hypothesis was the direction of influence.

Another recommendation for future research is an examination into whether the methodology of this study could predict the severity of a UA event. As noted in Chapter III, the PA uses a system that classifies violations of stabilized approach criteria into three separate severity categories, and then determines UA severity through a matrix that accounts for cumulative criteria violation severities. It may be possible to incorporate the criteria violation severity levels and UA severity matrix into methodology to produce a model that produces a prediction of the UA severity based on the EM and MV inputs.

The literature review revealed limited studies regarding EM in aviation safety. While the current analysis examined predicting UA events, similar methodologies can address other EM driven flight events. With the vast amount of data collected by the FDM system and the possibility of capturing precise data points, there are many possible avenues of EM research related to aviation safety include landing overruns and loss of control incidents. Each of these areas includes EM issues, and the necessary data should be available or computable from the FDM information. Creating a theoretical model representing the influences on the outcome, identifying potential moderators, extracting the necessary data from FDM information and other sources, and analyzing via the LR similar to the current study's methodology, should reveal the influences EM variables have on the studied event. Such additional studies would help increase safety, expand this research field, expand the body of knowledge, and further fill this gap.





## References

- 2017 Aviation sector data analysis. (2018). Association of Airline Companies.
- Airbus. (2005). Approach techniques: Aircraft energy management during approach. *Flight Operations Briefing Notes*. <https://skybrary.aero/bookshelf/books/166.pdf>
- Airbus. (2006). Descent management: Descent and approach profile management. *Flight Operations Briefing Notes*. <https://www.skybrary.aero/bookshelf/books/169.pdf>
- Albright, J. (2014, May 1). New approach to stabilized approaches: A practical way to ensure you're at the right place, configuration and speed. *Business and commercial aviation*, 110(5), 54. <https://aviationweek.com/business-aviation/new-approach-stabilized-approaches>
- Baker, E. R. (2017). *Comparative analysis of conventional electronic and OZ concept displays for aircraft energy management* (Publication Number 352) [Doctoral Dissertation, Embry-Riddle Aeronautical University]. Scholarly Commons. <https://commons.erau.edu/edt/352>
- Bennett, S. A. (2019, August 3). Pilot workload and fatigue on four intra-European routes: a 12-month mixed-methods evaluation. *Journal of Risk Research*, 22(8), 983-1003. <https://doi.org/10.1080/13669877.2018.1430704>
- Bewick, V., Cheek, L., & Ball, J. (2005, January 13). Statistics review 14: Logistic regression. *Critical Care (London, England)*, 9(1), 112-118. <https://doi.org/10.1186/cc3045>
- Boeing. (2018). *Statistical summary of commercial jet airplane accidents 2017*. Boeing Commercial Airplanes. <http://www.boeing.com/news/techissues/pdf/statsum.pdf>
- Box, G. E., & Tidwell, P. W. (1962, December 1). Transformation of the independent variables. *Technometrics*, 4(4), 531-550. <https://doi.org/10.1080/00401706.1962.10490038>
- Bruce, K., Kelly, J. R., & Person, J. L. (1986, August 18-20). *NASA B737 flight test results of the Total Energy Control System* [Paper Presentation]. Astrodynamics Conference, Williamsburg, VA, United States. <https://doi.org/10.2514/6.1986-2143>
- Bureau of Transportation Statistics. (2016). *Air carrier financial reports - 2015 (Form 41 financial data)* [Dataset]. <https://www.bts.dot.gov/topics/airlines-and-airports/airline-information-download>

- Callantine, T. J. (2001). *Analysis of flight operational quality assurance data using model-based activity tracking* [Paper Presentation]. Advances in Aviation Safety Conference & Exposition, <https://doi.org/10.4271/2001-01-2640>
- Carbaugh, D., Cashman, J., Carriker, M., Forsythe, D., Melody, T., Rockliff, L., & Wainwright, W. (1998). Aerodynamic principles of large-airplane upsets. *Aero(Qtr 03)*. <https://bit.ly/3b5C888>
- Casner, S. M., Geven, R. W., Recker, M. P., & Schooler, J. W. (2014, December 1). The retention of manual flying skills in the automated cockpit. *Human Factors*, *56*(8), 1506-1516. <https://doi.org/10.1177/0018720814535628>
- Charles, M. M. (2000, November 5). The stabilized approach. *AOPA Pilot*. <https://www.aopa.org/news-and-media/all-news/2000/november/pilot/the-stabilized-approach>
- European Organization for Civil Aviation Equipment. (2013). ED-112: Minimum operational performance standard for crash protected airborne recorder systems.
- Federal Aviation Administration. (2004). Flight operational quality assurance (AC120-82). Government Printing Office. [https://www.faa.gov/documentLibrary/media/Advisory\\_Circular/AC\\_120-82.pdf](https://www.faa.gov/documentLibrary/media/Advisory_Circular/AC_120-82.pdf)
- Federal Aviation Administration; Certification: Air Carriers and Commercial Operators, 76 Fed. Reg. 52235 (Aug. 22, 2011) (codified at 14 C.F.R. § 119).
- Federal Aviation Administration. (2013). *Glider flying handbook (FAA-H-8083-13A)* (US, Ed.). Government Printing Office. [https://www.faa.gov/regulations\\_policies/handbooks\\_manuals/aircraft/glider\\_handbook/media/faa-h-8083-13a.pdf](https://www.faa.gov/regulations_policies/handbooks_manuals/aircraft/glider_handbook/media/faa-h-8083-13a.pdf)
- Federal Aviation Administration. (2016). *Instrument flying handbook (FAA-H-8083-15B)*. Government Printing Office. [https://www.faa.gov/regulations\\_policies/handbooks\\_manuals/aviation/media/FAA-H-8083-15B.pdf](https://www.faa.gov/regulations_policies/handbooks_manuals/aviation/media/FAA-H-8083-15B.pdf)
- Federal Aviation Administration; Certification and Operations: Airplanes Having A Seating Capacity of 20 or More Passengers or A Maximum Payload Capacity Of 6,000 Pounds or More; And Rules Governing Persons On Board Such Aircraft, 82 Fed. Reg. 34399 (July 25, 2017) (codified at 14 C.F.R. § 125).
- Federal Aviation Administration. (2018a). Commercial pilot - airplane airman certification standards (FAA-S-ACS-7A, with Change 1). Government Printing Office. [https://www.faa.gov/training\\_testing/testing/acs/media/commercial\\_airplane\\_acs\\_change\\_1.pdf](https://www.faa.gov/training_testing/testing/acs/media/commercial_airplane_acs_change_1.pdf)

- Federal Aviation Administration. (2018b). Instrument rating - airplane airman certification standards (FAA-S-ACS-8B, with Change 1). Government Printing Office. [https://www.faa.gov/training\\_testing/testing/acs/media/instrument\\_rating\\_acs\\_change\\_1.pdf](https://www.faa.gov/training_testing/testing/acs/media/instrument_rating_acs_change_1.pdf)
- Federal Aviation Administration. (2018c). Mitigating the risks of a runway overrun upon landing (AC 91-79A, Chg 1 & 2). Government Printing Office. [https://www.faa.gov/documentLibrary/media/Advisory\\_Circular/AC\\_91-79A\\_Chg\\_2.pdf](https://www.faa.gov/documentLibrary/media/Advisory_Circular/AC_91-79A_Chg_2.pdf)
- Federal Aviation Administration. (2018d). Private pilot - airplane airman certification standards (FAA-S-ACS-6B, with Change 1). Government Printing Office. [https://www.faa.gov/training\\_testing/testing/acs/media/private\\_airplane\\_acs\\_change\\_1.pdf](https://www.faa.gov/training_testing/testing/acs/media/private_airplane_acs_change_1.pdf)
- Federal Aviation Administration. (2019). Airline transport pilot type rating for airplane airman certification standards (FAA-S-ACS-11, with Change 1). Government Printing Office. [https://www.faa.gov/training\\_testing/testing/acs/media/atp\\_acs.pdf](https://www.faa.gov/training_testing/testing/acs/media/atp_acs.pdf)
- Federal Aviation Administration. (2020). *Aeronautical information manual*. Government Printing Office. [https://www.faa.gov/air\\_traffic/publications/media/aim\\_basic\\_w\\_chg\\_1\\_and\\_2\\_7-16-20.pdf](https://www.faa.gov/air_traffic/publications/media/aim_basic_w_chg_1_and_2_7-16-20.pdf)
- Field, A. (2018). *Discovering statistics using IBM SPSS statistics: North American edition* (5th ed.). SAGE. <http://sro.sussex.ac.uk/id/eprint/77862>
- Flight crew operations manual*. (2017). Participating Airline.
- Flight Safety Foundation. (2009a). *Flight Safety Foundation ALAR briefing note 4.1*. <https://www.skybrary.aero/bookshelf/books/856.pdf>
- Flight Safety Foundation. (2009b). *Flight Safety Foundation ALAR briefing note 7.1*. <https://www.skybrary.aero/bookshelf/books/864.pdf>
- Flight Safety Foundation. (2009c). *Flight Safety Foundation ALAR briefingnote 4.2*. <https://www.skybrary.aero/bookshelf/books/857.pdf>
- George, F. (2007). Back to basics: The stabilized approach. *Business & Commercial Aviation*, 101(1), 36. <https://aviationweek.com/back-basics-stabilized-approach>
- Graeber, R. C. (2006). *The safety benefits of LOSA: A manufacturer's view* [PowerPoint]. International LOSA & TEM Workshop, Toulouse, France. [https://www.faa.gov/about/initiatives/maintenance\\_hf/losa/.../graeber\\_\(2006\).ppt](https://www.faa.gov/about/initiatives/maintenance_hf/losa/.../graeber_(2006).ppt)

- Grossi, D. R. (1999, May 3-5). *Aviation recorder overview* [Paper Presentation]. International Symposium On Transportation Recorders, Arlington, VA, United States. [http://www.iasa.com.au/folders/Publications/pdf\\_library/grossi.pdf](http://www.iasa.com.au/folders/Publications/pdf_library/grossi.pdf)
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Prentice Hall. [https://doi.org/10.1007/978-3-642-04898-2\\_395](https://doi.org/10.1007/978-3-642-04898-2_395)
- Hilbe, J. M. (2009). *Logistic regression models*. Chapman and Hall/CRC. <https://doi.org/10.1201/9781420075779>
- Hosmer Jr., D. W., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression* (Vol. 398). John Wiley & Sons. <https://doi.org/10.1002/9781118548387>
- Hurt, H. H. (1965). *Aerodynamics for naval aviators (NAVWEPS 00-80T-80)*. Office of the Chief of Naval Operations, Aviation Training Division.
- International Civil Aviation Organization. (2014). 2014 safety report. [https://www.icao.int/safety/Documents/ICAO\\_2014%20Safety%20Report\\_final\\_02042014\\_web.pdf](https://www.icao.int/safety/Documents/ICAO_2014%20Safety%20Report_final_02042014_web.pdf)
- International Civil Aviation Organization. (2015). Procedures for air navigation services: Training (Doc 9868). <https://bit.ly/2G4DVz9>
- International Civil Aviation Organization. (2020). *ICAO member states*. <https://www.icao.int/about-icao/Pages/member-states.aspx>
- Ison, D. (2006, January). Top 10 rules of thumb. *Plane & Pilot*, 42(1), 56-59. <https://www.planeandpilotmag.com/article/top-10-rules-of-thumb/#.WfEu9IZrw6g>
- Keller, J., MENDONCA, F. C., & Cutter, J. E. (2019). Collegiate aviation pilots: Analyses of fatigue related decision-making scenarios. *International Journal of Aviation, Aeronautics, and Aerospace*, 6(4), 9. <https://doi.org/10.15394/ijaaa.2019.1360>
- Kelly, D., & Efthymiou, M. (2019, June). An analysis of human factors in fifty controlled flight into terrain aviation accidents from 2007 to 2017. *Journal of Safety Research*, 69, 155-165. <https://doi.org/10.1016/j.jsr.2019.03.009>
- L3. (2018). *FA2100 family of flight recorders*. <https://www.l3aviationproducts.com/products/fa2100-series-cockpit-voice-and-data-recorders/>

- Laerd Statistics. (2019). *Binomial logistic regression using SPSS Statistics*.  
<https://statistics.laerd.com/premium/spss/blr/binomial-logistic-regression-in-spss.php>
- Lee, S., & Kim, J. K. (2018, March). 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>
- Merkt, J. R. (2013, October). Flight energy management training: Promoting safety and efficiency. *Journal of Aviation Technology and Engineering*, 3(1).  
<https://doi.org/10.7771/2159-6670.1072>
- Molter, B. A. (1918). *Knights of the air*. D. Appleton.
- Mouloua, M., Ferraro, J. C., Parasuraman, R., Molloy, R., & Hilburn, B. (2019). Human monitoring of automated systems. In *Human Performance in Automated and Autonomous Systems: Emerging Issues and Practical Perspectives* (pp. 1-26). CRC Press. <https://doi.org/10.1201/9780429458323-1>
- Noyes, J. (2007, July). Energy management displays: A new concept for the civil flight deck. *Applied Ergonomics*, 38(4), 481-489.  
<https://doi.org/10.1016/j.apergo.2007.01.008>
- Pepe, M. S. (2000, March). Receiver operating characteristic methodology. *Journal of the American Statistical Association*, 95(449), 308-311.  
<https://doi.org/10.1080/01621459.2000.10473930>
- Prats, X., Barrado, C., Perez-Batlle, M., Vilardaga, S., Bas, I., Birling, F., Verhoeven, R., & Marsman, A. (2014, 16-20 June). *Enhancement of a time and energy management algorithm for continuous descent operations* [Paper Presentation]. 14th AIAA Aviation Technology, Integration, and Operations Conference, Atlanta, GA, United States. <https://doi.org/10.2514/6.2014-3151>
- Rana, S., Midi, H., & Sarkar, S. (2010). Validation and performance analysis of binary logistic regression model. Proceedings of the WSEAS International Conference on Environmental, Medicine and Health Sciences, <http://www.wseas.us/e-library/conferences/2010/Penang/EMEH/EMEH-09.pdf>
- SAFRAN. (2012). *Analysis ground station V14 user manual*. SAFRAN.
- Schvaneveldt, R. W., Beringer, D. B., & Lamonica, J. A. (2001). Priority and organization of information accessed by pilots in various phases of flight. *The International Journal of Aviation Psychology*, 11(3), 253-280.  
[https://doi.org/10.1207/S15327108IJAP1103\\_02](https://doi.org/10.1207/S15327108IJAP1103_02)

- Shaw, R. L. (1985). *Fighter combat*. Naval Institute Press.  
<http://demovfw.com/firstfighterwing/1stVFW/Fighter%20Combat-Tactics%20and%20Maneuvering.pdf>
- Slatter, R. T. (1997, March). Technique and criteria for a stabilized approach need to be spelled out in the operations manual. *ICAO Journal*, 52(2), 15, 28.  
<https://www.icao.int/publications/journalsreports/1997/5202.djvu>
- Stolzer, A. J. (2002). *Fuel consumption modeling of a transport category aircraft using flight operations quality assurance data: a literature review*.  
<https://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/20020041933.pdf>
- Stolzer, A. J., & Halford, C. (2007). Data mining methods applied to flight operations quality assurance data: A comparison to standard statistical methods. *Journal of Air Transportation*, 12(1), 6. <https://commons.erau.edu/publication/116>
- Szurovy, G., & Goulian, M. (1997). *Advanced aerobatics*. McGraw-Hill Professional.
- Tabachnick, B. G., & Fidell, L. S. (2014). *Using multivariate statistics* (6th ed.). Pearson.
- Todd, M. A., & Thomas, M. J. W. (2012, August). Flight hours and flight crew performance in commercial aviation. *Aviation, Space, and Environmental Medicine*, 83(8), 776-782. <https://doi.org/10.3357/ASEM.3271.2012>
- Veillette, P. (2016, January 28). Preparing for descent during low workload phases of cruise prevents poor performance. *Business & Commercial Aviation*, 62.  
<https://aviationweek.com/business-aviation/preparing-descent-during-low-workload-phases-cruise-prevents-poor-performance>
- Vogt, W. P., Gardner, D. C., Haeffele, L. M., & Vogt, E. R. (2014). *Selecting the right analyses for your data: Quantitative, qualitative, and mixed methods*. Guilford Publications. [https://doi.org/10.1111/bjet.12260\\_5](https://doi.org/10.1111/bjet.12260_5)
- Wagener, F., & Ison, D. C. (2014, April). Crew resource management application in commercial aviation. *Journal of Aviation Technology and Engineering*, 3(2), 2. <https://doi.org/10.7771/2159-6670.1077>
- Wanyan, X., Zhuang, D., Lin, Y., Xiao, X., & Song, J.-W. (2018, March). Influence of mental workload on detecting information varieties revealed by mismatch negativity during flight simulation. *International Journal of Industrial Ergonomics*, 64, 1-7. <https://doi.org/10.1016/j.ergon.2017.08.004>
- Zagalsky, N. (1973, January 10-12). *Aircraft energy management* [Paper Presentation]. 11th Aerospace Sciences Meeting, Washington, DC, United States.  
<https://doi.org/10.2514/6.1973-228>

Zhang, X., Qu, X., Xue, H., Zhao, H., Li, T., & Tao, D. (2019, June). Modeling pilot mental workload using information theory. *The Aeronautical Journal*, 123(1264), 828-839. <https://doi.org/10.1017/aer.2019.13>

Zhao, X.-b., Li, B., & Wang, C.-g. (2017). There is a gold mine in flight data: A framework of data mining in civil aviation. *DEStech Transactions on Social Science, Education and Human Science*, (meit). <https://doi.org/10.12783/dtssehs/meit2017/12896>



**Appendix A**

**Permission to Conduct Research**

**Embry-Riddle Aeronautical University**  
**Application for IRB Approval**  
**Exempt Determination**

**Principle Investigator:** David A. Carroll

**Other Investigators:** Dr. David Esser, Dissertation Chair

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

**Project Title:** Providing Individualized Interventional Pilot Training Through Evaluation of Flight Data Monitoring Information

**Review Board Use Only**

**Initial Reviewer:** Teri Gabriel **Date:** 06/06/2018 **Approval #:** 18-147

**Exempt:** Yes

Dr. Michael Wiggins Michael E. Wiggins, Ed.D. Digitally signed by Michael E. Wiggins, Ed.D. DN: cn=Michael E. Wiggins, o=Embry Riddle Aeronautical University, ou=Embry Riddle Aeronautical University, email=Michael.E.Wiggins@erau.edu, c=US **Date:** 06/11/2018  
 IRB Chair Signature

**Brief Description:**

The purpose of this study is to determine the preferred learning style of the surveyed population, and to determine the level of retention of Energy Management concepts presented in training and supplementary presentations. This study will use a survey through SurveyMonkey and archival data that has been presented in previous pilot training events to provide an indication of energy management knowledge retention.

This research falls under the **exempt** category as per 45 CFR 46.101(b) under:

- (1) Research, conducted in established or commonly accepted educational settings, that specifically involves normal educational practices that are not likely to adversely impact students' opportunity to learn required educational content or the assessment of educators who provide instruction. This includes most research on regular and special education instructional strategies, and research on the effectiveness of or the comparison among instructional techniques, curricula, or classroom management methods.
- (2) Research that only includes interactions involving educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior (including visual or auditory recording) if at least one of the following criteria is met:
- (i) The information obtained is recorded by the investigator in such a manner that the identity of the human subjects cannot readily be ascertained, directly or through identifiers linked to the subjects;
  - (ii) Any disclosure of the human subjects' responses outside the research would not reasonably place the subjects at risk of criminal or civil liability or be damaging to the

subjects' financial standing, employability, educational advancement, or reputation.

- (3) (i) Research involving benign behavioral interventions in conjunction with the collection of information from an adult subject through verbal or written responses (including data entry) or audiovisual recording if the subject prospectively agrees to the intervention and information collection and at least one of the following criteria is met:
- (A) The information obtained is recorded by the investigator in such a manner that the identity of the human subjects cannot readily be ascertained, directly or through identifiers linked to the subjects;
  - (B) Any disclosure of the human subjects' responses outside the research would not reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, educational advancement, or reputation.
- (4) Secondary research for which consent is not required: Secondary research uses of identifiable private information or identifiable biospecimens, if at least one of the following criteria is met:
- (i) The identifiable private information or identifiable biospecimens are publicly available;
  - (ii) Information, which may include information about biospecimens, is recorded by the investigator in such a manner that the identity of the human subjects cannot readily be ascertained directly or through identifiers linked to the subjects, the investigator does not contact the subjects, and the investigator will not re-identify subjects.
- (6) Taste and food quality evaluation and consumer acceptance studies:
- (i) If wholesome foods without additives are consumed, or
  - (ii) If a food is consumed that contains a food ingredient at or below the level and for a use found to be safe, or agricultural chemical or environmental contaminant at or below the level found to be safe, by the Food and Drug Administration or approved by the Environmental Protection Agency or the Food Safety and Inspection Service of the U.S. Department of Agriculture.

An exempt research project does not require ongoing review by the IRB, unless the project is amended in such a way that it no longer meets the exemption criteria.

## **Appendix B**

### **Tables**

- B1 Summary of the Review of the Current Literature
- B2 Appendix E to 14 CFR Part 125
- B3 Logistic Regression Tables for Basic Model
- B4 Logistic Regression Tables for Forward and Backward Stepwise
- B5 Logistic Regression Tables for Moderating Variable Interactions

**Table B1***Summary of Literature Reviewed*

Subject Area: Unstable Approaches			
Author(s) and (Date)	Summary	Findings	Limitations
George (2007)	Technical Article: Discusses stabilized approach criteria common to non-airline jet operations.	Recommends adherence to standard operating procedures and stabilized approach criteria.	Does not discuss specific EM relationships to UA events.
Kelly & Efthymiou (2019)	Journal Article: Discusses how various factors influence CFIT events.	Identifies factors, including darkness and reliance on automation, that impact CFIT mishaps.	Does not discuss specific EM relationships to UA events.  Does discuss how some of the MV may impact CFIT, but not EM/UA events.
Lee and Kim (2018)	Journal Article: Discusses how fatigue influences pilot performance, which impact the execution of approach procedures.	Found that fatigue impacts mental acuity and decision making. May be significant on repeated short flights with little break before the high-workload descent and approach phase.	Does not discuss specific EM relationships to UA events.  Does discuss how pilot fatigue may impact UAs directly.
Ross (2018)	Thesis: Discusses human factors contributions to UAs.	Reports that of 95 UA incidents studied, 12.6% cited fatigue as a factor.	Does not discuss specific EM relationships to UA events.  Does discuss how pilot fatigue may impact UAs directly.

Subject Area: Unstable Approaches			
Author(s) and (Date)	Summary	Findings	Limitations
Schvaneveldt, Beringer, & Lamonica, (2001)	Journal Article: Discusses pilot information organization inflight and pilot workload.	Defines descent from cruise to landing as a high-workload phase of flight. Crew must accomplish numerous tasks while maintaining proper EM.	Does not discuss specific EM relationships to UA events.
Todd & Thomas (2012)	Journal Article: Discusses how pilot experience influences the execution of stabilized approaches.	Found that pilot experience levels were not statistically significant in directly influencing the occurrence of UA events.	Does not discuss specific EM relationships to UA events.  Does discuss how pilot experience may impact UAs directly but not as an MV of EM.
Wagener & Ison (2014)	Journal Article: Discusses how a focused training program allowed a carrier to reduce UA events.	Continental Airlines instituted focused EM training, resulted in a 70% reduction in UA events.	Does not discuss specific EM relationships to UA events.
Subject Area: Flight Data Monitoring			
Author(s) and (Date)	Summary	Findings	Limitations
Callentine (2001)	Journal Article: Discusses a way to enrich FDM information by examining pilot actions.	By comparing pilot actions against a model of correct and acceptable alternative actions, the system attempts to infer pilot intent.	Does not examine the use of FDM to identify EM variables influencing UAs.

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 Subject Area: Flight Data Monitoring
 

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Author(s) and (Date)	Summary	Findings	Limitations
FAA (2004)	FAA regulatory document detailing current flight data recorder mandatory capabilities.	Extensive list of requirements. The required information, however, is miniscule compared to the capabilities of current recorder technology.	Does not examine the use of FDM to identify EM variables influencing UAs.
Grossi (1999)	NTSB Paper: The history of flight data recorders. Describes the origins and evolution of flight data recording instruments and the requirements mandated of them.	Even the Wright brothers' aircraft has a rudimentary flight data recorder, as did Lindbergh's. Includes extensive detailing of the progress of FDR technology.	Does not examine the use of FDM to identify EM variables influencing UAs.
Stolzer & Halford (2007)	Journal Article: Discusses using FDM data to identify anomalous fuel burn rates.	Used data mining techniques to determine abnormal fuel burns taking into account several influencing parameters contained within FDM information.	Does not examine the use of FDM to identify EM variables influencing UAs.
Zhao, Li, and Wang (2017)	Journal Article: Discusses numerous possible ways to utilize FDM information and provides examples of DM possibilities.	Provides an overview of the potential for DM of FDM.	Does not delve into any specific area in depth. Just shows how various DM techniques might be applied to FDM.  Does not examine the use of FDM to identify emergent training needs.

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 Subject Area: Aircraft Energy Management
 

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Author(s) and (Date)	Summary	Findings	Limitations
Baker (2017)	Dissertation: A study evaluating a new concept for an EM situational awareness display.	Found that response times and accuracy for interpretation of new display did not differ statistically from conventional display.	Study focused on energy awareness, which would assist in EM, but not on EM directly.  Does not discuss any aspects of EM with respect to prevention of UAs.
Casner, Geven, Recker, & Schooler (2014)	Journal Article: Discusses issues regarding pilot skill retention in the highly automated cockpit.	Extensive automation, over time, ends up atrophying cognitive skills necessary to conduct EM.	Does not discuss influence on UAs specifically.
Hurt (1960)	Book: Aerodynamics text utilized by the U.S. Navy.	Provides detailed and extensive discussions of various forms of drag on an aircraft in flight.	Does not discuss any aspects of EM with respect to prevention of UAs.
Merkt (2013)	Journal Article: Discusses two aspects of EM: safety and efficiency. Highlights the need for improved EM training for pilots to increase both safety and efficiency and the trade-offs between the two.	Air carrier EM has focused on fuel efficiency, but the top three causes of commercial aviation fatalities include EM as a common element.	Does not discuss stabilized approaches or the prevention of UAs.

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 Subject Area: Aircraft Energy Management
 

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Author(s) and (Date)	Summary	Findings	Limitations
Molter (1918)	Book: Written in the World War I era, the book describes some of the tactics used by the earliest air-to-air pilots.	Demonstrates an understanding of the importance of energy management, though extremely rudimentary.	<p>With the limited understanding of aerodynamics at the time of its writing, altitude and airspeed were the only discussed elements of EM.</p> <p>Does not discuss any aspects of EM with respect to prevention of UAs.</p>
Noyes (2007)	Journal Article: Discusses 3 types of total energy display designed to provide the pilot with a single point of reference for the energy state of the aircraft.	The most simplified display produced the quickest reaction times, but also the most erroneous reactions.	<p>Small number of participants.</p> <p>Discusses how the display can assist the pilot in EM but does not discuss any aspects of EM with respect to prevention of UAs.</p>
Prats et al. (2014)	Journal Article: Describes EM technique of Continuous Descent Operations (CDO) and new, more accurate model.	New model provides increased accuracy in planning CDOs. Inclusion of wind into the model is identified as most significant improvement.	<p>Focused on CDO which emphasizes minimizing level flight segments during descent to minimize fuel consumption, noise, and emissions. Does not examine impact on UAs.</p>

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 Subject Area: Aircraft Energy Management
 

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Author(s) and (Date)	Summary	Findings	Limitations
Shaw (1985)	Book: Instructional manual on how to employ fighter aircraft and execute aerial combat maneuvers. Includes a 32-page appendix specific to fighter performance which includes a lengthy section on energy management and maneuverability.	EM is not a new subject in aviation. It is and has been a significant part of fighter aviation.	This manual is specific to fighter aviation. It does not include general or commercial aviation. While portions are technically applicable to these areas, the focus is air-to-air combat.  Does not discuss any aspects of EM with respect to prevention of UAs.
Stolzer (2002)	Journal article: Paper examining U.S. air carrier efficiency.	For U.S. air carriers, 10% of all 2010 operating expenditures were for fuel.	Does not discuss any aspects of EM with respect to prevention of UAs.
Szurovy & Goulian (1997)	Book: Instruction manual for precision aerobatic maneuvers.	Discusses EM from the perspective of precision aerobatics. EM is necessary to ensure that there is sufficient energy at the completion of one maneuver to begin execution of the next maneuver.	Does not discuss any aspects of EM with respect to prevention of UAs.
Wanyan, Zhuang, Lin, Xiao, & Song (2018)	Journal article. Examines influence of workload on pilots' ability to detect errors.	High-workload situations result in decreased accuracy and increased reaction times in addressing errors.	Does not discuss any specifics regarding EM, UAs, or possible relationships.

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 Subject Area: Aircraft Energy Management
 

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Author(s) and (Date)	Summary	Findings	Limitations
Wagener & Ison (2014)	Journal Article: Examines the relationship between airline management practices and accidents where crew resource management was a causal factor.	When EM was included a part of an air carriers recurrent training program, the incidents of UAs declined 70%.	Not all of the NTSB reports examined for the study contained the preferred detail on management procedures, training, and guidelines. Additional desired details were not always available.  Does not discuss any aspects of EM with respect to prevention of UAs.
Zagalsky (1973)	Book: Aerodynamics text.	Discusses potential and kinetic energy and provides formulae for their computation, including the total energy equation.	Does not discuss any aspects of EM with respect to prevention of UAs.
Zhang, Qu, Xue, Zhao, Li, & Tao (2019)	Journal Article: Discusses a method of modeling pilot workload; examines impact of experience.	Validated concepts that factors of experience and environment (visibility, task complexity) impact pilot performance.	Does not discuss influence on UAs specifically.

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*Note.* Regulatory and most technical articles excluded.

**Table B2***Appendix E to 14 CFR Part 125—Airplane Flight Recorder Specifications*

<b>Parameters</b>	<b>Range</b>	<b>Accuracy (sensor input)</b>	<b>Seconds per sampling interval</b>	<b>Resolution</b>	<b>Remarks</b>
1. Time or Relative Times Counts. <sup>1</sup>	24 Hrs, 0 to 4095	±0.125% Per Hour	4	1 sec	UTC time preferred when available. Count increments each 4 seconds of system operation.
2. Pressure Altitude	−1000 ft to max certificated altitude of aircraft. + 5000 ft	±100 to ±700 ft (see table, TSO C124a or TSO C51a)	1	5' to 35'	Data should be obtained from the air data computer when practicable.
3. Indicated airspeed or Calibrated airspeed	50 KIAS or minimum value to Max V <sub>so</sub> , to 1.2 V <sub>D</sub>	±5% and ±3%	1	1 kt	Data should be obtained from the air data computer when practicable.
4. Heading (Primary flight crew reference)	0-360° and Discrete “true” or “mag”	±2°	1	0.5°	When true or magnetic heading can be selected as the primary heading reference, a discrete indicating selection must be recorded.
5. Normal Acceleration (Vertical) <sup>9</sup>	−3g to +6g	±1% of max range excluding datum error of ±5%	0.125	0.004g.	
6. Pitch Attitude	±75°	±2°	1 or 0.25 for airplanes	0.5°	A sampling rate of 0.25 is recommended.

7. Roll Attitude <sup>2</sup>	±180°	±2°	operated under §125.226(f) 1 or 0.5 for airplanes operated under §121.344(f)	0.5°	A sampling rate of 0.5 is recommended.
8. Manual Radio Transmitter Keying or CVR/DFDR synchronization reference	On-Off (Discrete) None.		1		Preferably each crew member but one discrete acceptable for all transmission provided the CVR/FDR system complies with TSO C124a CVR synchronization requirements (paragraph 4.2.1 ED-55).
9. Thrust/Power on each engine— primary flight crew reference	Full Range Forward	±2%	1 (per engine)	0.3% of full range	Sufficient parameters (e.g., EPR, N1 or Torque, NP) as appropriate to the particular engine being recorded to determine power in forward and reverse thrust, including potential overspeed condition.
10. Autopilot Engagement	Discrete “on” or “off”		1.		
11. Longitudinal Acceleration	±1g	±1.5% max. range excluding	0.25	0.004g.	

		datum error of $\pm 5\%$			
12a. Pitch control(s) position (nonfly-by-wire systems) <sup>18</sup>	Full range	$\pm 2^\circ$ unless higher accuracy uniquely required	0.5 or 0.25 for airplanes operated under §125.226(f)	0.5% of full range	For airplanes that have a flight control breakaway capability that allows either pilot to operate the controls independently, record both control inputs. The control inputs may be sampled alternately once per second to produce the sampling interval of 0.5 or 0.25, as applicable.
12b. Pitch control(s) position (fly-by-wire systems) <sup>3 18</sup>	Full range	$\pm 2^\circ$ unless higher accuracy uniquely required	0.5 or 0.25 for airplanes operated under §125.226(f)	0.2% of full range	
13a. Lateral control position(s) (nonfly-by-wire) <sup>18</sup>	Full range	$\pm 2^\circ$ unless higher accuracy uniquely required	0.5 or 0.25 for airplanes operated under §125.226(f)	0.2% of full range	For airplanes that have a flight control break away capability that allows either pilot to operate the controls independently, record both control inputs. The control inputs may be sampled alternately once per second to produce the sampling interval of 0.5 or 0.25, as applicable.

13b. Lateral control position(s) (fly-by-wire) <sup>4 18</sup>	Full range	$\pm 2^\circ$ unless higher accuracy uniquely required	0.5 or 0.25 for airplanes operated under §125.226(f)	0.2% of full range	
14a. Yaw control position(s) (nonfly-by-wire) <sup>5 18</sup>	Full range	$\pm 2^\circ$ unless higher accuracy uniquely required	0.5	0.3% of full range	For airplanes that have a flight control breakaway capability that allows either pilot to operate the controls independently, record both control inputs. The control inputs may be sampled alternately once per second to produce the sampling interval of 0.5.
14b. Yaw control position(s) (fly-by-wire) <sup>18</sup>	Full range	$\pm 2^\circ$ unless higher accuracy uniquely required	0.5	0.2% of full range	
15. Pitch control surface(s) position <sup>6 18</sup>	Full range	$\pm 2^\circ$ unless higher accuracy uniquely required	0.5 or 0.25 for airplanes operated under §125.226(f)	0.3% of full range	For airplanes fitted with multiple or split surfaces, a suitable combination of inputs is acceptable in lieu of recording each surface separately. The control surfaces may be sampled alternately to produce the sampling interval of 0.5 or 0.25, as applicable.

16. Lateral control surface(s) position <sup>7</sup> 18	Full Range	±2° unless higher accuracy uniquely required	0.5 or 0.25 for airplanes operated under §125.226(f)	0.2% of full range	A suitable combination of surface position sensors is acceptable in lieu of recording each surface separately. The control surfaces may be sampled alternately to produce the sampling interval of 0.5 or 0.25, as applicable.
17. Yaw control surface(s) position <sup>8</sup> 18	Full range	±2° unless higher accuracy uniquely required	0.5	0.2% of full range	For airplanes fitted with multiple or split surfaces, a suitable combination of surface position sensors is acceptable in lieu of recording each surface separately. The control surfaces may be sampled alternately to produce the sampling interval of 0.5.
18. Lateral Acceleration	±1g	±1.5% max. range excluding datum error of ±5%	0.25	0.004g.	
19. Pitch Trim Surface Position	Full Range	±3° Unless Higher Accuracy Uniquely Required	1	0.6% of full range	
20. Trailing Edge Flap or Cockpit Control Selection. <sup>10</sup>	Full Range or Each Position (discrete)	±3° or as Pilot's indicator	2	0.5% of full range	Flap position and cockpit control may each be sampled at 4



					second intervals, to give a data point every 2 seconds.
21. Leading Edge Flap or Cockpit Control Selection. <sup>11</sup>	Full Range or Each Discrete Position	$\pm 3^\circ$ or as Pilot's indicator and sufficient to determine each discrete position	2	0.5% of full range	Left and right sides, or flap position and cockpit control may each be sampled at 4 second intervals, so as to give a data point every 2 seconds.
22. Each Thrust Reverser Position (or equivalent for propeller airplane)	Stowed, In Transit, and Reverse (Discrete)		1 (per engine).		Turbo-jet—2 discretely enable the 3 states to be determined. Turbo-prop—1 discrete.
23. Ground Spoiler Position or Speed Brake Selection <sup>12</sup>	Full Range or Each Position (discrete)	$\pm 2^\circ$ Unless higher accuracy uniquely required	1 or 0.5 for airplanes operated under §125.226(f)	0.2% of full range	
24. Outside Air Temperature or Total Air Temperature. <sup>13</sup>	$-50^\circ\text{C}$ to $+90^\circ\text{C}$	$\pm 2^\circ\text{C}$	2	$0.3^\circ\text{C}$ .	
25. Autopilot/Autothrottle /AFCS Mode and Engagement Status	A suitable combination of discretely		1		Discretely should show which systems are engaged and which primary modes are controlling the flight path and speed of the aircraft.
26. Radio Altitude <sup>14</sup>	$-20$ ft to $2,500$ ft	$\pm 2$ ft or $\pm 3\%$ Whichever is Greater	1	$1$ ft + 5% Above $500$ ft	For autoland/ category 3 operations. Each radio altimeter

		Below 500 ft and $\pm 5\%$ above 500 ft			should be recorded, but arranged so that at least one is recorded each second.
27. Localizer Deviation, MLS Azimuth, or GPS Lateral Deviation	$\pm 400$ Microamps or available sensor range as installed $\pm 62^\circ$	As installed. $\pm 3\%$ recommended	1	0.3% of full range	For autoland/category 3 operations. Each system should be recorded but arranged so that at least one is recorded each second. It is not necessary to record ILS and MLS at the same time; only the approach aid in use need be recorded.
28. Glideslope Deviation, MLS Elevation, or GPS Vertical Deviation	$\pm 400$ Microamps or available sensor range as installed. 0.9 to $+ 30^\circ$	As installed. $\pm 3\%$ recommended	1	0.3% of full range	For autoland/category 3 operations. each system should be recorded but arranged so that at least one is recorded each second. It is not necessary to record ILS and MLS at the same time; only the approach aid in use need be recorded.
29. Marker Beacon Passage	Discrete "on" or "off"		1		A single discrete is acceptable for all markers.
30. Master Warning	Discrete		1		Record the master warning and record each 'red' warning that cannot be determined from

					other parameters or from the cockpit voice recorder.
31. Air/ground sensor (primary airplane system reference nose or main gear)	Discrete “air” or “ground”		1 (0.25 recommended).		
32. Angle of Attack (If measured directly)	As installed	As Installed	2 or 0.5 for airplanes operated under §125.226(f)	0.3% of full range	If left and right sensors are available, each may be recorded at 4 or 1 second intervals, as appropriate, so as to give a data point at 2 seconds or 0.5 second, as required.
33. Hydraulic Pressure Low, Each System	Discrete or available sensor range, “low” or “normal”	±5%	2	0.5% of full range.	
34. Groundspeed	As Installed	Most Accurate Systems Installed	1	0.2% of full range.	
35. GPWS (ground proximity warning system)	Discrete “warning” or “off”		1		A suitable combination of discretes unless recorder capacity is limited in which case a single discrete for all modes is acceptable.
36. Landing Gear Position or Landing gear cockpit control selection	Discrete		4		A suitable combination of discretes should be recorded.

37. Drift Angle. <sup>15</sup>	As installed	As installed	4	0.1%.	
38. Wind Speed and Direction	As installed	As installed	4	1 knot, and 1.0°.	
39. Latitude and Longitude	As installed	As installed	4	0.002°, or as installed	Provided by the Primary Navigation System Reference. Where capacity permits, Latitude/longitude resolution should be 0.0002°.
40. Stick shaker and pusher activation	Discrete(s) "on" or "off"		1		A suitable combination of discretes to determine activation.
41. Windshear Detection	Discrete "warning" or "off"		1		
42. Throttle/power lever position. <sup>16</sup>	Full Range	±2%	1 for each lever	2% of full range	For airplanes with non-mechanically linked cockpit engine controls.
43. Additional Engine Parameters	As installed	As installed	Each engine each second	2% of full range	Where capacity permits, the preferred priority is indicated vibration level, N2, EGT, Fuel Flow, Fuel Cut-off lever position and N3, unless engine manufacturer recommends otherwise.
44. Traffic Alert and Collision Avoidance System (TCAS)	Discretes	As installed	1		A suitable combination of discretes should be recorded to determine the status of-

					Combined Control, Vertical Control, Up Advisory, and Down Advisory (ref. ARINC Characteristic 735 Attachment 6E, TCAS VERTICAL RA DATA OUTPUT WORD).
45. DME 1 and 2 Distance	0-200 NM	As installed	4	1 NM	1 mile.
46. Nav 1 and 2 Selected Frequency	Full range	As installed	4		Sufficient to determine selected frequency.
47. Selected barometric setting	Full range	±5%	(1 per 64 sec.)	0.2% of full range.	
48. Selected Altitude	Full range	±5%	1	100 ft.	
49. Selected speed	Full range	±5%	1	1 knot.	
50. Selected Mach	Full range	±5%	1	.01.	
51. Selected vertical speed	Full range	±5%	1	100 ft/min.	
52. Selected heading	Full range	±5%	1	1°.	
53. Selected flight path	Full range	±5%	1	1°.	
54. Selected decision height	Full range	±5%	64	1 ft.	
55. EFIS display format	Discrete(s)		4		Discretesshould show the display system status (e.g., off, normal, fail, composite, sector, plan, nav aids, weather radar, range, copy).
56. Multi-function/Engine Alerts Display format	Discrete(s)		4		Discretesshould show the display system status (e.g., off, normal, fail, and the identity of

					display pages for emergency procedures, need not be recorded).
57. Thrust command. <sup>17</sup>	Full Range	±2%	2	2% of full range	
58. Thrust target	Full range	±2%	4	2% of full range.	
59. Fuel quantity in CG trim tank	Full range	±5%	(1 per 64 sec.)	1% of full range.	
60. Primary Navigation System Reference	Discrete GPS, INS, VOR/DM E, MLS, Localizer Glideslope		4		A suitable combination of discretely to determine the Primary Navigation System reference.
61. Ice Detection	Discrete “ice” or “no ice”		4		
62. Engine warning each engine vibration	Discrete		1		
63. Engine warning each engine over temp	Discrete		1		
64. Engine warning each engine oil pressure low	Discrete		1		
65. Engine warning each engine over speed	Discrete		1		
66. Yaw Trim Surface Position	Full Range	±3% Unless Higher Accuracy Uniquely Required	2	0.3% of full range.	
67. Roll Trim Surface Position	Full Range	±3% Unless	2	0.3% of full range.	

		Higher Accuracy Uniquely Required			
68. Brake Pressure (left and right)	As installed	±5%	1		To determine braking effort applied by pilots or by autobrakes.
69. Brake Pedal Application (left and right)	Discrete or Analog “applied” or “off”	±5% (Analog)	1		To determine braking applied by pilots.
70. Yaw or sideslip angle	Full Range	±5%	1	0,5°.	
71. Engine bleed valve position	Discrete “open” or “closed”		4		
72. De-icing or anti-icing system selection	Discrete “on” or “off”		4		
73. Computed center of gravity	Full Range	±5%	(1 per 64 sec.)	1% of full range.	
74. AC electrical bus status	Discrete “power” or “off”		4		Each bus.
75. DC electrical bus status	Discrete “power” or “off”		4		Each bus.
76. APU bleed valve position	Discrete “open” or “closed”		4.		
77. Hydraulic Pressure (each system)	Full range	±5%	2	100 psi.	
78. Loss of cabin pressure	Discrete “loss” or “normal”		1.		
79. Computer failure (critical flight and	Discrete “fail” or “normal”		4.		

engine control systems)

80. Heads-up display (when an information source is installed)	Discrete(s) “on” or “off”			4.	
81. Para-visual display (when an information source is installed)	Discrete(s) “on” or “off”			1.	
82. Cockpit trim control input position—pitch	Full Range	$\pm 5\%$	1	0.2% of full range	Where mechanical means for control inputs are not available, cockpit display trim positions should be recorded.
83. Cockpit trim control input position—roll	Full Range	$\pm 5\%$	1	0.7% of full range	Where mechanical means for control inputs are not available, cockpit display trim position should be recorded.
84. Cockpit trim control input position—yaw	Full Range	$\pm 5\%$	1	0.3% of full range	Where mechanical input are not available, cockpit display trim positions should be recorded.
85. Trailing edge flap and cockpit flap control position	Full Range	$\pm 5\%$	2	0.5% of full range	Trailing edge flaps and cockpit flap control position may each be sampled alternately at 4 second intervals to provide a sample each 0.5 second.



86. Leading edge flap and cockpit flap control position	Full Range or Discrete	±5%	1	0.5% of full range.	
87. Ground spoiler position and speed brake selection	Full Range or Discrete	±5%	0.5	0.3% of full range	
88. All cockpit flight control input forces (control wheel, control column, rudder pedal) <sup>18,19</sup>	Full range Control wheel ±70 lbs Control column ±85 lbs Rudder pedal ±165 lbs	±5%	1	0.3% of full range	For fly-by-wire flight control systems, where flight control surface position is a function of the displacement of the control input device only, it is not necessary to record this parameter. For airplanes that have a flight control break away capability that allows either pilot to operate the control independently, record both control force inputs. The control force inputs may be sampled alternately once per 2 seconds to produce the sampling interval of 1.
89. Yaw damper status	Discrete (on/off)	0.5			
90. Yaw damper command	Full range	As installed	0.5	1% of full range	
91. Standby rudder valve status	Discrete	0.5			

*Note.* The recorded values must meet the designated range, resolution and accuracy requirements during static and dynamic conditions. Dynamic condition means the parameter is experiencing change at the maximum rate attainable, including the maximum rate of reversal. All data recorded must be correlated in

time to within one second. Adapted from “14 CFR Part 125, Appendix E”, 2017 by FAA. <sup>1</sup>For A300 B2/B4 airplanes, resolution = 6 seconds. <sup>2</sup>For A330/A340 series airplanes, resolution = 0.703°. <sup>3</sup>For A318/A319/A320/A321 series airplanes, resolution = 0.275% (0.088°>0.064°), for A330/A340 series airplanes, resolution = 2.20% (0.703°>0.064°). <sup>4</sup>For A318/A319/A320/A321 series airplanes, resolution = 0.22% (0.088°>0.080°), for A330/A340 series airplanes, resolution = 1.76% (0.703°>0.080°). <sup>5</sup>For A330/A340 series airplanes, resolution = 1.18% (0.703° >0.120°), for A330/A340 series airplanes, seconds per sampling interval = 1. <sup>6</sup>For A330/A340 series airplanes, resolution = 0.783% (0.352°>0.090°). <sup>7</sup>For A330/A340 series airplanes, aileron resolution = 0.704% (0.352°>0.100°). For A330/A340 series airplanes, spoiler resolution = 1.406% (0.703°>0.100°). <sup>8</sup>For A330/A340 series airplanes, resolution = 0.30% (0.176°>0.12°), for A330/A340 series airplanes, seconds per sampling interval = 1. <sup>9</sup>For B-717 series airplanes, resolution = .005g. For Dassault F900C/F900EX airplanes, resolution = .007g. <sup>10</sup>For A330/A340 series airplanes, resolution = 1.05% (0.250°>0.120°). <sup>11</sup>For A330/A340 series airplanes, resolution = 1.05% (0.250°>0.120°). For A330 B2/B4 series airplanes, resolution = 0.92% (0.230°>0.125°). <sup>12</sup>For A330/A340 series airplanes, spoiler resolution = 1.406% (0.703°>0.100°). <sup>13</sup>For A330/A340 series airplanes, resolution = 0.5°C. <sup>14</sup>For Dassault F900C/F900EX airplanes, Radio Altitude resolution = 1.25 ft. <sup>15</sup>For A330/A340 series airplanes, resolution = 0.352 degrees. <sup>16</sup>For A318/A319/A320/A321 series airplanes, resolution = 4.32%. For A330/A340 series airplanes, resolution is 3.27% of full range for throttle lever angle (TLA); for reverse thrust, reverse throttle lever angle (RLA) resolution is nonlinear over the active reverse thrust range, which is 51.54 degrees to 96.14 degrees. The resolved element is 2.8 degrees uniformly over the entire active reverse thrust range, or 2.9% of the full range value of 96.14 degrees. <sup>17</sup>For A318/A319/A320/A321 series airplanes, with IAE engines, resolution = 2.58%. <sup>18</sup>For all aircraft manufactured on or after December 6, 2010, the seconds per sampling interval is 0.125. Each input must be recorded at this rate. Alternately sampling inputs (interleaving) to meet this sampling interval is prohibited. <sup>19</sup>For all 737 model airplanes manufactured between August 19, 2000, and April 6, 2010: The seconds per sampling interval is 0.5 per control input; the remarks regarding the sampling rate do not apply; a single control wheel force transducer installed on the left cable control is acceptable provided the left and right control wheel positions also are recorded.

**Table B3***Logistic Regression Tables for Basic Model*Case Processing Summary

Unweighted Cases <sup>a</sup>		N	Percent
Selected Cases	Included in Analysis	10500	100.0
	Missing Cases	0	.0
	Total	10500	100.0
Unselected Cases		0	.0
Total		10500	100.0

Note. a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
Stabilized	0
Unstable Approach	1

Categorical Variables Codings

		Frequency	Parameter coding (1)
Speed Brake	0 (Not Used)	2,856	.000
	1 (Deployed)	7,644	1.000
High Speed	0 (Normal)	7,837	.000
	1 (Fast)	2,663	1.000
Late Start	0 (Timely)	10,471	.000
	1 (Late)	29	1.000

**Block 0: Beginning Block**Classification Table<sup>a,b</sup>

Observed		Predicted			
		Unstable Approach		Percentage Correct	
		Stabilized	Unstable Approach		
Step 0	Unstable Approach	Stabilized	10360	0	100.0
		Unstable Approach	140	0	.0
Overall Percentage					98.7

Note. a. Constant is included in the model; b. The cut value is .017

*Variables in the Equation*

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-4.304	.085	2,558.917	1	.000	.014

*Variables not in the Equation*

			Score	df	Sig.
Step 0	Variables	Late Start(1)	393	1	.531
		High Speed(1)	.467	1	.495
		Gear Speed	10.681	1	.001
		Gear Dist	.282	1	.596
		Flap Speed	19.266	1	.000
		Flap Dist	2.003	1	.157
		Speed Brake(1)	1.281	1	.258
	Overall Statistics		32.834	7	.000

Block 1: Method = Enter

*Omnibus Tests of Model Coefficients*

		Chi-square	df	Sig.
Step 1	Step	33.267	7	.000
	Block	33.267	7	.000
	Model	33.267	7	.000

*Model Summary*

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1,453.754 <sup>a</sup>	.003	.024

*Note.* a. Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

*Hosmer and Lemeshow Test*

Step	Chi-square	df	Sig.
1	13.033	8	.111

*Classification Table<sup>a</sup>*

Observed		Predicted			
		Unstable Approach		Percentage Correct	
		Stabilized	Unstable Approach		
Step 1	Unstable Approach	Stabilized	7,947	2,413	76.7
		Unstable Approach	81	59	42.1
Overall Percentage					76.2

*Note.* a. The cut value is .017.

*Variables in the Equation*

							95% C.I. for EXP(B)		
		B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Step 1 <sup>a</sup>	Late Start(1)	-16.908	7,301.899	.000	1	.998	.000	.000	.
	High Speed(1)	.064	.193	.109	1	.741	1.066	.730	1.557
	Gear Speed	.015	.005	8.065	1	.005	1.015	1.005	1.026
	Gear Dist	-.108	.043	6.277	1	.012	.898	.826	.977
	Flap Speed	.016	.005	9.020	1	.003	1.016	1.006	1.027
	Flap Dist	-.013	.022	.342	1	.559	.987	.945	1.031
	Speed Brake(1)	-.094	.188	.252	1	.616	.910	.629	1.315
	Constant	-9.541	1.167	66.825	1	.000	.000		

*Note.* a. Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake.

**Table B4***Logistic Regression Tables for Forward and Backward Stepwise*

Block 1: Method = Forward Stepwise (Likelihood Ratio)

<i>Omnibus Tests of Model Coefficients</i>				
		Chi-square	df	Sig.
Step 1	Step	18.406	1	.000
	Block	18.406	1	.000
	Model	18.406	1	.000
Step 2	Step	4.969	1	.026
	Block	23.375	2	.000
	Model	23.375	2	.000

<i>Model Summary</i>			
Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1,468.616 <sup>a</sup>	.002	.013
2	1,463.647 <sup>a</sup>	.002	.017

*Note.* a. Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

<i>Hosmer and Lemeshow Test</i>			
Step	Chi-square	df	Sig.
1	6.303	8	.613
2	2.593	8	.957

*Contingency Table for Hosmer and Lemeshow Test*

		Unstable Approach = Stabilized		Unstable Approach = Unstable Approach		Total
		Observed	Expected	Observed	Expected	
Step 1	1	1,062	1,061.901	8	8.099	1,070
	2	1,022	1,025.014	12	8.986	1,034
	3	1,061	1,060.693	10	10.307	1,071
	4	1,004	1,001.365	8	10.635	1,012
	5	1,040	1,035.041	7	11.959	1,047
	6	1,034	1,037.831	17	13.169	1,051
	7	1,010	1,009.603	14	14.397	1,024
	8	1,053	1,056.740	21	17.260	1,074
	9	1,019	1,015.838	16	19.162	1,035
	10	1,055	1,055.973	27	26.027	1,082
Step 2	1	1,045	1,043.629	5	6.371	1,050
	2	1,040	1,041.497	10	8.503	1,050
	3	1,041	1,040.271	9	9.729	1,050
	4	1,040	1,039.093	10	10.907	1,050
	5	1,034	1,037.892	16	12.108	1,050
	6	1,037	1,036.525	13	13.475	1,050
	7	1,035	1,034.827	15	15.173	1,050
	8	1,033	1,032.783	17	17.217	1,050
	9	1,033	1,029.835	17	20.165	1,050
	10	1,022	1,023.647	28	26.353	1,050

*Classification Table<sup>a</sup>*

Observed		Predicted			
		Unstable Approach Stabilized	Unstable Approach	Percentage Correct	
Step 1	Unstable Approach	Stabilized	8,211	2,149	79.3
		Unstable Approach	95	45	32.1
	Overall Percentage				78.6
Step 2	Unstable Approach	Stabilized	8,082	2,278	78.0
		Unstable Approach	91	49	35.0
	Overall Percentage				77.4

Note. a. The cut value is .017

*Variables in the Equation*

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
Step 1 <sup>a</sup>	Flap Speed	.020	.005	19.003	1	.000	1.020	1.011	1.029
	Constant	-8.821	1.055	69.979	1	.000	.000		
Step 2 <sup>b</sup>	Flap Speed	.022	.005	21.519	1	.000	1.023	1.013	1.032
	Flap Dist	-.045	.021	4.455	1	.035	.956	.917	.997
	Constant	-8.592	1.085	62.719	1	.000	.000		

Note. a. Variable(s) entered on step 1: Flap Speed.

b. Variable(s) entered on step 2: Flap Dist.

*Correlation Matrix*

		Constant	Flap Speed	Flap Dist
Step 1	Constant	1.000	-.997	
	Flap Speed	-.997	1.000	
Step 2	Constant	1.000	-.947	-.108
	Flap Speed	-.947	1.000	-.208
	Flap Dist	-.108	-.208	1.000

*Model if Term Removed*

		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	Flap Speed	-743.511	18.406	1	.000
Step 2	Flap Speed	-742.423	21.199	1	.000
	Flap Dist	-734.308	4.969	1	.026



*Variables not in the Equation*

			Score	df	Sig.
Step 1	Variables	Late Start(1)	.417	1	.519
		High Speed(1)	.483	1	.487
		Gear Speed	3.197	1	.074
		Gear Dist	1.072	1	.300
		Flap Dist	4.375	1	.036
		Speed Brake(1)	.564	1	.453
	Overall Statistics	13.651	6	.034	
Step 2	Variables	Late Start(1)	.434	1	.510
		High Speed(1)	.094	1	.759
		Gear Speed	1.498	1	.221
		Gear Dist	.723	1	.395
		Speed Brake(1)	.315	1	.574
	Overall Statistics	9.196	5	.101	

Block 1: Method = Backward Stepwise (Likelihood Ratio)

*Omnibus Tests of Model Coefficients*

		Chi-square	df	Sig.
Step 1	Step	33.267	7	.000
	Block	33.267	7	.000
	Model	33.267	7	.000
Step 2 <sup>a</sup>	Step	-.108	1	.742
	Block	33.159	6	.000
	Model	33.159	6	.000
Step 3 <sup>a</sup>	Step	-.243	1	.622
	Block	32.916	5	.000
	Model	32.916	5	.000
Step 4 <sup>a</sup>	Step	-.480	1	.488
	Block	32.436	4	.000
	Model	32.436	4	.000
Step 5 <sup>a</sup>	Step	-.792	1	.374
	Block	31.644	3	.000
	Model	31.644	3	.000

*Note.* a. A negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step.

*Model Summary*

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1,453.754 <sup>a</sup>	.003	.024
2	1,453.862 <sup>a</sup>	.003	.024
3	1,454.105 <sup>a</sup>	.003	.024
4	1,454.586 <sup>a</sup>	.003	.023
5	1,455.378 <sup>b</sup>	.003	.023

*Note.* a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

b. Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

*Hosmer and Lemeshow Test*

Step	Chi-square	df	Sig.
1	13.033	8	.111
2	11.417	8	.179
3	13.880	8	.085
4	15.786	8	.046
5	15.265	8	.054

*Contingency Table for Hosmer and Lemeshow Test*

		Unstable Approach = Stabilized		Unstable Approach = Unstable		Total
		Approach				
		Observed	Expected	Observed	Expected	
Step 1	1	1,041	1,044.661	9	5.339	1,050
	2	1,044	1,042.239	6	7.761	1,050
	3	1,038	1,040.919	12	9.081	1,050
	4	1,040	1,039.678	10	10.322	1,050
	5	1,040	1,038.372	10	11.628	1,050
	6	1,036	1,036.882	14	13.118	1,050
	7	1,034	1,034.959	16	15.041	1,050
	8	1,044	1,032.525	6	17.475	1,050
	9	1,028	1,029.254	22	20.746	1,050
	10	1,015	1,020.510	35	29.490	1,050
Step 2	1	1,041	1,044.659	9	5.341	1,050
	2	1,045	1,042.231	5	7.769	1,050
	3	1,038	1,040.926	12	9.074	1,050
	4	1,039	1,039.669	11	10.331	1,050
	5	1,040	1,038.385	10	11.615	1,050
	6	1,034	1,036.876	16	13.124	1,050
	7	1,036	1,034.938	14	15.062	1,050
	8	1,042	1,032.510	8	17.490	1,050
	9	1,029	1,029.243	21	20.757	1,050
	10	1,016	1,020.563	34	29.437	1,050
Step 3	1	1,041	1,044.637	9	5.363	1,050
	2	1,045	1,042.178	5	7.822	1,050
	3	1,037	1,040.858	13	9.142	1,050
	4	1,040	1,039.615	10	10.385	1,050
	5	1,037	1,038.363	13	11.637	1,050
	6	1,038	1,036.872	12	13.128	1,050
	7	1,035	1,034.989	15	15.011	1,050
	8	1,043	1,032.596	7	17.404	1,050
	9	1,031	1,029.334	19	20.666	1,050
	10	1,013	1,020.559	37	29.441	1,050
Step 4	1	1,042	1,044.523	8	5.477	1,050
	2	1,044	1,042.072	6	7.928	1,050
	3	1,034	1,040.802	16	9.198	1,050
	4	1,043	1,039.626	7	10.374	1,050
	5	1,038	1,038.401	12	11.599	1,050

	6	1,035	1,036.928	15	13.072	1,050
	7	1,037	1,035.027	13	14.973	1,050
	8	1,043	1,032.629	7	17.371	1,050
	9	1,029	1,029.403	21	20.597	1,050
	10	1,015	1,020.589	35	29.411	1,050
Step 5	1	1,041	1,044.357	9	5.643	1,050
	2	1,044	1,042.060	6	7.940	1,050
	3	1,035	1,040.803	15	9.197	1,050
	4	1,043	1,039.633	7	10.367	1,050
	5	1,038	1,038.413	12	11.587	1,050
	6	1,035	1,036.939	15	13.061	1,050
	7	1,037	1,035.042	13	14.958	1,050
	8	1,043	1,032.651	7	17.349	1,050
	9	1,029	1,029.426	21	20.574	1,050
	10	1,015	1,020.676	35	29.324	1,050

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*Classification Table<sup>a</sup>*

	Observed	Predicted			
		Unstable Approach		Percentage Correct	
		Stabilized	Unstable Approach		
Step 1	Unstable Approach	Stabilized	7,941	2,419	76.7
		Unstable Approach	81	59	42.1
	Overall Percentage				76.2
Step 2	Unstable Approach	Stabilized	7,937	2,423	76.6
		Unstable Approach	80	60	42.9
	Overall Percentage				76.2
Step 3	Unstable Approach	Stabilized	7,993	2,367	77.2
		Unstable Approach	81	59	42.1
	Overall Percentage				76.7
Step 4	Unstable Approach	Stabilized	7,993	2,367	77.2
		Unstable Approach	81	59	42.1
	Overall Percentage				76.7
Step 5	Unstable Approach	Stabilized	8,003	2,357	77.2
		Unstable Approach	81	59	42.1
	Overall Percentage				76.8

*Note.* a. The cut value is .017

*Variables in the Equation*

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
								Lower	Upper
Step 1 <sup>a</sup>	Late Start(1)	-16.908	7,301.899	.000	1	.998	.000	.000	.
	High Speed(1)	.064	.193	.109	1	.741	1.066	.730	1.557
	Gear Speed	.015	.005	8.065	1	.005	1.015	1.005	1.026
	Gear Dist	-.108	.043	6.277	1	.012	.898	.826	.977
	Flap Speed	.016	.005	9.020	1	.003	1.016	1.006	1.027
	Flap Dist	-.013	.022	.342	1	.559	.987	.945	1.031
	Speed	-.094	.188	.252	1	.616	.910	.629	1.315
	Brake(1)								
	Constant	-9.541	1.167	66.825	1	.000	.000		
Step 2 <sup>a</sup>	Late Start(1)	-16.886	7,304.596	.000	1	.998	.000	.000	.
	Gear Speed	.015	.005	8.092	1	.004	1.015	1.005	1.026
	Gear Dist	-.107	.043	6.265	1	.012	.898	.826	.977
	Flap Speed	.016	.005	9.059	1	.003	1.016	1.006	1.027
	Flap Dist	-.014	.022	.406	1	.524	.986	.945	1.029
	Speed	-.093	.188	.245	1	.620	.911	.630	1.317
	Brake(1)								
	Constant	-9.524	1.167	66.612	1	.000	.000		
Step 3 <sup>a</sup>	Late Start(1)	-16.900	7,301.974	.000	1	.998	.000	.000	.
	Gear Speed	.015	.005	7.998	1	.005	1.015	1.005	1.026
	Gear Dist	-.110	.043	6.573	1	.010	.896	.824	.975
	Flap Speed	.017	.005	9.525	1	.002	1.017	1.006	1.028
	Flap Dist	-.015	.022	.459	1	.498	.985	.944	1.028
	Constant	-9.603	1.154	69.221	1	.000	.000		
Step 4 <sup>a</sup>	Late Start(1)	-16.878	7,306.118	.000	1	.998	.000	.000	.
	Gear Speed	.017	.005	12.281	1	.000	1.017	1.007	1.026
	Gear Dist	-.119	.040	8.722	1	.003	.888	.820	.961
	Flap Speed	.015	.005	9.260	1	.002	1.016	1.005	1.026
	Constant	-9.788	1.117	76.860	1	.000	.000		
Step 5 <sup>a</sup>	Gear Speed	.017	.005	12.239	1	.000	1.017	1.007	1.026
	Gear Dist	-.120	.040	8.823	1	.003	.887	.820	.960
	Flap Speed	.015	.005	9.296	1	.002	1.016	1.006	1.026
	Constant	-9.785	1.117	76.781	1	.000	.000		

*Note.* a. Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake.

*Model if Term Removed*

Variable		Change in -2			Sig. of the Change
		Model Log Likelihood	Log Likelihood	df	
Step 1	Late Start	-727.285	.816	1	.366
	High Speed	-726.931	.108	1	.742
	Gear Speed	-730.898	8.041	1	.005
	Gear Dist	-730.295	6.835	1	.009
	Flap Speed	-731.321	8.888	1	.003
	Flap Dist	-727.055	.355	1	.551
	Speed Brake	-727.002	.250	1	.617
Step 2	Late Start	-727.330	.798	1	.372
	Gear Speed	-730.965	8.067	1	.005
	Gear Dist	-730.341	6.820	1	.009
	Flap Speed	-731.393	8.924	1	.003
	Flap Dist	-727.143	.423	1	.516
	Speed Brake	-727.053	.243	1	.622
Step 3	Late Start	-727.458	.810	1	.368
	Gear Speed	-731.038	7.971	1	.005
	Gear Dist	-730.636	7.166	1	.007
	Flap Speed	-731.753	9.400	1	.002
	Flap Dist	-727.293	.480	1	.488
Step 4	Late Start	-727.689	.792	1	.374
	Gear Speed	-733.357	12.129	1	.000
	Gear Dist	-732.316	10.046	1	.002
	Flap Speed	-731.783	8.981	1	.003
Step 5	Gear Speed	-733.731	12.084	1	.001
	Gear Dist	-732.793	10.209	1	.001
	Flap Speed	-732.197	9.017	1	.003



*Variables not in the Equation*

			Score	df	Sig.
Step 2 <sup>a</sup>	Variables	High Speed(1)	.109	1	.741
	Overall Statistics		.109	1	.741
Step 3 <sup>b</sup>	Variables	High Speed(1)	.102	1	.749
		Speed Brake(1)	.246	1	.620
	Overall Statistics		.354	2	.838
Step 4 <sup>c</sup>	Variables	High Speed(1)	.174	1	.676
		Flap Dist	.458	1	.498
		Speed Brake(1)	.304	1	.581
	Overall Statistics		.818	3	.845
Step 5 <sup>d</sup>	Variables	Late Start(1)	.400	1	.527
		High Speed(1)	.151	1	.698
		Flap Dist	.441	1	.507
		Speed Brake(1)	.316	1	.574
	Overall Statistics		1.219	4	.875

*Note.* a. Variable(s) removed on step 2: High Speed.

b. Variable(s) removed on step 3: Speed Brake.

c. Variable(s) removed on step 4: Flap Dist.

d. Variable(s) removed on step 5: Late Start.

**Table B5***Logistic Regression Tables for Moderating Variable Interactions**Lighting \* Late Start*

<i>Variables in the Equation</i>	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for	
							EXP(B)	
							Lower	Upper
Late Start(1)	-17.093	9,242.314	.000	1	.999	.000	.000	.
High Speed(1)	.059	.193	.093	1	.761	1.061	.726	1.550
Gear Speed	.015	.005	7.843	1	.005	1.015	1.004	1.026
Gear Dist	-.106	.043	6.108	1	.013	.900	.827	.978
Flap Speed	.016	.005	9.262	1	.002	1.017	1.006	1.027
Flap Dist	-.013	.022	.343	1	.558	.987	.945	1.031
Speed Brake(1)	-.099	.188	.275	1	.600	.906	.627	1.310
Lighting			3.222	2	.200			
Lighting(1)	-.277	.322	.739	1	.390	.758	.403	1.425
Lighting(2)	-.334	.196	2.897	1	.089	.716	.487	1.052
<b>Late Start *</b>			<b>.000</b>	<b>2</b>	<b>1.000</b>			
<b>Lighting</b>								
Late Start(1) by Lighting(1)	.803	29,853.365	.000	1	1.000	2.233	.000	.
Late Start(1) by Lighting(2)	.449	16,109.737	.000	1	1.000	1.567	.000	.
Constant	-9.435	1.169	65.110	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Lighting, Late Start \* Lighting.

*Lighting \* High Speed**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Late Start(1)	-16.918	7,288.233	.000	1	.998	.000	.000	.
High Speed(1)	.001	.239	.000	1	.996	1.001	.626	1.601
Gear Speed	.015	.005	7.917	1	.005	1.015	1.005	1.026
Gear Dist	-.106	.043	6.163	1	.013	.899	.827	.978
Flap Speed	.017	.005	9.299	1	.002	1.017	1.006	1.028
Flap Dist	-.013	.022	.344	1	.557	.987	.945	1.031
Speed Brake(1)	-.097	.188	.268	1	.605	.907	.627	1.312
Lighting			3.096	2	.213			
Lighting(1)	-.261	.377	.479	1	.489	.770	.368	1.613
Lighting(2)	-.399	.233	2.935	1	.087	.671	.425	1.059
<b>High Speed *</b>			<b>.318</b>	<b>2</b>	<b>.853</b>			
<b>Lighting</b>								
High Speed(1) by Lighting(1)	-.054	.722	.006	1	.940	.947	.230	3.902
High Speed(1) by Lighting(2)	.232	.433	.288	1	.592	1.262	.540	2.949
Constant	-9.437	1.169	65.139	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Lighting, High Speed \* Lighting.

*Lighting \* Gear Speed**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Late Start(1)	-16.956	7,274.021	.000	1	.998	.000	.000	.
High Speed(1)	.056	.194	.085	1	.771	1.058	.724	1.546
Gear Speed	.017	.006	8.563	1	.003	1.017	1.006	1.028
Gear Dist	-.107	.043	6.212	1	.013	.899	.827	.977
Flap Speed	.017	.005	9.383	1	.002	1.017	1.006	1.028
Flap Dist	-.013	.022	.355	1	.551	.987	.945	1.031
Speed Brake(1)	-.097	.188	.263	1	.608	.908	.628	1.313
Lighting			.809	2	.667			
Lighting(1)	2.179	2.443	.795	1	.372	8.834	.074	1,060.596
Lighting(2)	.353	1.402	.064	1	.801	1.424	.091	22.230
<b>Gear Speed *</b>			<b>1.116</b>	<b>2</b>	<b>.572</b>			
<b>Lighting</b>								
Gear Speed by Lighting(1)	-.013	.013	.990	1	.320	.987	.961	1.013
Gear Speed by Lighting(2)	-.004	.008	.243	1	.622	.996	.982	1.011
Constant	-9.807	1.243	62.218	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Lighting, Gear Speed \* Lighting.

*Lighting \* Gear Dist**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for	
							EXP(B)	
							Lower	Upper
Late Start(1)	-16.955	7,287.515	.000	1	.998	.000	.000	.
High Speed(1)	.059	.193	.093	1	.761	1.061	.726	1.550
Gear Speed	.015	.005	7.868	1	.005	1.015	1.004	1.026
Gear Dist	-.113	.048	5.587	1	.018	.893	.814	.981
Flap Speed	.017	.005	9.280	1	.002	1.017	1.006	1.028
Flap Dist	-.013	.022	.352	1	.553	.987	.945	1.031
Speed Brake(1)	-.098	.188	.271	1	.603	.907	.627	1.311
Lighting			1.138	2	.566			
Lighting(1)	-.080	.972	.007	1	.935	.923	.137	6.208
Lighting(2)	-.615	.579	1.127	1	.288	.541	.174	1.683
<b>Gear Dist *</b>			<b>.365</b>	<b>2</b>	<b>.833</b>			
<b>Lighting</b>								
Gear Dist by	-.023	.109	.044	1	.834	.977	.790	1.209
Lighting(1)								
Gear Dist by	.033	.063	.270	1	.604	1.033	.913	1.170
Lighting(2)								
Constant	-9.383	1.182	62.972	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Lighting, Gear Dist \* Lighting.

*Lighting \* Flap Speed**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Late Start(1)	-16.939	7,284.414	.000	1	.998	.000	.000	.
High Speed(1)	.062	.193	.101	1	.750	1.064	.728	1.554
Gear Speed	.015	.005	7.868	1	.005	1.015	1.004	1.026
Gear Dist	-.106	.043	6.114	1	.013	.900	.827	.978
Flap Speed	.016	.006	6.243	1	.012	1.016	1.003	1.029
Flap Dist	-.013	.022	.327	1	.567	.987	.945	1.031
Speed Brake(1)	-.099	.188	.276	1	.600	.906	.627	1.310
Lighting			.813	2	.666			
Lighting(1)	2.254	4.037	.312	1	.577	9.527	.003	26,004.101
Lighting(2)	-1.508	2.526	.357	1	.550	.221	.002	31.235
<b>Flap Speed *</b>			<b>.735</b>	<b>2</b>	<b>.692</b>			
<b>Lighting</b>								
Flap Speed by Lighting(1)	-.011	.018	.390	1	.532	.989	.955	1.024
Flap Speed by Lighting(2)	.005	.011	.218	1	.641	1.005	.984	1.027
Constant	-9.340	1.415	43.561	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Lighting, Flap Speed \* Lighting.

*Lighting \* Flap Dist**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Late Start(1)	-17.006	7,226.597	.000	1	.998	.000	.000	.
High Speed(1)	.042	.194	.047	1	.828	1.043	.713	1.525
Gear Speed	.014	.005	6.608	1	.010	1.014	1.003	1.024
Gear Dist	-.098	.043	5.295	1	.021	.907	.834	.986
Flap Speed	.017	.005	10.404	1	.001	1.018	1.007	1.028
<b>Flap Dist</b>	<b>-.062</b>	<b>.031</b>	<b>3.997</b>	<b>1</b>	<b>.046</b>	<b>.940</b>	<b>.885</b>	<b>.999</b>
Speed Brake(1)	-.099	.188	.277	1	.599	.906	.626	1.310
Lighting			9.327	2	.009			
Lighting(1)	-1.759	.879	4.009	1	.045	.172	.031	.964
Lighting(2)	-1.998	.700	8.141	1	.004	.136	.034	.535
<b>Flap Dist *</b>			<b>7.095</b>	<b>2</b>	<b>.029</b>			
<b>Lighting</b>								
Flap Dist by Lighting(1)	.089	.047	3.612	1	.057	1.093	.997	1.197
<b>Flap Dist by Lighting(2)</b>	<b>.101</b>	<b>.040</b>	<b>6.282</b>	<b>1</b>	<b>.012</b>	<b>1.107</b>	<b>1.022</b>	<b>1.198</b>
Constant	-8.702	1.215	51.300	1	.000	.000		

Note. Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Lighting, Flap Dist \* Lighting.

*Lighting \* Speed Brake**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Late Start(1)	-16.872	7,230.285	.000	1	.998	.000	.000	.
High Speed(1)	.051	.194	.068	1	.794	1.052	.720	1.538
Gear Speed	.015	.005	7.784	1	.005	1.015	1.004	1.025
Gear Dist	-.107	.043	6.261	1	.012	.898	.826	.977
Flap Speed	.017	.005	9.356	1	.002	1.017	1.006	1.028
Flap Dist	-.014	.022	.370	1	.543	.987	.945	1.030
<b>Speed Brake(1)</b>	<b>.271</b>	<b>.250</b>	<b>1.176</b>	<b>1</b>	<b>.278</b>	<b>1.311</b>	<b>.803</b>	<b>2.139</b>
Lighting			4.739	2	.094			
Lighting(1)	-1.236	1.025	1.453	1	.228	.291	.039	2.167
Lighting(2)	.499	.308	2.615	1	.106	1.647	.900	3.013
<b>Lighting * Speed Brake</b>			<b>13.359</b>	<b>2</b>	<b>.001</b>			
Lighting(1) by Speed Brake(1)	1.134	1.081	1.102	1	.294	3.109	.374	25.842
<b>Lighting(2) by Speed Brake(1)</b>	<b>-1.383</b>	<b>.416</b>	<b>11.069</b>	<b>1</b>	<b>.001</b>	<b>.251</b>	<b>.111</b>	<b>.567</b>
Constant	-9.688	1.177	67.780	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Lighting, Lighting \* Speed Brake.



*Experience \* Late Start**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for	
							EXP(B)	
							Lower	Upper
Late Start(1)	-15.659	23,419.920	.000	1	.999	.000	.000	.
High Speed(1)	.083	.193	.185	1	.667	1.087	.744	1.588
Gear Speed	.015	.005	7.683	1	.006	1.015	1.004	1.025
Gear Dist	-.100	.043	5.499	1	.019	.905	.833	.984
Flap Speed	.008	.007	1.426	1	.232	1.008	.995	1.022
Flap Dist	-.009	.022	.149	1	.699	.992	.950	1.035
Speed Brake(1)	.026	.197	.017	1	.896	1.026	.698	1.509
Experience(1)	.527	.267	3.887	1	.049	1.693	1.003	2.859
<b>Experience(1) by Late Start(1)</b>	<b>-.772</b>	<b>14,698.893</b>	<b>.000</b>	<b>1</b>	<b>1.000</b>	<b>.462</b>	<b>.000</b>	<b>.</b>
Constant	-8.706	1.240	49.281	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Experience, Experience \* Late Start.

*Experience \* High Speed**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Late Start(1)	-16.923	7,313.335	.000	1	.998	.000	.000	.
High Speed(1)	.854	.763	1.254	1	.263	2.349	.527	10.476
Gear Speed	.015	.005	7.806	1	.005	1.015	1.004	1.025
Gear Dist	-.100	.043	5.565	1	.018	.905	.832	.983
Flap Speed	.008	.007	1.353	1	.245	1.008	.995	1.021
Flap Dist	-.008	.022	.136	1	.713	.992	.950	1.036
Speed Brake(1)	.030	.197	.023	1	.880	1.030	.701	1.515
Experience(1)	.669	.305	4.803	1	.028	1.952	1.073	3.549
<b>Experience(1) by High Speed(1)</b>	<b>-.443</b>	<b>.428</b>	<b>1.074</b>	<b>1</b>	<b>.300</b>	<b>.642</b>	<b>.277</b>	<b>1.485</b>
Constant	-8.943	1.267	49.842	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Experience, Experience \* High Speed.

*Experience \* Gear Speed**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Late Start(1)	-16.847	7,284.51	.000	1	.998	.000	.000	.
		2						
High Speed(1)	.082	.193	.181	1	.670	1.086	.743	1.587
Gear Speed	.002	.021	.009	1	.925	1.002	.962	1.044
Gear Dist	-.098	.043	5.271	1	.022	.907	.834	.986
Flap Speed	.008	.007	1.489	1	.222	1.008	.995	1.022
Flap Dist	-.010	.022	.199	1	.656	.990	.948	1.034
Speed Brake(1)	.020	.197	.010	1	.919	1.020	.694	1.501
Experience(1)	-.634	1.873	.114	1	.735	.531	.013	20.861
<b>Experience(1) by Gear Speed</b>	<b>.007</b>	<b>.010</b>	<b>.388</b>	<b>1</b>	<b>.533</b>	<b>1.007</b>	<b>.986</b>	<b>1.027</b>
Constant	-6.515	3.719	3.069	1	.080	.001		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Experience, Experience \* Gear Speed.

*Experience \* Gear Dist**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Late Start(1)	-16.900	7,304.21	.000	1	.998	.000	.000	.
		1						
High Speed(1)	.083	.193	.184	1	.668	1.087	.744	1.588
Gear Speed	.015	.005	7.767	1	.005	1.015	1.004	1.025
Gear Dist	-.062	.127	.238	1	.626	.940	.732	1.206
Flap Speed	.008	.007	1.426	1	.232	1.008	.995	1.022
Flap Dist	-.008	.022	.136	1	.712	.992	.950	1.036
Speed Brake(1)	.029	.197	.021	1	.884	1.029	.699	1.514
Experience(1)	.710	.651	1.190	1	.275	2.035	.568	7.290
<b>Gear Dist by Experience(1)</b>	<b>-.022</b>	<b>.070</b>	<b>.097</b>	<b>1</b>	<b>.756</b>	<b>.978</b>	<b>.853</b>	<b>1.123</b>
Constant	-9.078	1.729	27.557	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Experience, Gear Dist \* Experience.

*Experience \* Flap Speed**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Late Start(1)	-16.885	7,294.947	.000	1	.998	.000	.000	.
High Speed(1)	.083	.193	.185	1	.667	1.087	.744	1.588
Gear Speed	.015	.005	7.682	1	.006	1.015	1.004	1.025
Gear Dist	-.100	.043	5.499	1	.019	.905	.833	.984
Flap Speed	.008	.041	.036	1	.849	1.008	.930	1.092
Flap Dist	-.009	.022	.148	1	.701	.992	.949	1.036
Speed Brake(1)	.026	.197	.017	1	.897	1.026	.697	1.509
Experience(1)	.497	4.554	.012	1	.913	1.644	.000	12,368.041
<b>Experience(1) by Flap Speed</b>	<b>.000</b>	<b>.021</b>	<b>.000</b>	<b>1</b>	<b>.995</b>	<b>1.000</b>	<b>.959</b>	<b>1.043</b>
Constant	-8.650	8.720	.984	1	.321	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Experience, Experience \* Flap Speed.

*Experience \* Flap Dist**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Late Start(1)	-16.896	7,295.113	.000	1	.998	.000	.000	.
High Speed(1)	.083	.193	.184	1	.668	1.087	.744	1.588
Gear Speed	.015	.005	7.788	1	.005	1.015	1.004	1.025
Gear Dist	-.100	.043	5.547	1	.019	.905	.832	.983
Flap Speed	.008	.007	1.204	1	.272	1.008	.994	1.021
Flap Dist	-.043	.086	.247	1	.619	.958	.809	1.134
Speed Brake(1)	.025	.197	.016	1	.898	1.026	.698	1.508
Experience(1)	.217	.786	.076	1	.782	1.243	.266	5.799
<b>Flap Dist by Experience(1)</b>	<b>.020</b>	<b>.047</b>	<b>.174</b>	<b>1</b>	<b>.677</b>	<b>1.020</b>	<b>.930</b>	<b>1.119</b>
Constant	-8.069	1.966	16.852	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Experience, Flap Dist \* Experience.

*Experience \* Speed Brake**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Late Start(1)	-16.885	7,293.491	.000	1	.998	.000	.000	.
High Speed(1)	.086	.194	.197	1	.657	1.090	.746	1.592
Gear Speed	.015	.005	7.758	1	.005	1.015	1.004	1.025
Gear Dist	-.100	.043	5.523	1	.019	.905	.833	.984
Flap Speed	.008	.007	1.485	1	.223	1.008	.995	1.022
Flap Dist	-.008	.022	.144	1	.704	.992	.950	1.035
Speed Brake(1)	1.007	1.477	.464	1	.496	2.736	.151	49.504
Experience(1)	.982	.740	1.761	1	.185	2.669	.626	11.376
<b>Experience(1) by Speed Brake(1)</b>	<b>-.513</b>	<b>.759</b>	<b>.456</b>	<b>1</b>	<b>.499</b>	<b>.599</b>	<b>.135</b>	<b>2.652</b>
Constant	-9.645	1.881	26.283	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Experience, Experience \* Speed Brake.

*Duration \* Late Start**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Late Start(1)	-16.893	8,196.005	.000	1	.998	.000	.000	.
High Speed(1)	.073	.193	.142	1	.706	1.076	.736	1.571
Gear Speed	.015	.005	7.959	1	.005	1.015	1.005	1.026
Gear Dist	-.105	.043	6.030	1	.014	.900	.827	.979
Flap Speed	.016	.005	8.899	1	.003	1.016	1.006	1.027
Flap Dist	-.014	.022	.414	1	.520	.986	.944	1.030
Speed Brake(1)	-.098	.188	.271	1	.603	.907	.627	1.311
Duration	-.244	.211	1.341	1	.247	.783	.518	1.184
<b>Duration by Late Start(1)</b>	<b>-.105</b>	<b>18,116.856</b>	<b>.000</b>	<b>1</b>	<b>1.000</b>	<b>.900</b>	<b>.000</b>	<b>.</b>
Constant	-9.450	1.174	64.795	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Duration, Duration \* Late Start.



*Duration \* High Speed**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for	
							EXP(B)	
							Lower	Upper
Late Start(1)	-16.889	7,285.372	.000	1	.998	.000	.000	.
High Speed(1)	-.159	.232	.471	1	.493	.853	.542	1.343
Gear Speed	.015	.005	7.546	1	.006	1.015	1.004	1.025
Gear Dist	-.102	.043	5.693	1	.017	.903	.830	.982
Flap Speed	.016	.005	8.715	1	.003	1.016	1.005	1.027
Flap Dist	-.015	.022	.450	1	.502	.985	.943	1.029
Speed Brake(1)	-.093	.188	.244	1	.621	.911	.630	1.318
Duration	-.577	.282	4.186	1	.041	.562	.323	.976
<b>Duration by High Speed(1)</b>	<b>.924</b>	<b>.440</b>	<b>4.408</b>	<b>1</b>	<b>.036</b>	<b>2.519</b>	<b>1.063</b>	<b>5.968</b>
Constant	-9.291	1.171	62.945	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Duration, Duration \* High Speed.

*Duration \* Gear Speed**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for	
							Lower	Upper
Late Start(1)	-16.909	7,293.349	.000	1	.998	.000	.000	.
High Speed(1)	.076	.193	.154	1	.695	1.079	.738	1.576
Gear Speed	.016	.006	8.248	1	.004	1.016	1.005	1.028
Gear Dist	-.106	.043	6.134	1	.013	.899	.827	.978
Flap Speed	.016	.005	8.914	1	.003	1.016	1.006	1.027
Flap Dist	-.014	.022	.400	1	.527	.986	.944	1.030
Speed Brake(1)	-.098	.188	.271	1	.603	.907	.627	1.311
Duration	.641	1.439	.198	1	.656	1.898	.113	31.832
<b>Duration by Gear Speed</b>	<b>-.005</b>	<b>.008</b>	<b>.383</b>	<b>1</b>	<b>.536</b>	<b>.995</b>	<b>.980</b>	<b>1.010</b>
Constant	-9.670	1.224	62.453	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Duration, Duration \* Gear Speed.

*Duration \* Gear Dist**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for	
							EXP(B)	
							Lower	Upper
Late Start(1)	-16.910	7,298.293	.000	1	.998	.000	.000	.
High Speed(1)	.072	.193	.139	1	.709	1.075	.736	1.570
Gear Speed	.015	.005	8.032	1	.005	1.015	1.005	1.026
Gear Dist	-.100	.045	4.994	1	.025	.905	.829	.988
Flap Speed	.016	.005	8.867	1	.003	1.016	1.006	1.027
Flap Dist	-.014	.022	.415	1	.519	.986	.944	1.030
Speed Brake(1)	-.097	.188	.264	1	.607	.908	.628	1.313
Duration	.022	.653	.001	1	.973	1.023	.284	3.677
<b>Gear Dist by</b>	<b>-.031</b>	<b>.072</b>	<b>.183</b>	<b>1</b>	<b>.669</b>	<b>.970</b>	<b>.841</b>	<b>1.117</b>
<b>Duration</b>								
Constant	-9.509	1.181	64.788	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Duration, Gear Dist \* Duration.

*Duration \* Flap Speed**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for	
							EXP(B)	
							Lower	Upper
Late Start(1)	-16.935	7,311.348	.000	1	.998	.000	.000	.
High Speed(1)	.070	.194	.129	1	.719	1.072	.734	1.567
Gear Speed	.015	.005	7.822	1	.005	1.015	1.004	1.026
Gear Dist	-.105	.043	5.930	1	.015	.901	.828	.980
Flap Speed	.015	.006	6.304	1	.012	1.015	1.003	1.027
Flap Dist	-.014	.022	.422	1	.516	.986	.944	1.030
Speed Brake(1)	-.100	.188	.282	1	.596	.905	.626	1.309
Duration	-1.512	2.623	.332	1	.564	.221	.001	37.658
<b>Duration by Flap Speed</b>	<b>.006</b>	<b>.011</b>	<b>.236</b>	<b>1</b>	<b>.627</b>	<b>1.006</b>	<b>.983</b>	<b>1.028</b>
Constant	-9.155	1.322	47.934	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Duration, Duration \* Flap Speed.

*Duration \* Flap Dist**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for	
							EXP(B)	
							Lower	Upper
Late Start(1)	-16.925	7,312.534	.000	1	.998	.000	.000	.
High Speed(1)	.074	.193	.146	1	.702	1.077	.737	1.573
Gear Speed	.015	.005	8.018	1	.005	1.015	1.005	1.026
Gear Dist	-.106	.043	6.057	1	.014	.900	.827	.979
Flap Speed	.016	.005	8.862	1	.003	1.016	1.006	1.027
Flap Dist	-.017	.024	.519	1	.471	.983	.938	1.030
Speed Brake(1)	-.099	.188	.275	1	.600	.906	.627	1.310
Duration	-.519	.810	.411	1	.522	.595	.122	2.911
<b>Flap Dist by</b>	<b>.017</b>	<b>.049</b>	<b>.125</b>	<b>1</b>	<b>.724</b>	<b>1.017</b>	<b>.925</b>	<b>1.119</b>
<b>Duration</b>								
Constant	-9.400	1.183	63.104	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Duration, Flap Dist \* Duration.

*Duration \* Speed Brake**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for	
							EXP(B)	
							Lower	Upper
Late Start(1)	-16.906	7,309.813	.000	1	.998	.000	.000	.
High Speed(1)	.071	.193	.133	1	.715	1.073	.735	1.568
Gear Speed	.015	.005	7.903	1	.005	1.015	1.005	1.026
Gear Dist	-.105	.043	5.974	1	.015	.901	.828	.979
Flap Speed	.016	.005	8.996	1	.003	1.016	1.006	1.027
Flap Dist	-.014	.022	.424	1	.515	.986	.944	1.029
Speed Brake(1)	-.025	.213	.013	1	.908	.976	.642	1.482
Duration	-.024	.352	.004	1	.947	.977	.490	1.947
<b>Duration by</b>	<b>-.334</b>	<b>.439</b>	<b>.578</b>	<b>1</b>	<b>.447</b>	<b>.716</b>	<b>.303</b>	<b>1.694</b>
<b>Speed Brake(1)</b>								
Constant	-9.513	1.177	65.303	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Duration, Duration \* Speed Brake.

*Automation \* Late Start**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for	
							EXP(B)	
							Lower	Upper
Late Start(1)	-16.823	7,702.411	.000	1	.998	.000	.000	.
High Speed(1)	.046	.194	.058	1	.810	1.048	.717	1.532
Gear Speed	.015	.005	7.707	1	.006	1.015	1.004	1.025
Gear Dist	-.104	.043	5.904	1	.015	.901	.829	.980
Flap Speed	.017	.005	9.344	1	.002	1.017	1.006	1.028
Flap Dist	-.012	.022	.288	1	.591	.988	.947	1.032
Speed Brake(1)	-.078	.188	.170	1	.680	.925	.640	1.338
Automation(1)	1.128	.338	11.165	1	.001	3.090	1.594	5.989
Automation(1) by Late Start(1)	-1.416	24,404.703	.000	1	1.000	.243	.000	.
Constant	-9.644	1.168	68.191	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Automation, Automation \* Late Start.

*Automation \* High Speed**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for	
							Lower	Upper
Late Start(1)	-17.026	7,235.987	.000	1	.998	.000	.000	.
High Speed(1)	.069	.201	.118	1	.732	1.071	.723	1.587
Gear Speed	.015	.005	7.678	1	.006	1.015	1.004	1.025
Gear Dist	-.104	.043	5.879	1	.015	.901	.829	.980
Flap Speed	.017	.005	9.349	1	.002	1.017	1.006	1.028
Flap Dist	-.012	.022	.298	1	.585	.988	.947	1.031
Speed Brake(1)	-.078	.188	.171	1	.679	.925	.640	1.338
Automation(1)	1.224	.402	9.253	1	.002	3.402	1.546	7.486
<b>Automation(1) by High Speed(1)</b>	<b>-.297</b>	<b>.735</b>	<b>.163</b>	<b>1</b>	<b>.686</b>	<b>.743</b>	<b>.176</b>	<b>3.136</b>
Constant	-9.645	1.168	68.177	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Automation, Automation \* High Speed.



*Automation \* Gear Speed**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Late Start(1)	-17.078	7,195.16	.000	1	.998	.000	.000	.
		9						
High Speed(1)	.047	.194	.058	1	.809	1.048	.717	1.532
Gear Speed	.014	.005	7.170	1	.007	1.015	1.004	1.025
Gear Dist	-.104	.043	5.846	1	.016	.902	.829	.981
Flap Speed	.017	.005	9.355	1	.002	1.017	1.006	1.028
Flap Dist	-.012	.022	.277	1	.599	.989	.947	1.032
Speed Brake(1)	-.077	.188	.167	1	.683	.926	.640	1.339
Automation(1)	.582	2.192	.070	1	.791	1.789	.024	131.493
<b>Automation(1) by Gear Speed</b>	<b>.003</b>	<b>.012</b>	<b>.064</b>	<b>1</b>	<b>.800</b>	<b>1.003</b>	<b>.981</b>	<b>1.026</b>
Constant	-9.603	1.179	66.333	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Automation, Automation \* Gear Speed.

*Automation \* Gear Dist**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Late Start(1)	-17.020	7,240.47	.000	1	.998	.000	.000	.
		3						
High Speed(1)	.051	.194	.068	1	.794	1.052	.720	1.538
Gear Speed	.015	.005	7.803	1	.005	1.015	1.004	1.025
Gear Dist	-.095	.043	4.986	1	.026	.909	.837	.988
Flap Speed	.017	.005	9.378	1	.002	1.017	1.006	1.028
Flap Dist	-.013	.022	.324	1	.569	.988	.946	1.031
Speed Brake(1)	-.083	.189	.192	1	.661	.921	.636	1.332
Automation(1)	3.097	1.323	5.477	1	.019	22.140	1.654	296.294
<b>Automation(1) by Gear Dist</b>	<b>-.261</b>	<b>.181</b>	<b>2.076</b>	<b>1</b>	<b>.150</b>	<b>.771</b>	<b>.541</b>	<b>1.098</b>
Constant	-9.748	1.170	69.447	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Automation, Automation \* Gear Dist.

*Automation \* Flap Speed**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Late Start(1)	-17.074	7,199.938	.000	1	.998	.000	.000	.
High Speed(1)	.046	.194	.056	1	.813	1.047	.716	1.530
Gear Speed	.015	.005	7.749	1	.005	1.015	1.004	1.025
Gear Dist	-.104	.043	5.916	1	.015	.901	.829	.980
Flap Speed	.017	.006	9.560	1	.002	1.017	1.006	1.029
Flap Dist	-.012	.022	.291	1	.590	.988	.947	1.032
Speed Brake(1)	-.080	.188	.180	1	.671	.923	.638	1.335
Automation(1)	3.305	4.360	.575	1	.448	27.246	.005	140,144.615
<b>Automation(1) by Flap Speed</b>	<b>-.010</b>	<b>.019</b>	<b>.248</b>	<b>1</b>	<b>.618</b>	<b>.990</b>	<b>.954</b>	<b>1.029</b>
Constant	-9.789	1.203	66.199	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Automation, Automation \* Flap Speed.

*Automation \* Flap Dist**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for	
							EXP(B)	
							Lower	Upper
Late Start(1)	-17.208	7,089.102	.000	1	.998	.000	.000	.
High Speed(1)	.041	.194	.044	1	.834	1.042	.712	1.524
Gear Speed	.014	.005	6.799	1	.009	1.014	1.003	1.024
Gear Dist	-.100	.043	5.493	1	.019	.905	.833	.984
Flap Speed	.017	.005	9.781	1	.002	1.017	1.006	1.028
Flap Dist	-.004	.022	.034	1	.853	.996	.954	1.039
Speed Brake(1)	-.081	.188	.185	1	.667	.922	.638	1.334
Automation(1)	3.512	1.347	6.793	1	.009	33.510	2.389	470.042
<b>Automation(1) by Flap Dist</b>	<b>-.167</b>	<b>.098</b>	<b>2.923</b>	<b>1</b>	<b>.087<sup>a</sup></b>	<b>.846</b>	<b>.699</b>	<b>1.025</b>
Constant	-9.713	1.167	69.321	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Automation, Automation \* Flap Dist.

a. Single-tailed significance = 0.044

*Automation \* Speed Brake**Variables in the Equation*

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for	
							EXP(B)	
							Lower	Upper
Late Start(1)	-17.142	7,143.270	.000	1	.998	.000	.000	.
High Speed(1)	.048	.194	.061	1	.804	1.049	.718	1.534
Gear Speed	.015	.005	7.731	1	.005	1.015	1.004	1.025
Gear Dist	-.103	.043	5.800	1	.016	.902	.830	.981
Flap Speed	.017	.005	9.385	1	.002	1.017	1.006	1.028
Flap Dist	-.011	.022	.267	1	.605	.989	.947	1.032
Speed Brake(1)	-.149	.194	.591	1	.442	.862	.590	1.260
Automation(1)	.381	.734	.269	1	.604	1.463	.347	6.169
<b>Automation(1) by Speed Brake(1)</b>	<b>1.061</b>	<b>.827</b>	<b>1.645</b>	<b>1</b>	<b>.200</b>	<b>2.889</b>	<b>.571</b>	<b>14.612</b>
Constant	-9.626	1.166	68.151	1	.000	.000		

*Note.* Variable(s) entered on step 1: Late Start, High Speed, Gear Speed, Gear Dist, Flap Speed, Flap Dist, Speed Brake, Automation, Automation \* Speed Brake.