DIMENSIONS OF PILOT EXPERIENCE AND THEIR CONTRIBUTION TO ADVERSE WEATHER DECISION MAKING

by

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For My Family

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To my family, I am truly grateful for your love and sacrifice.

To my mom, for all your faith and encouragement.

To Dr Landry, my most profound gratitude…thank you sir.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Erroneous decisions made by pilots during encounters with adverse weather is often cited as a cause of General Aviation accidents. Pilot experience, which can be measured in several ways, is believed to play a role in the outcome of such encounters. However, it is unclear whether any of the elements of experience alone or in combinations affect the likelihood of General Aviation accidents during actual encounters with adverse weather, or how they do so. One barrier to conclusively determining such effects is the danger in extrapolating simulation results to the real world; nearly all work done to date has used simulators to identify accident risk. Therefore, the extent to which such results can be applied to actual flying is not clear.

In this work, two conceptual models for analyzing experience and its role in encounters with adverse weather during the cruise phase of General Aviation Part 91 fixed wing operations are presented. A novel method for evaluating accident risk, specifically the likelihood that an incident turns into an accident is also presented and then used to evaluate the experience profile of 595 pilots, detailed in actual accident and incident reports from the NTSB and ASRS databases. The effect of various elements of experience, alone and in combinations, on that risk is evaluated using regression modeling. The level of significance for each experience variable is first established, and then a series of discrete models is developed to progressively evaluate accident risk along a hypothetical experience continuum. This approach obviates commonly encountered challenges with research in the area and provides results that are ecologically valid.

The focus of this research work was on the role of cognitive aspects of experience in the outcome of flights during the cruise phase of General Aviation Part 91 fixed wing flights between January 1, 2005 and December 31, 2015. Only flights which encountered adverse weather during the cruise phase and for which experience and/or errors in decision making were determined to be a cause or factor in the outcome were included in the study. All flights during the period that involved takeoff and landing, equipment failure or student pilots were not considered for the study. The emphasis of the research was on the effect of experience on cognitive aspects of pilot performance during adverse weather encounters, rather than “stick and rudder” skills.

It was found that variables related to the breadth or variety of pilots' experience are more predictive of the likelihood of adverse weather encounters turning into accidents compared to those related to the duration or length of experience. While several commonly used measures of experience provide some level of insulation against accidents, the relationship between elements that define the length or duration of experience and outcomes is not linear. Furthermore, this relationship is mediated by variables that define the breadth of experience, especially at their lower levels. These findings may be leveraged to design specifically targeted regulatory or training policies and interventions to expedite the transition from novice to expert pilots in General Aviation weather-related decision making.

CHAPTER 1. INTRODUCTION

1.1 Experience as a Factor in General Aviation Accidents During Adverse Weather Encounters

Erroneous decisions made by pilots during encounters with adverse weather are often cited as a cause of General Aviation (GA) accidents [Simpson, 2001; O'Hare and Smitheram, 1995; Goh and Wiegmann, 2001; Wiggins and O'Hare, 1995; 2003a; 2003b]. It seems reasonable to believe that experience plays a role in the outcome of such encounters, a belief that has been evaluated by researchers [Wiggins and O'Hare, 1995; Johnson and Wiegmann, 2011; Goh and Wiegmann, 2002], although there has been no consensus on the role it plays.

More specifically, there is no consensus on the roles that different aspects of experience might play in making accidents more or less likely in general aviation. Experience can be measured in a number of ways, such as total flight hours, flight hours in a particular type of aircraft, whether the pilot is instrument rated or not, what type of certificate the pilot has, and recent flying experience. It is unknown whether any of these elements, alone or in combinations, reflect or are predictive of the likelihood of an accident.

One barrier to conclusively determining such effects is the danger in extrapolating simulation results to the real world; nearly all work done to date has used simulators to identify accident risk. It is unclear whether such results can be applied to actual flying. In this work, a novel method for evaluating accident risk, specifically the likelihood that an *incident* turns into an *accident* is evaluated using actual incident and accident reports. The effect of the various elements listed above, alone and in combinations, on that risk is evaluated using regression modeling.

1.2 Motivation

Weather is a critical consideration for flying and is often cited as a causal or contributory factor in aircraft accidents [AOPA, 2009; Prinzo, 2007; Knecht and Lenz, 2010; Knecht, 2008; Latorella and Chamerlain, 2001; Latorella, Lane and Garland, 2002; Yuchnovicz, Novacek, Burgess, Heck, and Stokes, 2001]. Weather related GA accidents consistently involve the highest rate of fatalities of all GA accident causes [AOPA, 2009; Knecht, 2008; Latorella and Chamerlain, 2001; Latorella, et al, 2002; Yuchnovicz, et al, 2001]. In 2011 for instance, 40 out of 54 weather related accidents in the non-commercial fixed-wing GA flights were fatal and 28 out of 43 were fatal in 2010 [AOPA 2011; AOPA 2012].

Most accidents caused by adverse weather generally give reasonable warning to the pilot [AOPA, 2011]. Therefore, some experts have suggested most accidents and incidents in weather are preventable [Weener, 2014]. However, adverse weather presents pilots with a dynamic, safety critical situation in which time is often limited and information uncertain. Decision making under such contexts has been described as "Naturalistic Decision Making (NDM) [Klein, Orasanu, Calderwood & Zsambok, 1993; Orasanu and Martin, 1998; Lipshitz, Klein, Orasanu and Salas, 2001].

Decision making within naturalistic contexts has been the subject of much research and our current understanding is that experience plays an important role in them [Klein, 1993; 2008]. There is some consensus across different fields of endeavor that operators with high levels of experience make more accurate decisions under conditions with severe time pressure and information uncertainty than inexperienced operators [Calderwood et al, 1988; Klein et al, 1989; Klein et al, 1995, Ericsson and Charness, 1994; Ericsson, 2004].

Despite some evidence that experience is a multifaceted attribute, not much research has been focused on the role different elements of experience play in decision making or the interactions between them. According to Lanicci [2012], most studies on weather related accidents in GA have focused on either identifying the factors associated with weather-related accidents, identifying the pilot decision-making processes that contribute to weather-related accidents or understanding how new technologies could contribute to improve pilot decision making. Experience has been identified as a factor associated with weather-related accidents, but its dimensions and their and their contribution to adverse weather decision making has received little attention. An understanding of the different aspects of experience and an understanding of the relationships between them could be leveraged to develop precisely targeted training interventions to improve the efficacy of weather-related decision making in GA.

1.3 Contribution

This dissertation identified some of the plausible variables which make up GA pilot experience, determine the relationships between them and identify their contributions to decision making during encounters with adverse weather situations.

Experience comes with continuous application of knowledge and therefore, can be modified through training [Jensen, 1995; FAA, 2009]. Some of the insights gained from research on expert pilot decision making have been used to develop pilot decision making training interventions with varying levels of success [Ayers, 2006; Schumacher and Lease, 2007; Ball, 2008; Wiggins and O'Hare, 2003a]. However, not all such training interventions have been successful [Keller, 2015] and, the prevalence of weather-related accidents points to a need for more precisely targeted training interventions.

The key to expert performance is to create targeted challenges through which experience and performance across pertinent and essential dimensions can be incrementally improved [Ericsson, 2006; Adams, 1993]. However, as Wiggins and O'Hare [1995] have noted, the "characteristics necessary for an optimal training program remain unclear". A prerequisite for doing this effectively is identifying those aspects of experience that support accurate weather decision making and the dynamics between them. This knowledge can then be used to develop germane scenarios to expedite the accumulation of the body of experienced based knowledge that brings about decision making expertise.

The work contained in this dissertation differs from previous work in three ways. First, it establishes the level of significance of each experience variable to the outcome of adverse weather encounters and then determines the effect of different levels of exposure to the elements on the outcome of adverse weather encounters. This is the first research effort to quantify how each element of experience affects the outcome of adverse weather encounters and determine how it does so.

Secondly, although researchers have used several experience related variables in studying the decision-making performance of expert and novice pilots, these variables are typically treated as independent, linear elements. However, some elements of experience are intrinsically linked to one another and therefore, cannot be acquired independently. For instance, pilot certificates and rating require minimum levels of total flight hours. This research is novel in the sense that it investigates the simultaneous effect of varying levels of multiple elements of experience on the outcome of encounters with adverse weather, as well as the interaction between them.

Thirdly, a tacit assumption underpinning research into experience and its effects on adverse weather decision making is that a direct relationship exists between each variable and the outcome of adverse weather encounters. This research effort adopts a different approach and in the first of its kind, models pilots' total experience as a multi-element attribute, comprising two main dimensions, duration and relevance. These are in turn made up of various elements of experience acquired along a hypothetical experience continuum. This novel approach facilitates the investigation any interactive relationships that may exist between experience elements, potentially giving new insights into the nature of experience, how it is acquired, and what its effects are.

This dissertation, therefore, makes three distinct contributions to the currently existing body of knowledge. First, it provides a novel methodological approach for experience and decision making research in aviation that overcomes several challenges typically associated with approaches currently used. Secondly, it introduces a conceptual framework which captures the key relationships between various elements of pilot experience and facilitates analysis of the interactions between them to identify elements that impact the outcome of adverse weather encounters in a manner that ensures ecologically validity. The first contribution is expected to have some value for future research work within the field by eliminating commonly encountered challenges in related research. The second contribution is a conceptual framework that facilitates new ways of thinking about the acquisition of experience and the transition from novice to expert in general aviation weather decision making. Thirdly, although a few researchers have suggested the accumulation of total flight hours does not automatically confer pilots with decision making expertise, there has only been anecdotal evidence within the aviation community to support this assertion. However, the results from this study provide empirical evidence that is ecologically valid to support the assertion. It is expected that if the recommendations that have ensued from this research are implemented, there will be a reduction in general aviation accidents during encounters with adverse weather.

1.4 Limitations and Delimitations

This research work focused on the role of experience in the outcome of General Aviation Part 91 fixed wing flights between January 1, 2005 and December 31, 2015 that encountered adverse weather during the cruise phase. Only flights for which experience and/or errors in decision making were determined to be a cause or factor in the outcome were considered for the study. Accordingly, all flights during the period that involved takeoff and landing, equipment failure or student pilots were not considered for the study. The emphasis of the research was on the effect of experience on cognitive aspects of pilot performance during adverse weather encounters, rather than “stick and rudder” skills.

1.5 Organization of the Document

This dissertation is made up of ten Chapters. Following this first Chapter, an overview of trends and efforts to improve GA safety with a focus on weather related accidents and pilots’ response to adverse weather encounters is discussed in Chapter 2. Chapter 3 takes a look at the role of decision making in aviation safety, highlighting the evolution of ideas on pilot error and aeronautical decision making and then goes on to review various decision making theories and their relationship with aeronautical decision making. It then focuses on naturalistic decision making and naturalistic contexts as the environment for decision making during encounters with adverse weather. The chapter also highlights efforts to improve pilot decision making and how those have focused on experience as a key requirement for decision making during encounters with adverse weather. The chapter concludes with a look at the transition process novice to expert pilot in adverse weather decision making and how that may be expedited through training

The methodological approach for the first part of the research is presented in chapter 4. A novel approach adopted for the research is also presented in the chapter along with an overarching conjecture for the first part of the study. Following this, the results from the first study are presented in Chapter 5, followed by a discussion of the results in Chapter 6.

In Chapter 7, a conceptual framework is presented to anchor the methodology adopted for the second study in the research. The analytical approach used is also presented. The results obtained from the second study are then presented in Chapter 8 and their meaning and implications are discussed in Chapter 9. In Chapter 10, conclusions from the study are presented, and future related research work discussed.

CHAPTER 2. BACKGROUND AND LITERATURE REVIEW

2.1 Trends in General Aviation Safety Performance

In this chapter, trends in General Aviation safety performance are presented and efforts to improve General Aviation safety are discussed. Some of the safety challenges pertinent to General Aviation are highlighted and weather as a cause of General Aviation accidents are discussed. Pilot response to adverse weather encounters, along with some of the factors that impact such response are also highlighted

The safety performance data for General Aviation (GA) in the United States (U.S.) between 2000 and 2013 shows a relatively flat accident rate, with an average of 6.73, ranging between 5.83 and 7.07 accidents per 100,000 flight hours as shown in Figure 1 (BTS Table 2-14, 2015). In terms of fatalities, GA averaged 529 fatalities between 2000 and 2013, ranging between 387 and 706 deaths per year (BTS Table 2-1, 2015). GA accidents typically account for a high percentage of total accidents and fatalities in U.S Aviation. In 2010 for instance, about 51 percent of the estimated total flight time of all U.S. civil aviation were GA flights, but accounted for about 96 percent of the total accidents and about 97 percent of the fatal accidents as depicted in Figure 2 (NTSB, 2012a). Similarly, in 2011, GA accidents accounted for 95 percent of total aircraft accidents and 94 percent of the fatal accidents (NTSB, 2014).

Several design, operational, human and technological challenges impact GA safety. According to the Aircraft Owners and Pilots Association (AOPA) Air Safety Institute, "most GA aircraft cannot fly over or around weather the way airliners can, and they often do not have the systems to avoid or cope with hazardous weather conditions, such as ice" (AOPA, 2011; 2013). Additionally, GA covers a wider range of operations, requiring more take offs and landings, often from facilities that may not be fully supported (AOPA 2011; 2013, Op Cit). There is also a greater variability of pilot training, certification and experience level within GA compared to Airlines and GA pilots have limited access to cockpit resources and flight support (AOPA 2011; 2013, Op Cit). Not surprisingly therefore, GA accounts for over 90% of all US aviation accidents and fatalities

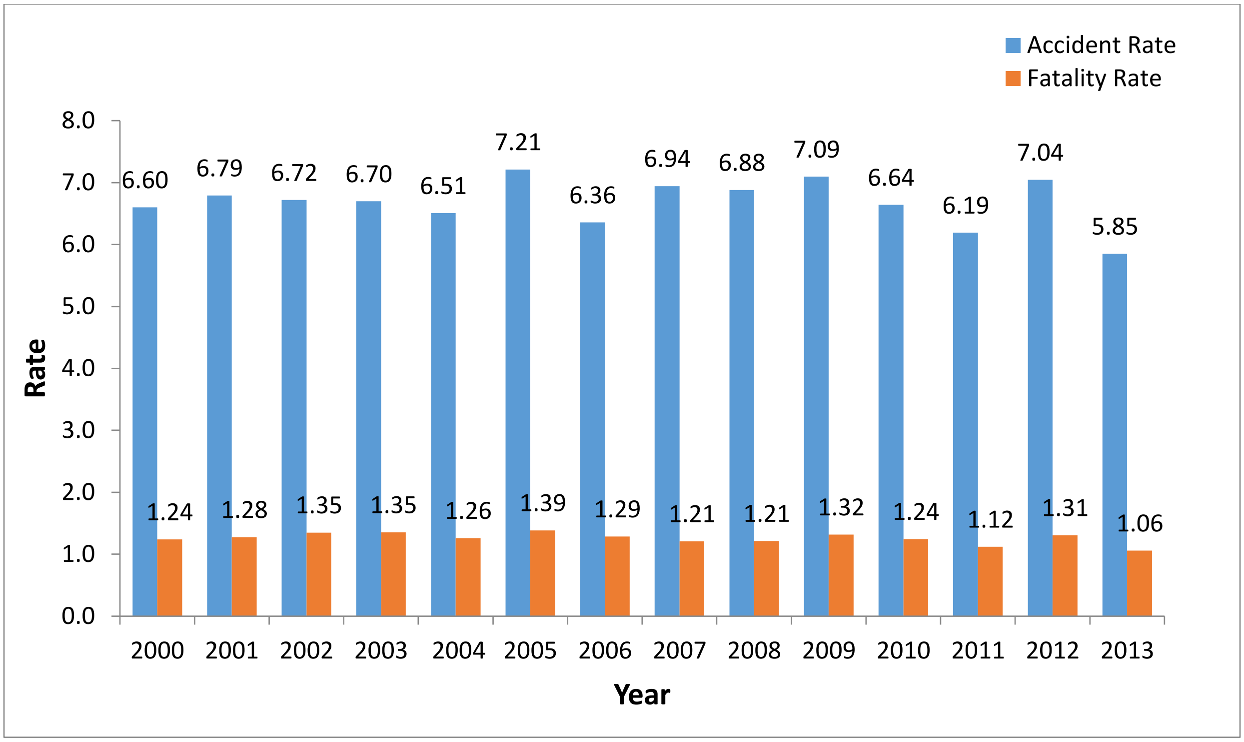

Figure 1: Total GA Accident and Fatality Rate (2000 – 2013)

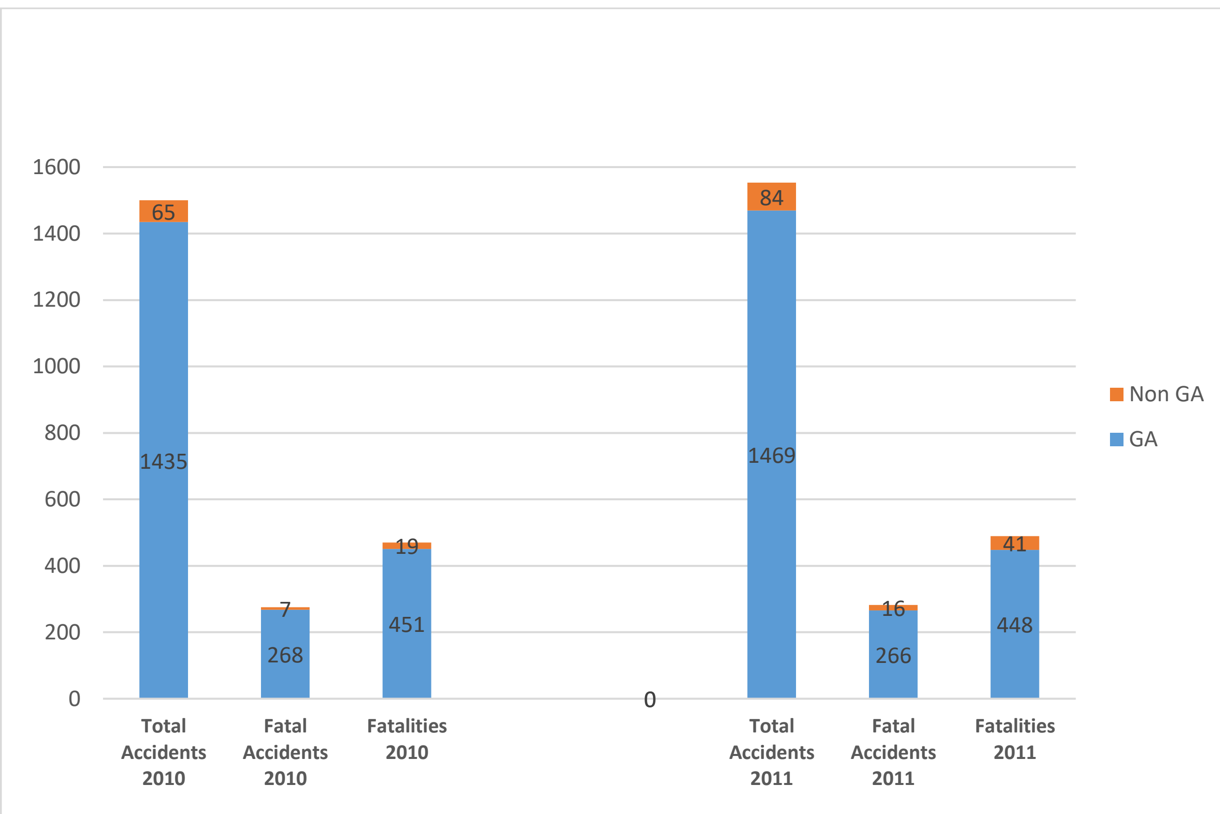

Figure 2: GA Accidents and Fatalities Vs Total U.S. Aviation Accidents and Fatalities (2010 - 2011)

In spite of these challenges, there has been significant improvement in the GA accident record in the past decade compared to what existed in the 1960s and 1970s, which saw double digit accident rates (BTS, 2015; GAMA; 2010). However, the improvements appear to have stalled, and there has been no significant sustained improvement in the GA safety performance between 2000 and 2013. Although individual segments within GA have seen improvements in their safety performance in some of the years within the period, the sector as a whole has witnessed no sustained improvement. The trend has been that improvements in one segment are negated by increased accident numbers in other segments. In 2011 for instance, a reduction in non-commercial helicopter accidents fatalities was cancelled out by an increased number of fatalities in commercial and non-commercial fixed wing as well as in the commercial helicopter segments (AOPA, 2013). Similarly, safety performance improvements in categories of GA operations such as corporate and executive flights were cancelled out by a disproportionately high number of accidents in operations classified as personal flights (AOPA, 2012; AOPA, 2014a). Overall, the GA accident rate has remained generally flat, with no significant sustained improvement over the last decade. As a result, significant efforts have been directed at finding ways to improve current GA safety performance.

2.2 Efforts to Improve General Aviation Safety

Significant efforts have been made by stake holders and researchers in government, industry and academia to improve safety in GA operations. In 1997 a national goal to reduce the fatal accident rate for aviation by 80% within ten years was proposed by the government based on a strategic plan to improve safety outlined in the report of the White House Commission on Aviation Safety (Gore, 1997; Stough, Shafer and Schaffner, 2000). It called for research to be carried out in support of the goal. Pursuant to this, the National Aeronautics and Space Administration (NASA) established the Aviation Safety Program (AvSP), a partnership between the Federal Aviation Administration (FAA), the Department of Defense and the aviation industry. The AvSP was tasked with developing advanced, affordable technologies to help make travel safer on airplanes (NASA FS-2000-02-47-LaRC). Similarly, the FAA established the Safer Skies initiative in 1998 as a government-industry initiative with the aim of achieving significant reductions in fatal accidents (FAA, 2001).

Safer Skies is made up of three teams; the Commercial Aviation Safety Team, the Partners in Cabin Safety and the General Aviation Joint Steering Committee (GAJSC). The GAJSC focuses on the leading causes of general aviation accidents with the aim of eliminating the equivalent of an entire year's worth of accidents by 2007 (FAA Op Cit). Initially launched in 1997, the GAJSC was revitalized in 2011 after a period of relative inactivity and tasked with improving GA safety through data-driven risk reduction efforts that focus on education, training, and enabling new equipment in GA aircraft (GAJSC, 2014). Additionally, the FAA also established Centers of Excellence for General Aviation Research (CGAR) in 2001, made up of several universities tasked with focusing on "those areas of aviation safety that apply to the General Aviation Community" (FAA, 2014). In 2012, the Center of Excellence for the Partnership to Enhance General Aviation Safety, Accessibility and Sustainability (PEGASAS) was established, partnering the FAA with a national network of researchers, educators, and industry leaders with the goal of enhancing GA safety, accessibility, and sustainability (FAA 2014 Op Cit). As a result of these efforts, issues associated with GA safety have been given a high priority within the government, industry and the research community. A major thrust of the efforts to improve the GA safety performance has been directed at accidents that occur as a result of adverse weather encounters. Weather is a major cause of GA accidents and nearly 75% of weather-related accidents are fatal (AOPA, 2015). The FAA has made reducing the number of fatal GA accidents a priority, using non-regulatory, proactive, and data-driven strategy to get results (FAA, 2014a). One such method involves the use of GA operations data for research to identify risks before they become accidents.

This research work therefore, seeks to contribute to this effort, by using GA operations data to model the odds for accidents in adverse weather conditions based on variables related to the pilot's operational experience.

2.3 Weather as a Causal Factor in General Aviation Accidents

Weather is a critical consideration for flying and is often cited as a causal or contributory factor in aircraft accidents (AOPA, 2009; Prinzo, 2007; Knecht and Lenz, 2010; Knecht, 2008; Latorella and Chamerlain, 2001; Latorella, Lane and Garland, 2002; Yuchnovicz, Novacek, Burgess, Heck, and Stokes, 2001). Weather related GA accidents consistently involve the highest rate of fatalities of all GA accident causes (AOPA, 2009; Knecht, 2008; Latorella and Chamerlain, 2001; Latorella, et al, 2002; Yuchnovicz, et al, 2001). In 2011 for instance, 40 out of 54 weather related accidents in the non-commercial fixed-wing GA flights were fatal and 28 out of 43 were fatal in 2010 (AOPA 2011; AOPA 2012). The trend for total and fatal GA accidents during encounters with weather from 2002 and 2011 depicted in figure 3 shows no significant sustained reduction in either the total number of accidents or fatalities over the period. However, a closer look at the statistics show certain trends that follow the type of weather-related accident.

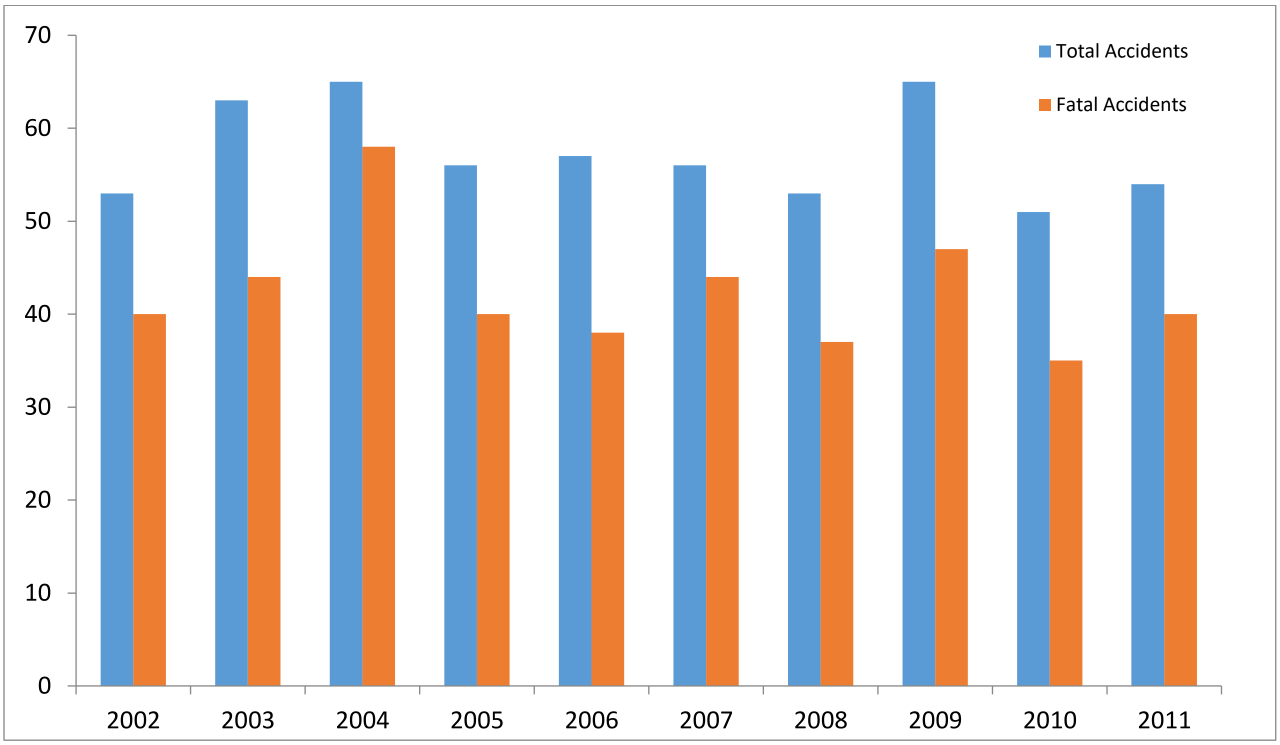

Figure 3: Weather Accident Trend for GA Aircraft – 2002 – 2011 (AOPA 2012)

2.3.1 Types of Weather-Related General Aviation Accidents

Five major types of weather accidents in GA operations have been identified by AOPA'S Air Safety Institute. These are Visual Flight Rules (VFR) Flight into Instrument Meteorological Conditions (IMC), Poor Instrument Flight Rules (IFR) Technique, Thunderstorm, Turbulence and Icing (AOPA, 2010; AOPA, 2011; AOPA, 2012). Out of the five types, transitions of VFR flights into IMC, whether inadvertent or deliberate, have been especially fatal (Goh and Wiegmann, 2001; Coyne, Baldwin & Latorella, 2008; NASA, 2007; Ball, 2010; AOPA 2009; AOPA 2012). About two-thirds of all IMC accidents over the previous 20 years had led to at least one fatality, a rate three times higher than the fatality rate for all GA accidents (NTSB 2005). Similarly, more than 86% of all fixed-wing VFR-into-IMC accidents since 2002 have been fatal (AOPA 2014). Overall, the fatality rate for accidents involving VFR flights into IMC is about 80%, while other types of GA accidents account for about 19% of GA accident deaths (Goh and Wiegmann, 2001). The major types of weather-related accidents and their contribution to the GA accidents in 2011 is shown in Figure 4 (AOPA 2012).

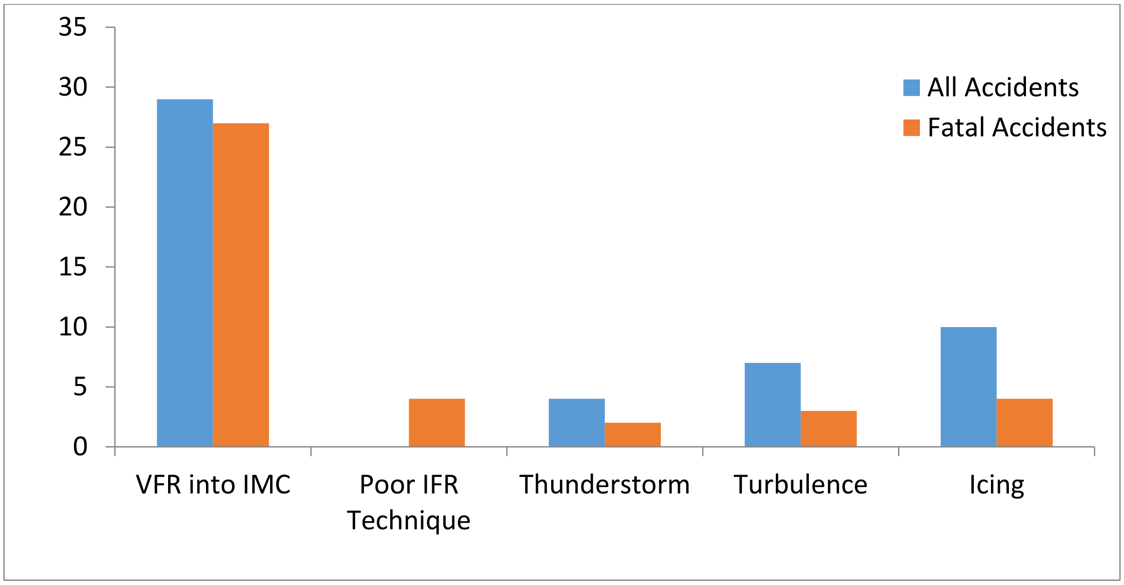

Figure 4: Types of Weather Accidents for GA Aircraft 2011 (AOPA 2012)

The number of accidents and fatalities due to transitions from VFR flights into IMC far exceeds those due to all other types of weather accidents for GA aircraft in 2011. The trend is similar for other years between 2000 and 2012 (AOPA 2013; 2014). The magnitude of the safety challenge posed by weather to GA operations is associated with its dynamic nature. Pilots have no control over environmental factors that may impact a flight, particularly weather. It may be possible to plan a flight to avoid mountainous terrain for instance, but the dynamic nature of weather means conditions may deteriorate suddenly or unexpectedly and require immediate action by the pilot to ensure the safety of the flight. This is the case with some of the transitions of VFR flights into IMC. Not all weather related accidents result from sudden and unpredictable change in the weather conditions. Most accidents caused by adverse weather generally give reasonable warning to the pilot (AOPA, 2011; NTSB 1989; 1994) therefore, some experts have suggested most accidents and incidents in weather are preventable (Weener, 2014). Transitions of VFR flights into IMC for instance, represent the prototypical Plan Continuation Error (PCE). PCE refers to the continuation of an original plan, even in the face of new evidence suggesting that the plan should be abandoned (Orasanu, Martin, & Davison, 2001).

2.3.2 Pilot Response to Adverse Weather Encounter

Pilots' response to adverse weather encounters is affected their understanding of the situation. Therefore, factors which impact this understanding affect the outcome of the flight. A great deal of research has been carried out to determine how pilots respond during adverse weather encounters (Capobianco and Lee, 2001; Wiggins, Goh and O'Hare, 2002; NTSB, 2005, 2007; Knecht, 2006; 2008a; 2008b; Hunter, Martinussen and Wiggins, 2009). According to Lanicci (2012), most studies on weather related accidents in GA have focused on either identifying the factors associated with weather-related accidents, identifying the pilot decision making processes that contribute to weather-related accidents or understanding how new technologies could contribute to improve pilot decision making. Some of these studies have shown pilot errors and in particular, pilot decision making is responsible for the majority of both fatal and non-fatal accidents in adverse weather (Jensen and Benel, 1977). This study will therefore, focus on pilot decision making processes that contribute to weather-related accidents, to determine how factors that shape these may be leveraged to reduce weather-related decision making errors. One cause of decision errors lies in the way humans process information; the working memory available is limited, as is the ability to retrieve information from long-term memory. Training, past experience, organizational pressures and other stressors may influence or disrupt the process.

Researchers have identified important cognitive and contextual factors that affect decision making during encounters with adverse weather (Burian, Orasanu and Hitt, 2000; Goh and Wiegmann, 2001; Stokes, Kemper, and Marsh, 1992; Wiegmann, Goh, and O'Hare, 2002; Wiggins and O'Hare, 1995; McCoy and Mikunas, 2000; O'Hare and Smitheram, 1995). Cognitive factors are intrinsic or innate to the pilot and represent the sum of a pilot's skill, knowledge and experience, while contextual factors are extrinsic considerations such as motivation, which mediate intrinsic factors. The interaction between these factors determines the decision making process employed and the outcome of the process. Some of the findings from these studies are reviewed in the next section.

2.4 Pilots Related Causes of General Aviation Accidents

The pilot-in-command of an aircraft is directly responsible for and is the final authority as to the safe operation of that aircraft (U.S. CFR 14-1-A1.1; AIM 5-5-1). The pilot has to continually monitor and evaluate several variables and parameters pertinent to the flight and decide on the best course of action to safely complete the flight. According to (AOPA 2013), all accidents except those due to mechanical failures or improper maintenance, those with undetermined causes, and those due to circumstances beyond the pilot's control are pilot related. Pilot related causes of GA accidents consistently account for about 75 percent of non-commercial fixed wing fatal and non-fatal accidents (AOPA 2013) and weather-related accidents produce the largest proportion of these fatalities. Such accidents arise from the improper actions or inactions of the pilot and reflect specific failures of flight planning or decision making (AOPA 2012; Burian et al, 2000) due to erroneous cognitive processing of pertinent information or the influence of contextual factors on cognitive processing of information available.

2.4.1 Cognitive Factors

Cognitive factors are personal characteristics that modulate performance to bring about improvements or decline (Roy, 2013). Cognitive factors that cause GA accidents during adverse weather encounters are associated with information processing and decision making. Studies have identified two main phases in the decision making process used by pilots; the situation assessment phase and the course of action selection phase. (Jensen, 1995, Orasanu and Martin 1998). In the situation assessment phase, the problem is defined, associated variables are evaluated, and potential solutions identified. A course of action is then selected from the options identified, taking cognizance of the response requirements posed by the situation (Orasanu and Martin, Op Cit).

Weather-related decision making is influenced by how well a pilot understands the weather situation from assessing available weather information available (McAdaragh, 2002). The level of situation awareness developed is determined by the accuracy of the situation assessment. This in turn depends on the quality of information about the situation that is available. The information presented to the pilot should be relevant, complete and presented in a timely and useable manner to allow full evaluation the situation.

Information about flight weather may be obtained from a host of information systems on the ground and in the air (McAdaragh, 2002 Op. Cit). There has been a substantial increase in the number and variety of systems that provide weather information to pilots. The interaction between cognitive factors and cues from information presented by information systems generates decision options from which a course of action is selected. Since the course of action chosen derives from the assessment of the situation, the decision maker should fully identify variables pertinent to the situation and accurately evaluate their significance in order to accurately identify viable options for solving them.

Three categories of response options have been identified; rule based, choice and creative response options (Orasanu and Fischer, 1997). Rule based decisions prescribe a specific course of action in response to a particular situation, while choice-based decisions present different options from which a selection may be made depending on the goals to be achieved and constraints presented by the situation. A creative decision situation is one in which the decision maker must create one or several options based on an evaluation of the situation. The three decision structures are related to the skill, rules and knowledge-based classification of human error (Rasmussen 1979; 1982 and 1987; Reason, 1990).

It follows therefore, that errors may either result from a wrong interpretation of the problem, i.e. a situation assessment error, or the selection of a wrong choice of action, having accurately assessed the situation (Orasanu and Martin, 1998). Situation assessment errors in turn may occur either because pertinent information about the situation is not available, inadequate, unclear or because the pilot is unable to piece available information together to generate an accurate assessment of the situation. This may happen because the pilot ignores or does not fully understand the implications of information available. It may also be that the time to fully evaluate information may be limited and situation assessment is hurried and incomplete. Errors in situation assessment represent mistakes in planning and increase the chance that a wrong course of action is selected. Thus, the selection of a wrong course of action is the end product of a flawed process of recognizing, gathering, and evaluating information.

GA flight operations in adverse weather present pilots with a creative decision situation in which they must evaluate the situation and determine the best course of action to take. The level of skills, knowledge and experience the pilot possesses determine the kind of cognitive processing the pilot employs to assess the situation (Adams, 1993). Studies have identified inadequacies in pilot' skills, knowledge and experience as factors that adversely affect the cognitive processing that leads selection of a course of action (Klein, 1993; Orasanu and Martin, 1998, Carney et al, 2015; Knecht and Lenz, 2010; Detwiler, Holcomb, Hackworth and Shappel, 2008; Johnson, Wiegmann, and Wickens; 2006).

Inadequate Weather Knowledge, Skill and Experience. Pilots are expected to acquire adequate knowledge and skills to safely plan and complete a flight from their training. According to the FAA, the overall purpose of flight training is the "acquisition and honing of basic airmanship skills" (FAA, 2004), including "the exercise of sound judgment that results in optimal operational safety and efficiency" (FAA, 2004 Op. Cit).

Knowledge is acquaintance with or understanding of a science, art, or technique. Skill refers to the ability to use one's knowledge effectively and readily in execution or performance, while experience is practical knowledge, skill, or practice derived from direct observation of or participation in events or in a particular activity. (Merriam Webster). Studies indicate a relationship between the three terms; skill follows from the application of knowledge, and experience from continued application of both knowledge and skill (Adams and Erikson, 1992; Adams, 1993). Pilots acquire knowledge pertinent to operating an aircraft during training, and become skillful pilots as they use apply this knowledge during flights. Experience results from continued application of knowledge and skills. There is therefore, a progression along a hypothetical continuum from knowledgeable to skilled to expert pilot.

Studies have identified inadequacies in the level of weather knowledge, skills and experience some GA pilots possess (Carney et al, 2015). This inadequacy exists in two main areas; first, in knowledge and application of basic weather theory, and secondly, in the understanding and use of weather information technology. Research suggests some pilots do not fully understand the meaning and implication of observed and forecasted weather information available during both the preflight and in-flight phases of flight. For instance, some pilots are unable to completely project the implication of weather information such as forecasted minimum VFR (MVFR) conditions for a flight and determine how to proceed. Additionally, some pilots have been unable to consistently apply available weather information to assess the situation and generate the level of preflight and in-flight situational awareness required for accurate weather-related decision making (Carney et al, 2015).

Studies further indicate the inadequacies in the level of weather knowledge, skills and experience some pilots possess stem from gaps and inconsistencies in the type and quality of weather-related training they receive (Carney et al, 2015). The weather training materials and scenarios used are ineffective and do not imbue pilots with the ability to correlate weather knowledge to actual flight conditions and make safe, timely and appropriate weather-related decisions under VFR conditions (Carney et al, 2015). The challenge is exacerbated by the fact that this ability is neither tested nor required to pass the Private Pilot written exam (Carney et al, 2015). Therefore, there is no mandatory requirement to improve pilots understanding of weather phenomenon.

Furthermore, flight training occurs in a controlled and regulated environment, which may insulate student pilots from experience with sub-optimal weather conditions that may be encountered during normal flying operations. Outside the training environment pilots are free to fly under less than optimal weather conditions if they choose to. Given the minimal level of experience flying in such weather conditions during training, some pilots are unable to develop an accurate representation of the situation and select a safe course of action (Orasanu and Martin, 1998). Finally, inconsistencies have been observed in the training pilots receive on the features and limitations of weather technology available for use in the cockpit. As a result, some pilots are unable to accurately and efficiently use the information cockpit weather information systems to make expeditious weather-related decisions (Carney et al, 2015).

Effects of Inadequate Weather Knowledge, Skill and Experience. Inadequate knowledge, skill and experience are known to adversely affect task performance in aviation (Orasanu and Martin, 1998; Carney et al, 2015). Studies have linked pilots with limited weather knowledge and experience with PCEs such as transitions from VFR into IMC (Goh & Wiegmann, 2002; Burian, Orasanu, and Hitt 2000; Knecht and Lenz, 2010). Although some competent and experienced pilots have been known to transition from VFR flights into IMC (AOPA 2012), the evidence from research suggests inadequate knowledge, skills and experience are predisposing factors to such accidents (Johnson and Wiegmann, 2011; Carney et al, 2015). Studies further suggest non-instrument rated, inexperienced instrument rated, and pilots with low total flight hours are particularly vulnerable (Goh and Wiegmann, Op Cit, Burian et al, 2000 Op Cit).

Pilot knowledge, skills and experience appear to significantly impact pilot performance in deteriorating or adverse weather conditions. A sound knowledge of basic weather theory which provides an understanding of issues like the extent or spread of different weather fronts and how these may be affected by other weather systems operating nearby is required to accurately assess and avoid adverse weather phenomena such as updrafts or cloud clearance that may not be evident from mere visual observation, (Knecht and Lenz, 2010). Similarly, while a scattered cloud layer may not constitute a hazard on its own, several layers together may interfere with visibility on VFR flights (Carney et al, 2015). Since pilots may encounter multiple weather types during a flight and the condition of the weather may deteriorate during the course of the flight, (Knecht and Lenz, 2010), a good understanding of basic weather theory as well as experience with different weather types is essential for accurate and timely situation assessment and response selection (Orasanu and Martin, 1998). Additionally, an understanding of the features and limitations of the technology which brings the weather information to the pilot is required to piece together the true weather situation from all the information available.

Both aspects of knowledge and skill are important and related; the ability to evaluate available information, understand its implication and accurately determine the potential risk the weather poses requires a good understanding of basic weather theory. However, this is predicated on the assumption that the most up to date weather is available and being evaluated. Where that is not the case, the assessment of the situation could be inaccurate, and may affect the decisions made, resulting in the selection of an erroneous course of action. In practice, the latter corresponds to experience with a specific airplane make and model and its equipment.

2.4.2 Contextual Factors

Contextual factors are personal, psycho-social or other considerations that may induce a pilot to select a course of action different from the one suggested by an assessment of the situation. They include factors such as stress, motivation, as well as peer or other social pressures. Contextual factors are pervasive background factors that can affect the process of situation assessment and course of action selection in a way that keeps pilots from making a purely rational decision (Jensen, 1995). For instance, they could lower a pilot's risk perception and increase optimism about the outcome of a potential course of action even when there are significantly less risky alternatives. The concepts of "Get-home-itis" (FAA, 2013), and "framing" (Kahneman and Tversky, 1979) illustrate the scope of motivational and contextual factors. According to the FAA (2013), get-home-itis is the "urge to push on regardless of the data telling you that it might not be the best decision" and occurs "when the desire to get to a destination overrides logic, sound decision making and basic instinct." Get-home-itis is a form of goal fixation that may result in a plan continuation error.

Kahneman and Tversky's (1979) Prospect theory suggests people frame the outcome of available options in risky decision making situations in terms of gains and loss; when faced with a choice between two options, the tendency is to select the option that is framed as a gain over the one framed as a loss. For instance, a decision to divert to an alternative airfield due to adverse weather during a flight may be framed as a loss in terms of wasted time, effort and money may induce a pilot to press on with the flight and possibly, a transition from VFR into IMC. In addition, Kahneman and Tversky (1979) also suggested the perceived likelihood of occurrence of an undesirable event influences the weight assigned to the decision. For pilots, the perceived likelihood of occurrence of an undesirable outcome is affected by self-assessments of their level of competence and ability as well as personality traits such as risk tolerance. Studies indicate pilots who consider themselves highly competent and skillful have a greater propensity to continue with a flight in deteriorating weather conditions (Wiegmann and Goh, 2000). These personal assessments may be overly optimistic but still act as a motivator, affecting the situation assessment and course of action selection process, especially when cues are ambiguous.

The term "sunk cost' (Arkes and Blumer, 1985; O'Hare and Owen, 2002) has been used to further explain how decision framing works in practice. Sunk costs represent the amount of resources i.e. time, effort and money that a pilot has already invested into a flight. Early on into the flight, few resources have been invested in the flight, so the cost sunk into it is low. Therefore, the loss from a decision to discontinue the flight due to adverse weather is low and pilots may be more inclined to do so. As the flight proceeds towards its destination, the sunk cost gradient increases, as does the extent of perceived loss and consequently, the likelihood of pressing on towards the destination increases. Pilots have been found to be less likely to continue with a flight in adverse weather when the transition from VFR into IMC is framed as a loss and diverting as a gain than when left to use their own natural frames (O'Hare and Smitheram, 1995). Experienced pilots are believed to understand that safety should be framed as a gain, rather than productivity; pilots should be more highly motivated to be safe than complete a flight.

2.4.3 Impact of Cognitive and Contextual Factors on Pilot Decision Making

Cognitive and contextual factors directly impact pilot decision making process. Pilot knowledge and experience determine the speed and accuracy of situation assessment, while motivation and other contextual factors impact risk assessment and therefore the final decision made as well as the course of action selected. This is depicted in Figure 5.

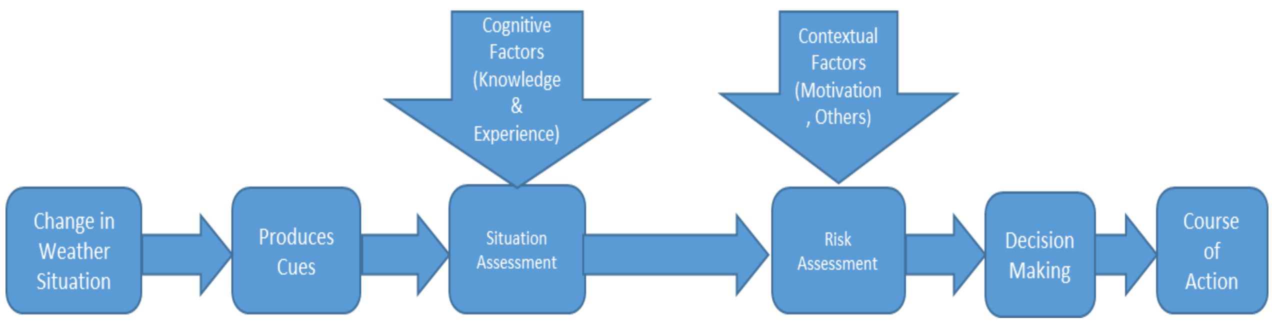

Figure 5: Impact of Cognitive and Contextual Factors on Decision Making

CHAPTER 3. PILOT DECISION MAKING AND AVIATION SAFETY

This chapter takes a look at the role of decision making in aviation safety. It starts with a discussion of the evolution of ideas on pilot error and aeronautical decision making and then goes on to review various decision making theories and their relationship with aeronautical decision making. It then focuses on naturalistic decision making and naturalistic contexts as the environment for decision making during encounters with adverse weather. The chapter also highlights efforts to improve pilot decision making and how those have focused on experience as a key requirement for decision making during encounters with adverse weather. The chapter concludes with a look at the transition process novice to expert pilot in adverse weather decision making and how that may be expedited through training

3.1 The Role of Decision Making in Aviation Safety

Erroneous decision making by pilots during encounters with adverse weather is often cited as a cause of GA accidents (Simpson, 2001; O'Hare and Smitheram, 1995; Goh and Wiegmann, 2001; Wiggins and O'Hare, 1995; 2003a; 2003b). Decision making within the context of aviation has been defined as:

> *"the ability of a pilot to respond to cues from the environment, evaluate the situation, come to conclusions and act on those conclusions"* (Green and Muir, 1991).

The ADM process starts long before getting into the aircraft, during preflight preparations and continues throughout all phases of the flight. After takeoff, pilots often have no control over some of the variables that could affect the safety of their flight, such as changes in the weather. Rather, they must identify information or cues relevant to the situation and decide on the best course of action to take. The decision made is the outcome of a complex interaction between cognitive factors mediated by contextual factors. This outcome is reflected in the course of action selected and eventually, the outcome of the flight. Accurate decision making is therefore, fundamental to safety in aviation.

The importance of decision making to safe flying operations has been underscored by AOPA (2013), which noted:

> *"While pilot-related accidents involving maneuvering or descent and approach may be an indication of poor airmanship, they also raise questions about the pilot's decision making. Since pilots typically receive some form of warning about deteriorating or adverse weather in advance, related accidents may be considered failures of decision making during both the flight planning and in-flight phases (AOPA 2013)".*

Flying is a process made up of several deliberate actions. Each action is preceded by a decision, which in turn is predicated on the conclusion reached from evaluating the situation. Factors that affect pilot situation awareness impact decision making and potentially affect the outcome of a flight. Given the central role decision making plays in aviation safety, there has been considerable effort to understand pilot decision making and the factors that impact it.

3.2 Evolution of Ideas on Pilot Error and Aeronautical Decision Making

The evolution of ideas on ADM is in many ways related to developments in research on accident causation and decision making in general. A majority of the early work on accident causation adopted the view of a single causal event, which could be attributed to a single entity (Griffen, Young and Stanton, 2015). In aviation, this has historically been the pilot. Hence, pilot error has been cited as the cause of a majority of aircraft mishaps (O'Hare and Smitheram, 1995; Goh and Wiegmann, 2001; Wiggins and O'Hare, 1995; 2003a; 2003b). Studies by Greenwood and Woods (1919), Newbold (1926) as well as Farmers and Chambers (1940) led to the development and propagation of an 'accident proneness' theory. This held that certain individuals were predisposed towards accidents due to behavioral, attitudinal and personality factors. The accident proneness theory was used to explain human error in aviation, suggesting some pilots were just behaviorally predisposed to errors. Kalez and Hovde (1945) as well as Kunkle (1946) drew on the concept to characterize a group of military pilots who seemed to be involved in a high number of violations or accidents. The attraction behind the notion of single cause accidents attributable to a single entity was that once both were identified (cause and responsible entity), related accidents could be prevented by removing individuals with such traits from flying. However, subsequent work cast doubts on the accident proneness theory (Mintz and Blum, 1949; Arbous and Kerrich, 1951). In addition to shortcomings in the methodology used in much of the work from which the idea emerged, researchers found no meaningful evidence for a consistent or measurable personality trait that predisposes operators to accidents (Johnson, 1946; Mohr and Clemmer, 1988; Wagenaar and Groeeweg 1987).

While the accident proneness theory was being questioned, other research work had begun to suggest human errors were due to errors in judgement or decision making, rather than behavioral traits (Kelly and Ewart, 1942). Indeed, in their subsequent work on pilot performance, Kalez and Hovde (1953) suggested a group of supposedly error prone pilots exhibited error in judgement. Additionally, research on tests for aircrew members by Guilford and Lacy (1947) identified judgement as an essential requirement for pilot performance. Judgement in this sense, referred to cognitive rather than perceptual or memory abilities (Kochan, Jensen and Chubb, 1997). These developments heralded a move away from the understanding that pilot error was caused by behavioral traits to the belief that it is associated with cognitive factors and decision making, exposing a need for better understanding of pilot decision making.

3.2.1 Decision Making Theories and Aeronautical Decision Making

Research in the late 1970s suggested the main underlying cause of pilot error accidents was erroneous decision making (Jensen and Benel, l977). As a result, efforts were geared towards finding ways to improve pilot decision making. Studies show decision making skills can be improved through training (Thorpe, Martin, Edwards and Eddows 1976; Jensen and Benel, 1976 and Roscoe, 1980), and there have been several attempts to identify and measure the skills required for accurate decision making (Kochan et al, 1997). Decision making in general is complex and several different perspectives, theories and models have been put forward to explain the process. Decision making models follow one of three broad approaches, based on the assumptions and frames of reference adopted. These are the normative, prescriptive and descriptive approaches (Baron, 1988).

Normative decision making models like the Subjective Expected Utility and Bayesian Inference models assume a “rational” decision maker. According to O’Hare (1992), they “define standards of decision making that can be shown to be optimal if certain axioms are accepted.” These models assume the decision maker is able to accurately determine all relevant variables associated with all possible options and thus weigh the possible outcomes and select the one that optimizes utility. Due to the dynamic nature of flying and the uncertainties associated with adverse weather encounters, this approach has limited applicability in aviation.

Prescriptive decision making models advocate the use of a systematic approach or sequence of actions to acquire and analyze information and determine a correct course of action. This approach, which is predicated on the use of heuristics rather than detailed analysis of options to speed up the decision making process are quite common in aviation. They include models such as the 3Ps (Perceive, Process, Perform), PAVE (Pilot, Aircraft, enVironment, and External pressures) and DECIDE (Detect, Estimate, Choose, Identify, Do, Evaluate).

Rather than focusing on finding an optimal decision to maximize utility or a standardized sequence of steps to reach a decision, descriptive approaches focus on how people typically make decisions and describe what people do during the process. The approaches recommended by the normative and prescriptive decision making models are based on some implicit assumptions, such as an ideal decision maker with accurate and complete information about all variables relevant to the decision making situation, or with sufficient time to apply a systematic evaluation scheme. However, this is rarely the case in practice. Descriptive models of decision making attempt to replace the ideal decision maker and conditions required by normative models with a rational decision maker having access to imperfect information and limited computational capacities representative of that actually possessed by decision makers in realistic decision making situations (Simon, 1933; Kahneman and Tversky, 1979, 1984). Descriptive models of decision making take cognizance of these limitations by introducing concepts such bounded rationality and satisficing. According to Gigerenzer and Selten (2001), bounded rationality describes "how a judgement or decision is reached (that is, the heuristic processes or proximal mechanisms) rather than merely the outcome of the decision, and they describe the class of environments in which these heuristics will succeed or fail". Bounds on rationality result in 'satisficing' (Simon, 1955), where decision makers choose the first satisfactory alternative they find rather than searching for one that is optimal or maximizes utility.

Descriptive decision making approaches have been applied to study how people make decisions in the natural, dynamic, real-world environments in which they operate. These studies reveal seasoned operators do not generate and compare between option sets (Klein, 2008). Rather they use their experience to rapidly categorize situations they encounter and determine an appropriate course of action based on the category (Klein, 2008). This kind of decision making has been termed "Naturalistic Decision Making (NDM)."

3.2.2 Naturalistic Decision Making

NDM describes how people actually make decisions in the real-world settings they operate in (Klein, Orasanu, Calderwood & Zsambok, 1993; Orasanu and Martin, 1998; Lipshitz, Klein, Orasanu and Salas, 2001, Klein, 2008). According to Simpson (2001), it "describes how experienced people make decisions in dynamic, naturalistic environments, under conditions of time pressure, dynamic goals, uncertain cues and high risk." NDM emphasizes the operator's knowledge and experience of as the basis for decision making (Zsambok, 1997; Pruitt, Cannon-Bowers and Salas, 1997). The operational environment determines the conditions under which decisions are made and shape the decisions themselves through their "constraints and affordances" (Lipshitz, Klein, Orasanu and Salas, 2001). NDM focuses on experts relying directly on their experience to make decisions within their field of expertise, with the aim of describing the cognitive processes these experts employ in reaching decisions (Lipshitz et al, 2001).

Several NDM have been proposed, illustrating different ways decision making occurs in operational settings. For instance, experience and domain knowledge may be used to recognize patterns, classify situations and retrieve a decision based on the classification under the Recognition Primed Decision Making (RPD) model, (Klein, 1993, 1998), or a search for the dominant alternative where more than one candidate solution is possible (Montgomery, 1989). It may also be based on argument driven action, where actions are selected based on their appropriateness for the situation (Lipshitz, 1988). Decision making varies along a continuum from analytical to intuitive, depending on how the situation identified is classified (Hammond, Hamm, Grassia and Pearson, 1987). Analytic decision making employs a more cognitively intensive process, while intuitive decision making employs pattern matching and determine whether the decision maker employs a skill, rule or knowledge-based level of cognitive control (Rasmussen, 1985; 1993).

NDM models share some common characteristics. The decision making situation presents cues which are recognized and become inputs used to rapidly assess the situation. Situation assessment is aided by a repertoire of mental images built from the decision maker's experiences and familiarity the context surrounding the decision making process. The situation and decision making process are dynamic; the problem may be ill-structured, available information may be incomplete and/or of dubious quality, and the goals the decision making process seeks to achieve may be ill-defined, dynamic or competing. Additionally, NDM environments often involve some time pressure and high safety or other stakes.

Decision making may be located at any point along a cognitive continuum and its location determines whether analytic or intuitive decision making process is employed. Cohen, Freeman and Wolf (1996) developed a recognition/metacognition model, which suggests the location of the decision making process is determined by the familiarity of the situation, time available for decision making as well as the potential consequences an erroneous decision. A recognition strategy, where candidate solutions are evaluated serially until a satisfactory one is found is adopted if the test determines time is a concern. Otherwise, the metacognitive component is employed, and more detailed analysis is given to the problem during a re-evaluation process.

The decision making mechanism espoused by NDM approaches has been supported by field observations of experts at work. The RPD model in particular was developed from cognitive task analysis of experienced fire ground commanders working under conditions characterized by extreme time pressure and significant safety consequences (Klein, Calderwood and Clinton-Cirocco, 1986; 2010). RPD describes how expert operators make decisions under naturalistic situations using intuitive rather than analytical strategies. According to the RPD, experience builds up a repertoire of patterns which enables them to recognize the important factors within a decision making situation and develop a picture of what to expect, and what action to take in response (Klein, Calderwood, and Clinton-Cirocco, 1986). In this way, the decision making task becomes on of matching the situation to learned patterns and selecting an appropriate course of action in response.

Results from the study by Klein et al (1986) indicates fire ground commanders used their experience to identify and classify situations they faced and then identified appropriate course of action to deal with the situation. Similarly, Kobus, Proctor and Holste (2001), found that highly experienced military officers were significantly more accurate in developing an appropriate course of action during a dynamic tactical scenario than those with low-experience. The recognition primed decision making process is shown below.

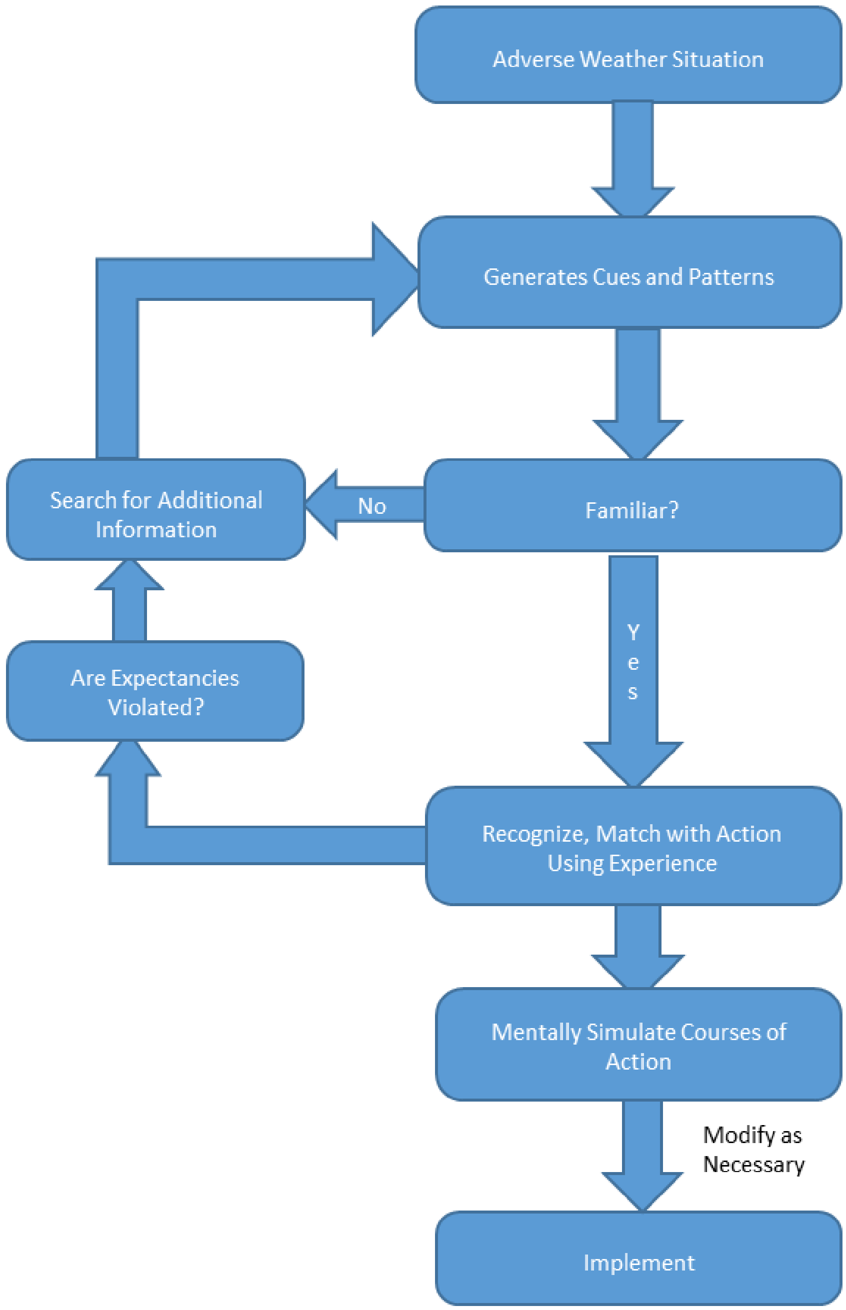

Figure 6: Model of Recognition Primed Decision Making. (Adapted from Klein et al, (1993)

The RPD model is made up of an intuitive and an analytic component; matching cue patterns and selecting a course of action is done intuitively, while mental simulation is carried out analytically (Klein, 1998). During mental simulation, decision makers analyze how decision options may play out within the decision making context. The process continues and decision options may be modified for use if required. NDM models emphasize the importance of contexts in decision making. Variables within the operating environment determines the kind of decision making process utilized to determine the appropriate course of action.

3.3 Context for Decision Making During Encounters with Adverse Weather

Adverse weather presents pilots with a dynamic, safety critical situation in which time is often limited and information uncertain. This is a naturalistic decision making environment. Pilots' response in this environment is based on their understanding and interpretation of the situation. Decision making error, when they occur, originate from the decision maker's knowledge base which supports the decision making process (Orasanu and Martin, 1998).

Normative and prescriptive models of decision making cannot be realistically applied under naturalistic conditions, as decision making performance deteriorates under the stress imposed by the prevailing conditions. Naturalistic decision making models which consider experience, dynamic situations with ambiguous cues, and significant safety implications are better suited to decision making during adverse weather encounters in aviation. Naturalistic decision making contexts preclude a search for optimal decisions through careful analytical or structured approaches. Rather, some form of satisficing occurs, and a decision is made on the first satisfactory course of action selected and the process repeated as the situation demands. This decision making process is not arbitrary. Indeed, findings from research suggest decision makers within naturalistic contexts leverage knowledge and experience acquired over many years of training to decide on an accurate course of action. A significant amount of effort has gone into enabling pilots make better decisions through training as discussed in the next section.

3.4 Efforts to Improve Pilot Decision Making

Efforts to improve pilot decision making have been led by the FAA, working with researchers and other stake holders in industry to develop training materials aimed at improving ADM. One outcome of this effort was the publication of a series of six training manuals (DOT/FAA//PM-86/41 - DOT/FAA//PM-86/46) and an Advisory Circular (AC No: 60-22), which provided guidance and recommendations on the management of human factors issues that had been identified as causing or contributing to aviation accidents. The series of manuals included "introductory material, background information, and reference material on Aeronautical Decision Making" (AC 60-22). They were primarily prescriptive, outlining a "systematic approach to risk assessment and stress management in aviation" (AC 60-22). They also highlighted the influence personal attitudes could have on decision making and how those attitudes could be modified to enhance safety in the cockpit (AC 60-22). Methods for teaching ADM techniques and skills alongside conventional flight instruction were also prescribed. The documents recommended a conservative approach to ADM, aimed at helping inexperienced pilots avoid common human factors and decision making pitfalls, with the belief that as they accumulated accident free flight hours they would gain the experience required to handle more challenging situations.

The development resulted in what has been described as "first generation ADM training" (Adams, 1993). First generation ADM training was quite successful; pilots who had received the training made significantly fewer ADM errors compared to those who had not (FAA 1991; Adams 1993). Despite these improvements however, pilot error continued to account for a large proportion of the now reduced GA accidents (Driskall and Adam, 1993; Adam and Erikson, 1992).

Adam and Erikson (1992) have observed that, the training approach advocated by these efforts had two main shortcomings. First generation ADM training advocated a "serial checklist evaluation of alternative decisions" (Adams 1993), it was not readily applicable to naturalistic decision making environments like aviation (Orasanu 2010). Furthermore, the approach advocated by first generation ADM did not account for differences between expert and novice decision makers. As a result, some shortcomings were observed when it was applied for recurrency training involving more experienced pilots (Adam and Erikson, 1992; Adams, 1993).

Notwithstanding the large proportion of aviation mishaps deemed to have been caused by pilot error, some pilots successfully handled challenging situations or failures during flights despite never having previously encountered similar situations. Such pilots typically had many years of flying experience and were considered expert aviators. Therefore, researchers began to explore the differences between expert and novice pilots to understand the differences between then and gain insights into what was required to transform novice pilots to experts.

Research on expert performance in other fields of endeavor show exceptional performance is the result of high levels of knowledge and skill acquired through the aggregation of experience over time (Newell and Simon, 1972; Chase and Simon, 1973). Since experienced pilots had performed exceptionally in many challenging situations, experience was recognized as an essential requirement for accurate judgment and ADM (Adams 1992; FAA 1991; Diehl, Hwoschinsky, Lawton and Licack, 1987).

At first, it was generally assumed that the level of experience required for good judgment in ADM only came with the accumulation of accident free flight hours over an extended period spent flying (Kochan, Jensen and Chubb, 1997). However, research showed a close relationship between experience and training; exposure to highly structured and focused training facilitated the aggregation of experience (Diehl, Hwoschinsky, Lawton and Licack, 1987). Therefore, researchers began to look more closely at the more complex ADM approach and problem solving strategies expert pilots seemed to adopt (Adams and Erikson, 1992), in order to identify differences between expert and novice pilot decision making mechanism and strategies.

These studies have shown expertise in ADM is correlated with training and experience and increased with the accumulation of flight time. Despite well-known limitations placed on human cognition by attention span as well as the capacity of both short and long term memory, expert pilots have developed the ability to quickly and efficiently access and leverage a well-organized body of knowledge acquired through experience to make accurate decisions in naturalistic situations. The main difference observed between expert and novice pilots is in the speed and accuracy of decision making. Experts have a “perceptual superiority” based on well-structured memory traces formed and stored from experiences acquired over time spent flying. This allows experienced pilots to quickly and efficiently assess a situation, reach an accurate decision, and take effective action. The whole process occurs so quickly that it seems automatic or intuitive (Adams and Erikson, 1992; Adams, 1993). This high speed, efficient cognitive processing is facilitated by experience, which the pilot leverages to quickly recognize what available cues foretell of uncertain situations (Adams and Erikson, 1992).

These insights led to the second generation of ADM, known as the expertise approach. In contrast to first generation ADM training which advocated an assessment of own abilities along with the management of hazardous attitudes and a structured approach to decision making, the expertise approach was directed at enhancing memory and problem solving during training. Training here emphasized applications to real world problems using techniques such as Scenario and Computer Based Training (SBT and CBT) to increase the knowledge base of novice pilots and the organization of this knowledge (Adams and Erikson 1992).

3.4.1 Findings from Research into Second Generation Aeronautical Decision Making

Two important issues emanate from research that has led to the development of the expertise approach to ADM, as follows:

Experience is Central in the Expertise Approach to ADM. Experience is central to expert decision making and is accumulated from practical knowledge acquired over time spent flying.it is reflected in a seemingly intuitive response to changing situations in an NDM environment. According to Bastic, (1982), intuition is "knowledge based on experiences and acquired through sensory contact". It is the way we translate our experiences into action Klein 2003). Adams and Erikson (1992) have suggested intuition is reflected in automatic responses to situations based on "an implicit perception of the whole problem". It is a response to cues and the context of a naturalistic situation brought about by extensive knowledge from experience acquired within a particular domain.

Experience is accumulated through repeated encounters with different decision making situations. This allows pilots increase their knowledge about those situations and develop pertinent memory traces. These memory traces serve as the basis for intuitive decision making in naturalistic situations. Expert decision making therefore, is based on rapidly accessing a structured repertoire of memory traces systematically archived from knowledge and experience.

Training is Important for Building Experiences Which Drive Expertise. The foregoing suggests the memory traces that support rapid decision making by experienced operators may be modified through training that provides opportunities for repeated encounters with different decision making situations a pilot may encounter. Since aviation training emphasizes procedure oriented training for developing flying and decision making skills, it lays the foundation for the development of more sophisticated decision making as experience is accumulated (Adams and Erikson, 1992; Adams, 1993). Training establishes and expands the knowledge and experience base on which expertise is built. It follows therefore, that increased understanding of the types of experience that support expert performance would allow for the refinement of pilot training programs. Therefore, the right kind of training is essential to build the kind of experience profile that can help novice pilots improve their judgment and decision making skills.

3.5 The Role of Experience In Decision Making During Encounters With Adverse Weather

Considerable evidence from general research on decision making in naturalistic environments as well as studies of human performance in several fields shows experience is an essential requirement for expert performance. Operators with high levels of experience make more accurate decisions under conditions with severe time pressure and information uncertainty (Adams and Erikson, 1992; Adams, 1993; Calderwood et al, 1988; Klein et al, 1989; Klein et al, 1995, Ericsson and Charness, 1994; Ericsson, 2004; Simon and Chase, 1973; De Groot, 1978). The decisions are made intuitively rather than analytically (Adams and Erikson, 1992; Adams, 1993; Klein, 1997; 2008; Klein, Calderwood and Clinton-Cirocco, 2010; Orasanu, 1993; Simpson, 2001). Indeed, one NDM model, the Recognition Primed Decision making (RPD) emphasizes experience as *the* essential requirement for good decision making. According to the RPD, experience enables quick recognition and classification of the critical information within a naturalistic situation which facilitates timely formulation, selection and implementation of the correct course of action (Klein, Calderwood and McGregor, 1989; Klein, 1989; 1993; Pruitt, Cannon-Bowers and Salas, 1997; Lipshitz, Klein, Orasanu and Salas 2001).

In aviation, studies have shown pilot experience is an insulating factor against erroneous decision making during encounters with adverse weather. Wiegmann, Goh and O'Hare (2002) as well as Li, Baker and Grabowski, (2001) found experience to have an insulating effect against erroneous decision making during adverse weather encounters by GA pilots.

Some researchers have suggested expertise results from the experiences accumulated from time spent practicing within a domain (Chase and Simon, 1873; De Groot, 1978; Chi, Glaser and Farr, 1988; Ericsson and Charness, 1994; Ericsson, 2004). In aviation, this has been taken to correspond to the total flying hours a pilot has accrued. Therefore, pilot experience is typically evaluated on the total number of flying hours a pilot has accumulated (Li and Baker, 1999; Wiegmann, Goh and O'Hare, 2002; Wiggins and O'Hare, 2003a; Johnson and Wiegmann, 2011). Indeed, several studies have found that pilots with higher total flying hours (more experienced) make better judgements and decisions about hazardous weather situations than pilots with lower total flying hours (Wiggins and O'Hare 1995; Johnson and Wiegmann, 2011; Goh J, & Wiegmann D, 2002; O'Hare D & Owen D, 2002).

However, two problems arise from the use of total flying hours as a measure of experience. First, reviews of NTSB GA accident reports in which weather was determined to be a causal factor reveal many of the accidents involve pilots with a high number of total flying hours (Landsberg, 2004; NASA, 2007; Keller, 2015). Accidents which involve such experienced pilots raise questions about the use of total flying hours as the sole measure of experience. Does experience only help pilots make accurate decisions in certain situations? If that is the case, in what situations does experience help?

It appears the use of total flying hours does not permit the level of resolution or discriminatory power required to fully elucidate the nature of experience that supports accurate naturalistic decision making. Kochan, Jensen and Chubb (1997) have noted that more than total flying hours is required to make an expert pilot and suggested other dimensions including relevance, meaningfulness, recency, number and variety of the experience. However, so far, no studies have been conducted to investigate the role these dimensions play in decision making.

Secondly, some studies have found experience had no positive effect on decision making during simulated adverse weather encounters. Burian, Orasanu and Hitt, (2000), Li and Baker, (1999) as well as the NTSB (2005) have reported finding no positive effect on decision making from experience based on total flying hours during adverse weather encounters. Furthermore, some researchers have found other measures of experience may be more appropriate in determining superior decision making performance in certain situations. For instance, Wiggins and O'Hare (1995) found that a proximal measure of experience, such as cross country flying hours was a better predictor of differences between the weather related decision making performance of experienced and inexperienced pilots than a global measure of experience such as total flying hours. Similarly, Wiegmann, Goh and O'Hare (2001) found that recent flight experience (hours flown in the last 90 days) was a more relevant experience variable in determining the accuracy of weather related decision making than total flying hours.

The foregoing suggests a one-dimensional definition of experience, based on total flying hours may lack the resolution or discriminatory power required to fully elucidate the nature of experience in General Aviation. This means our ability to fully understand and take advantage of its contribution to decision making during adverse weather encounters is limited. Indeed, some research suggests experience is a multifaceted attribute with several elements. In addition to the number of total flying hours, several other elements are also important for accurate decision making during encounters with adverse weather (Jensen, 1995; Shappell, Hackworth, Holcomb, Lanicci, Bazargan, Baron and Halperin, 2010; Wiggins and O'Hare, 1995; Wiegmann, Goh and O'Hare, 2001; Kochan, Jensen and Chubb, 1997; Jensen, 1995; Li, Baker and Grabowski, 2001; Burian and Orasanu, 2000; Johnson and Wiegmann, 2011; Coyne, Baldwin and Latorella, 2008; FAA, 2005). These variables include total flight hours, total hours in event aircraft make/model, total hours in last 90 days, cross-country hours, cross-country hours in last 90 days, Actual instrument hours, simulated instrument hours, total instrument hours.

Despite considerable evidence suggesting experience may be made of several dimensions, researchers are yet to empirically investigate and ascertain what these dimensions are, what role they play and how they interact to help pilots make a decision during adverse weather encounters.

This study is designed to investigate aspects if experience identified from previous research and the interaction between them.

Studies have shown experience can be modified through training (Jensen, 1995; FAA 2009). Currently, many training interventions designed to elevate the experience level of novice pilots are based on findings and recommendations from research using total flying hours as the sole measure of experience (Jensen, 1995; Yuchnovicz,, Novacek, Burgess, Heck and Stokes, 2001; O'Hare and Smitheram, 1995). Some of the recommendations have been successfully implemented (Ayers, 2006; Schumacher and Lease, 2007; Ball, 2008; Wiggins and O'Hare, 2003a), but others appear not to have been effective, since desired results were not achieved. (Keller, 2015). Furthermore, the number of pilots with high total flight hours involved in weather related accidents suggests a need to investigate and gain additional insights into the composition and dynamics of experience in order to design more effective training routines. An understanding of the relationship between aspects of experience be leveraged to develop precisely targeted training interventions to increase important aspects of pilot experience and improve the accuracy of weather related decision making.

3.6 Transition from Novice to Expert Pilot In Adverse Weather Decision Making

The transition from novice to expert in GA weather related decision making weather depends on knowledge derived from experience accumulated from flying (Adams and Erikson, 1992; Drefus and Drefus 1986; Eriksson, 2006). While pilots typically receive some form of warning about deteriorating or adverse weather in advance (AOPA XXXX), research suggests novice pilots and some pilots with a high number of total flying hours do not possess the kind of experience that enables accurate weather related decision making.

Pilot experience determines the type of cognitive processing used in decision making, as well as the speed and accuracy of both situation and risk assessment (Orasanu, 2010; Adams and Ericsson, 1992; Klein, 1998; Adams 1993). Novice pilots do not possess the deep and well-integrated knowledge of experts (Chi et al, 1988; Klein, 1998) and so, are at a disadvantage in naturalistic decision making situations (Orasanu 2010). Wiegmann et al (2002) found more experienced pilots made decisions quicker than less experienced pilots while flying simulated adverse weather conditions. This allowed them act quicker to avoid adverse weather compared to less experienced pilots. Similarly, Fischer, Davison and Orasanu (2003) found experienced pilots showed a more complex understanding or safety risk compared to novice pilots. Expert pilots can rapidly access and utilize experience based knowledge to accurately assess the situation and select an appropriate course of action (Adams 1993). However, what constitutes the kinds of experience based knowledge that enables accurate weather related situation and risk assessment advantages to pilots is yet to be empirically investigated.

Studies indicate expertise is not an automatic consequence of lengthy experience. Many types of experience exist, with different quantitative and qualitative impacts on performance (Eriksson, 2002; Ericcson and Adams 1993, Ericsson, Krampe and Tesch-Romer, 1993; Adams 1993; Ericsson, 1996; Vicente and Wang, 1998). Experienced operators adapt to the demands of the task they are engaged in and their responses become increasingly automated. As a result, they lose conscious control over their actions and rather than expand their experience base, they only repeat them (Ericsson, 2006).

Ericsson (2006) has suggested only some types of domain related experience bring about improved performance. Mindless training and the accumulation of flying hours from flying in routine weather conditions will not support the development of cognitive representations required for accurate situation assessment (Ericsson, 2006). Experience that supports the transition from novice to expert performance includes a diverse body of practical knowledge that forms memory traces which support intuitive decision making. This kind of experience results from precisely targeted, deliberate training that is relevant and changes the mechanism that drives expert performance (Eriksson, 2006). This mechanism is revealed in cognitive processing during situation assessment and risk assessment that evaluates cues as pieces of a puzzle rather than in isolation. The superior performance of experts is largely due to well-developed cognitive representations that mediate performance during this process (Ericcson, 2006). Therefore, training for expertise in weather related decision making should focus on tasks that develop cognitive representations that expedite cognitive processes.

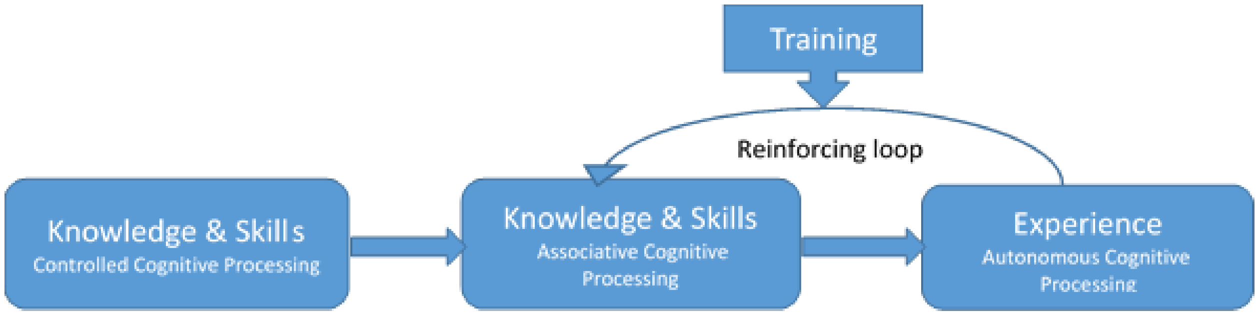

Figure 7: Impact of Training on Expertise

Training could also be aimed at enabling pilots increase their associative cognitive processing and problem solving capabilities, eventually leading to the development of autonomous cognitive processing characterized by efficient and dynamic decision making. The relatively high number of pilots with high total flying hours involved in weather related accidents suggests the composition of these tasks is not fully known. We are currently unable to design training programs that target areas in which pilots have inadequate experience.

3.6.1 Training for Expertise in Weather Decision Making

Domain specific training is an effective strategy for improving decision making (Glaser and Bassok, 1989). Adams (1993) found that the development of expertise in decision making is influenced by the kinds of decision making task demands encountered during training. Similarly, a study of pilot response to emergency situations in aviation by McKinney and Davies (2004) found that pilots who had prior simulator experience with a similar emergency situation responded more successfully to the actual event compared to those who had not. This suggests increasing the amount of contact pilots have with germane scenarios should expedite the accumulation of the body of experienced based knowledge that brings about decision making expertise. Furthermore, the RPD model holds that experience builds up a repertoire of patterns which supports recognition of the important factors within a decision making situation and development of a complete picture of what to expect and what action to take in response (Klein, Calderwood, and Clinton-Cirocco, 1986). The decision making task then becomes one of matching the situation to learned patterns and selecting the appropriate course of action in response. Therefore, training for expertise in GA weather decision making should ensure contact with scenarios that facilitate accumulation of the right kinds of experience.

One way to achieve this is through precisely targeted training that elicits responses that are pertinent and can expand their pilots' knowledge and experience base. Research suggests the greatest amount of improvement occurs during training and from the duration of experience (Ericsson and Smith, 1991). However, routine training that does not increase the experiential knowledge base is of little help. Therefore, there is a need to empirically determine what types of experience are required to support expertise in adverse weather decision making in order to develop training scenarios that can help pilots build this experience base.

Research further shows the key to expert performance is to induce targeted challenges through which performance across pertinent and essential dimensions can be incrementally improved (Ericsson, 2006). Expertise in ADM during encounters with adverse weather requires extensive experience. Since there are several dimensions to experience, the challenge is in identifying the specific dimensions that contribute most significantly to building the experiential knowledge base that facilitates superior performance during such encounters. This will allow the development of precisely targeted training interventions to achieve weather decision making goals on each element within the spectrum of experience identified. Customized scenarios that provide weather decision making challenges representative of those a pilot may encounter while flying in a particular airspace along with proficiency goals can then be developed from historical weather data and accident/incident databases for use in training.

Based on the foregoing therefore, we can develop a typology of challenging weather scenarios for any flight region, identify the kinds of experience based knowledge known to support decision making in those situations and develop training that builds the kinds of experience identified. The use of computer simulated cue recognition training has shown some promise in improving the timeliness of weather related decision making (Wiggins and O'Hare, 2003). However, even when cues have been identified, some pilots have been seen to lack the ability to accurately and reliably determine the significance of cues identified and consequently, make an erroneous decision (Stokes, Kemper, and Kite, 1997). Recognition of pertinent cues in a dynamic flying environment during adverse weather requires experience that is relevant and useful for the recognition process, not just experience based on the number of flying hours. Furthermore, misdiagnosis of the significance of the cues indicates relevant experience in itself is not enough to guarantee accurate decision making during such adverse weather encounters. For instance, a range of different outcomes may be associated with certain cues depending on the context. Experience with a wide variety of weather situations is necessary to accumulate the kind of practical knowledge required for expert decision making during such encounters.

CHAPTER 4. **METHOD – FIRST STUDY**

The first part of this study sought to answer two research questions: first, what is the relationship between each element of experience and the outcome of encounters with adverse weather? Next, is there a relationship between different levels of each experience elements and the odds of accidents from encounters with adverse weather? To answer these questions, a novel method for evaluating accident risk, specifically the likelihood that an incident turns into an accident is evaluated using actual pilot experience data from incident and accident reports. The details of this methodology are presented in this chapter. The overarching conjecture for this part of the research and related hypotheses are also presented, the dependent and independent variables are defined, along with the inclusion and exclusion criteria for the study data. The approach for collecting the study data collection is then presented, followed by the details of the analysis carried out.

4.1 Conjecture

Adverse weather encounters occur randomly, so nothing prevents a pilot from encountering one during a flight. For this study, incidents and accidents are considered to have a hierarchical relationship; an incident is an encounter with adverse weather that was resolved, while an accident is refers to one that was not resolved. Viewed in this way, it then becomes possible to consider and investigate the key variables that that prevent a transition from incidents to accidents, since that is the preferred outcome.

The general belief is that what prevents these randomly occurring incident involving adverse weather encounters from transitioning into accidents is the pilot's experience. If that truly is the case, it then follows that:

If experience truly determines outcome of adverse weather encounters, we should see significant differences between the experience profile of pilots who had accidents during adverse weather encounters and those who did not.

The corollary to this conjecture, therefore, is:

The experience profile of a pilot has no effect on the outcome of adverse weather encounters

One challenge to establishing the veracity of this conjecture is that there is no single database that contains experience information on pilots whose adverse weather encounter resulted in incidents as well as those whose resulted in accidents. So, there is no way to evaluate the likelihood that an incident transitions into an accident. One way to handle this is to search for a similar sample of pilots within the aviation community to act as a control group, typically through surveys, but this often introduces several additional challenges, including low response rates, incomplete or inaccurate responses, which may inadvertently bias the selection of participants, to mention a few.

4.2 Methodological Approach

To overcome the aforementioned challenges, a novel methodological approach was adopted for this study. Rather than seeking a population based sample of pilots who did not have accidents during encounters with adverse weather, a comparable sample of "incident pilots" was drawn from a different, independent database - the FAA administered Aviation Safety Reporting System (ASRS) database and used as the control group. This is a methodological innovation that marks the first contribution of this research.

In addition to obviating some of the challenges commonly encountered in related research, the methodological approach adopted in this study also provides results that are ecologically valid. Additionally, it allows the research to go beyond analysis of the demographic characteristics of pilots who had accident to determine what their effects might be, as is often is the case. By creating a control group, comparisons can be carried out between the two groups to determine how individual or different combinations of variables are distributed between the groups or associated with the outcome and determine whether significant patterns of differences exist.

4.3 Criteria for Data Collection

To gather the data required for the study, queries were run on both the NTSB and ASRS databases to identify reports of General Aviation (Part 91) fixed wing accidents and incidents respectively, between January 1, 2005 and December 31, 2015, in which experience or decision making during adverse weather encounters was determined to be a cause or factor. Each report identified by the query was subsequently reviewed to ensure it met the criteria specified for the study.

There were four exclusion and three inclusion criteria each for the reports from which the study data was collated. For the exclusion criteria, accidents and incidents during the take-off and landing phases of flights were excluded, since they could be indicative of short comings in airmanship, rather than decision making mediated by experience. Similarly, accidents and incidents during adverse weather encounters involving student pilots or those in which equipment failure was determined to be a cause or factor were also excluded. Reports with incomplete data were also excluded from the study since there was no way to determine whether the pattern of missing data was random

To be included in the study, accident and incident reports had to be for flights under GA (Part 91) operations and carried out in a fixed wing airplane. Flights involving rotary wing or amateur build airplanes were therefore, excluded from the study. Additionally, adverse weather must have encountered during the flight and experience and/or errors in decision making determined to be causal or contributory factor to the outcome.

The inclusion and exclusion criteria ensure only GA encountered adverse weather in which experience was determined to be a cause or factor in the outcome are included. Since the focus of the study is on the mediating effect of experience on the outcome of encounters with adverse weather, the inclusion and exclusion criteria ensure accidents due to other reasons like equipment failure or airmanship are excluded, because they may not reflect the mediating effect of experience on the outcome of such encounters. If experience does indeed affect the outcome of such encounters, then its effect should be evident in the purest cases. So, to avoid the potential confounding effect that such cases may introduce, they were not considered and only the purest cases were used for the study.

Based on the foregoing criteria, a total of 595 reports, comprising 218 accident and 377 non-accident flights between January 1 2005 to December 31 2015 satisfied all seven criteria. Pilot experience data was then extracted from the reports and collated for analysis.

4.4 Dependent and Independent Variables

The dependent variable for this study was the outcome of adverse weather encounters, coded "0" for incidents and "1" for accidents. Incidents were defined as encounters that did not result in loss of life, injury to persons, or damage to property. Accidents were encounters that resulted in one of the three outcomes. Six variables identified as elements of experience by previous studies and commonly used in NTSB, ASRS and other aviation accident and incident databases to detail pilots' experience profile were extracted and tabulated. A list of some of the previous research, variables studied, and a summary of their findings are provided in Appendix A.

The experience elements included in this study were total flight hours, hours in last 90 days, hours in make and model, certificate type, instrument rating and airplane rating. Airplane rating had two categories: Single Engine Rating and Multi-Engine Rating; certificate type had three categories: Private Pilots License (PPL), Commercial Pilots License (CPL) and Airline Transport Pilots License (ATPL). Table 1 contains the variables and their coding for this study.

Table 1: Experience Variables and Their Coding for the Study

Experience Variable	**Coding**
Total Flight Hours	Number of Hours
Hours in Last 90 days	Number of Hours
Hours in Make and Model	Number of Hours
Certificate Type	Private Pilot License (PPL) = 1
	Commercial Pilot License (CPL) = 2
	Airline Transport Pilot License (ATPL) = 3
Instrument Rating	Non-Instrument Rated = 0
	Instrument Rated = 1
Airplane Rating	Single-Engine Rated = 1
	Multi-Engine Rated = 2
Outcome	Incident = 0
	Accident = 1

4.5 Analytical Approach

After extracting and collating the data, analysis started with exploration of the data using descriptive statistics, to summarize and gain some insight into the composition and nature of each experience variable and their distribution for the two groups of pilots in the study. Standard measures of central tendency including mean, median and mode as well as measures of dispersion such as standard deviation, minimum and maximum values were computed along with the frequency distribution for each variable.

Individual experience variables were then analyzed to determine whether they had any relationship with the outcome of adverse weather encounters. Specifically, Chi-square tests were used to determine the extent to which each element of experience or different levels of multi-level experience variables was associated with accidents. This was followed by a determination of the strength of any such associations in terms of odds ratios.

4.5.1 Chi-square Tests

Chi-square tests use cross-tabulation or contingency tables to present data on categorical variables analyze the relationship between variables so analysis can be carried out to identify relationships which may exist between such variables. Chi-square statistic is then used to evaluate the statistical significance of the relationship between variables in the table. For this study, the table took the format shown in Table 2:

Table 2: Cross Tabulation for Chi-Square Tests

		Experience Variable		*Total*
		Yes	*No*	
Accidents	*Observed*	**a**	**b**	**a + b**
	Expected	**a′**	**b′**	
Incidents	*Observed*	**c**	**d**	**c + d**
	Expected	**c′**	**d′**	
Total		**a + c**	**b + d**	**a + b + c + d**

Where:

a represents the number of pilots with the type of experience and had an accident

b represents the number of pilots without the type of experience and had an accident

c represents the number of pilots with the type of experience and did not have an accident

d represents the number of pilots without the type of experience and did not have an accident

So,

$$\text{The prevalence of accidents for any type of experience is} = \frac{a+b}{a+b+c+d}$$

$\text{There are } a + c \text{ pilots with the experience type so, we would expect}$

$$a' = \frac{(a+b) * (a+c)}{a+b+c+d} \text{ pilots who have the experience to have accidents}$$

$\text{This is the expected value of a for the null hypothesis that experience has no effect}$
$\text{on accidents, and the same holds for b, c and d } (H_0)$

If the observed values are significantly different from their expected values under the null hypothesis, we can conclude that our null hypothesis is unlikely to be true

Chi-square tests can only be carried out on categorical variables so, the regulatory categories of each categorical experience variable (certificate type, instrument rating and airplane rating) as detailed in Table 1 were used. The continuous experience variables were broken into different categories. Total flight hours was broken into three categories; <=250 total flight hours, 251 – 1500 total flight hours, and > 1500 total flight hours, based on Federal Aviation Regulations for minimum hours of flight time required for specific certificates. The first category represents total flight hour range and cut off point to earn and operate as a privately licensed pilot before becoming eligible to earn a commercial license, while the second represents that to earn and operate as a commercial pilot before eligibility to earn an airline transport license and transition to the third category. Hours flown in the last 90 days and hours in make and model were broken into two categories each, using the upper and lower median value for the pilot sample studied as the cut off values.

The chi-square tests tell us which of the elements of experience is associated with the outcome of adverse weather encounters, in this case, using real pilot experience data. In some ways, it also tests the ecological validity of findings from previous studies. Odds ratios were used to quantify the strength of association between each experience variable and the outcome of adverse weather encounters as well as to determine the association between different levels of the variables and the outcome of adverse weather encounters. However, significant difference between two groups on any variable does not mean the variables are causally related to the outcome used to distinguish between the two groups. It also does not mean the variables are predictive of the likelihood of the outcome. Additionally, it does not tell us how the variables of interest covary. While it provides some insight into the relationships within the variables, it provides no indication of which variables are strongest or most important in predicting the outcome. So, to explore which combinations of experience elements are predictive of the likelihood of accidents during encounters with adverse weather, we turn to logistic regression.

4.5.2 Logistic Regression

The objective of logistic regression is to find an equation that best predicts the probability of an outcome or dependent variable as a function of one or a set of independent variables. It models variables in a manner that allows for the determine the unique effect of each variable by controlling for all other variables being considered. It also allows us examine how the variables being studied interact to produce the outcome being studied. Therefore, logistic regression gives us a more sophisticated and nuanced look at each variable's predictive contribution to the likelihood of the outcome.

The logistic regression model developed in this first study contained all six experience variables studies. All the continuous variables (total flight hours, hours in make and model and hours in last 90 days) were entered as single variables, while certificate type was broken into their regulatory categories of PPL, CPL and ATPL, with PPL set as the base category. Similarly, Airplane rating was broken into single and multiple engine ratings, with single engine rating set as the base category.

The descriptive statistics for the data as well as the results of the Chi-square tests and logistic regression model are presented in the next chapter.

CHAPTER 5. RESULTS FROM FIRST STUDY

5.1 Distribution of Pilot Experience Variables

Experience information was collected for a total of 595 pilots, comprising 218 accident and 377 non-accident pilots from the NTSB and ASRS databases respectively. The breakdown of the data by experience variable for both groups is detailed in Table 3. The mean total flight hours for all pilots in the study was 4675.37 hours, while accident and non-accident pilots had mean total flight hours of 2223.54 and 6093.14 hours respectively. Similar values for the median total flight hours were 2500.00, 760.00 and 3900.00 flight hours respectively. Hours flown in the last 90 days had a mean of 65.42 hours overall, 48.49 hours for pilots in the accident group and 75.21 hours for those in the non-accident group, while the median hours flown in the last 90 days were 30.00 and 60.00 hours respectively and 50 hours overall. The mean hours flown in make and model for accident and non-accident pilots were 610.06 and 972.21 hours respectively while the overall mean was 300 hours. The median was 300 hours overall, while the values for accident and incident pilots were 174.00 and 453.00 hours respectively.

There were 183 pilots with a private pilot's license, 187 with a commercial pilot's license and 225 with airline transport pilot's license. Additionally, 147 pilots had single engine rating and 448 multi engine rating. There were 516 pilots with instrument rating, while 79 were non instrument rated. Details of the descriptive statistics are presented in Table 3 and Figures 8 - 14.

Table 3: Descriptive Statistics

Experience Variable		*Total*	*Accident Pilots*	*Incident Pilots*	
Total Flight Hours	*N*	595.00	218.00	377.00	
	Mean	4675.37	2223.54	6093.14	
	SD	8879.98	3528.57	10577.62	
	Median	2500.00	760.00	3900.00	
	Min	50.00	50.00	57.00	
	Max	178000.00	22228.00	178000.00	
Hours in Last 90 days	*N*	595.00	218.00	377.00	
	Mean	65.42	48.49	75.21	
	SD	64.71	51.51	69.43	
	Median	50.00	30.00	60.00	
	Min	0.00	0.00	1.00	
	Max	680.00	250.00	680.00	
Hours in Make and Model	*N*	595.00	218.00	377.00	
	Mean	300.00	610.06	972.21	
	SD	1453.13	1580.37	1358.76	
	Median	300.00	174.00	453.00	
	Min	1.00	2.00	2.00	
	Max	18300.00	9200.00	9200.00	
		Frequency	*Percent*	*Accident Pilots*	*Incident Pilots*
Certificate Type	*PPL*	183	30.80	135.00	48.00
	CPL	187	31.40	55.00	132.00
	ATPL	225	37.80	28.00	197.00
Airplane Rating	*Single Engine*	147	24.70	125.00	22.00
	Multi Engine	448	75.30	93.00	355.00
Instrument Rating	*Non-Instrument Rated*	79	13.30	73.00	6.00
	Instrument Rated	516	86.70	145.00	371.00

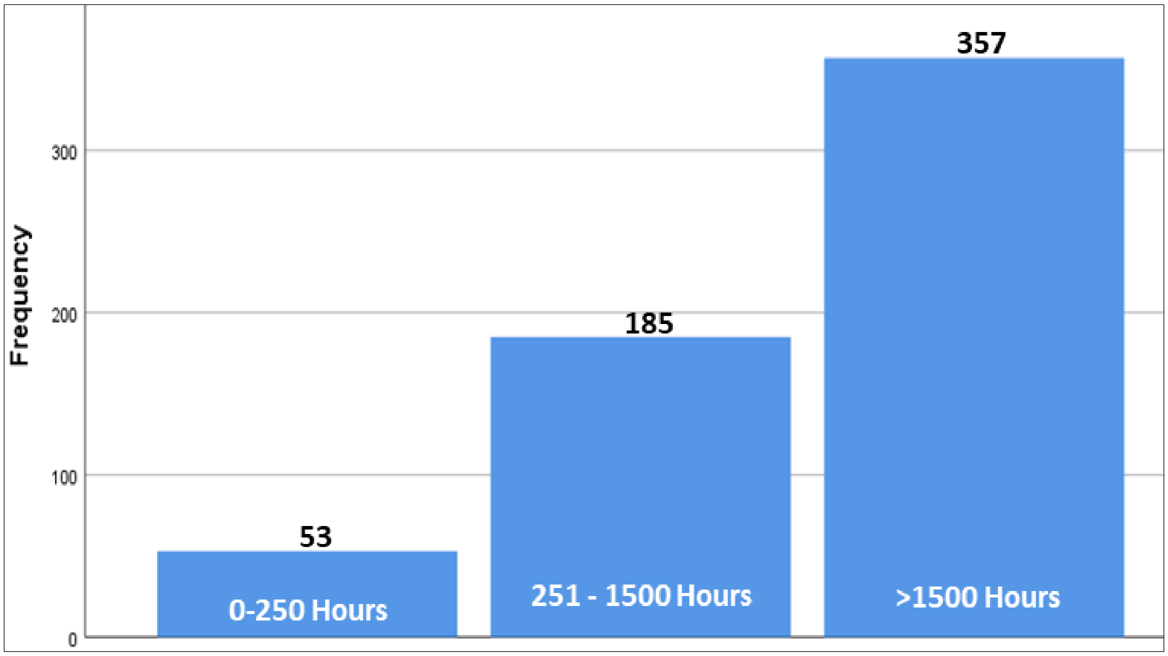

Figure 8: Distribution of Total Flight Hours by Categories

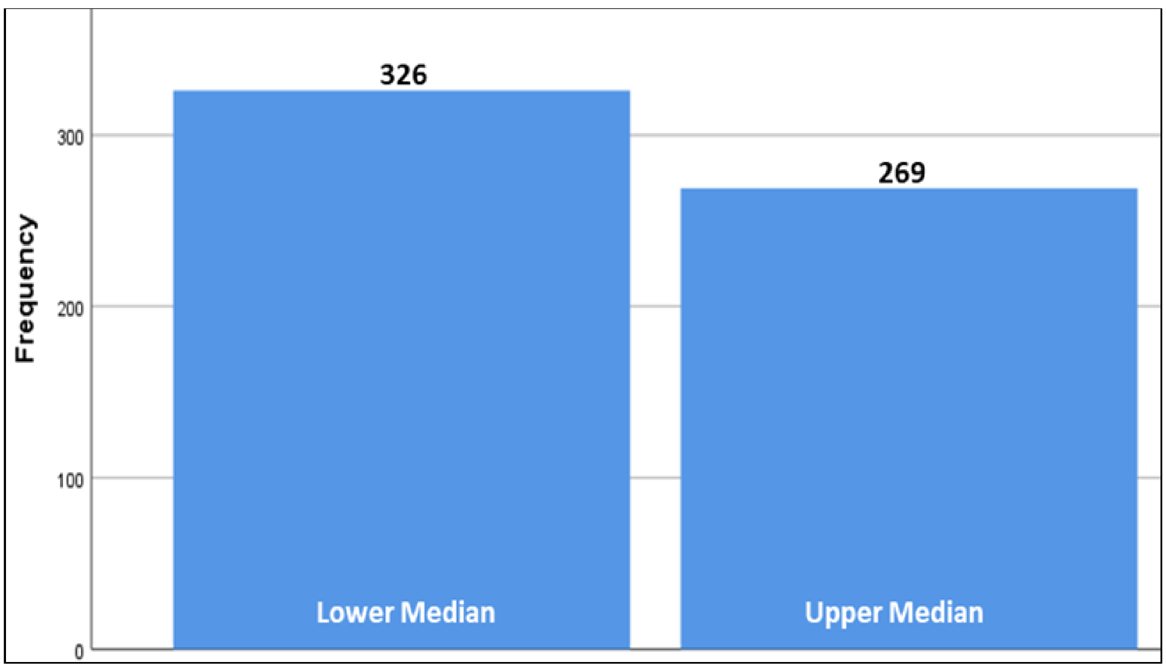

Figure 9: Distribution of Hours in Last 90 Days by Categories

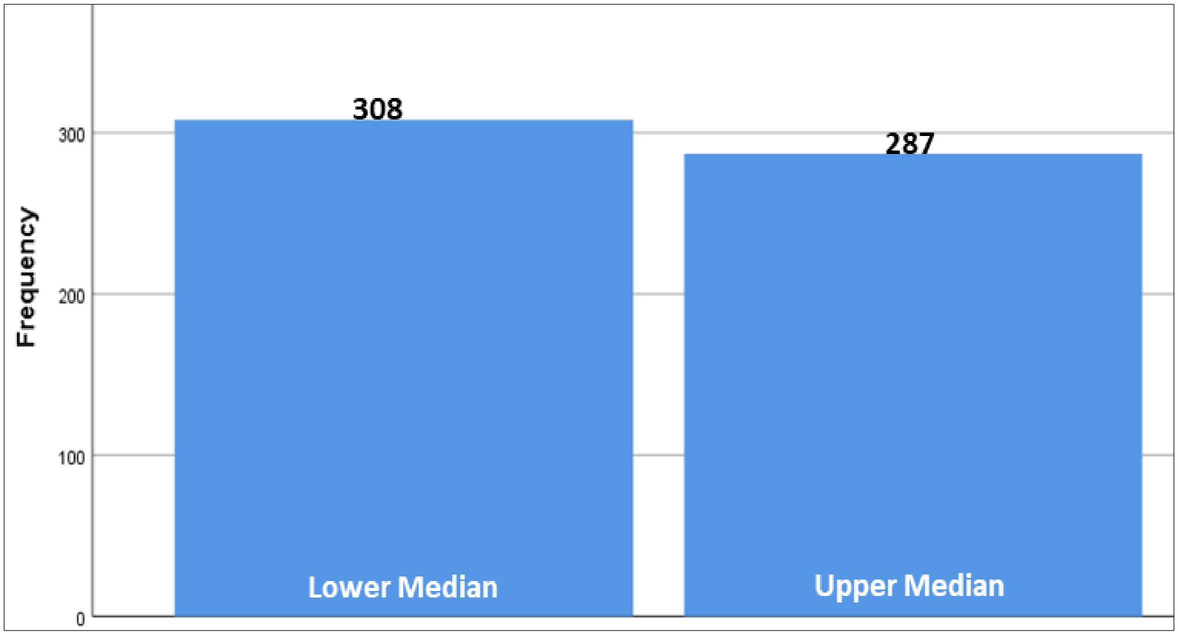

Figure 10: Distribution of Hours in Make and Model by Categories

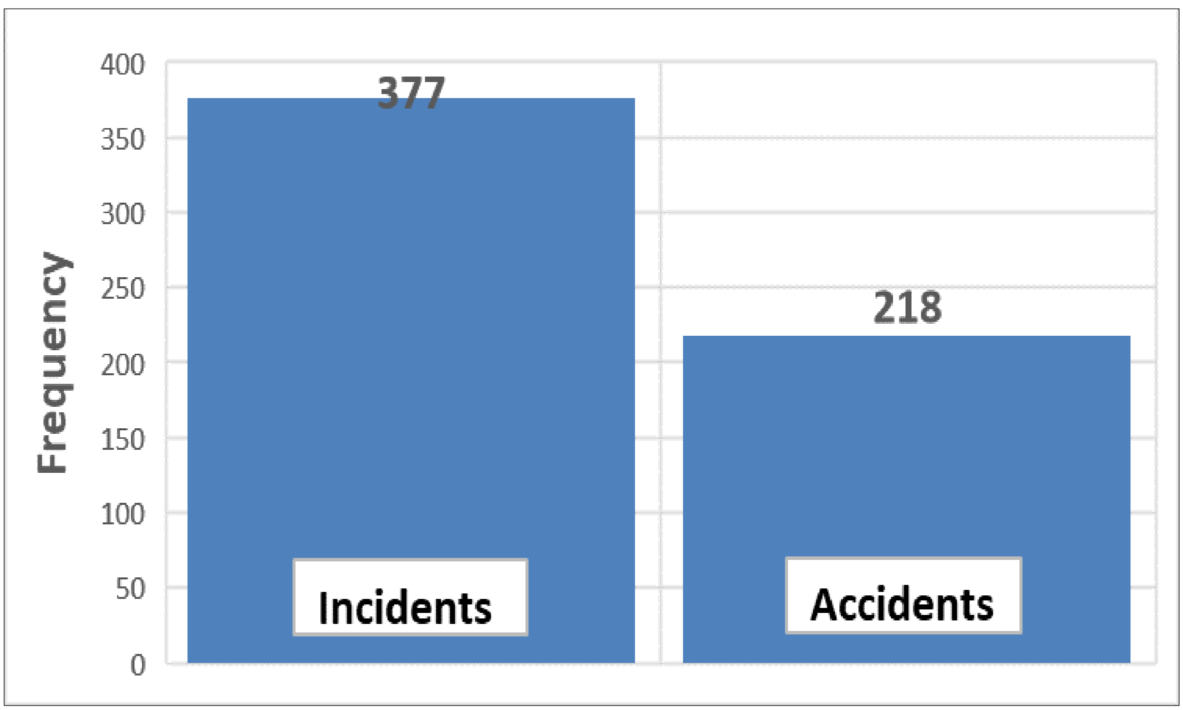

Figure 11: Distribution of Outcome

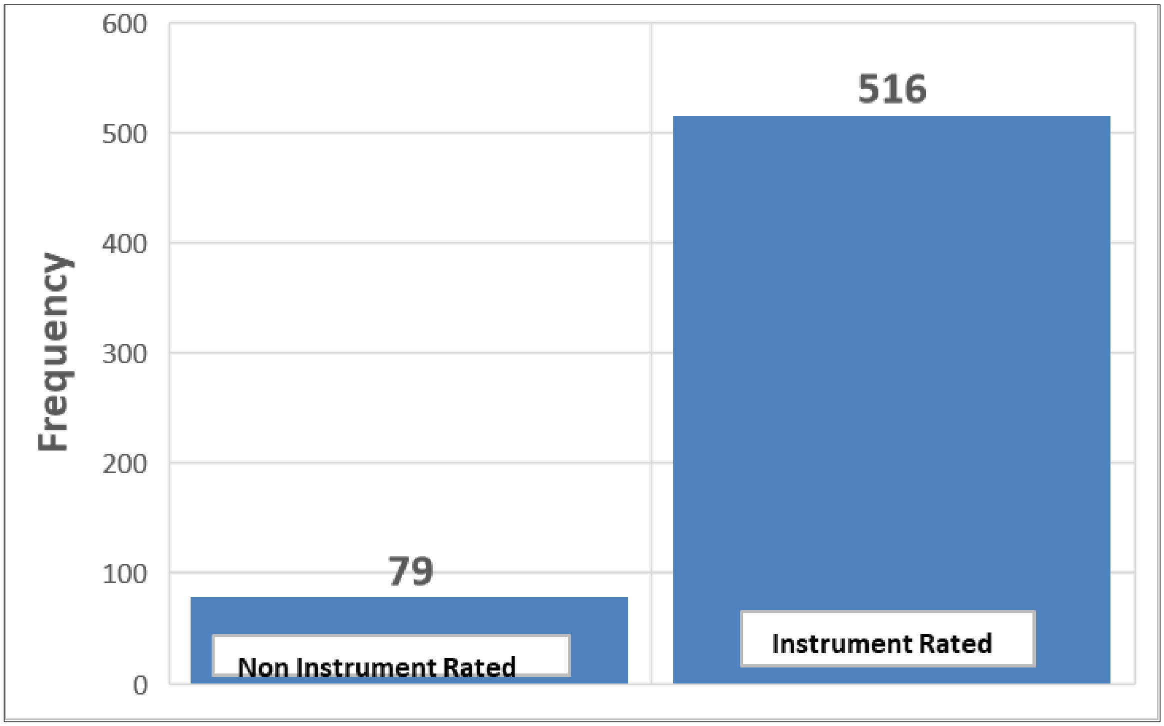

Figure 12: Distribution of Instrument Rating

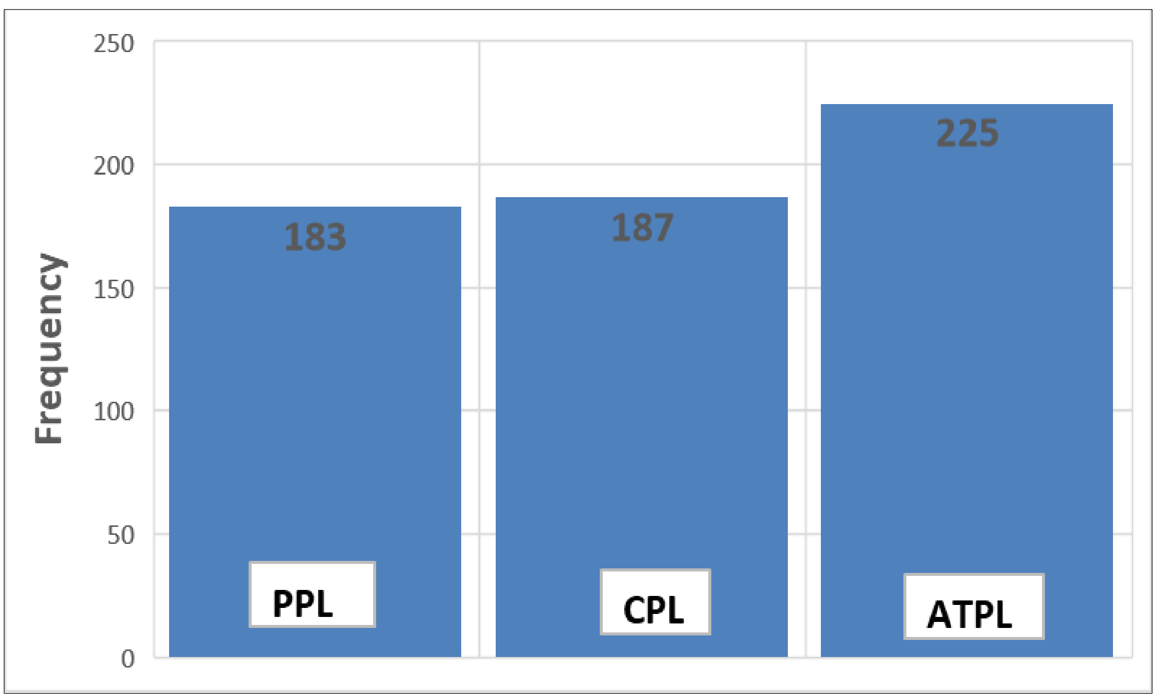

Figure 13: Distribution of Certificate Type

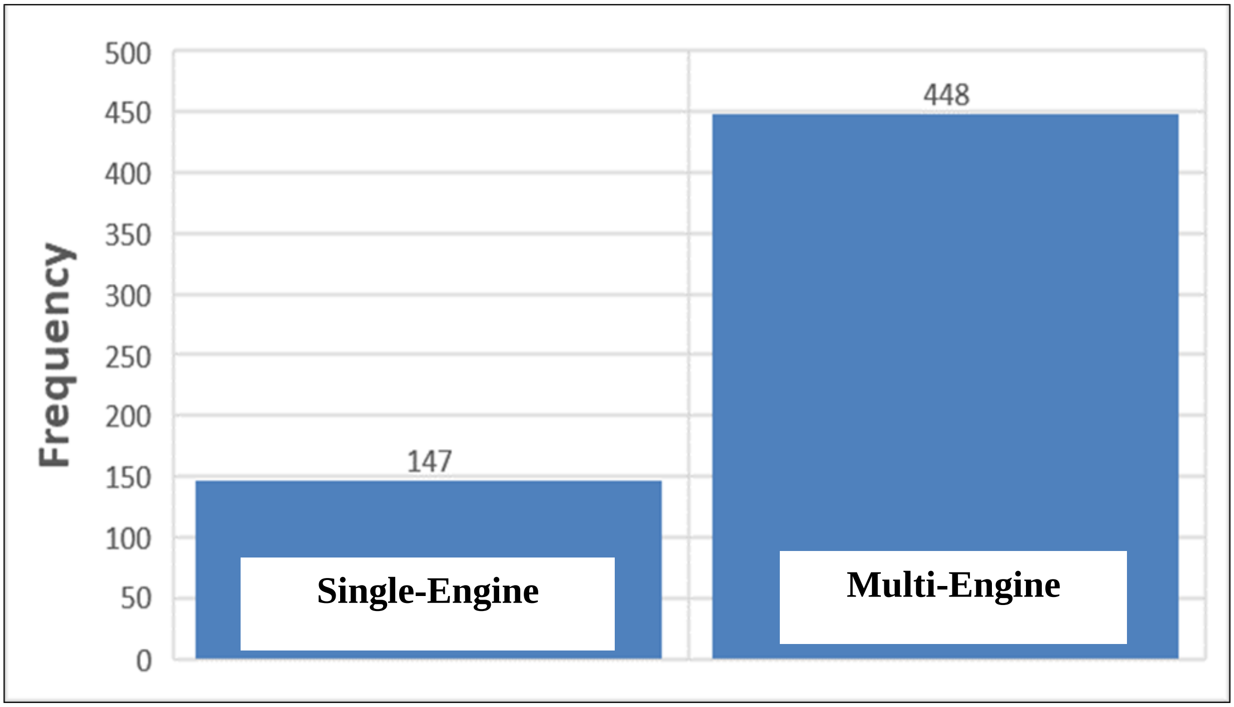

Figure 14: Distribution of Airplane Rating

5.2 Evaluation of Individual Experience Variables

Categorical Experience Variables. Chi-square tests on experience variables showed significant associations between accidents during adverse weather encounters and certificate type ($\chi^2 = 169.63$, $p < .001$), instrument rating ($\chi^2 = 122.03$, $p < .001$) and airplane rating ($\chi^2 = 196.97$, $p < .001$). Pilots with a private pilot's license were most highly associated with accidents (61.9%), compared to those with a commercial pilot's license (25.2%) or airline transport license (12.8%). Within the same certificate type, 73.8% of the pilots in the study with only a private license had accidents during adverse weather encounters, while only 26.2% who did not. The percentages dropped dramatically when pilots had already earned a commercial license (70.6% versus 29.4%) or an air transport pilots license (12.4% versus 87.6%). Pilots with only a private pilot's license made up 30.8% of the study pilots but were associated with 62.02% of the accidents during adverse weather encounters, while those with a commercial and airline transport license made up 31.4% and 37.8% but made up 25.13% and 12.8% respectively of the accidents. Details of the Chi-square results for certificate type are displayed in Figure 15 and Table 4, while the test of significance is shown in Table 5 below:

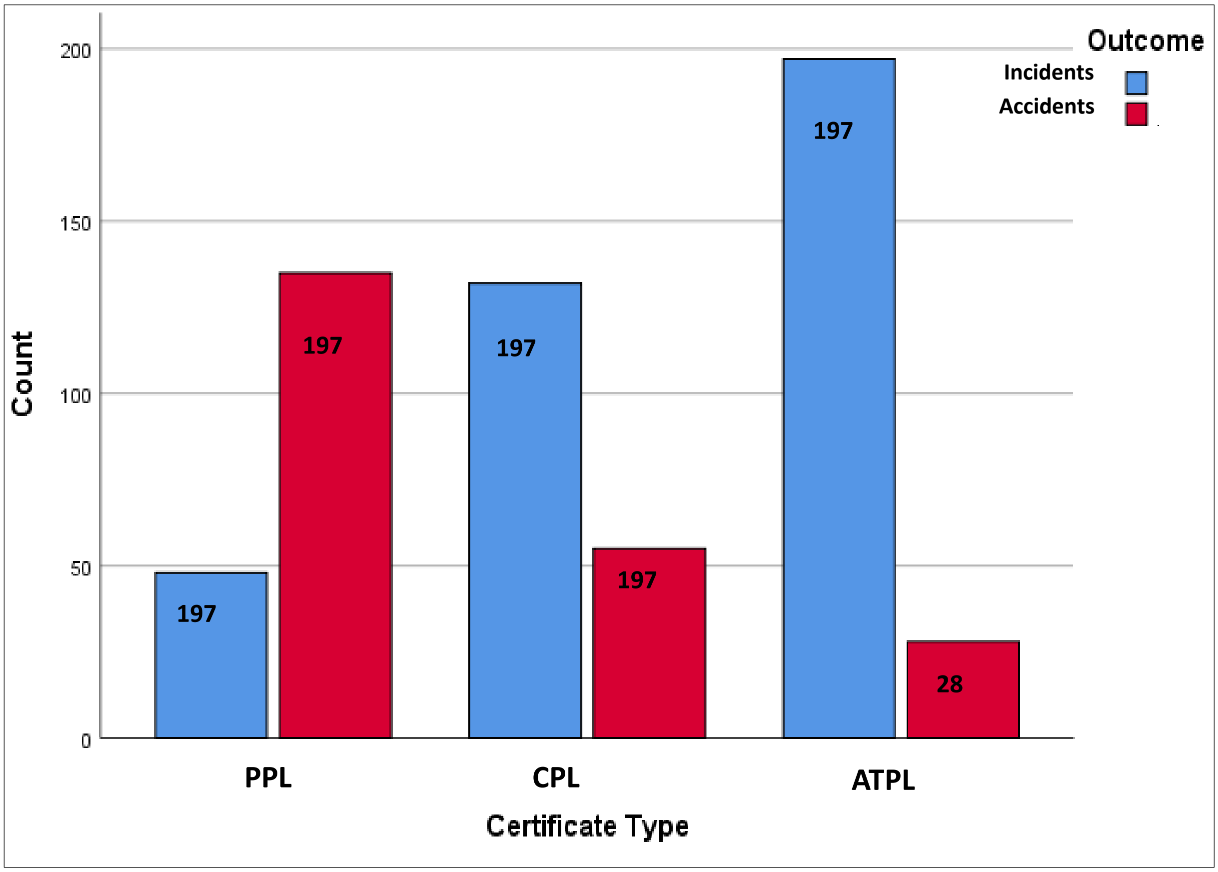

Figure 15: Chi-Square Tests for Certificate Type

Table 4: Chi-Square Tests for Certificate Type

			Outcome		*Total*
			Incidents	*Accidents*	
Certificate Type	*Private Pilot License*	*Count*	48	135	183
		Expected Count	116	67	183
		% within Certificate Type	26.20%	73.80%	100.00%
		% within Outcome	12.70%	61.90%	30.80%
		% of Total	8.10%	22.70%	30.80%
	Commercial Pilots License	*Count*	132	55	187
		Expected Count	118.5	68.5	187
		% within Certificate Type	70.60%	29.40%	100.00%
		% within Outcome	35.00%	25.20%	31.40%
		% of Total	22.20%	9.20%	31.40%
	Airline Transport License	*Count*	197	28	225
		Expected Count	142.6	82.4	225
		% within Certificate Type	87.60%	12.40%	100.00%
		% within Outcome	52.30%	12.80%	37.80%
		% of Total	33.10%	4.70%	37.80%
Total		*Count*	377	218	595
		Expected Count	377	218	595
		% within Certificate Type	63.40%	36.60%	100.00%
		% within Outcome	100.00%	100.00%	100.00%
		% of Total	63.40%	36.60%	100.00%

Table 5: Significance Table for Certificate Type Chi-Square Test

Chi-Square Tests			
Value		*df*	*Asymptotic Significance (2-sided)*
Pearson Chi-Square	169.628	2	0
Likelihood Ratio	175.595	2	0
Linear-by-Linear Association	159.035	1	0
N of Valid Cases	595		

Pilots without an instrument rating were more highly associated with accidents during adverse weather encounters, compared to those with an instrument rating. For pilots without an instrument rating, 92.4% had accidents, while only 7.6% did not. The association was reversed for pilots with an instrument; only 28.1% had accidents, while 71.9% did not. Instrument rated pilots made up 86.7% of pilots in the study and accounted for only 24.4% of the accidents. Non-instrument rated pilots on the other hand, accounted for 12.3% of pilots in the study and accounted for 12.3% of the accidents. Details of the Chi-square results for instrument rating are displayed in Figure 16 and Table 6, while the test of significance is shown in Table 7 below:

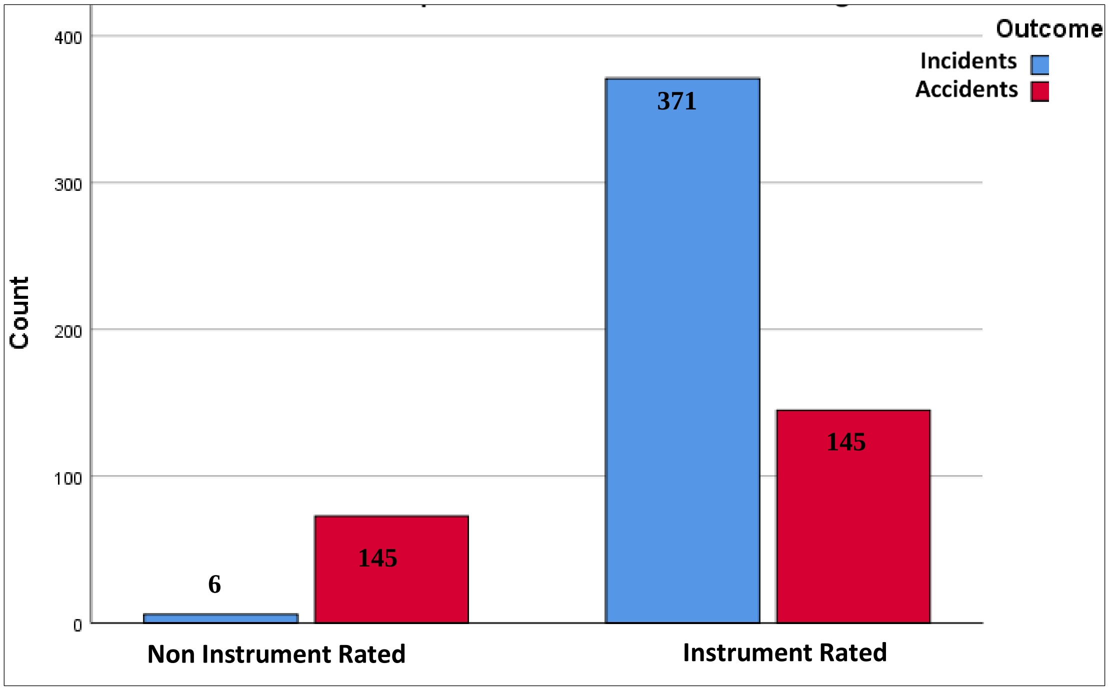

Figure 16: Chi-Square Tests for Instrument Rating

Table 6: : Chi-Square Tests for Instrument Rating

			Outcome		*Total*
			Incidents	*Accidents*	
Instrument Rating	*Non Instrument Rated*	*Observed*	6	73	79
		Expected	50.1	28.9	79
		% within Instrument Rating	7.60%	92.40%	100.00%
		% within Outcome	1.60%	33.50%	13.30%
		% of Total	1.00%	12.30%	13.30%
	Instrument Rated	*Count*	371	145	516
		Expected Count	326.9	189.1	516
		% within Instrument Rating	71.90%	28.10%	100.00%
		% within Outcome	98.40%	66.50%	86.70%
		% of Total	62.40%	24.40%	86.70%
Total		*Count*	377	218	595
		Expected Count	377	218	595
		% within Instrument Rating	63.40%	36.60%	100.00%
		% within Outcome	100.00%	100.00%	100.00%
		% of Total	63.40%	36.60%	100.00%

Table 7: Significance Table for Instrument Rating Chi-Square Tests

Chi-Square Tests					
Value		*df*	*Asymptotic Significance (2-sided)*	*Exact Sig. (2-sided)*	*Exact Sig. (1-sided)*
Pearson Chi-Square	122.033	1	0		
Continuity Correction	119.278	1	0		
Likelihood Ratio	126.463	1	0		
Fisher's Exact Test				0	0
Linear-by-Linear Association	121.827	1	0		
N of Valid Cases	595				

Pilots with a single-engine airplane rating were more highly associated with accidents during adverse weather encounters compared to those with a multi-engine airplane rating. Those with a single-engine rating made up 24.7% of the pilots studied, but accounted for 21% of the accidents. Those with a multi-engine airplane rating made up 75.3% and had only 15.6% of the accidents. Within pilots with a single engine rating, 85% had accidents, while only 15% did not, while the corresponding percentages were 20.8% and 79.2% respectively for pilots with a multi-engine rating. Details of the Chi-square results for airplane rating are displayed in Figure 17 and Table 8, while the test of significance is shown in Table 9 below:

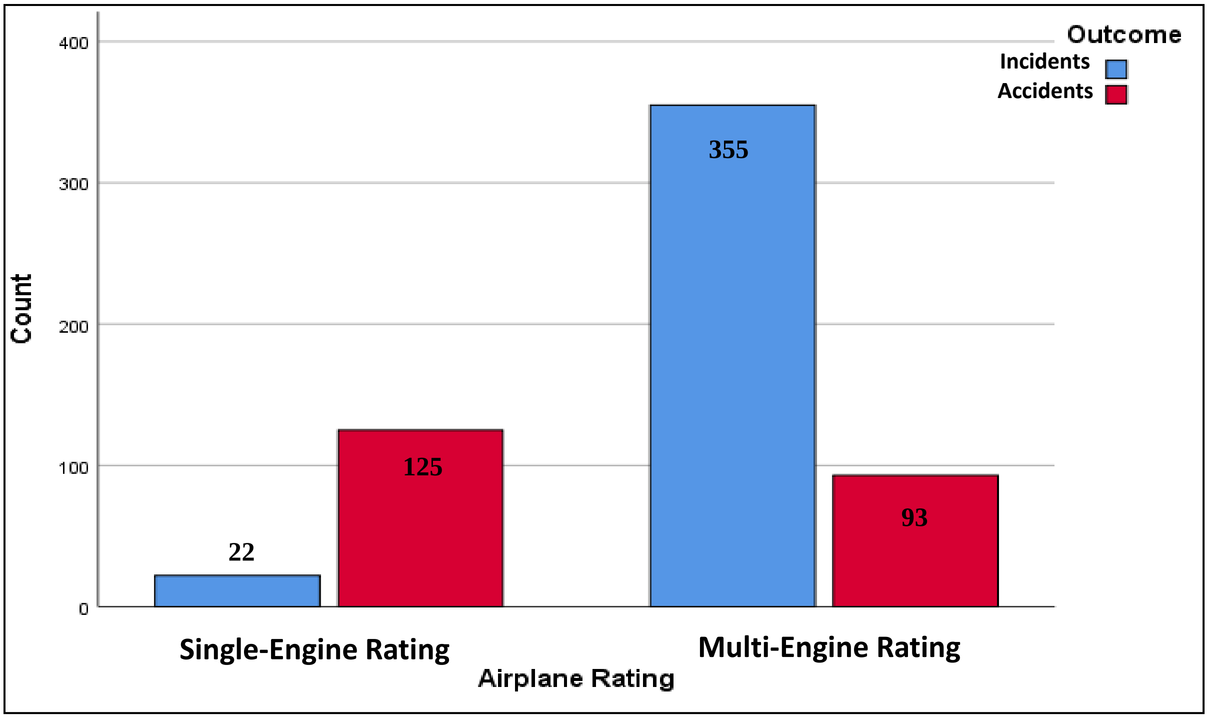

Figure 17:Chi-Square Tests for Airplane Rating

Table 8: Chi-Square Test for Airplane Rating

			Outcome		*Total*
			Incidents	*Accidents*	
Airplane Rating	*Single Engine Rating*	*Count*	22	125	147
		Expected Count	93.1	53.9	147
		% within Airplane Rating	15.00%	85.00%	100.00%
		% within Outcome	5.80%	57.30%	24.70%
		% of Total	3.70%	21.00%	24.70%
	Multi Engine Rating	*Count*	355	93	448
		Expected Count	283.9	164.1	448
		% within Airplane Rating	79.20%	20.80%	100.00%
		% within Outcome	94.20%	42.70%	75.30%
		% of Total	59.70%	15.60%	75.30%
Total		*Count*	377	218	595
		Expected Count	377	218	595
		% within Airplane Rating	63.40%	36.60%	100.00%
		% within Outcome	100.00%	100.00%	100.00%
		% of Total	63.40%	36.60%	100.00%

Table 9: Significance Table for Airplane Rating Chi-Square Tests

Chi-Square Tests					
Value		*df*	*Asymptotic Significance (2-sided)*	*Exact Sig. (2-sided)*	*Exact Sig. (1-sided)*
Pearson Chi-Square	196.97	1	0		
Continuity Correction	194.211	1	0		
Likelihood Ratio	200.105	1	0		
Fisher's Exact Test				0	0
Linear-by-Linear Association	196.639	1	0		
N of Valid Cases	595				

Continuous Experience Variables. There were significant associations between total flight hours, (χ^2 = 109.37, p < 0.00), hours in the last 90 days (χ^2 = 16.22, p<0.00) and hours in airplane make and model (χ^2 = 19.83, p < 0.00) and the outcome of adverse weather accidents. For total flight hours, the largest differences existed between pilots within the lowest and highest categories. Pilots with 250 total flight hours or less accounted for 8.9% of the total number of accidents pilots but were associated with 20.20% of the accidents during adverse weather encounters. At the other end, pilots with more than 1500 total flight hours accounted for 60% of the total number of accidents pilots in the study and were associated with 34.4% of the accidents. Pilots that had between 251 and 1500 total flight hours made up 31.1% of accident pilots and were associated with 45.4% of the total accidents. Pilots with 250 total flight hours or less were much more associated with accidents (83%) than incidents (17%). Those with between 251 to 1500 total flight hours were more evenly spread (53.50% and 46.50% for accidents and incidents respectively). The percentages for accident and incident were 79% and 21% respectively for pilots who had more than 1500 total flight hours. Details of the Chi-square results for certificate type are displayed in Figure 18 and Table 10, while the test of significance is shown in Table 11.

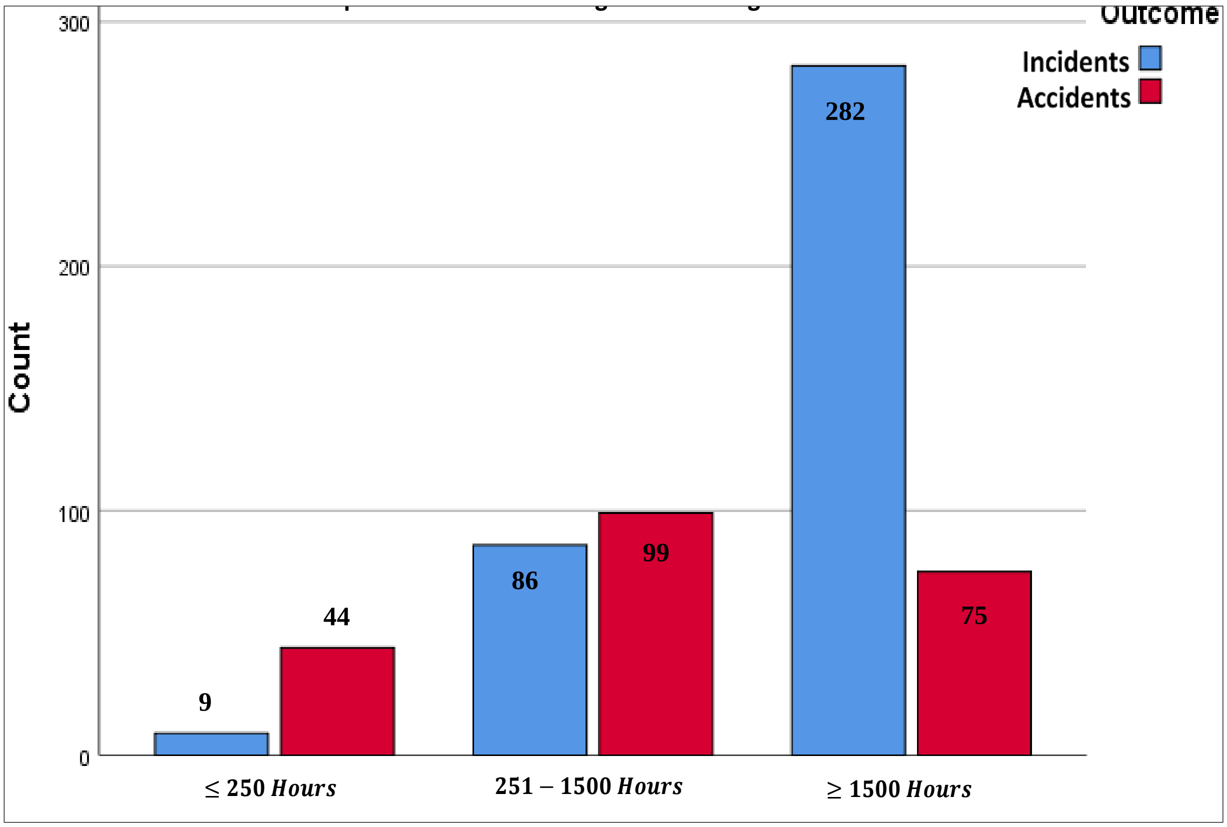

Figure 18: Chi-Square Tests for Total Flight Hour Categories

Table 10: Chi-Square Tests for Total Flight Hour Categories

			Outcome		*Total*
			Incidents	*Accidents*	
Total Flight Hour Categories (TFH_Cats)	*0-250 Total Flight Hours*	*Count*	9	44	53
		Expected Count	33.6	19.4	53
		% within TFH_Cats	17.00%	83.00%	100.00%
		% within Outcome	2.40%	20.20%	8.90%
		% of Total	1.50%	7.40%	8.90%
	251 - 1500 Total Flight Hours	*Count*	86	99	185
		Expected Count	117.2	67.8	185
		% within TFH_Cats	46.50%	53.50%	100.00%
		% within Outcome	22.80%	45.40%	31.10%
		% of Total	14.50%	16.60%	31.10%
	> 1500 Total Flight Hours	*Count*	282	75	357
		Expected Count	226.2	130.8	357
		% within TFH_Cats	79.00%	21.00%	100.00%
		% within Outcome	74.80%	34.40%	60.00%
		% of Total	47.40%	12.60%	60.00%
Total		*Count*	377	218	595
		Expected Count	377	218	595
		% within TFH_Cats	63.40%	36.60%	100.00%
		% within Outcome	100.00%	100.00%	100.00%
		% of Total	63.40%	36.60%	100.00%

Table 11: Significance Table for Chi-Square Test on Total Flight Hour Categories

Chi-Square Tests			
Value		*df*	*Asymptotic Significance (2-sided)*
Pearson Chi-Square	109.373	2	0.00
Likelihood Ratio	110.948	2	0.00
Linear-by-Linear Association	109.100	1	0.00
N of Valid Cases	595		

For hours in last 90 days, 54.8% of all the pilots studied were in the lower median, while 45.2% were in the upper median. However, 65.6% of pilots in the lower median were associated with accidents, while only 34.4% of those in the upper category were. A larger percentage of pilots in the lower category were associated with accidents (43.9%), compared to those in the upper median

(27.9%). Details of the Chi-square results for certificate type are displayed in Figure 19 and Table 12, while the test of significance is shown in Table 13 below:

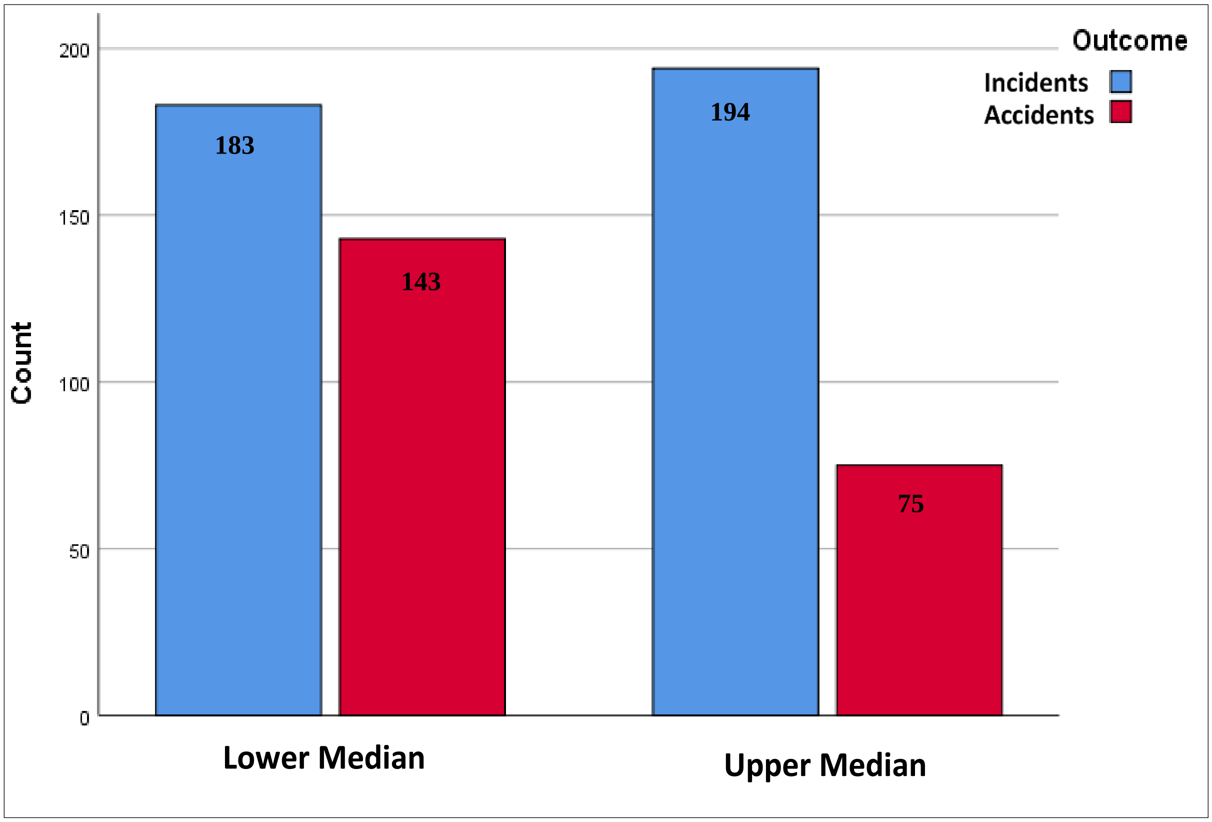

Figure 19: Chi-Square Test for Hours in Last 90 Days

Table 12: Chi-Square Test for Hours in Last 90 Days

			Outcome		Total
			Incidents	Accidents	
Hours in Last 90 Days (Last_90Cats)	*Lower Median*	*Count*	183	143	326
		Expected Count	206.6	119.4	326.0
		% within Last_90 Cats	56.1%	43.9%	100.0%
		% within Outcome	48.5%	65.6%	54.8%
		% of Total	30.8%	24.0%	54.8%
	Upper Median	*Count*	194	75	269
		Expected Count	170.4	98.6	269.0
		% within Last_90Cats	72.1%	27.9%	100.0%
		% within Outcome	51.5%	34.4%	45.2%
		% of Total	32.6%	12.6%	45.2%
Total		*Count*	377	218	595
		Expected Count	377.0	218.0	595.0
		% within Last_90Cats	63.4%	36.6%	100.0%
		% within Outcome	100.0%	100.0%	100.0%
		% of Total	63.4%	36.6%	100.0%

Table 13: Significance Table for Chi-Square Test on Hours in Last 90 Days

Value		*df*	*Asymptotic Significance (2-sided)*	*Exact Sig. (2-sided)*	*Exact Sig. (1-sided)*
Pearson Chi-Square	16.22	1	0		
Continuity Correction	15.539	1	0		
Likelihood Ratio	16.421	1	0		
Fisher's Exact Test				0	0
Linear-by-Linear Association	16.193	1	0		
N of Valid Cases	595				

Hours in airplane make and model followed the same trend as hours in the last 90 days. A total of 51.8% of all the pilots studied were in the lower median, while 48.2% were in the upper median.

However, 63.8% of pilots in the lower median were associated with accidents, while only 36.2% of those in the upper category were. A larger percentage of pilots within the lower median were associated with accidents (45.1%), compared to the percentage in the upper median (27.5%). Details of the Chi-square results for certificate type are displayed in Figure 20 and Table 14, while the test of significance is shown in Table 15 below:

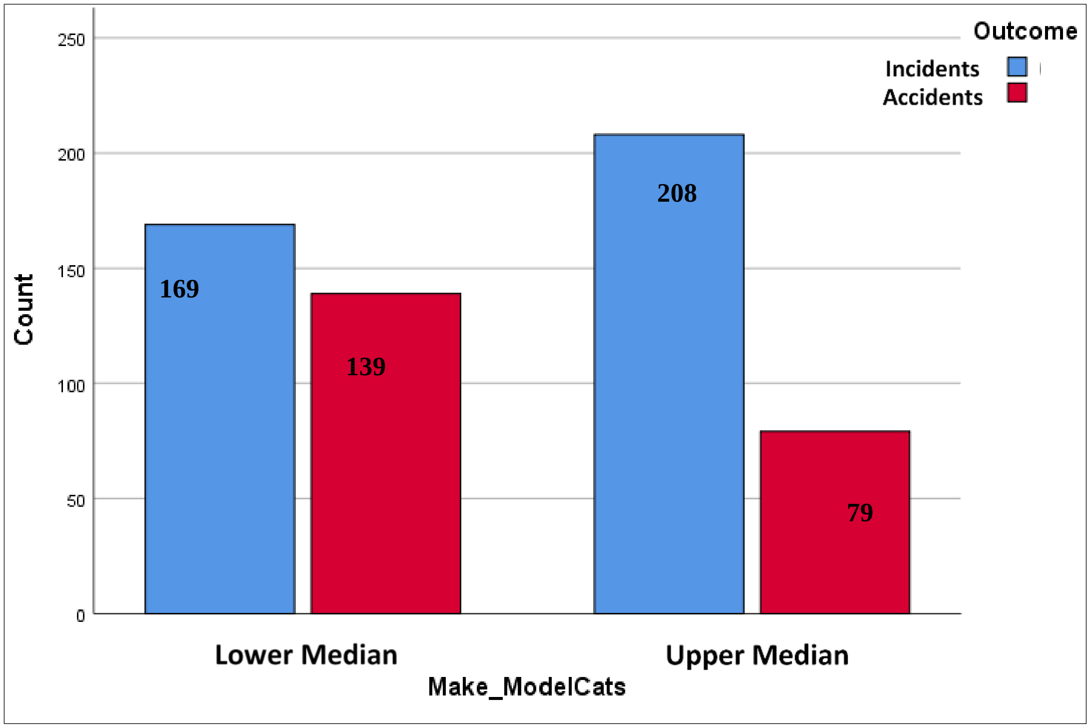

Figure 20: Chi-Square Test for Hours in Make and Model

Table 14: Chi-Square Test for Hours in Make and Model

			Outcome		Total
			Incidents	*Accidents*	
Make_ModelCats	*1.00*	*Count*	169	139	308
		Expected Count	195.2	112.8	308.0
		% within Make_ModelCats	54.9%	45.1%	100.0%
		% within Outcome	44.8%	63.8%	51.8%
		% of Total	28.4%	23.4%	51.8%
	2.00	*Count*	208	79	287
		Expected Count	181.8	105.2	287.0
		% within Make_ModelCats	72.5%	27.5%	100.0%
		% within Outcome	55.2%	36.2%	48.2%
		% of Total	35.0%	13.3%	48.2%
Total		*Count*	377	218	595
		Expected Count	377	218	595
		% within Make_ModelCats	63.4%	36.6%	100.0%
		% within Outcome	100.0%	100.0%	100.0%
		% of Total	63.4%	36.6%	100.0%

Table 15: Significance Table for Chi-Square Test on Hours in Make and Model

	Value	*df*	*Asymptotic Significance (2-sided)*	*Exact Sig. (2-sided)*	*Exact Sig. (1-sided)*
Pearson Chi-Square	19.832	1	0.000		
Continuity Correction	19.081	1	0.000		
Likelihood Ratio	20.029	1	0.000		
Fisher's Exact Test				0.000	0.000
Linear-by-Linear Association	19.798	1	0.000		
N of Valid Cases	595				

5.3 Logistics Regression Model

A multi-predictor logistic regression model based on the results of the Chi-Square tests was fitted to the data to identify which of the variables deemed significantly associated with accidents by the Chi-square tests were most predictive of the likelihood of accidents. The objective was to develop a model that predicts the likelihood of accidents so that the hypothesis that pilots with lower levels of different combinations of different experience variable were more vulnerable to accidents during adverse weather encounters could be tested. The logistic regression analysis was carried out with IBM® SPSS Statistics Version 26 in a Windows 10 Operating System Environment. Private pilot's license was set as the reference category for certificate type and the continuous experience variable were not broken into categories. The results of the logistic regression are detailed in Table 16.

Table 16: Logistic Regression Results for First Study

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*	*95% C.I .for EXP(B)*	
							Lower	*Upper*
Total Flight Hours	0.000	0.000	0.401	1	0.527	1.000	1.000	1.000
Hours in Last 90 Days	0.002	0.002	0.913	1	0.339	1.002	0.998	1.005
Hours in Make and Model	0.000	0.000	0.577	1	0.447	1.000	1.000	1.000
Instrument Rating	-1.623	0.486	11.137	1	0.001	0.197	0.076	0.512
Certificate Type			13.040	2	0.001			
Commercial Pilot License	-0.556	0.321	3.000	1	0.083	0.574	0.306	1.076
Air Transport Pilot License	-1.400	0.398	12.386	1	0.000	0.247	0.113	0.538
Multi Engine Rating	-1.801	0.345	27.336	1	0.000	0.165	0.084	0.324
Constant	4.604	0.607	57.568	1	0.000	99.904		

From the model, the log odds of accidents during adverse weather encounters decreased significantly for pilots who had an instrument rating ($\beta = -1.62$; $p < .001$; OR = 0.20, 95% CI: .08 - .51), had an air transport pilots license (($\beta = -1.40$; $p < .001$; OR = 0.25, CI: .11 - .54) and a multiple-engine rating ($\beta = -1.80$; $p < .001$; OR = 0.17, CI: .08 -.32). Commercial pilot license was significant at the .1 level of significance ($\beta = -1.62$; $p < .08$; OR = 0.57).

As aggregates, neither total flight hours, hours flown in the last 90 days nor hours flown in airplane make and model had a significant effect on the odds of accidents during adverse weather encounters.

5.4 Evaluation of the Logistics Regression Model and Validation of Predicted Probabilities

The regression model fitted to the data was statistically significant (X^2 =239.91, (7), $p < .001$), with a -2 log likelihood of 541.92. The Hosmer & Lemeshow goodness-of-fit test was (X^2 = 10.51, (8), $p > .05$). The Nagelkerke R Square value was .45, while the Cox & Snell R Square value was 0.33. The overall predictive power for the model was 82%. Details are in Table 17.

Table 17: Model Evaluation, Fit and Validation Statistics for Logistic Regression Model

Test of Model Coefficients	X^2 =239.91, (7), $p < .001$
-2Log-Likelihood	541.92
Nagelkerke R Square	0.45
Cox & Snell R Square	0.33
Hosmer & Lemeshow Test	X^2 = 10.51, (8), $p > .05$
Overall Predictive Power	81.80%

5.5 Reduced Logistic Regression Model

A more parsimonious logistic regression model was fitted to the data using only independent variables significant from the full model. There were little or no changes in either coefficients for the predictor variables or model evaluation statistics. The model fit and validation statistics were also similar to those for the full logistic regression model. Details of the reduced model and model evaluation, fit and validation statistics are detailed in Tables 18 and 19.

Table 18: Results of Reduced Logistic Regression Model

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*	*95% C.I. for EXP(B)*	
							Lower	*Upper*
Instrument Rating	-1.614	0.486	11.035	1	0.001	0.199	0.077	0.516
Certificate Type			18.585	2	0.000			
Commercial Pilot License	-0.504	0.311	2.626	1	0.105	0.604	0.328	1.111
Air Transport Pilot License	-1.387	0.344	16.249	1	0.000	0.250	0.127	0.490
Airplane Rating	-1.797	0.344	27.351	1	0.000	0.166	0.084	0.325
Constant	4.645	0.606	58.783	1	0.000	104.057		

Table 19: Model Evaluation, Fit and Validation Statistics Reduced Logistic Regression Model

Test of Model Coefficients	X^2 =238.11, (4), $p < .001$
-2Log-Likelihood	543.72
Nagelkerke R Square	0.45
Cox & Snell R Square	0.33
Hosmer & Lemeshow Test	X^2 = 1.334 (3), $p > .05$
Overall Predictive Power	81.80%

The results presented in this chapter are interpreted and their significance discussed in the next chapter.

CHAPTER 6. DISCUSSION – FIRST STUDY

This study sought to determine pilot experience variables most associated with, and predictive of the likelihood of an accident during encounters with adverse weather in General Aviation. Much of the previous research carried out in this area have involved the use of simulation and surveys to identify risk factors associated with accidents during adverse weather encounters or the decision-making processes that contribute to such accidents (Lanicci et al., 2012). Amongst other factors, poor situation assessment and experience have been proposed as important factors in weather related accidents (Wiegmann and Goh, 2001). Experience is believed to enable more accurate situation assessment and decision making during dynamic, safety critical encounters in which time pressure exists. How different aspects of pilot experience facilitate this during encounters with adverse weather, or which specific elements of experience more significantly impact the likelihood of accidents is not quite clear. In this study, experience data for pilots who had accidents from actual encounters with adverse weather during the cruise phase of GA part 91 fixed wing flights was compared with that of pilots who did not, to identify and quantify differences between the two groups. The purpose, therefore, was to determine the relationship between each of six elements of experience considered in this study and the outcome of encounters with adverse weather and then develop a model predictive of the likelihood of an accident given different levels of each experience variable.

6.1 Associations between Experience and Accidents.

There were significant differences between accident and non-accident pilots on each of the experience variables evaluated in this study. Lower levels of each experience element were significantly associated with accidents during adverse weather encounters compared to higher levels for each. This result agrees with those from several previous research efforts that have variously found different elements of experience to be associated with the outcome of adverse weather encounters (Shappell, et al., 2010; Johnson, & Wiegmann, 2015; Li, et al., 2001; Burian, et al., 2000; NTSB, 2005; Wiegmann, et al., 2002). However, the results also appear to contradict findings from some other studies that have reported no associations between some of the experience elements and the outcome of adverse weather encounters (Wiegmann, et al., 2001;

Burian, et al., 2000; Coyne, et al., 2008; Wiggins, 2014). This was expected, given the contradictory findings on the issue in published research literature. However, the results in this study were obtained from the experience profile of 595 real pilots who flew real missions and therefore, have a high level of ecological validity.

6.2 Dimensions of Experience – Length Versus Breadth of Experience

The elements of experience in this study fell into either of two categories. The first were flight hour-based and delineated experience in terms of length/duration, while the second were license/certification-based and expressed experience in terms of breadth/variety. The relationship between the latter set of experience variables (instrument rating, airplane rating and certificate type) and accidents during adverse weather encounters was much clearer and consistent. Results from the Chi-square tests and logistic regression showed higher levels of each variable (CPL over PPL; ATPL over CPL and PPL) led to significantly reduced association with, and odds of accidents during adverse weather encounters. For example, the Chi-square tests showed that in terms of accidents given pilots' certificate type, those with a 61.9% of accident pilots had a PPL, while only 25.2% and 12.8% had a CPL and ATPL respectively. The results of the Chi-square tests followed a similar pattern for purely dichotomous independent experience variables. For instance, 92.4% of pilots without instrument rating were associated with accidents, compared to only 28.1% of pilots that were instrument rated.

Results from the logistic regression model confirmed that the categorical variables were indeed significant predictors of the likelihood of accidents during adverse weather encounters. All the categorical independent experience variables had increasingly negative coefficients with increasing levels of the variable. For instance, with private pilot's license set as the reference pilot certification category, the logistic regression coefficient was -0.556 for a commercial pilot's license and -1.40 for an air transport pilot's license. Although the coefficient for commercial pilot's license was significant at the .1 level of significance rather than the .05 level, increasing levels of all categorical variables considered in the study had an insulating effect against accidents during adverse weather encounters.

Unlike variables that expressed experience in terms of breadth/variety, the relationship between the length/duration-based experience variables (total flight hours, hours in make and model and hours in last 90 days) and accidents during adverse weather encounters was not quite clear. Although Chi-square tests on categorized levels of each duration variable showed statistically significant and increasing associations between increasing levels of each variable and accidents during adverse weather encounters similar to the breadth/variety experience variables, the results of the logistic regression was completely different from the case with the latter. As aggregates, none of the length-based experience variables were statistically significant. Indeed, there was no change in the odds of accidents during adverse weather encounters with increasing levels of any of the length/duration experience elements.

The foregoing suggests variables related to the breadth or variety of General Aviation pilots' experience are more predictive of the likelihood of accidents during adverse weather encounters compared to those related to the duration or length of experience. There was no change in the efficacy of a reduced logistic regression model without flight hour related variables to accurately discriminate and predict correct responses, and the predictive power of the reduced model remained at value remained at 81.80%. This result was somewhat baffling, because it affirmed none of the flight hour related variable is predictive of the likelihood of accidents during adverse weather encounters, despite clear associations between these variables and accidents identified by the Chi-square tests. There were significant differences in association with accidents between lower and higher categories of each variable. One reason for this may be because both sets of pilots in the study could be considered quite experienced considering the fact that the mean and median total flight hours in this study were much higher than values used to distinguish between experienced and novice pilots in previous studies as detailed in Appendix B.

It is plausible from the foregoing that the length of experience may only be a significant factor in preventing accidents up to a certain point, or between certain ranges of total flight hours and not others. For instance, 83% of pilots with 250 total flight hours or less were associated with accidents, but this reduced to 53% for pilots with 251 to 1500 total flight hours and then to only 21% for pilots with more than 1500 total flight hours. Whether this trend is due to increasing total flight hours or due only to the addition of breadth/variety elements of experience is not clear.

The findings in this first study have some implications for the evaluation of experience. The aviation community traditionally measures pilot experience by the total number of flight hours accumulated (NTSB, 2005; Burian, Orasanu and Hitt, 2000; Li and Baker, 1999). A pilot's total flight hours is the primary eligibility criterion for additional certifications and/or licenses. There is some anecdotal evidence to suggest total flight hours is an important but insufficient measure of experience. Much of this evidence has come from stories of pilot encounter with adverse weather encounters and studies primarily carried out using computer based simulations of adverse weather flying conditions. Such evidence has therefore, been inconclusive. A major reason for this has been that the extent to which results from laboratory based studies can be extrapolated to actual flying is unclear. However, the results in this study provide empirical, ecologically valid evidence that total flight hours as a single measure, is indeed an insufficient determinant of experience.

Results from this study show the likelihood of accidents during adverse weather encounters reduced significantly, as the variety/breadth of pilots' experience increased, especially in what may be considered low to intermediate ranges of flight hour related variables. Similar results were not obtained for the duration-based experience variables. These results therefore, reaffirm suggestions that cognate or task related experience significantly impact pilot judgement and performance during adverse weather encounters (Wiggins and O'Hare, 1995; 2003; Kochan et al, 1997). The results also agree with findings from studies on expertise in other fields, suggesting a wide variety of experience, spanning the spectrum of tasks within a domain expedite the transition from novice to expert operator within the domain (Ericsson and Charness, 1994; Ericsson, 2004).

In terms of situation assessment and decision making, the recognition primed decision making model which is based on the recognition of patterns within a situation, presupposes the decision maker has had enough experience with similar situations to have built up an adequate repertoire of solutions from which to draw upon. Klein (1989) observed that "experience enables a person to understand a situation in terms of plausible goals, relevant cues, expectancies, and typical actions." Furthermore, the selection of a course of action in recognition primed decision making is intuitive, which also requires a fair amount of cognate experience. A unidimensional measure of experience, based on total number of flight hours alone may therefore, be somewhat deficient, lacking the resolution or discriminatory power required to fully elucidate the nature of experience. If this is the case, our ability to take advantage of the insulating effect of experience on erroneous decision making during adverse weather encounters may be limited. Defining experience using only one of its attributes restricts our ability to influence its acquisition by limiting the range of training to which pilots could be exposed.

Expertise is generally believed to result from the accumulation of experience over time, but there is some debate over how long it takes to become an expert. The results from this study suggest the variety of experience may be more impactful towards achieving expertise than its duration. The knowledge can be leveraged to design specifically targeted training interventions to increase those aspects of weather decision making experience determined to most significantly impact the outcome of adverse weather encounters for pilots with deficiencies in those areas. In this way, it may be possible to expedite the transition from novice to expert pilots in weather-related decision making.

CHAPTER 7. METHOD FOR SECOND STUDY

This chapter presents the methodology for the second study. The conjecture underpinning the study is first discussed, followed by the methodology, which details the dependent and independent variables, hypotheses and statistical model developed to test them.

7.1 Acquisition of Pilot Experience

The aviation community traditionally evaluates pilot experience by the total flight hours accumulated. Generally, pilot experience and therefore, accident vulnerability is treated as a linear function of the number of flight hours accumulated (Knecht, 2015). However, there is no empirical evidence to suggest this is the case. Indeed, there has been some attempt to link total flight hours and accident rates using a gamma based function, with some success (Knecht, 2015). In practice however, pilots acquire experience along hypothetical continuum. This hypothetical continuum may be considered to consist of a horizontal component defined by the length of experience and a vertical component defined by the variety of experience possessed by the pilot. The length of experience is parameterized by the total flight hours accumulated and can be broken into three distinct zones based on Federal Aviation Regulations. The zones are as described in the previous study and include 0-250 total flight hours, 251 – 1500 total flight hours, and > 1500 total flight hours. The variety of experience is parameterized by different categorical experience variables, and some of these elements can only be acquired within specific zones. This framework for the acquisition of experience in practice is depicted Figure 21:

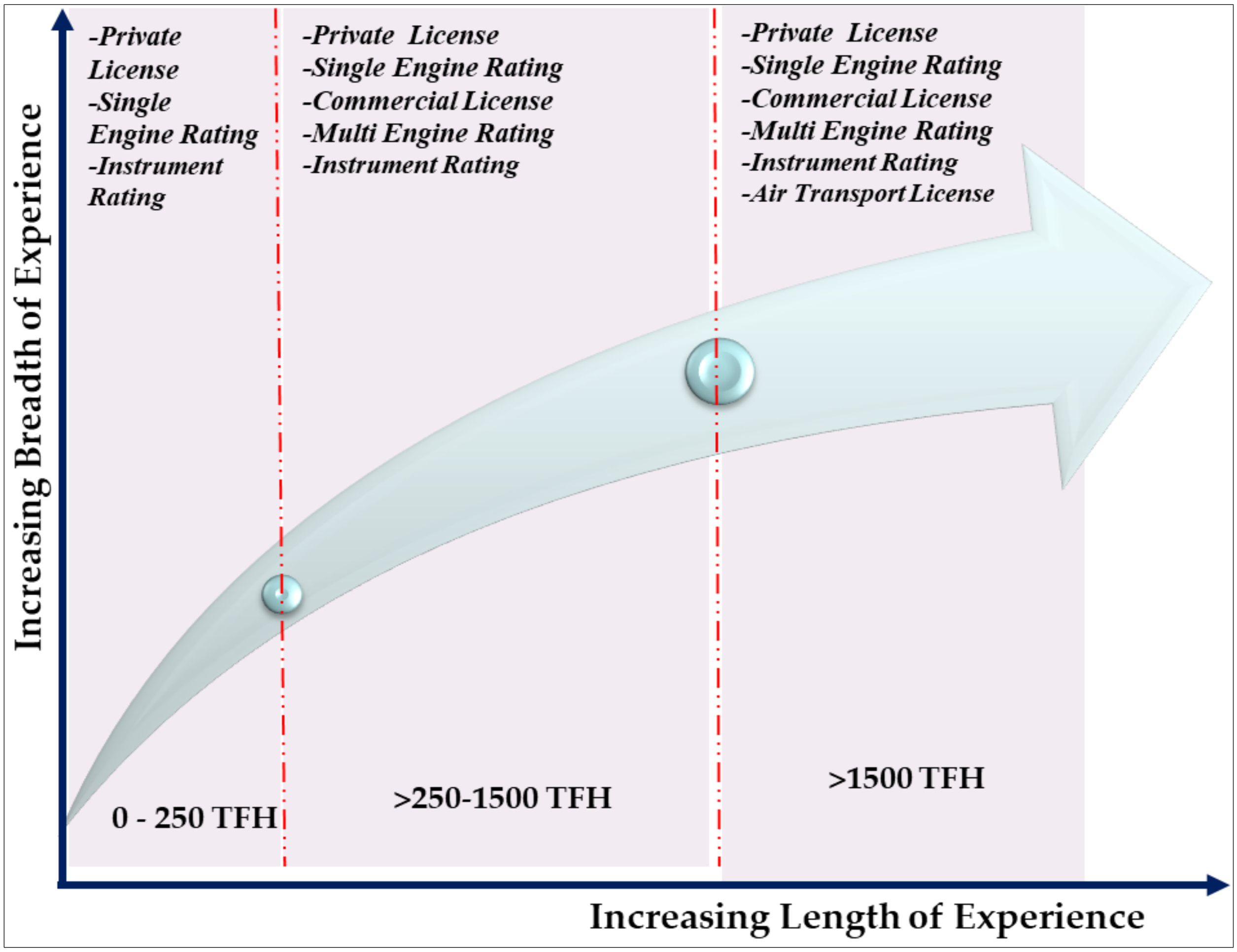

Figure 21: Framework for Acquisition of Pilot Experience

Based on the foregoing therefore, it is reasonable to conject that pilot experience is not a linear function of total flight hours. As pilots acquire total flight hours, some interaction occurs between experience elements along both the horizontal and vertical dimensions. Overall pilot experience, therefore, is some function of the interaction of multiple elements of experience. Consequently, since it is generally understood that experience insulates pilots from erroneous decision making during encounters with adverse weather, this function that determines overall pilot experience also determines the extent to which it insulates pilots and accordingly, the likelihood of accidents during adverse weather encounters.

In the first study, elements that address the length/duration of a pilot's experience were found to be associated with the outcome of adverse weather encounters but not predictive of the likelihood of the outcome of such encounters. It was surmised that the elements are an important but insufficient measure of pilot experience. United States Federal Aviation Regulations only mandate pilot certifications or licenses as eligibility preconditions to independently carry out specified kinds of flight operations (U.S. CFR 14, 1F, Part 91). For instance, a private pilot's license is required to independently operate a flight, a commercial pilots license is required to operate a flight for reimbursement and so on. It is, therefore, not uncommon to find pilots who have never chosen to acquire additional licenses or ratings other than a private license and single engine rating. It is reasonable to believe such pilots grow in experience over time. However, they may not benefit from the insulating effect of elements of experience that address the breadth of experience and their overall experience may increase more slowly than if they had those elements. Yet, many of such pilots fly for extended periods without accident. It therefore seems that on its own, increasing total flight hours provides some insulating effect against accidents, and the results of the Chi-square tests from the first study indicate that is the case. What is unclear is how the likelihood of accidents for such pilots change over time and how that compares with pilots who have additional elements of experience.

7.2 Conjecture and Logistic Regression Model

Research on the acquisition of expertise indicates that expert performance in any task results from exposure to a wide range of scenarios across the task spectrum (Adams and Ericsson, 1991; Ericsson and Charness, 1994; Ericsson, 2004; Wiggins and O'Hare, 1995; 2003; Kochan et al, 1997). In aviation, each additional license and certification requires pilots to demonstrate some level proficiency in a range of flight related tasks. For instance, it is possible to obtain a private pilot's license with little or no weather knowledge and minimal instrument flying skills (Carney et al. 2015). However, to earn an instrument rating, pilots must amongst other requirements, demonstrate some level of competence on the acquisition and use of weather information as well as the use of cockpit instruments and other aids to where necessary, safely evaluate the weather situation and decide how to proceed to ensure a safe outcome. Additional requirements for knowledge, skills and abilities also exist for other licenses and certifications. These requirements ensure pilots are exposed to, acquire and demonstrate some level of proficiency a wide spectrum of tasks that may be encountered in the course of operations permitted by the license or ratings possessed.

This, therefore, implies:

Pilots with experience spanning both hypothetical experience dimensions will have significantly reduced likelihood of accidents during adverse weather encounters compared to those with experience only along one dimension (total flight hours only).

To test this conjecture, a hierarchical logistic modelling approach was adopted, and each element of experience was introduced successively into the model in the order in which it is acquired in practice. The logistic regression models for this study were developed to closely mimic the accumulation of experience in practice. Changes in likelihood of accidents during adverse weather encounter were then evaluated for each additional element of experience added to the model. The aim was to determine the effect of each additional element of experience on the likelihood of accidents during adverse weather encounters.

7.3 Dependent and Independent Variables

The dependent variable for this study was the outcome of adverse weather encounters, coded "0" for incidents and "1" for accidents. Incidents were defined as encounters that did not result in loss of life, injury to persons, or damage to property. Accidents were encounters that did. Total flight hours was added to the three experience variables found to be significant from the first study. The three categories describes previously (<=250 flight hours, 251 – 1500 flight hours, and > 1500 flight hours), based on Federal Aviation Regulations were used respectively for the three zones in the framework as discussed in section 7.1. Hours flown in the last 90 days and hours flown in airplane make and model were excluded from this study since they were not significant from the first study. As in the first study, the regulatory categories of the categorical experience variables were retained. Therefore, airplane rating had two categories: Single Engine Rating and Multi-Engine Rating; certificate type had three categories: Private Pilot's License (PPL), Commercial Pilots License (CPL) and Airline Transport Pilots License (ATPL).

In addition to each independent variable added successively to the model, interactions terms were included in the logistic regression model to evaluate the effect of potential interactions that occur as breadth elements are added to total flight hours. For instance, if a pilot earned an instrument rating after a private license, the logistic regression model included total flight hours, instrument rating and a total flight hours * instrument rating interaction term.

7.4 Analysis Methodology

An initial reference logistic regression model was first developed based on the stated conjecture to determine the likelihood of accidents assuming that elements of experience that define the breadth of experience interact with total flight hours, which determines its length. The model was then evaluated to ascertain for significance, fit and predictive power. Next, a hierarchical approach was adopted, and different elements of experience were incrementally added to total flight hours within each of the three experience acquisition zones discussed in section 7.1. As successive certifications, licenses and interaction terms were added to the model, the model was evaluated to determine changes to the reference model, significance of individual predictors goodness of fit for the model. Finally, the predicted probabilities for each iteration was assessed and compared to the base line as well as to previous models within the experience acquisition zone.

CHAPTER 8. RESULTS FOR SECOND STUDY

In this chapter, detailed results from the second study are presented, as a prelude to the discussion of the implications of the results in the next chapter. A multivariable logistic regression model was fitted to the data to test the hypotheses that pilots with multi-dimensional experience profile have a lower likelihood of accidents during adverse weather encounters compared to pilots with unidimensional experience profile. The logistic regression analysis was carried out with IBM® SPSS Statistics Version 26 in a Windows 10 Operating System Environment.

8.1 Reference Logistic Regression Model with Interaction Terms

The results of the reference logistic regression model in this study was similar to the results of the logistic regression model from the first study. Only instrument rating ($\beta = -2.16$, $p < .001$; OR =.12, CI (.06 - .25) and air transport pilot's license ($\beta = -1.158$, $p < .001$; OR = .31, CI = .14 - .71) were negatively related to the log odds of a pilot having an accident during adverse weather encounters at the .05 level of significance. Commercial pilots license ($\beta = -0.229$) and multi-engine rating ($\beta = -0.003$) were also negatively related, but insignificantly so. Total flight hours had no effect on the odds of accidents during adverse weather encounters. None of the interaction terms were associated with the outcome of adverse weather encounters. The results of the logistic regression are detailed in Table 20.

Table 20: Results of Reference Logistic Regression Model with Interaction Terms

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*	*95% C.I. for EXP(B)*	
							Lower	*Upper*
Total Flight Hours	0.00	0.00	0.54	1.00	0.46	1.00	1.00	1.00
Instrument Rating	-2.13	0.39	30.65	1.00	0.00	0.12	0.06	0.25
CPL	-0.23	0.39	0.35	1.00	0.55	0.80	0.37	1.70
ATPL	-1.16	0.42	7.72	1.00	0.01	0.31	0.14	0.71
MER	0.00	0.39	0.00	1.00	0.99	1.00	0.46	2.14
Instrument Rating by Total Flight Hours	0.00	0.00	0.03	1.00	0.85	1.00	1.00	1.00
CPL by Total Flight Hours	0.00	0.00	0.83	1.00	0.36	1.00	1.00	1.00
ATPL by Total Flight Hours	0.00	0.00	0.00	1.00	0.95	1.00	1.00	1.00
MER by Total Flight Hours	0.00	0.00	1.00	1.00	0.32	1.00	1.00	1.00
CPL by Instrument Rating by MER by Total Flight Hours	0.00	0.00	1.04	1.00	0.31	1.00	1.00	1.00
ATPL by Instrument Rating by MER by Total Flight Hours	0.00	0.00	0.00	1.00	0.98	1.00	1.00	1.00
Constant	1.77	0.32	29.82	1.00	0.00	5.86		

Table 21: Statistics for Reference Logistic Regression Model

Test of Model Coefficients	X^2 =169.95, (11), $p < .001$
-2Log-Likelihood	741.26
Nagelkerke R Square	0.29
Cox & Snell R Square	0.22
Hosmer & Lemeshow Test	X^2 = 8.93, (8), $p > .05$
Overall Predictive Power	70%

8.1.1 Evaluation of Reference Logistic Regression Model with Interaction Terms

The logistic regression model fitted to the data was statistically significant (X^2 = 169.95, (11), $p < .001$). The -2 log likelihood was 741.26, while the Hosmer & Lemeshow goodness-of-fit test was (X^2 = 8.93, (8), $p > .05$). Hypothesis tests on individual experience variables in the model showed only instrument rating and airline transport license were significant, with chi-square values of 30.652 and 7.720 respectively. Corresponding p-values for both were .00 and .01 respectively. Predicted probabilities for the model agreed well with actual outcomes. Overall predictive accuracy was 70%, compared with 56.2% for the null model.

8.2 Logistic Regression Models for First Experience Acquisition Zone

Logistic Regression Model 1-1. The initial logistic regression model fitted to the data with total flight hours as the only explanatory variable was not statistically significant (X^2 =.917, (1), $p > .05$). The null hypothesis that total flight hours made no difference to the likelihood of accidents during adverse weather encounters failed to be rejected ($p > .05$), and there was no change in the odds (0.99) of accidents during adverse weather encounters, with increasing total flight hours alone. Details are shown in Tables 22 and 23.

Table 22: Results for Logistic Regression Model 1-1

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*	*95% C.I. for EXP(B)*	
							Lower	*Upper*
Total Flight Hours	-0.004	0.004	0.907	1	0.341	0.996	0.988	1.004
Constant	1.593	0.713	4.987	1	0.026	4.917		

Table 23: Statistics for Logistic Regression Model 1-1

Test of Model Coefficients	X^2 = .917, (1), $p > .05$
-2Log-Likelihood	101.57
Nagelkerke R Square	.015
Cox & Snell R Square	.01
Hosmer & Lemeshow Test	X^2 = 4.21, (7), $p > .05$
Overall Predictive Power	72.4%

Logistic Regression Model 1-2. The significance of the logistic regression model did not change ($p > .05$) when private pilot's license was added it. Neither the Cox and Snell R Square (.01), nor the Nagelkerke R Square (.015) was different. Similarly, statistical tests on individual predictors were not significant ($p > .05$) and there was no change in the odds ratio or predictive power of the model. Details are in Tables 24 and 25.

Table 24: Results for Logistic Regression Model 1-2

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*	*95% C.I. for EXP(B)*	
							Lower	*Upper*
Total Flight Hours	-0.004	0.004	0.860	1	0.354	0.996	0.988	1.004
PPL	-0.003	1.284	0.000	1	0.998	0.997	0.081	12.347
Constant	1.596	1.565	1.040	1	0.308	4.933		

Table 25: Statistics for Logistic Regression Model 1-2

Test of Model Coefficients	X^2 = .917, (1), p > .05
-2Log-Likelihood	101.57
Nagelkerke R Square	.015
Cox & Snell R Square	.01
Hosmer & Lemeshow Test	X^2 = 4.01, (7), p > .05
Overall Predictive Power	72.4%

Single engine rating was found to be significantly correlated to private pilot's license (Pearson's correlation coefficient > .81) at the .01 level (2-tailed) of significance. So, the model with single-engine was very similar to the model with private pilot's license and was not developed any further. The correlation results are in Table 26.

Table 26: Table of Correlation for Single Engine Rating and Private Pilot's License

		SER	*PPL*
SER	*Pearson Correlation*	1	.812**
	Sig. (2-tailed)		0.000
	Sum of Squares and Cross-products	1.954	1.931
	Covariance	0.023	0.022
	N	87	87
PPL	*Pearson Correlation*	.812**	1
	Sig. (2-tailed)	0.000	
	Sum of Squares and Cross-products	1.931	2.897
	Covariance	0.022	0.034
	N	87	87
***. Correlation is significant at the 0.01 level (2-tailed).*			

Logistic Regression Model 1-3. Adding instrument rating to the model with total flight hours and private pilot's license provided significant improvements to the overall model (p < .05; $\chi^2(3)\ 21.19$). The Hosmer and Lemeshow goodness-of-fit statistic was significant $\chi^2(7)\ 8.58$; (p > .05). The-2 Log likelihood was 82.43, while the Cox and Snell R Square was .22, and the Nagelkerke R Square was .31. Of the three predictors now in the model, only instrument rating was significant (p < .05; OR = .034, CI =.01 - .20); neither private pilot's license not total flight hours were significant. The model was able to predict 80.5% of the outcome, an improvement over the previous model. The variables in the equation are shown in Table 27.

Table 27: Results for Logistic Regression Model 1-3.

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*	*95% C.I. for EXP(B)*	
							Lower	*Upper*
Total Flight Hours	0.011	0.007	2.613	1	0.106	1.011	0.998	1.024
PPL	-1.386	1.343	1.065	1	0.302	0.250	0.018	3.477
Instrument Rating	-3.381	0.888	14.509	1	0.000	0.034	0.006	0.194
Constant	1.628	1.644	0.980	1	0.322	5.091		

Table 28: Statistics for Logistic Regression Model 1-3

Test of Model Coefficients	X^2 = 21.19 (3), p < .001
-2Log-Likelihood	81.29
Nagelkerke R Square	.31
Cox & Snell R Square	.22
Hosmer & Lemeshow Test	X^2 = 8.58, (7), p > .05
Overall Predictive Power	80.50%

Logistic Regression Model 1-4. The logistic regression model with interaction terms was significant. Although the interaction between total flight hours and instrument rating had a negative coefficient, the term itself was not significant. However, the model closely resembled the previous model without the interaction term and was significant ($\chi^2(3)\ 201.4;\ (\mathrm{p}\ >\ .05)$, and provided a good fit $\chi^2(8)\ 7.075;\ (\mathrm{p}\ >\ .05)$. The -2 Log likelihood was 82.35, while the Cox and Snell R Square was .21, and the Nagelkerke R Square was .30. The variables in the equation are shown in Table 29, while the model statistics are in Table 30.

Table 29: Logistic Regression Model 1-4

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*	*95% C.I. for EXP(B)*	
							Lower	*Upper*
Total Flight Hours	0.012	0.008	2.681	1	0.102	1.012	0.998	1.028
Instrument Rating	-2.207	3.461	0.407	1	0.524	0.110	0.000	97.206
Instrument Rating by Total Flight Hours	-0.005	0.017	0.087	1	0.768	0.995	0.962	1.029
Constant	0.066	0.941	0.005	1	0.944	1.068		

Table 30: Statistics for Logistic Regression Model 1-4

Test of Model Coefficients	X^2 = 20.14, (3), p < .001
-2Log-Likelihood	82.35
Nagelkerke R Square	.30
Cox & Snell R Square	.21
Hosmer & Lemeshow Test	X^2 = 7.08, (8), p > .05
Overall Predictive Power	80.50%

8.3 Logistic Regression Models for Second Experience Acquisition Zone

Logistic Regression Model 2-1. The initial logistic regression model fitted to the data for the second experience acquisition zone with total flight hours as the only explanatory variable was not statistically significant ($\chi^2(1)$ .74; $(p > .05)$). The -2 Log likelihood ratio was 405.69, the Cox and Snell R Square was .002, while the Nagelkerke R Square was .003. The null hypothesis on total flight hours failed to be rejected, and there was no change in the odds (OR = 1) of accidents during adverse weather encounters, based on total flight hours alone within this zone. The model was only able to correctly classify 55.7% of the outcome. Details are contained in Tables 31 and 32.

Table 31: Results for Logistic Regression Model 2-1

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*	*95% C.I. for EXP(B)*	
							Lower	*Upper*
Total Flight Hours	0.000	0.000	0.738	1	0.390	1.000	0.999	1.000
Constant	0.455	0.287	2.520	1	0.112	1.576		

Table 32:Statistics for Logistic Regression Model 2-1

Test of Model Coefficients	X^2 = .739 (1), p > .05
-2Log-Likelihood	405.69
Nagelkerke R Square	.003
Cox & Snell R Square	.002
Hosmer & Lemeshow Test	X^2 = 13.59 (8), p > .05
Overall Predictive Power	55.70%

Logistic Regression Model 2-2. The logistic regression model was significant when instrument license was added $(\chi^2(2) = 50.332;\ p < .05)$. The -2 Log likelihood ratio was 356.08, while the Cox and Snell R Square was .16 and the Nagelkerke R Square was .21. The model was able to predict 62.2% of outcomes correctly. Statistical tests on individual predictors was significant (p > .05) for instrument rating and the odds ratio was .071 (CI = .03 - .18). However, total flight hours was not significant to the model (p > .05). Details are in Table 33 and 34.

Table 33: Results for Logistic Regression Model 2-2

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*	*95% C.I. for EXP(B)*	
							Lower	*Upper*
Total Flight Hours	0.000	0.000	0.287	1	0.592	1.000	0.999	1.001
Instrument Rating	-2.650	0.489	29.331	1	0.000	0.071	0.027	0.184
Constant	2.328	0.518	20.189	1	0.000	10.260		

Table 34: Statistics for Logistic Regression Model 2-2

Test of Model Coefficients	X^2 =50.33 (2), p < .001
-2Log-Likelihood	356.10
Nagelkerke R Square	.21
Cox & Snell R Square	.16
Hosmer & Lemeshow Test	X^2 = 17.45, (8), p > .05
Overall Predictive Power	62.20%

Logistic Regression Model 2-3. The logistic regression model with total flight hours * instrument interaction term within this second experience acquisition zone was significant. Although the interaction between total flight hours and instrument rating had a negative coefficient, the term itself was not significant. The model itself closely resembled the previous model without the interaction term and was significant ($\chi^2(3)\ 354.22;\ (\mathrm{p}\ >\ .05)$, and provided a good fit $\chi^2\ 15.48\ (8);\ (\mathrm{p}\ >\ .05)$. The -2 Log likelihood was 354.22, while the Cox and Snell R Square was .16, and the Nagelkerke R Square was .22. The variables in the equation are shown in Table 35, while the model statistics are in Table 36.

Table 35: Results for Logistic Regression Model 2-3

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*	*95% C.I. for EXP(B)*	
							Lower	*Upper*
Total Flight Hours	0.003	0.002	1.564	1	0.211	1.003	0.998	1.008
Instrument Rating	-1.117	1.237	0.816	1	0.366	0.327	0.029	3.695
Instrument Rating by Total Flight Hours	-0.003	0.002	1.431	1	0.232	0.997	0.992	1.002
Constant	0.882	1.192	0.547	1	0.459	2.415		

Table 36: Statistics for Logistic Regression Model 2-3

Test of Model Coefficients	X^2 =52.21, (3), p < .001
-2Log-Likelihood	354.22
Nagelkerke R Square	0.22
Cox & Snell R Square	0.16
Hosmer & Lemeshow Test	X^2 = 15.48 (8), p > .05
Overall Predictive Power	62.20%

Logistic Regression Model 2-4. There was no change in predictive power (62.2%) when commercial pilot license was added to the model with total flight hours and instrument rating. The model was significant $\chi^2(3)\ 55.49;\ (\text{p} <\ .05)$, and there was a reduction in the -2 Log likelihood ratio (350.94). There was a slight increase in both the Cox and Snell R square (.17) and the Nagelkerke R square (.23) values. The Hosmer and Lemeshow goodness-of-fit statistic was significant $\chi^2(8) of\ 9.70;\ (\text{p}\ >\ .05)$. Of the three predictors in the model, only total flight hours was not significant (p > .05). Both instrument rating and commercial pilot's license were both significant (p < .05). The variables in the equation are shown in Table 37, while Table 38 contains the statistics for the model.

Table 37: Results for Logistic Regression Model 2-4

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*	*95% C.I. for EXP(B)*	
							Lower	*Upper*
Total Flight Hours	0.000	0.000	0.280	1	0.597	1.000	0.999	1.001
Instrument Rating	-2.469	0.496	24.786	1	0.000	0.085	0.032	0.224
CPL	-0.623	0.277	5.073	1	0.024	0.536	0.312	0.922
Constant	2.367	0.519	20.781	1	0.000	10.670		

Table 38: Statistics for Logistic Regression Model 2-4

Test of Model Coefficients	X^2 (3) = 55.49, p < .001
-2Log-Likelihood	350.94
Nagelkerke R Square	.23
Cox & Snell R Square	0.17
Hosmer & Lemeshow Test	X^2 (3) = 9.70; p > .05
Overall Predictive Power	62.20%

Logistic Regression Model 2-5. The logistic regression model with total flight hours * instrument * commercial pilot license interaction term within this second experience acquisition zone was significant. The interaction term itself was not significant, but the model had a good fit χ^2 5.49 (8); (p > .05). The -2 Log likelihood was 350.10, while the Cox and Snell R Square was .17, and the Nagelkerke R Square was .23.The variables in the equation are shown in Table 39, while the model statistics are in Table 40.

Table 39: Results for Logistic Regression Model 2-5

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*	*95% C.I. for EXP(B)*	
							Lower	*Upper*
Total Flight Hours	0.000	0.000	0.851	1	0.356	1.000	1.000	1.001
Instrument Rating	-2.470	0.498	24.640	1	0.000	0.085	0.032	0.224
CPL	-0.056	0.683	0.007	1	0.934	0.945	0.248	3.605
CPL by Instrument Rating by Total Flight Hours	-0.001	0.001	0.821	1	0.365	0.999	0.998	1.001
Constant	2.206	0.544	16.415	1	0.000	9.079		

Table 40: Statistics for Logistic Regression Model 2-5

Test of Model Coefficients	X^2 =239.91, (7), p < .001
-2Log-Likelihood	541.92
Nagelkerke R Square	0.45
Cox & Snell R Square	0.33
Hosmer & Lemeshow Test	X^2 = 10.51, (8), p> .05
Overall Predictive Power	82%

Logistic Regression Model 2-6. The logistic regression model remained significant when multiple engine rating was added to total flight hours, instrument rating and commercial pilot's license (p < .05; $\chi^2(4), 57.08$). The -2 Log likelihood ratio dropped to (349.35), while the Cox and Snell R Square was .18 and the Nagelkerke R Square was .24. The Hosmer and Lemeshow goodness-of-fit statistic was significant $\chi^2(8)$ 8.06; (p $>$ .05). The model was able to predict 62.50% of outcomes correctly. Only instrument rating was significant (p > .05); neither total flight hours, commercial pilot's license nor multi engine rating was significant. Details are in Tables 41, and 42.

Table 41: Results for Logistic Regression Model 2-6

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*	*95% C.I. for EXP(B)*	
							Lower	*Upper*
Total Flight Hours	0.000	0.000	0.470	1	0.493	1.000	1.000	1.001
Instrument Rating	-2.449	0.497	24.334	1	0.000	0.086	0.033	0.228
CPL	-0.328	0.363	0.818	1	0.366	0.720	0.354	1.467
MER	-0.436	0.346	1.589	1	0.208	0.647	0.328	1.274
Constant	2.382	0.521	20.943	1	0.000	10.828		

Table 42: Statistics for Logistic Regression Model 2-6

Test of Model Coefficients	$\chi^2(4), 57.08,$ p < .001
-2Log-Likelihood	349.35
Nagelkerke R Square	.24
Cox & Snell R Square	.18
Hosmer & Lemeshow Test	$\chi^2(8)$ 8.06; (p $>$ .05)
Overall Predictive Power	62.50%

Logistic Regression Model 2-7. The logistic regression model with total flight hours * instrument rating* commercial pilot license* multiple engine rating interaction term within this second experience acquisition zone was significant ($\chi^2(5)$ $66.13;$ (p $<$ .00). The interaction term had a very small negative coefficient (-.002) and was significant (p < .05). The model provided a good fit χ^2 4.01 (8); (p $>$ .05) to the data. The -2 Log likelihood was 340.30, the Cox and Snell R Square was .20, and the Nagelkerke R Square was .27. The variables in the equation are shown in Table 43, while the model statistics are in Table 44. Its overall productive power was 65.50%

Table 43: Results for Logistic Regression Model 2-7

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*	*95% C.I. for EXP(B)*	
							Lower	*Upper*
Total Flight Hours	0.001	0.000	2.612	1	0.106	1.001	1.000	1.002
Instrument Rating	-2.484	0.501	24.567	1	0.000	0.083	0.031	0.223
CPL	0.805	0.552	2.128	1	0.145	2.236	0.758	6.593
MER	-0.074	0.373	0.039	1	0.843	0.929	0.447	1.931
CPL by Instrument Rating by MER by Total Flight Hours	-0.002	0.001	8.149	1	0.004	0.998	0.996	0.999
Constant	2.028	0.530	14.659	1	0.000	7.602		

Table 44: Statistics for Logistic Regression Model 2-7

Test of Model Coefficients	χ^2 4.01 (8); (p $>$ .05)
-2Log-Likelihood	340.30
Nagelkerke R Square	0.27
Cox & Snell R Square	0.20
Hosmer & Lemeshow Test	χ^2 4.01 (8); (p $>$ .05)
Overall Predictive Power	66.5%

8.4 Logistic Regression Models for Third Experience Acquisition Zone

Logistic Regression Model 3-1. The logistic regression model with only total flight hours for pilots within the third experience acquisition zone was not statistically significant, $\chi^2(1) = 1.87;\ (p > .05)$. The -2 Log likelihood was 462.44, while the Cox and Snell R Square was .005 and the Nagelkerke R Square was .007. Increasing total flight hours was not associated with any change in the odds of accidents during adverse weather encounters. The Hosmer and Lemeshow goodness-of-fit statistic was significant $\chi^2(8) = 12.53;\ (p > .05)$. The model was able to predict 66.5% of outcomes correctly, but this was the same predictive power as the null model. Total flight hours was not a significant predictor of the outcome of adverse weather encounters. Th Details are presented in Tables 45 and 46.

Table 45: Results for Logistic Regression Model 3-1

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*	*95% C.I. for EXP(B)*	
							Lower	*Upper*
Total Flight Hours	0.000	0.000	1.224	1	0.269	1.000	1.000	1.000
Constant	-0.559	0.155	13.066	1	0.000	0.572		

Table 46: Statistics for Logistic Regression Model 3-1

Test of Model Coefficients	$\chi^2(1) = 1.87;\ (\mathrm{p} > .05)$
-2Log-Likelihood	541.92
Nagelkerke R Square	0.007
Cox & Snell R Square	0. 005
Hosmer & Lemeshow Test	$\chi^2(8) = 12.53;\ (\mathrm{p} > .05)$
Overall Predictive Power	66.50%

Logistic Regression Model 3-2. The logistic regression model with air transport pilot's license added to total flight hours was statistically significant, $\chi^2(2) = 42.94;\ (\mathrm{p} < .00)$. The -2 Log likelihood ratio was 421.36, while the Cox and Snell R Square was .11 and the Nagelkerke R Square was .15. The Hosmer and Lemeshow goodness-of-fit statistic was significant $\chi^2(8) = 5.84;\ (\mathrm{p} > .05)$. The model's predictive power increased to 67%. Total flight hours was not a significant predictor of the outcome of adverse weather encounters and there was no change in odds of accidents with increasing total flight hours. However, the odds ratio for air transport lance was .13. Details are presented in Tables 47 and 48.

Table 47: Results for Logistic Regression Model 3-2.

	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B)	
							Lower	Upper
Total Flight Hours	0.000	0.000	0.465	1	0.495	1.000	1.000	1.000
ATPL	-1.549	0.251	38.138	1	0.000	0.213	0.130	0.347
Constant	-0.003	0.158	0.000	1	0.986	0.997		

Table 48: Statistics for Logistic Regression Model 3-1.

Test of Model Coefficients	X^2 =239.91, (7), p < .001
-2Log-Likelihood	541.92
Nagelkerke R Square	0.45
Cox & Snell R Square	0.33
Hosmer & Lemeshow Test	X^2 = 10.51, (8), p> .05
Overall Predictive Power	82%

Logistic Regression Model 3-3. The logistic regression model with interaction of air transport pilots license and total flight hours was statistically significant, χ^2 (3)= 43.55; (p < .001). The -2 Log likelihood ratio was 420.75, while the Cox and Snell R Square was .11 and the Nagelkerke R Square was .16. The Hosmer and Lemeshow goodness-of-fit statistic was χ^2 (8)=5.53; (p > .05). The model's predictive power increased to 6870%. Neither total flight hours nor the interaction of air transport pilots license and total flight hours was a significant predictor of the outcome of adverse weather encounters (p > .05) and there was no change in odds of accidents with changes in either variable. However, air transport pilots license was significant and produced a .25 reduction in the odds of accidents during adverse weather encounters with an air transport pilots license compared to having either a commercial pilots license or private pilot's license. Details are presented in Tables 49 and 50.

Table 49: Results for Logistic Regression Model 3-3

	B	*S.E.*	*Wald*	*df*	*Sig.*	*Exp(B)*	*95% C.I. for EXP(B)*	
							Lower	*Upper*
Total Flight Hours	0.000	0.000	0.812	1	0.367	1.000	1.000	1.000
ATPL	-1.403	0.314	19.950	1	0.000	0.246	0.133	0.455
ATPL by Total Flight Hours	0.000	0.000	0.588	1	0.443	1.000	1.000	1.000
Constant	-0.127	0.226	0.317	1	0.573	0.881		

Table 50: Statistics for Logistic Regression Model 3-3

Test of Model Coefficients	X^2 =239.91, (7), $p < .001$
-2Log-Likelihood	541.92
Nagelkerke R Square	0.45
Cox & Snell R Square	0.33
Hosmer & Lemeshow Test	X^2 = 10.51, (8), $p > .05$
Overall Predictive Power	82%

CHAPTER 9. DISCUSSION – SECOND STUDY

In this chapter, the results from the second study presented in chapter 8 are interpreted and their significance discussed in light of the research objective.

9.1 Aim and Objective of the Second Study

The aim of the second study was to determine the effect of elements that address the breadth/variety of experience on the likelihood of accidents during adverse weather encounters. For pilots, the time spent flying an airplane counts towards their total flight hours, However, acquiring additional elements of experience like instrument rating or commercial pilots license is at the discretion of each pilot, and some opt not to acquire such additional ratings or certifications. Results from the first study indicated elements of experience which address the breadth or variety of experience were both associated with, and predictive of accidents during adverse weather encounters. Although total flight hours was associated with accidents during encounters with adverse weather, it was not predictive of the likelihood of accidents during such encounters.

The objective for this study therefore, was to test the conjecture that pilots with experience spanning both the horizontal and vertical dimensions of a hypothetical experience continuum proposed as a framework for the acquisition of experience in practice would have significantly reduced likelihood of having accidents during adverse weather encounters compared to those with experience only along the length/duration dimension. The conjecture was based on the understanding that cognate or task related experience significantly impact the attainment of expertise and outcome of task performance. Previous studies have found that the transition from novice to expert is mediated and expedited by the kinds of experience acquired over time (Ericsson 1993, Adams and Ericsson, 1992; Ericsson and Charnes, 1994; Klein, 1989; Andersson 1982, 1987, 1993). Therefore, flying tasks that allow pilots experience and become proficient with different kinds of flying conditions would expedite their transition to experts in adverse weather flying, compared to those that restricted their exposure.

9.2 Implications of the Reference Logistic Regression Model

Results from the reference logistic regression model with interactions developed for this study showed only instrument rating and air transport pilot's license were predictive of the likelihood of accidents during adverse weather encounters. Therefore, the conjecture was supported for instrument rating and air transport pilot license. However, neither total flight hours, commercial pilot license or airplane rating was found to be significant. The findings, therefore, did not support the conjecture that pilots with a commercial pilot license or multi engine rating would be less likely to have accidents during encounters with adverse weather. Furthermore, none of the interaction terms in the reference model was a significant predictor of the likelihood of accidents during adverse weather encounters.

On the surface, some of these findings appears contrary to results from previous studies, such as those that have found total flight hours to be a significant indicator of the likelihood of accidents during adverse weather encounters or expertise in weather decision making. However, that may not necessarily be the case, since many of the studies provide no information on participants' instrument rating status or certification level. Other than Schvaneveldt et al. (2001) pilots classified as experts in previous research have had less than 1500 total flight hours and were generally not eligible for air transport licenses. It is plausible therefore, that the differences in performance observed in such studies were due to the presence or absence of instrument rating and air transport license as the results in this study indicate, rather than total flight hours.

9.3 Interaction of Variables within the Experience Acquisition Zones

First Experience Acquisition Zone (0 – 250 Total Flight Hours). The initial model for the first experience acquisition zone for this study had only total flight hours and was not significant. The model could only explain 1.5% of the variance in outcome (Nagelkerke R Square value). This finding was not surprising given the earlier observation that weather related accidents involve pilots with varying amounts of total flight hours. The model with private pilot license or single engine rating and total flight hours was not significant. This too, was not surprising, since every pilot in the study had a least a private license and by association, at least a single engine rating. In addition to being highly correlated, both elements of experience provided no discriminatory value.

The next model with instrument rating added was significant and improved the overall model fit statistics. Indeed, instrument rating was the only additional element of experience pilots in the study could acquire within this zone. Although the model with the first order interaction term between instrument rating and total flight hours was significant, the interaction term itself was not significant. This result was unexpected, since the accident insulating effect of instrument rating was expected to increase as a function of total flight hours. The coefficient for the interaction term was -.005, but this was negligible, as was the odds ratio (.995) given the high p-value (.7) and confidence interval (.96 – 1.03). It appears instrument rating has a unique effect that is distinct from total flight hours. Furthermore, there was barely any change in the model statistics between the model with and without the total flight hour * instrument rating interaction term.

Second Experience Acquisition Zone (251 – 1500 Total Flight Hours). Pilots within this zone could acquire an instrument rating, a multi engine rating or a commercial license individually or in different combinations. Therefore, individual models were developed for each combination with additional elements added successively to those already in the previous model.

The models within this zone followed the trend set by those developed for the first experience zone. The initial model with only total flight hours was not significant. The model could only explain 0.3% of the variance in outcome (Nagelkerke R Square value). The addition of instrument rating significantly improved the model as well as overall model fit statistics and predictive power. The model retained its significance with the addition of subsequent elements like commercial pilot license and multi engine rating and had slightly improved fit statistics and predictive power. As was the case in the first experience acquisition zone, the models with interaction terms was significant but none of the first (total flight hours * commercial license/multi engine rating) or second order (total flight hours * commercial license/multi engine rating * instrument rating) interaction terms was significant. The third order interaction term (total flight hours * commercial license * multi engine rating * instrument rating) was significant, but this could have been by chance, since the odds ratio was .996. Other than some slight changes in model statistics, the models with interaction terms were very similar to their equivalent models with main effects only.

Third Experience Acquisition Zone (>1500 Total Flight Hours). Pilots within this zone could only add an air transport pilot license, so only the effect that had on the likelihood of accidents was investigated. The pattern seen in the first two experience acquisition zones continued here. The initial model with total flight hours was not significant but became significant with improved fit and predictive statistics once air transport license added. The model with air transport license * total flight hour interaction was not significant and was similar to the model with only the two main effects.

9.4 Implications of the Results from Experience Acquisition Zone Framework

The conjecture that pilots with experience spanning both the length and breadth dimensions of a hypothetical experience continuum proposed as a framework for the acquisition of experience in practice would have significantly reduced likelihood of having accidents during adverse weather encounters compared to those with experience only along the length/duration dimension was supported by the results of the models within each experience acquisition zone.

Although none of the primary interaction terms investigated was significant, there were slight improvements in each model with their addition. It is not clear why the first and second order interaction terms were not significant, but the third order interaction term was within the second experience acquisition zone. One reason for this may be that the interaction terms may be of a different order than was investigated in this study.

The major difference between the reference logistic regression model and the models within each experience acquisition zone is the contradictory results on the effect of both commercial pilot license and multi engine rating on the likelihood of accidents during adverse weather encounters. Both elements of experience were not significant in the reference model but were in the models for the second experience zone. A large number of the pilots whose profiles were extracted for this study had more than 1500 total flight hours. The results from the reference model may have been impacted by the aggregation and the break down into different categories based on the experience acquisition zone framework revealed hitherto hidden effects.

CHAPTER 10. CONCLUSIONS, CONTRIBUTION AND RECOMMENDATIONS FOR FUTURE WORK

10.1 Conclusion

The first part of this research sought to identify pilot experience variables that individually, or in combinations are predictive of the likelihood of accidents during adverse weather encounters. The conjecture investigated was that if experience truly determines outcome of adverse weather encounters, there should be significant differences between the experience profile of pilots who had accidents during adverse weather encounters and those who did not. The results obtained show that variables related to the breadth or variety of General Aviation pilots' experience are more predictive of the likelihood of accidents during adverse weather encounters than those related to the duration or length of experience. The results also affirmed findings that task related experience expedites the transition from novice to expert pilot. The foregoing suggests increased emphasis on aspects of training that increase the breadth and variety of pilots' experience could help reduce the likelihood of accidents during adverse weather encounters. One way to facilitate this could be by modifying the regulatory requirements for pilot certifications and ratings to require an increased level of task related proficiency.

In the second part of the study, an experience acquisition framework was proposed and used to investigate the effect of multi-dimensional experience on the likelihood of accidents, based on the conjecture that pilots with experience spanning both hypothetical dimensions of the framework have significantly reduced likelihood of accidents during adverse weather encounters compared to those with experience only along one dimension. The conjecture was supported, and significant relationship between elements that address the breadth of experience and total flight hours were identified. However, the conjecture that the dimensional interaction experience terms were not supported.

10.2 Contribution

This dissertation contributes to the current body of knowledge on experience and its impact on pilot performance and aviation safety in three ways. The first contribution is methodological; it presents a new methodological approach for research on experience and pilot performance that obviates some of the challenges commonly associated with currently used approaches. The second contribution is conceptual; the experience acquisition framework introduced in this study is a novel way to view the accumulation of experience in General Aviation and allows for nuanced and insightful study of weather related expertise. The third contribution is utilitarian; the findings from this study, which are ecologically valid, may be applied in conjunction with other considerations to formulate policies that increase opportunities for, and support the transition of pilots from novice to expert in aviation weather related operations and decision making. This would then have the effect of reducing weather related accidents and improving overall aviation safety.

10.3 Recommendations Future Work

This research work presents a new conceptual framework and methodological approach for evaluating experience and pilot performance during adverse weather encounters in General Aviation operations. The approach has the advantage of allowing for the clear identification and specification of pertinent variables which impact the outcome. While this research focused on ten experience variables within six major categories, these are by no means exhaustive list of variables. Furthermore, only outcomes occurring during the cruise phase of flights was considered in this study. However, a significant proportion of weather related General Aviation accidents and incidents occur during the take-off and landing phases of flights. Therefore, future work could expand the variables evaluated to include variables not included in this study such as cross-country flight experience and instructor ratings. Similarly, future work should also include phases of flight such as take-off and landing, which were not considered in this study.

Finally, in terms of immediate follow on outcome from this study, plans are underway to leverage the predictive models developed in this study to develop a web based and mobile application, the "Experience Adequacy Assessment Tool" to provide a means for pilots to evaluate whether they have adequate experience to embark on a planned flight where weather may be a consideration. The tool would provide the likelihood of an encounter with adverse weather transitioning to an accident, based on experience information provided by the pilot.

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APPENDIX A: ELEMENTS OF PILOT EXPERIENCE FROM PREVIOUS RESEARCH

Serial	Reference	Variable	Finding
1	Wiggins MW, & O'Hare D (1995). Expertise in Aeronautical Weather-Related Decision Making: A Cross-Sectional Analysis of General Aviation Pilots. Journal of Experimental Psychology: Applied, 1, 305-320.	Cross country flying	Pilots with more cross-country flight experience were more likely to continue with a flight than those with less experience in simulated scenarios involving flight into adverse weather
2	Wiegmann, D. A., Goh, J., & O'Hare, D. (2001). Pilots' Decisions to Continue Visual Flight Rules (VFR) Flight into Adverse Weather: Effects of Distance Traveled and Flight Experience.	Flight hours in last 90 days Total flight hours	No effect from total flight hours, but the number of flight hours in the previous 30 and 90 days were found to be the most relevant experience variables, suggesting that recency of experience may be as important as total experience in some cases.
3	Shappell, S., Hackworth, C., Holcomb, K., Lanicci, J., Bazargan, M., Baron, J., and Halperin, D. (2010). Developing proactive methods for general aviation data collection (No. DOT-FAA-AM-10-16). CLEMSON UNIV SC.	Total flight hours Total hours in event aircraft make/model Total hours in last 90 days Cross-country hours Cross-country hours in last 90 days Actual instrument hours Simulated instrument hours Total instrument hours	Pilot decision making (and hence outcome of flights) is largely dependent on experience, amongst other factors. The likelihood that a decision will be successful is markedly reduced if it is absent or lacking.
4.	Johnson, C. M., & Wiegmann, D. A. (2015). VFR into IMC: Using Simulation to Improve Weather-Related Decision-Making. The International Journal of Aviation Psychology, 25(2), 63-76.	IFR rating	Previous experience with actual instrument weather was found to be the only statistically significant demographic predictor of safe performance

5	Kochan, J. A., Jensen, R. S., Chubb, G. P., & Hunter, D. R. (1997). A New Approach to Aeronautical Decision-Making: The Expertise Method. OHIO STATE UNIV COLUMBUS.	Total number of flying hours	Total number of flying hours is important but not the only important factor
6	Li, G., Baker, S. P., Grabowski, J. G., & Rebok, G. W. (2001). Factors associated with pilot error in aviation crashes. Aviation, space, and environmental medicine, 72(1), 52-58.	Pilot Gender Total number of flying hours Certificate Type	Certificate type and total flight time showed a positive effect on GA accidents caused by pilot error.
7	Burian, B. K., Orasanu, J., & Hitt, J. (2000, July). Weather-related decision errors: Differences across flight types. In Proceedings of the Human Factors and Ergonomics Society Annual Meeting (Vol. 44, No. 1, pp. 22-25). Sage CA: Los Angeles, CA: SAGE Publications.	Total flight hours Pilot rating Certificate type	Increased total flight hours had an insulating effect, but certificate type and rating did not show any insulating effect
8	Wiggins, M. W., Hunter, D. R., O’Hare, D., & Martinussen, M. (2012). Characteristics of pilots who report deliberate versus inadvertent visual flight into instrument meteorological conditions. Safety science, 50(3), 472-477.	Total flight hours Instrument experience Recent flight experience	Previous experience with similar conditions yielded a positive relationship with deliberate transitions of VFR flights into adverse weather.
9	Wiegmann, D. A., Goh, J., & O'Hare, D. (2002). The role of situation assessment and flight experience in pilots' decisions to continue visual flight rules flight into adverse weather. *Human factors*, *44*(2), 189-197.	Total flight hours Cross-country flight experience Instrument flight experience Flight hours in last 90 days Flight hours in last 30 days	VFR flight into IMC may be attributable, at least in part, to experience amongst other things. Total flight hours as well as flight hours in last 30 and 90 days were associated with VFR flight into IMC Pilots with more total flight hours were more conservative in their estimates of certain weather conditions

10	National Transportation Safety Board. (2005). Risk Factors Associated with Weather-Related General Aviation Accidents. (NTSB/SS-05/01). Washington, DC.	Age Pilot rating Instrument flight experience Total flight hours	No significant association between total flight hours and outcome. Significant association between pilot rating and IFR rating with outcome
11	Goh, J., & Wiegmann, D. A. (2001). Visual flight rules flight into instrument meteorological conditions: An empirical investigation of the possible causes. The International Journal of Aviation Psychology, 11(4), 359-379.	Total flight hours Certificate Type	No statistically significant differences between pilots based on TFH and Certificate Type. Instead, accuracy of visibility estimates, appraisal of one's own skill and judgment, and frequency of risk-taking behavior were most important in predicting whether a pilot would continue or divert the flight
12	Coyne, J. T., Baldwin, C. L., & Latorella, K. A. (2008). Pilot weather assessment: Implications for visual flight rules flight into instrument meteorological conditions. The International Journal of Aviation Psychology, 18(2), 153-166.	Instrument flight experience Cross-country flight experience	No difference from instrument experience perhaps due to similar cross country flying experience
13	Wiggins, M. W. (2014). Differences in situation assessments and prospective diagnoses of simulated weather radar returns amongst experienced pilots. International Journal of Industrial Ergonomics, 44(1), 18-23.	Total Flight Hours	Experienced pilots were unable to reliably interpret weather radar displays
14	Wiggins, M. W., Azar, D., Hawken, J., Loveday, T., & Newman, D. (2014). Cue-utilization typologies and pilots' pre-flight and in-flight weather decision-making. Safety Science, 65, 118-124.	Certificate type Total flying hours Flight hours in last 90 days	No relationship between typology and the level of the pilot's license or flight hours. Expertise was a product of factors other than experience and level of qualification
15	Johnson, C. M., & Wiegmann, D. A. (2011). Pilot Error During Visual Flight into Instrument Weather: An Experiment Using Advanced Simulation and Analysis Methods.	Instrument flight experience	IMC experience was significantly correlated with VFR adherence.

	In Proceedings of the Human Factors and Ergonomics Society Annual Meeting (Vol. 55, No. 1, pp. 138-142). Sage CA: Los Angeles, CA: Sage Publications.		
16	Wiggins, M & Henley, I., (1997) A Computer-Based Analysis of Expert and Novice Flight Instructor Preflight Decision Making, The International Journal of Aviation Psychology, 7:4, 365-379, DOI: 10.1207/s15327108ijap0704_8	Cross-country flight experience Total flight hours	The instrument-rated pilots did not outperform the non-instrument-rated pilots Differences in cross-country experience made a difference in decision making. However, differences were also found between experienced pilots, suggesting the context of the scenario may have contributed to the outcome
17	Pauley, K., O'Hare, D., & Wiggins, M. (2009). Measuring expertise in weather-related aeronautical risk perception: the validity of the Cochran–Weiss–Shanteau (CWS) Index. The International Journal of Aviation Psychology, 19(3), 201-216.	Total flight hours Flight hours in last 90 days Certificate type Instrument flight experience	*First Study*: There was no relationship between the CWS and any measure of aeronautical experience, other than hours flown cross-country in the last 90 days *Second Study*: Pilot certification and rating was strongly related to the CWS score,
18	Wiggins, M., Stevens, C., Howard, A., Henley, I., & O'Hare, D. (2002). Expert, intermediate and novice performance during simulated pre-flight decision-making. Australian Journal of Psychology, 54(3), 162-167.	Cross-country flight experience Total flight hours	There were no significant differences in the decision making of pilot groups, but qualitative difference emerged between the information acquisition strategies employed by novice and intermediate level pilots, and the strategies employed by expert pilots.
19	Wiggins, M. W., & O'Hare, D. (2003). Expert and novice pilot perceptions of static in-flight images of weather. The International Journal of Aviation Psychology, 13(2), 173-187.	Total flight hours Cross-country flight experience Instrument flight experience Weather related encounters Experience in command	Significant differences found between expert and novice performance on several considerations.
20	Sawyer, M. W., & Shappell, S. A. (2009). Eye Tracking Analysis of the Effects of	Total flight hours	Experienced pilots had a higher decision-making accuracy and eye tracking data showed

	Experience and Training on Pilots' Ability to Identify Adverse Weather Conditions. In Proceedings of the Human Factors and Ergonomics Society Annual Meeting (Vol. 53, No. 1, pp. 46-50). Sage CA: Los Angeles, CA: Sage Publications.		many differences in visual scan behavior between experience groups
21	Wiggins, M. W. (2014). Differences in situation assessments and prospective diagnoses of simulated weather radar returns amongst experienced pilots. International Journal of Industrial Ergonomics, 44(1), 18-23.	Total flight hours	There was a lack of reliability in experienced pilots' interpretations of weather radar displays and difficulties associated with classifications of expertise on the basis of experienced related metrics.
22	Schriver, A. T., Morrow, D. G., Wickens, C. D., & Talleur, D. A. (2008). Expertise differences in attentional strategies related to pilot decision making. Human Factors, 50(6), 864-878.	Total flight hours Instrument flight hours (actual and simulated combined) Type of pilot certificate and rating Aviation knowledge	The more expert pilots completed more necessary and corrective and diagnostic actions than less expert pilots and made more appropriate decisions quickly

APPENDIX B: NOVICES/ EXPERIENCED PILOT CLASSIFICATION CRITERIA FROM PREVIOUS RESEARCH

Serial	Study	Novice	Intermediate	Experienced	Finding
1	Beringer, D. B., & Schvaneveldt, R. (2002). Priorities of weather information in various phases of flight. In Proceedings of the Human Factors and Ergonomics Society Annual Meeting (Vol. 46, No. 1, pp. 86-90). Sage CA: Los Angeles, CA: SAGE Publications.	Less than 500	NA	More than 500	Both novice and experienced pilots rank weather factors similarly, however, pilots having more experience tend to rate weather information factors as being more important overall than do those having less experience
2	Wiggins, M., Stevens, C., Howard, A., Henley, I., & O'Hare, D. (2002). Expert, intermediate and novice performance during simulated pre-flight decision-making. Australian Journal of Psychology, 54(3), 162-167.	Less than 100	100- 1000	More than 1000	No significant differences in the decision making of pilot groups, but qualitative differences between the information acquisition strategies employed by novice and intermediate level pilots, and the strategies employed by expert pilots.
3	Wiggins, M., & Henley, I. (1997). A computer-based analysis of expert and novice flight instructor preflight decision making. The International Journal of Aviation Psychology, 7(4), 365-379.	Less than 301	NA	More than 301	Differences between experienced and inexperienced flight instructors in terms of the decision-outcome; no differences were evident relating to the process of information acquisition
4	Coyne, J. T., Baldwin, C. L., & Latorella, K. A. (2008). Pilot weather assessment:	Less than 1000	NA	More than 1000	No difference from instrument experience perhaps due to

	Implications for visual flight rules flight into instrument meteorological conditions. The International Journal of Aviation Psychology, 18(2), 153-166.				similar cross country flying experience
5	Sawyer, M. W., & Shappell, S. A. (2009). Eye Tracking Analysis of the Effects of Experience and Training on Pilots' Ability to Identify Adverse Weather Conditions. In Proceedings of the Human Factors and Ergonomics Society Annual Meeting (Vol. 53, No. 1, pp. 46-50). Sage CA: Los Angeles, CA: Sage Publications.	Less than 500	NA	More than 500	Experienced pilots had a higher decision-making accuracy and eye tracking data showed many differences in visual scan behavior between experience groups
6	Wiggins, M., & O'Hare, D. (2003b). Expert and Novice Pilot Perceptions of Static In-Flight Images of Weather, The International Journal of Aviation Psychology, 13:2, 173-187, DOI: 10.1207/S15327108IJAP1302_05.	Less than 1000	NA	More than 1000	Significant differences found between expert and novice performance on several considerations.
7	Latorella, K. A., & Chamberlain, J. P. (2004). Decision-making in flight with different convective weather information sources: Preliminary Results.	135	379	738	VMC and GWIS augmented conditions seemed to provide similar pilot support
8	Chamberlain, J. P., & Latorella, K. A. (2001). Convective weather detection by general aviation pilots with conventional and data-linked graphical weather information sources. In Digital Avionics Systems, 2001. DASC. 20th Conference (Vol. 2, pp. 6A3-1). IEEE.	135	379	738	NA
9	Schvaneveldt, R. W., Beringer, D. B., & Lamonica, J. A. (2001). Priority and organization of information accessed by pilots in various phases of flight. The	68-820	NA	1,600-17,000	Pilot experience had little influence on the form of the network of associations formed

	International Journal of Aviation Psychology, 11(3), 253-280.				between information required for flight
10	Sawyer, M. W., & Shappell, S. A. (2009, October). Eye Tracking Analysis of the Effects of Experience and Training on Pilots' Ability to Identify Adverse Weather Conditions. In Proceedings of the Human Factors and Ergonomics Society Annual Meeting (Vol. 53, No. 1, pp. 46-50). Sage CA: Los Angeles, CA: Sage Publications.	Less than 500	NA	More than 500	Experienced pilots had a higher decision-making accuracy and eye tracking data showed many differences in visual scan behavior between experience groups
11	Wiggins, M. W. (2014). Differences in situation assessments and prospective diagnoses of simulated weather radar returns amongst experienced pilots. International Journal of Industrial Ergonomics, 44(1), 18-23	NA	NA	1000	Experienced pilots were unable to reliably interpret weather radar displays

APPENDIX B: STUDY DATA

Reference Number	Total Flight Hours	Hours in Last 90 Days	Hours in Make and Model	Instrument Rating	Certificate Type	Airplane Rating	Outcome
CHI08CA094	50	10	42	0	1	1	1
CEN11FA240	55	17	55	0	1	1	1
NYC08CA110	60	6	60	0	1	1	1
ACN1210434	144	11	58	0	1	1	0
CEN14FA071	98	29	98	0	1	1	1
CHI08CA086	190	5	1	0	1	1	1
WPR14CA019	257	94	257	0	1	1	1
ACN1284009	57	2	57	0	1	1	0
CEN13FA214	64	1	61	0	1	1	1
SEA03FA013	70	3	70	0	1	1	1
ERA11FA147	73	3	73	0	1	1	1
ERA12FA193	74	8	74	0	1	1	1
DFW07FA049	85	3	85	0	1	1	1
ACN752740	90	40	20	0	1	1	0
ACN1310045	91	1	28	0	1	1	0
WPR13FA183	93	28	26	0	1	1	1
NYC06FA215	96	40	96	0	1	1	1
NYC07FA173	99	13	10	0	1	1	1
WPR10CA344	100	35	80	0	1	1	1
ERA10FA415	101	101	8	0	1	1	1
CHI07FA032	103	20	30	0	1	1	1
DEN08LA079	110	60	110	0	1	1	1
ANC07CA010	129	10	129	0	1	1	1
CEN12LA414	136	28	56	0	1	1	1
NYC03LA121	137	4	113	0	1	1	1
ERA09LA079	146	11	103	0	1	1	1
ERA14LA122	150	30	150	0	1	1	1
ACN734803	152	4	4	0	1	1	0
DFW08CA174	162	9	28	0	1	1	1
ACN748467	163	70	163	0	1	1	0
ERA14FA002	163	4	30	0	1	1	1
ERA09FA185	168	6	126	0	1	1	1
WPR18FA001	170	23	16	0	1	1	1
CHI06CA046	192	4	106	0	1	1	1

NYC06FA133	193	19	34	0	1	1	1
NYC08FA138	193	9	113	1	1	1	1
CHI06LA061	201	52	107	1	1	1	1
LAX05FA193	206	0	191	0	1	1	1
CEN11FA437	207	14	51	0	1	1	1
ERA13FA083	208	19	123	0	1	1	1
CHI04FA284	220	10	25	0	1	1	1
ERA15FA220	220	20	143	0	1	1	1
CHI07FA182	224	2	65	0	1	1	1
ERA14FA377	230	46	230	0	1	1	1
ERA13CA362	233	50	71	1	1	1	1
ACN1376849	235	175	55	1	1	1	0
LAX07LA143	237	15	15	1	1	1	1
ANC17FA018	250	0	250	0	1	1	1
CEN12FA196	250	7	24	0	1	1	1
CEN14LA074	250	10	250	0	1	1	1
ERA18FA022	256	6	447	0	1	1	1
SEA06LA029	258	7	258	0	1	1	1
ACN672967	260	20	125	1	1	1	0
NYC08CA283	264	30	123	0	1	1	1
CHI05CA052	267	34	76	1	1	1	1
CHI06FA043	272	37	42	0	1	1	1
ACN694657	273	39	180	1	1	1	0
WPR17LA124	280	102	50	0	1	1	1
CEN16LA084	300	100	200	0	1	1	1
CEN09CA136	306	32	297	1	1	1	1
ERA15CA116	311	42	67	1	1	1	1
ERA10FA503	330	6	240	0	1	1	1
WPR12FA031	333	14	246	0	1	1	1
DEN04FA043	339	10	70	1	1	1	1
CEN10LA103	341	39	107	1	1	1	1
WPR10FA459	352	54	277	0	1	1	1
ACN1307052	356	20	134	1	1	1	0
ACN737370	375	10	20	1	1	1	0
ACN690143	385	30	225	1	1	1	0
ERA11FA118	388	20	388	1	1	1	1
ERA10CA168	400	7	60	0	1	1	1
MIA05FA045	400	27	308	0	1	1	1
ACN686249	410	8	30	1	1	1	0
CEN09FA369	412	53	45	0	1	1	1
GAA15CA051	415	16	210	1	1	1	1

NYC05FA100	415	13	305	1	1	1	1
ERA12FA433	452	17	98	1	1	1	1
CHI08FA054	456	2	255	1	1	1	1
CHI03LA072	460	4	297	1	1	1	1
LAX05FA088	473	100	69	1	1	1	1
CEN13FA456	475	38	154	1	1	1	1
IAD03FA005	478	38	2	1	1	1	1
CEN18FA144	496	10	245	1	1	1	1
ACN723957	500	15	75	1	1	1	0
ANC04FA021	506	12	450	0	1	1	1
CEN11FA401	509	57	236	1	1	1	1
CHI07LA260	520	7	495	0	1	1	1
CHI07LA051	544	26	298	1	1	1	1
NYC07FA083	546	65	55	1	1	1	1
NYC04FA179	560	53	536	1	1	1	1
CHI04FA044	583	16	103	0	1	1	1
ERA13LA111	598	31	537	1	1	1	1
ERA17FA108	606	3	300	0	1	1	1
WPR09FA176	609	14	496	0	1	1	1
ERA12CA177	610	24	239	1	1	1	1
IAD05LA051	611	4	315	1	1	1	1
NYC08FA180	616	20	400	0	1	1	1
LAX08FA002	690	3	425	1	1	1	1
ERA10FA359	691	4	100	1	1	1	1
ACN685787	700	10	80	1	1	1	0
WPR11FA082	710	47	456	0	1	1	1
ERA10LA506	711	52	600	1	1	1	1
ERA12FA385	755	38	38	1	1	1	1
CEN13FA067	765	10	38	0	1	1	1
ERA17LA113	790	30	710	1	1	1	1
DEN07CA070	837	22	697	1	1	1	1
GAA16CA066	856	11	662	1	1	1	1
CEN10FA044	885	29	500	1	1	1	1
LAX03FA051	890	25	740	1	1	1	1
ERA12CA211	899	7	827	0	1	1	1
CEN15FA388	920	4	40	1	1	1	1
WPR11FA032	940	100	138	1	1	1	1
CEN15FA008	1003	77	100	1	1	1	1
GAA17CA215	1069	12	32	1	1	1	1
WPR10FA142	1083	20	443	1	1	1	1
ACN690509	1085	9	700	1	1	1	0

WPR16FA042	1262	4	962	1	1	1	1
ACN726815	1377	21	801	1	1	1	0
ERA16CA246	1446	15	1134	1	1	1	1
LAX04FA162	1550	15	842	1	1	1	1
ACN688719	1614	3	1483	1	1	1	0
IAD03FA045	1773	24	365	1	1	1	1
WPR09LA079	1900	66	40	1	1	1	1
ERA13LA012	1948	45	1450	1	1	1	1
CEN10FA057	2269	18	780	0	1	1	1
ERA16FA143	2330	2	345	1	1	1	1
ERA11CA262	2525	10	392	1	1	1	1
NYC03FA205	2660	30	210	1	1	1	1
ACN730104	4200	20	4100	1	1	1	0
ERA14LA433	4399	92	1423	1	1	1	1
ANC07CA019	5060	24	24	0	1	1	1
GAA17CA388	5365	35	3	1	1	1	1
NYC08CA272	6164	19	6000	1	1	1	1
SEA07FA012	408	11	280	1	2	1	1
ACN1477818	410	16	17	1	2	1	0
DFW07FA149	457	59	36	1	2	1	1
ACN787804	470	15	470	1	2	1	0
ACN1468179	800	20	40	1	2	1	0
NYC05FA075	815	101	613	1	2	1	1
NYC05FA075-1	815	101	613	1	2	1	1
DFW07CA014	1164	54	100	0	2	1	1
ERA13FA336	1335	221	35	0	2	1	1
CEN16FA295	1455	0	1019	1	2	1	1
NYC08TA130	2030	60	30	0	2	1	1
CEN12FA639	5300	60	1100	1	2	1	1
ANC16FA023	7190	5	5700	0	2	1	1
DFW07FA051	7563	151	3546	1	2	1	1
ATL07FA005	250	41	111	1	1	2	1
LAX08FA092	274	7	29	0	1	2	1
ACN964253	300	60	270	1	1	2	0
ACN648279	320	25	80	1	1	2	0
ACN10134177	357	10	28	1	1	2	0
CHI06FA117	379	30	144	1	1	2	1
CEN11FA302	438	30	18	1	1	2	1
ACN812721	525	39	175	1	1	2	0
NYC08FA231	539	1	222	0	1	2	1

ACN1214769	550	10	150	1	1	2	0
DEN08FA059	565	52	52	1	1	2	1
ATL06CA031	600	30	600	0	1	2	1
CEN15FA087	627	53	348	0	1	2	1
ACN1143993	630	30	143	1	1	2	0
CHI07FA102	633	15	92	1	1	2	1
ACN982115	710	50	55	1	1	2	0
DEN06FA065	737	10	107	1	1	2	1
CEN15LA021	750	0	156	1	1	2	1
CEN13FA039	783	0	29	0	1	2	1
CEN13FA039	783	0	29	0	1	2	1
WPR09CA003	792	59	25	1	1	2	1
ACN885926	800	15	250	1	1	2	0
ACN1045952	1018	31	260	1	1	2	0
ERA09FA074	1057	28	144	1	1	2	1
CHI05CA057	1096	40	413	1	1	2	1
ACN1137952	1100	12	1000	1	1	2	0
LAX07FA200	1177	30	284	1	1	2	1
CEN14IA139	1262	31	984	1	1	2	1
IAD05LA034	1403	22	70	1	1	2	1
ACN1329503	1530	10	453	1	1	2	0
ACN1012995	1533	16	326	1	1	2	0
ACN1346187	1562	42	961	1	1	2	0
ACN712674	1563	60	117	1	1	2	0
ACN938703	1605	17	199	1	1	2	0
ACN788183	1720	37	1200	1	1	2	0
ACN1255948	1756	32	856	1	1	2	0
ACN719576	1950	25	188	1	1	2	0
ACN943902	2015	27	615	1	1	2	0
NYC07CA137	2221	19	1890	1	1	2	1
ACN1461629	2300	80	200	1	1	2	0
ACN715336	2500	40	1000	1	1	2	0
ACN955888	2800	26	300	1	1	2	0
ACN785363	3000	20	1800	1	1	2	0
ACN843072	3280	40	1620	1	1	2	0
ACN721654	3561	23	790	1	1	2	0
ACN711699	3700	30	1000	1	1	2	0
ACN1409504	4300	60	2200	1	1	2	0
WPR12FA040	4582	12	728	1	1	2	1
ACN839556	6000	20	3000	1	1	2	0
ACN967962	10000	50	8500	1	1	2	0

ACN788048	105	100	105	1	2	2	0
LAX08LA179	231	109	17	1	2	2	1
ACN822764	235	30	160	1	2	2	0
ACN886534	266	19	244	1	2	2	0
ACN814611	300	11	115	1	2	2	0
ACN1315980	305	18	157	1	2	2	0
ACN698598	315	21	21	1	2	2	0
CEN10FA101	322	1	189	1	2	2	1
ACN1119387	330	15	316	1	2	2	0
DEN06LA036-2	378	50	180	1	2	2	1
ACN792762	390	100	40	1	2	2	0
ACN819791	420	25	15	1	2	2	0
ACN858396	425	30	200	1	2	2	0
ACN955097	450	40	300	1	2	2	0
ACN1208020	460	100	10	1	2	2	0
ACN652801	474	2	3	1	2	2	0
ACN674682	480	60	2	1	2	2	0
ERA17FA017	494	134	188	1	2	2	1
ACN1078312	505	50	30	1	2	2	0
ACN882812	505	110	75	1	2	2	0
NYC07FA226	530	59	84	1	2	2	1
ACN789173	560	120	400	1	2	2	0
ACN1204986	570	10	200	1	2	2	0
ACN737363	575	40	500	1	2	2	0
ACN923741	575	60	100	1	2	2	0
ACN1234848	600	60	271	1	2	2	0
ACN772046	600	20	100	1	2	2	0
ACN957162	600	30	130	1	2	2	0
ACN983052	600	250	20	1	2	2	0
ERA11FA146	603	183	502	1	2	2	1
NYC06FA156	626	43	585	1	2	2	1
ACN655613	630	120	15	1	2	2	0
ACN837782	662	72	82	1	2	2	0
MIA05LA083	680	45	500	1	2	2	1
ACN1119625	700	80	300	1	2	2	0
ACN1245094	700	150	30	1	2	2	0
ACN982906	724	183	709	1	2	2	0
ACN1312872	734	13	140	1	2	2	0
ACN764448	740	160	120	1	2	2	0
ACN1060935	750	150	450	1	2	2	0

ACN703636	760	12	8	1	2	2	0
ACN931528	775	20	11	1	2	2	0
ACN1358513	800	100	80	1	2	2	0
ACN813619	800	20	500	1	2	2	0
CHI06LA072	803	37	91	1	2	2	1
CEN13LA088	841	135	135	1	2	2	1
DEN06LA036-1	850	65	650	1	2	2	1
ACN982902	860	680	30	1	2	2	0
ERA12LA180	922	87	55	1	2	2	1
ACN933857	925	100	60	1	2	2	0
ACN705336	946	118	337	1	2	2	0
ACN802644	970	170	170	1	2	2	0
ACN1223672	984	29	645	1	2	2	0
CHI06FA232	998	247	33	1	2	2	1
ACN1117811	1000	50	150	1	2	2	0
ACN734567	1000	90	100	1	2	2	0
ACN1155193	1020	50	60	1	2	2	0
ACN930173	1020	23	2750	1	2	2	0
ACN999603	1025	30	30	1	2	2	0
ACN1073146	1060	50	217	1	2	2	0
ACN1054605	1097	180	460	1	2	2	0
ACN1221676	1100	80	35	1	2	2	0
ACN765342	1100	20	20	1	2	2	0
ANC16LA032	1150	141	78	1	2	2	1
ACN705189	1200	30	750	1	2	2	0
ACN1449039	1230	50	200	1	2	2	0
ACN1343580	1250	30	300	1	2	2	0
ACN792965	1255	6	32	1	2	2	0
WPR16FA059	1291	10	133	1	2	2	1
ACN1291557	1300	126	119	1	2	2	0
ACN1333059	1335	120	350	1	2	2	0
ACN820593	1348	40	197	1	2	2	0
ACN870569	1350	85	225	1	2	2	0
ACN1502815	1400	45	1050	1	2	2	0
ACN692950	1460	470	750	1	2	2	0
ACN1398464	1500	55	550	1	2	2	0
ACN674376	1580	25	300	1	2	2	0
NYC07LA178	1580	81	275	1	2	2	1
ACN1254263	1600	12	300	1	2	2	0
ACN1299979	1610	31	1500	1	2	2	0

CHI02FA284	1645	137	58	1	2	2	1
LAX06FA071-2	1650	146	56	1	2	2	1
ACN1022976	1660	38	1020	1	2	2	0
ACN934925	1700	50	50	1	2	2	0
NYC06FA155	1718	42	1606	1	2	2	1
ERA13FA253	1746	24	1000	1	2	2	1
DFW06FA021	1796	66	43	1	2	2	1
ACN770817	1800	100	1400	1	2	2	0
ACN810006	1800	100	120	1	2	2	0
ACN1115965	1850	50	350	1	2	2	0
ACN946672	1850	6	480	1	2	2	0
CEN15FA119	1873	206	65	1	2	2	1
ACN869774	1884	240	493	1	2	2	0
ACN696548	1900	40	130	1	2	2	0
DEN08CA133-1	1951	49	121	1	2	2	1
ACN905407	2000	200	200	1	2	2	0
LAX08MA007	2054	191	296	1	2	2	1
ACN1246917	2090	23	329	1	2	2	0
ACN1336289	2120	15	1600	1	2	2	0
ACN1013959	2174	20	669	1	2	2	0
ACN1412187	2248	88	1012	1	2	2	0
ACN1240864	2300	10	110	1	2	2	0
ACN1252612	2300	45	1100	1	2	2	0
NYC05CA127	2300	50	750	1	2	2	1
ACN946647	2350	25	2100	1	2	2	0
CEN13FA131	2365	57	127	1	2	2	1
ACN1013943	2500	20	250	1	2	2	0
ACN1141540	2500	30	1400	1	2	2	0
ACN714827	2500	15	500	1	2	2	0
ERA11LA398	2500	25	10	1	2	2	1
GAA16CA107-2	2500	5	800	1	2	2	1
ACN1317193	2523	89	953	1	2	2	0
ACN1227053	2600	6	1200	1	2	2	0
ACN907750	2600	150	260	1	2	2	0
ACN1089305	2650	14	150	1	2	2	0
ACN655792	2650	70	135	1	2	2	0
ACN732454	2700	25	650	1	2	2	0
ACN798520	2700	45	330	1	2	2	0
ACN1103931	2800	200	150	1	2	2	0

ACN723667	2800	60	200	1	2	2	0
ACN990341	2800	50	75	1	2	2	0
ACN922300	2950	20	300	1	2	2	0
GAA16CA107-1	2985	98	290	1	2	2	1
ERA15FA215	2998	2	168	1	2	2	1
ACN1034308	3000	30	500	1	2	2	0
ACN937851	3000	40	300	1	2	2	0
DFW06LA073	3000	23	1100	1	2	2	1
ACN1426758	3200	20	600	1	2	2	0
ERA09LA204	3257	34	10	1	2	2	1
ACN1160077	3275	52	873	1	2	2	0
ACN943163	3385	25	800	1	2	2	0
ACN1135239	3500	50	1200	1	2	2	0
ACN689185	3500	40	1000	1	2	2	0
ACN826976	3500	50	1700	1	2	2	0
GAA16LA031	3643	127	1984	0	2	2	1
ACN835626	3800	65	310	1	2	2	0
ACN930426	3862	9	2750	1	2	2	0
ACN1337805	3900	100	300	1	2	2	0
ACN983750	4015	27	250	1	2	2	0
ACN711793	4050	45	2000	1	2	2	0
ACN1182340	4084	55	550	1	2	2	0
ACN1307814	4200	100	200	1	2	2	0
NYC02FA142	4312	42	4022	1	2	2	1
ACN927264	4600	15	500	1	2	2	0
ERA11LA344	4837	78	87	1	2	2	1
ACN888864	4915	35	677	1	2	2	0
ACN1413837	5000	20	500	1	2	2	0
ACN959434	5000	45	4600	1	2	2	0
ACN981761	5000	50	200	1	2	2	0
CEN14FA032	5055	218	903	1	2	2	1
CEN15FA081	5150	25	4700	1	2	2	1
ACN772873	5200	120	1500	1	2	2	0
ACN828469	5200	42	2650	1	2	2	0
ACN843383	5500	234	3000	1	2	2	0
ERA14LA006	5541	40	600	1	2	2	1
ACN1198716	5600	30	5000	1	2	2	0
ACN878185	5600	20	3600	1	2	2	0
ANC05LA150-1	5696	141	98	1	2	2	1

ACN1356261	6000	50	50	1	2	2	0
ACN729297	6000	150	200	1	2	2	0
ANC12FA073	6000	17	125	1	2	2	1
ACN1066431	7000	50	14	1	2	2	0
ACN1134221	7200	50	1000	1	2	2	0
ACN820587	7300	30	750	1	2	2	0
ACN1310986	8540	200	620	1	2	2	0
ANC02FA025	9403	98	8772	1	2	2	1
ANC05LA027	10000	70	700	1	2	2	1
ACN935230	13360	80	360	1	2	2	0
ACN720093	15000	50	90	1	2	2	0
ERA13FA275	16561	44	56	1	2	2	1
ACN1247324	19000	70	500	1	2	2	0
CEN09LA054	22228	96	2525	1	2	2	1
ACN818665	29742	60	9200	1	2	2	0
ACN717486	800	50	1000	1	3	2	0
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ACN900960	2650	150	1200	1	3	2	0
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ACN1313421-1	2800	100	600	1	3	2	0
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ACN1307319	2850	60	600	1	3	2	0
NYC06CA177	2875	17	2300	1	3	2	1
NYC06MA192	2877	84	84	1	3	2	1
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ACN1416209	2900	45	70	1	3	2	0
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ACN718672	3000	125	750	1	3	2	0
ERA15FA326	3000	15	100	1	3	2	1
ACN1020135	3200	80	1000	1	3	2	0
ACN1471540	3300	100	410	1	3	2	0
ACN945977	3300	120	12	1	3	2	0
DEN06LA041	3347	19	2257	1	3	2	1
ACN1080994	3391	108	151	1	3	2	0
ACN854927	3400	65	400	1	3	2	0
ACN1257400	3500	125	1500	1	3	2	0
ACN1360479	3500	25	2000	1	3	2	0
ACN648006	3500	180	150	1	3	2	0
ANC06FA018	3584	90	129	1	3	2	1
ACN839154	3700	80	130	1	3	2	0
ANC05LA150-2	3712	46	948	1	3	2	1
DEN05FA051	3778	118	414	1	3	2	1
NYC08CA188	3790	150	1040	1	3	2	1
ACN1307577	3800	100	15	1	3	2	0
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ACN1099064	4000	60	1700	1	3	2	0
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ERA12LA435	4080	119	389	1	3	2	1
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ACN1128508	4300	20	230	1	3	2	0
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ERA11IA007	4500	62	724	1	3	2	1
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ACN865482	4600	200	150	1	3	2	0
ACN717053	4700	60	30	1	3	2	0
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LAX06FA071-1	4880	143	2200	1	3	2	1
ACN1344524	4900	200	3800	1	3	2	0
ACN1006821	4950	27	650	1	3	2	0
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ACN763168	5000	100	300	1	3	2	0
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DEN05CA050-1	5320	75	1253	1	3	2	1
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ACN1153151	7105	105	1600	1	3	2	0
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MIA05LA049-1	8020	91	553	1	3	2	1
NYC08LA164	8200	150	120	1	3	2	1
LAX04FA113	8230	110	1037	1	3	2	1
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GAA16CA383	15750	6	150	1	3	2	1
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ACN682713	30000	85	55	1	3	2	0
ACN1243605	17800 0	90	30	1	3	2	0

VITA

Nsikak Effiong Udo-Imeh received his bachelor’s degree in Mechanical Engineering from the Nigerian Defense Academy, Kaduna – Nigeria. He served as an officer in the Nigerian Air Force for 20 years, where he was responsible at various times, for scheduled and unscheduled maintenance on the Nigerian Air Force Dornier 128-6, Airbeetle-18 and Dornier 228 aircraft fleets. Nsikak obtained a master’s degree in safety science from Embry Riddle Aeronautical University, Prescott Arizona. Nsikak is a member of the Human Factors and Ergonomics Society and the American Society and Safety Professionals.