STATE-BASED ANALYSIS OF GENERAL AVIATION LOSS OF CONTROL ACCIDENTS USING HISTORICAL DATA AND PILOTS' PERSPECTIVES

by

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विद्या ददाति विनयम् विनयाद् याति पात्रताम् ।
पात्रत्वात् धनमाप्नोति धनात् धर्मं ततः सुखम् ॥

Sri Narayana Pandita, Hitopadesha Verse 0.6

Knowledge brings humility, humility begets worthiness,
worthiness leads to wealth and enrichment, which leads to righteousness, and eventually joy.

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ABBREVIATIONS

AAM	Advanced Air Mobility
ACS	Airman Certification Standards
ADM	Aeronautical Decision Making
AFH	Airplane Flying Handbook
AI	Artificial Intelligence
AIAA	American Institute of Aeronautics and Astronautics
AOPA	Aircraft Owners and Pilots Association
ASRS	Aviation Safety Reporting System
ATC	Air Traffic Control
ATP	Airline Transport Pilot
BERT	Bidirectional Encoder Representations from Transformers
CFI	Certified Flight Instructor
CFII	Certified Flight Instructor-Instrument
CFIME	Certificated Flight Instructor-Multiengine
CFIT	Controlled Flight into Terrain
CFR	Code of Federal Regulations
DPE	Designated Pilot Examiner
FAA	Federal Aviation Administration
FAR	Federal Aviation Regulations
FCM	Fuzzy Cognitive Map
FOD	Foreign Object Debris
GA	General Aviation
GAJSC	General Aviation Joint Safety Committee
HFACS	Human Factors Analysis and Classification System
IFR	Instrument Flight Rules
IMC	Instrument Meteorological Conditions

IOCFS	Improved Oscillated Correlation Feature Selection
IRR	Inter-Rater Reliability
LDA	Latent Dirichlet Allocation
LOC	Loss of Control
LOC-I	Inflight Loss of Control
LSA	Latent Semantic Analysis
LSTM	Long Short-Term Memory
ML	Machine Learning
MSL	Mean Sea Level
NLP	Natural Language Processing
NTSB	National Transportation Safety Board
OOV	Out-of-Vocabulary
PEGASAS	Partnership to Enhance General Aviation Safety, Accessibility, and Sustainability
PHAK	Pilot's Handbook of Aeronautical Knowledge
PIC	Pilot-in-command
RoBERTA	Robustly Optimized BERT Pretraining Approach
STUCCO	Search and Testing for Understandable Consistent Contrast
SVM	Support Vector Machines
TF-IDF	Term Frequency-Inverse Document Frequency
UAV	Unmanned Aerial Vehicle
UPRT	Upset Prevention and Recovery Training
VFR	Visual Flight Rules
VMC	Visual Meteorological Conditions

ABSTRACT

General Aviation (GA) encompasses all aircraft operations, excluding scheduled, military, and commercial operations. GA accidents comprise approximately 94% of all aviation accidents in the United States annually. 75% of these accidents involve pilot-related factors (pilot actions or conditions). Inflight loss of control means that the flight crew was unable to maintain control of the aircraft in flight. With almost 50% of loss of control accidents being fatal yearly, it continues to be the deadliest cause of GA accidents.

The most common approach to understanding accident causation is analyzing historical data from sources such as the National Transportation Safety Board (NTSB) database. The NTSB database has abundant rich information. In contrast to the extensive investigations into and detailed reports on commercial aviation accidents, GA accident investigations tend to be shorter, and the resulting reports tend to be brief and limited—especially regarding human factors' role in accidents. Only relying on historical data cannot provide a complete understanding of accident causation.

There is a clear need to better understand the role of human factors involved in GA accidents to prevent such accidents and thus improve aviation safety. In my research, I focus on a specific type of accidents, inflight loss of control (LOC-I), the deadliest cause of GA accidents. I aim to address the following research questions:

1. What causes LOC-I?
   - 1.1 Which types of errors do pilots make in LOC-I incidents?
   - 1.2 What causes pilots to make these errors—what is the role of human factors in LOC-I accidents?
2. How might we find additional causes from accident reports that are not coded?
   - 2.1 Can we better model accidents using all the available information in reports to gain a deeper understanding of accident causation?

I use historical data analysis and human-subjects research with pilots to investigate the role of human factors in loss of control accidents. Building on previous work, I created a state-based modeling framework that maximizes data extraction and insight formation from the NTSB

accident reports by (1) developing a structured modeling language to represent accident causation in the form of states and triggers; (2) populating the language lexicon of states and triggers using insights from accident reports and pilots perspectives via surveys and interviews; and (3) applying Natural Language Processing (NLP) and machine learning techniques to automatically translate accident narratives into the language lexicon. The framework is focused on LOC-I but can be extended to other types of accidents. Figure 1 outlines my research. Findings from my study may help in consistent accident analysis, better accident reporting, and improving training methods and operating procedures for GA pilots.

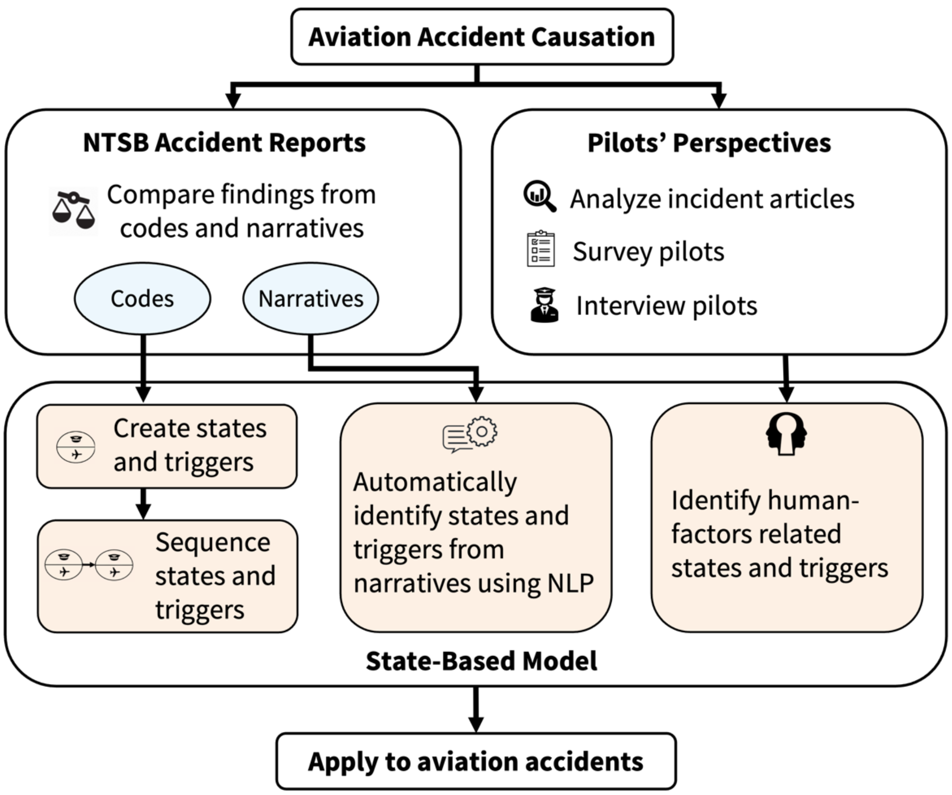

Figure 1: Research outline for the state-based modeling framework to analyze aviation accidents using historical data and human-subjects research. The modeling framework automatically translates NTSB codes into states and triggers to model accidents. I also used Natural Language Processing to predict states and triggers from accident narratives. The findings from the pilot survey and interviews provide insights into the role of human factors in aviation incidents.

1. INTRODUCTION

The International Civil Aviation Organization (ICAO) defines General Aviation (GA) as a category of aircraft operations, exclusive of all military operations, scheduled air services and non-scheduled air transport operations for remuneration or hire (ICAO, 2009). GA accidents comprise approximately 94% of all aviation accidents in the United States annually (NTSB, 2023). Around 70% of the GA accidents involved fixed-wing aircraft. 75% of these accidents involve pilot-related factors (i.e., pilot actions such as improper corrective action or pilot conditions such as disorientation). In my research, I take two main approaches to better understand the causes of LOC-I: (1) historical data analysis by using the accident reports recorded in the National Transportation Safety Board (NTSB); and (2) human-subjects research by surveying and interviewing pilots and certified flight instructors (CFIs) about their experiences, training, and perspectives. In this chapter, I discuss the research motivation and present the research outline. Section 1.1 discusses the background and motivation for the research and Section 1.2 presents the research outline and lays out the thesis outline.

1.1 Background and Motivation

Most fixed wing GA accidents result from inflight loss of control (LOC-I), controlled flight into terrain (CFIT), continued visual flight rules (VFR) flight into instrumental meteorological conditions (IMC), engine failures, and fuel exhaustion or contamination (cf. AOPA, 2018; GAJSC 2016). Inflight loss of control (LOC-I) continues to be a significant cause of GA fixed-wing aircraft accidents each year. Loss of control is "a hazardous condition that involves an unintended departure of an aircraft from controlled flight regime" (FAA, 2019). In simple words, LOC-I means that the flight crew was unable to maintain control of the aircraft in flight. Nearly 20% of fixed-wing GA accidents in the last two decades in the United States (U.S.) involved LOC-I (NTSB, 2023). In 2020, 19% of total fixed-wing GA accidents involved LOC-I; for fatal accidents, this percentage increases to 52%. 49.2% of all LOC-I accidents in 2010–2020 were fatal with an average of 163 fatalities per year (NTSB, 2023). Figure 2 shows the number of fatal GA accidents that happened in 2010–2021, as recorded by the NTSB database.

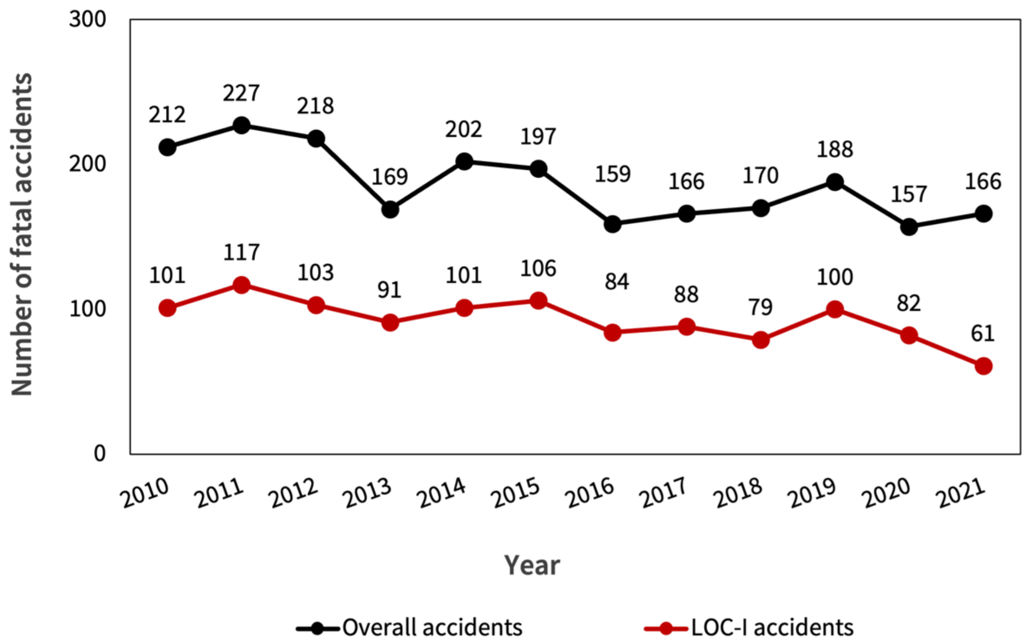

Figure 2: Number of overall fatal accidents versus LOC-I fatal accidents involving GA fixed-wing aircraft. LOC-I is the deadliest cause in fatal GA accidents. Note that, as of March 2023, the NTSB has not completed its investigation for all 2021 accidents.

Most LOC-I incidents involve some kind of pilot error (Belcastro et al., 2014). In 2019, 65% of LOC-I accidents and 51% of fatal LOC-I accidents were pilot-related (NTSB, 2023). Two of the most cited pilot-related triggers in 2009–2019 LOC-I accidents were improper inflight planning (12.91%) and improper action performance (7.08%) (Majumdar et al., 2021). These pilot-related NTSB codes tend to be broad and vague. The accident reports do not explain specifically what lacked in inflight planning or pilot actions.

There is a clear need to better understand the reasons for LOC-I accidents. One approach to improving our understanding is by analyzing historical accident reports. In the U.S., the National Transportation Safety Board (NTSB) investigates all civil aviation accidents. After concluding their investigation, the NTSB publishes a final report, which includes a prose section with summary analysis of the accident, a discussion of the probable cause and findings, and "factual information" on the flight history, personnel, aircraft, meteorological conditions, medical and pathological information, and any tests and research the investigators conducted (NTSB, 2019). Each accident is also coded using a set of codes for occurrences, findings, and phases of flight to facilitate trend analysis. Rao et al. (2016) provides a detailed discussion of this system.

Several researchers have used NTSB codes to identify GA accident causes. Boyd (2015) found that failure to follow single engine procedures following loss of an engine was the highest factor in fatal twin-engine piston aircraft GA accidents under visual weather conditions. Fultz and Ashley's (2016) found that 60% of weather-related fatal accidents occurred in IMC. Bazargan and Guzhva (2007) found that hazardous weather and light conditions such as IMC and dark night conditions increased the likelihood that accidents would be fatal. Goldman et al. (2002) found that of maintenance errors, installation errors such as using the wrong parts were most likely to cause injury or fatality. Aguiar et al. (2017) found that GA accidents in mountainous terrain and high elevation environments most commonly involved CFIT and wind gusts/shear. Other analyses used NTSB accident narratives. Boyd and Stolzer (2016) identified accident-precipitating factors and found that not following the checklist/flight manual contributed the most to fatal or serious turbine-powered GA accidents. Ballard et al. (2013) considered three major risk factors for fatalities, post crash fires, crashes after flight in IMC, and off-airport crashes (in other words, away from emergency services), and found that fatalities were most likely to occur in accidents occurring after flight in IMC contributed the most to fatal air tour accidents. Wiegmann et al. (2005) used the Human Factors Analysis and Classification System (HFACS) to identify unsafe operator acts. 80% of the GA accidents were associated with at least one skill-based error such as handling. While these studies uncovered part of what causes GA accidents (e.g., flight into IMC is often involved in fatal accidents), they were not able to explain how, for example, IMC leads to fatal accidents.

Studies using NTSB data to understand LOC-I accidents face similar challenges. Previous work attempted to build chains of events in accidents using occurrence codes in the NTSB database. Rao et al. (2016) provides a detailed discussion of this system. But their efforts have been stymied by the lack of (coded) data in the reports. For example, Rao and Marais (2015) found that 13.8% of 5051 GA rotorcraft fatal accidents had LOC-I as the first occurrence in accident sequences of events. Houston et al. (2012) found that 75% of the 147 instructional LOC-I accident reports cited LOC-I as the first occurrence—thus we cannot determine what led to the LOC-I. Franza and Fanjoy (2012) also found that pilots' failure to maintain directional control contributed to 50% of fatal accidents in both aircraft models.

General Aviation accident reports include limited detail on human factor related causes. Houston et al. (2012) also identified top causal factors in LOC such as failure to maintain directional control, improper airspeed, inadequate supervision, and stalls or spins. In my MS thesis work, I used a state-based approach to find the most frequent causes in 10,417 GA LOC-I accidents (Majumdar, 2019). The study found some additional causes to LOC-I as compared to the previous research findings, such as improper angle of attack, exceeding aircraft performance limits, pilot's improper remedial action, and lack of action. However, none of these causes that were cited in the NTSB reports specifically mention what kind of pilot actions were lacking or were improper. Understanding specific pilot actions and conditions rather than general aspects may help to focus on improving GA training methods and evaluating standard operating procedures (Ud-Din & Yoon, 2018).

A few researchers focused on identifying the role of human factors in LOC-I by analyzing accident reports that were not necessarily GA related. Belcastro and Foster (2010) studied 126 Federal Aviation Regulations (FAR) Part 121 (including large transport and smaller regional carriers) loss of control (LOC) accidents and identified causal factor categories such as adverse onboard conditions (such as aircraft damage and inappropriate crew actions and crew impairment), vehicle upsets (such as abnormal attitude), and external hazards and disturbances (such as poor weather). While the study identifies the number of accidents that cited factors related to inappropriate crew response, it does not provide further detail on these pilot actions and conditions.

Ancel and Shih (2012) developed a generic integrated LOC accident framework (LOCAF) model expressed in an Object-Oriented Bayesian belief network and applied it to 54 FAR Part 121 and Part 135 (including private air charter and air taxi flights). They found that 42 out of 54 accidents included human error either directly or indirectly. The study revealed that failure in aircraft systems, poor environmental conditions, and deficient air traffic management guidance can have a negative impact on the flight crew performance (such as distraction, performance overload, confusion, panic, and task fixation or saturation). Other external disturbances can lead to spatial disorientation, fatigue, or medical illness. Ud-Din and Yoon (2018) found that poor health and impairment due to medication, followed by poor manual control and inadequate flight procedures were the most significant events for LOC during maneuvering.

One way to improve understanding is by modeling accidents. Several researchers have used Bayesian networks to identify causal factors and assess risk (Ancel & Shih, 2012; Ancel et al., 2015; Ayra et al., 2019; Xiao et al., 2020; Uğurlu et al., 2020). Ancel et al. (2015) developed an object-oriented Bayesian network (OOBN), based on HFACS, to model Part 121 and 135 LOC-I accidents. They identified organizational deficiencies as underlying flight-related and maintenance crew-related airline accidents. Bayesian networks are useful to visually represent a summary analysis of accidents. But they require detailed information that is often not available for GA accidents. The probability calculation for each node in a Bayesian network requires expert judgment and information from sources such as operators and aviation agencies. Further, some accident sequences have cyclic relationships, e.g., an aircraft stall may cause an LOC-I and vice versa. Since Bayesian networks are directed acyclic graphs, they cannot capture such cyclic relationships between aircraft states.

Another way to identify LOC-I accident causation is by conducting surveys and interview pilots to reveal insights into aviation risk. Most of these studies were focused on military pilots to understand pilot fatigue and spatial disorientation (Caldwell & Gilreath, 2002; Holmes et al., 2003; Pennings et al., 2020; Lewkowicz & Biernacki, 2020; Taneja, 2007; and Dawson et al., 2017). Other studies on human factors of commercial airline pilots were focused on number of work hours per incident, fatigue, and pilots' awareness of human factors related to aviation safety (O'Hagan et al., 2016; Bourgeois-Bougrine et al., 2003; and Zhou et al., 2018). Studies pertaining to General Aviation investigated pilots' experiences with hypoxia, fatigue flying, pilots' flight planning and decision-making processes, (Holt et al., 2019; Teo, 2020; Keller et al., 2019; and Psyllou et al., 2017). To the best of our knowledge, no published survey or interview studies to date have investigated pilots' LOC-I experiences and related human factors.

While all these studies based on the NTSB database uncovered part of what causes LOC-I accidents (e.g., improper airspeed is often involved in LOC-I accidents), they were not able to explain how these conditions initiate and lead to LOC-I accidents. Although the NTSB database has an abundance information for all aviation accidents, the accident data is not always logically complete, and information is often missing. Certain challenges of using the NTSB database are:

1. Accident Coding Model and Redundant NTSB Codes

The NTSB's accident coding system is based on an event-based model, where one event in an accident leads to another, but not all aspects of accidents are events. For example, an impaired pilot is better understood as a continuing condition, or a state (Rao & Marais, 2020). The pilot's impaired condition makes subsequent errors more likely, and therefore does not fit well as "only" an initiating event. Additionally, multiple codes in the NTSB database have similar meanings. For example, the subject codes 24518: Altitude and 24519: Proper altitude both indicate that the pilot did not maintain the correct altitude. Such redundancy in codes can lead to inaccurate counts in accident causes. Finally, the NTSB database does not present all findings as codes, for example, in the pre-2008 coding system, there are no codes to capture improper aircraft heading.

2. Lack of Detailed Information

Unfortunately, the prose content for GA accidents tends to be short. For example, in 2019, the average narrative length for the 144 accidents that had LOC-I codes was 971 words. The number of occurrence and finding codes for these 144 accidents is also short (mean chain length = 7.30, standard deviation = 2.29), albeit somewhat longer than that for all GA fixed-wing aircraft accidents (mean number of codes = 6.29, standard deviation = 2.19). 80% of these reports included a code related to crashing into terrain/water. 9.6% of LOC-I accidents do not record any codes relevant to the preflight state definitions (Majumdar, 2019). Thus, the potentially wide range of accident stories is reduced to a small set of short stories, most of which are some variation of "the pilot lost control and crashed into the ground/water." For instance, the most frequently used cause for fixed-wing LOC-I accidents is aircraft control not maintained – in other words, the pilot lost control because they did not maintain control (Houston et al., 2012; Franza & Fanjoy, 2012). So, we have limited information to determine why LOC-I happens, what most often causes it, or whether there have been any changes in its causes. These problems are compounded by the limited information about pilot conditions and actions in LOC-I.

3. Limited Information About Pilot Conditions and Actions

Most fatal GA accident reports do not provide detailed information about human factors. Due to lack of survivors, limited information is available about pilot's conditions and actions. Even for non-fatal accidents, there is very little pilot-related information per accident. For example, in April 2011, a private pilot was on a solo cross-country flight from Lafayette, Louisiana to Tulsa, Oklahoma (NTSB Number: CEN11FA285). He was continuing his flight after spending the night at an enroute airport waiting for a storm to pass. Witnesses reported that during takeoff, it sounded like the engines were cutting out and it seemed like the pilot was trying to make a 180 degree turn back to the runway before the aircraft stalled and spun into the ground. The National Transportation Safety Board (NTSB) determined the probable cause of the accident to be the pilot's loss of control during takeoff for undetermined reasons. The report mentioned the pilot's action/decision as one of the findings in the accident, but it does not specify the type of pilot's action or decision that contributed to the accident.

4. Incomplete Translation of Accident Information from Narratives to Codes

In some GA accident reports, the narratives provide detailed information about the accidents, but the codes cited in the reports do not represent all the findings mentioned in the narratives. Also, the type of codes used to describe the accidents do not describe the full story. Consider a Bellanca 8KCAB accident from January 2009 in Moscow, Tennessee (NTSB Number: ERA09LA147). According to the detailed narrative of the accident, the private pilot was witnessed to be maneuvering at less than 1,000 feet above the ground and was observed vertically going up, nose over to the right, and eventually impacting the ground. The NTSB codes cited for this accident were: (1) loss of control in flight while maneuvering; (2) collision with terrain during uncontrolled descent phase of flight; and (3) Reason not determined. Additional findings that could have been considered (but were not cited) for this accident are low altitude and improper maneuvering. This incomplete translation of accident information from narratives to NTSB codes leads to a partial understanding of accident causation. Analyzing both the accident narratives as well the NTSB codes may provide a more accurate understanding of accident causation.

Although the NTSB database has an abundance of information for the accidents, the accident data is not always logically complete and has missing information, which limits our understanding of accident causation. Due to this shallow detail of accident information, a population level analysis of pilot conditions and actions becomes difficult by using only accident data. Additionally, because nearly half of the LOC-I accidents are fatal, and because GA aircraft typically do not have "black boxes", it is often impossible to find out what exactly happened before and during the accident flight. Efforts to reduce LOC-I have focused on novel technology to prevent hazardous conditions (e.g., angle-of-attack based systems can help pilots avoid inadvertent stall which may lead to LOC-I), and various safety programs and training methods that are intended to reduce pilot error in general (GAJSC, 2014). Because the specific underlying issues and human factors that contribute to LOC-I are not completely known, we cannot determine whether these efforts are successful in reducing these factors. What we do know is that LOC-I continues to be a significant cause of accidents. Understanding the specific pilot actions and conditions that lead to LOC-I may help focus GA training methods appropriately to reduce LOC-I accidents.

1.2 Research and Thesis Outline

To better understand how pilot actions and other unsafe conditions lead to LOC-I, I lay out a two-fold approach where I (1) analyze the NTSB accident reports using their narratives and the NTSB codes and (2) gain pilots' perspectives from sources such as articles, surveys, and interviews to provide a richer understanding of LOC-I accident causation. I extend my master's work by using the state-based approach to model LOC-I accidents (Majumdar, 2019). The findings from my studies provides a deeper understanding of LOC-I causation and the role of human factors in LOC-I accidents to prevent LOC-I in the future.

In this research, I aim to address the following research questions:

1. What causes LOC-I?
    1.3 Which types of errors do pilots make in LOC-I incidents?
    1.4 What causes pilots to make these errors—what is the role of human factors in LOC-I accidents?

2. How might we find additional causes from accident reports that are not coded?
    2.1 Can we better model accidents using all the available information in reports to gain a deeper understanding of accident causation?

I created a state-based modeling framework by (1) modeling LOC-I accidents in the form of states and triggers and creating sequencing (grammar) rules for the states and triggers; (2) providing insights into pilots' perspectives on their experiences and training using lessons learned articles, surveys, and interviews; and (3) extracting more information (states and triggers) from accident reports using Natural Language Processing (NLP) (see Figure 1).

This thesis is laid out as follows: Chapter 2 presents aircraft and demographic data analysis of LOC-I accidents, Chapter 3 introduces the state-based approach for modeling fixed-wing aircraft accidents. Chapter 4 describes a comparison of findings using the NTSB codes and narratives in accident reports. Chapter 5 discusses an analysis of LOC-I related lessons learned articles from the AOPA Pilot magazine. Chapter 6 presents my study on pilots' survey on their LOC-I experiences. Chapter 7 presents the interviews with pilots on LOC-I experiences and training. Chapter 8 lays out the method and results for extracting information from reports using NLP, and Chapter 9 (a) concludes the work and summarizes the contributions of this research; (b) provides recommendations for pilots and their training based on the insights gained from the survey and interviews to prevent LOC-I in the future; and (c) provides recommendations for future work.

2. AIRCRAFT AND DEMOGRAPHIC DATA ANALYSIS OF INFLIGHT LOSS OF CONTROL ACCIDENTS

In this chapter, I present an analysis of the demographic and aircraft data, as recorded in the NTSB database for inflight loss of control accidents in 2010–2022.

2.1 Method

The NTSB records LOC-I accidents using the occurrence code *240: Loss of control inflight*. I identified 5,914 Part 91 LOC-I accidents from the NTSB database that occurred in 2010–2022 using the code *240*. The NTSB database has a downloadable M.S. Access dataset. The Access file has different tables titled "aircraft", "flight crew", "flight time", etc. that contain relevant information about accidents. For example, the "aircraft" table includes information such as *aircraft's category* (e.g., airplane, helicopter), *FAR part* under which aircraft was flying (e.g., 121, 91), *aircraft's make and model* (e.g., Cessna 172, Piper pa 28-161), and *aircraft damage* (e.g., substantial, minor). Similarly, the "flight crew" table consists demographic data for the pilots involved in accidents, such as *crew category* (e.g., pilot, flight instructor), *crew age*, and *crew sex*. The "flight time" table includes accident pilots' hours of flying experience for different categories such as total flying hours, actual instrument, and make and model of accident aircraft.

I analyzed aircraft data for the LOC-I accidents from the "aircraft" table and demographic data for the pilots involved in these accidents from the "flight crew" and "flight time" tables. In the next few sub-sections, I will discuss my findings from the demographic and aircraft data for LOC-I accidents. Of the 5,914 LOC-I accidents, 24.97% were fatal, 9.12% involved serious injuries, and 12.14% had minor injuries. There were a total of 2,497 fatalities in 2010–2022 LOC-I accidents.

2.2 Aircraft Data

92.63% of the accident aircraft were single-engine and 7.37% were twin-engine. 87.98% of all aircraft had substantial damage. According to the Code of Federal Regulations 49 CFR 830.2, substantial damage means “damage or failure which adversely affects the structural strength, performance, or flight characteristics of the aircraft, and which would normally require major repair or replacement of the affected component. Engine failure or damage limited to an engine if only one engine fails or is damaged, bent fairings or cowling, dented skin, small, punctured holes in the skin or fabric, ground damage to rotor or propeller blades, and damage to landing gear, wheels, tires, flaps, engine accessories, brakes, or wingtips are not considered “substantial damage” for the purpose of this part.” (CFR, 2023). 11.82% of aircraft were destroyed. The FAA considers an aircraft to be destroyed if all its primary structure is damaged to the extent that it would be impracticable to return the aircraft to an airworthy condition by repair (FAA, 2018a). 0.17% of aircraft had minor damage. Minor damage means the aircraft either is in an airworthy condition or is restorable to airworthy condition by minor repairs (FAA, 2018a).

The majority of accident aircraft were Cessnas (29.97%). 17.29% were Pipers, and 4.86% were of the Beech make. The remaining 47.88% aircraft were of other makes such as Mooney, Cirrus, and Boeing. Table 1 shows the most common aircraft make and model combinations involved in LOC-I accidents.

Table 1: Top aircraft make and model involved in 2010–2022 LOC-I accidents.

Aircraft make and model	Percentage
Cessna 172	10.35%
Piper PA28	5.22%
Cessna 182	3.40%
Cessna 180	2.16%
Cessna 152	1.35%

Four of the top five models involved in LOC-I accidents were Cessnas (Cessna 172, 182, 180, and 152). Cessna 172 was the most common aircraft model involved in LOC-I, followed by Piper PA28. Cessna 172 is also the most registered aircraft in the U.S. The FAA maintains a registry that records total aircraft registrations in the U.S. for different aircraft models (FAA, n.d.). The Cessna 172 constitutes 36% of the top five aircraft models registered in the U.S. Table 2 shows the most registered aircraft models in the U.S., as recorded by the FAA registry in March 2023. Piper PA28 is the second most registered aircraft model, followed by Cessnas 182, 180 and 152.

Table 2: Total registrations for top aircraft models in the U.S. (FAA, n.d.)

Aircraft make and model	Total registered
Cessna 172	19,951
Piper PA28	17,870
Cessna 182	13,323
Cessna 180	2,560
Cessna 152	1,697

2.3 Demographic Data

Of the 5,914 accidents, 77.7% were solo flights. Student pilots were flying solo in 6% of the total accidents. 5.95% of the flights were instructional and 10.80% of the flights had passengers. Figure 3 shows the pilot age distribution at the time of LOC-I. I analyzed the age for the following flight crew categories: pilot, co-pilot, student pilot, flight instructor, and check pilot. Almost half of the flight crew (47.05%) were 55–69 years at the time of their accident (55–59 years: 11.88%; 60–64 years: 13.23%; and 65–69 years: 12.57%). These findings are consistent with previous NTSB accident analyses (Bazargan & Guzhva, 2011; Mortimer, 1991; AOPA Air Safety Institute, n.d.). Bazargan and Guzhva (2011) found that male pilots over age 60 were more likely to be involved in fatal accidents in 1983–2002. Mortimer (1991) analyzed 1985-1986 accidents and found that pilots aged 60 or older had an accident rate about twice that of the younger pilots. A 2006 Air Safety Institute study (AOPA Air Safety Institute, n.d.) found that pilots from age 55 and above had more accidents. These findings may account for the possibility that older pilots fly more often than younger pilots (possibly due to more leisure time or disposable income for flying). Without sufficient data to eliminate these factors, it is difficult to draws conclusions about the susceptibility of older pilots to accidents.

There were two student pilots of age 14 and 15 years each. There were 17 pilots who were 90 years and older. The oldest pilot was 94 years old.

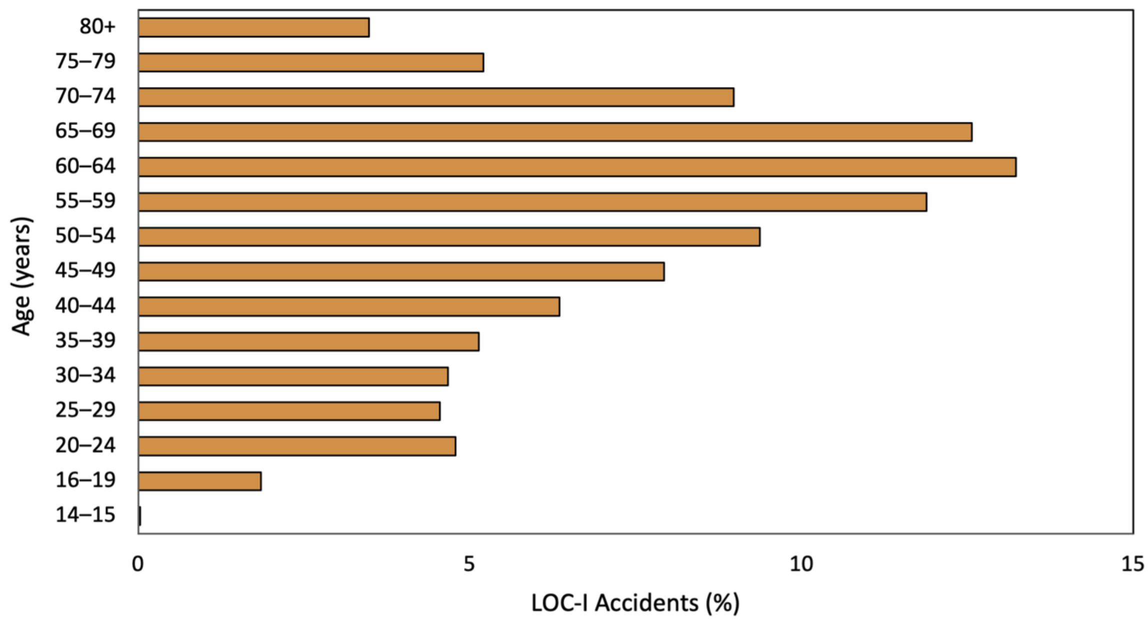

Figure 3: Age distribution of pilots at the time of LOC-I accident

The FAA releases annual statistics for active civil airmen in the U.S. The statistics include pilot information such as the estimated active pilot certificates held by category and age group, and the average age of pilots by category (FAA, 2023). The FAA includes these statistics for pilots with an airplane, helicopter, glider, and gyroplane certificate in six categories: student, sport, recreational, private, commercial, and airline transport pilots. Table 3 shows the estimated active pilot certificates by category and age group (FAA, 2023). The FAA included private and airline transport pilots with an airplane, helicopter, glider, and gyroplane certificate. Pilots with multiple ratings were reported under the highest rating. For example, a pilot with a private helicopter and commercial airplane certificates was reported in the commercial category.

Table 3: Estimated active pilot certificates by category and age group (FAA, 2023).

Age Group	Total	Student	Sport	Recreational	Private	Commercial	Airline Transport
Total	**882,002**	**280,582**	**6,957**	**80**	**176,328**	**119,832**	**173,148**
14–15	640	640	0	0	0	0	0
16–19	27,564	20,927	12	2	6,020	446	0
20–24	87,798	43,183	69	0	20,231	14,689	1,496
25–29	107,261	52,235	139	6	14,858	18,810	7,982
30–34	96,373	45,265	232	8	13,434	12,894	11,846
35–39	88,942	33,162	334	2	13,614	10,557	17,229
40–44	79,074	24,407	346	0	12,632	8,595	19,842
45–49	65,325	16,390	365	5	10,819	6,632	19,890
50–54	68,909	13,520	515	4	12,897	7,355	22,949
55–59	69,676	11,030	765	8	14,771	7,561	24,955
60–64	65,526	8,417	999	6	17,101	7,887	21,745
65–69	51,483	5,678	1,151	18	16,942	7,915	11,730
70–74	35,309	3,300	899	9	12,089	6,688	6,425
75–79	23,655	1,660	664	9	7,085	5,597	4,301
80+	14,467	768	467	3	3,835	4,206	2,758

Based on the FAA statistics, most pilots (of all six certificate categories) are aged 25–29 years (12.42%), followed by 30–34 years (11.06%) (FAA, 2023). 20.96% of active pilots are 55–69 years old. The mean age of pilots involved in LOC-I accidents was 54 years. According to the FAA's statistics, the average age of all six pilot certificate holders in 2010–2022 is 47 years (FAA, 2023). Since the FAA does not release these statistics explicitly for Part 91 or GA pilots, we do not have sufficient information to comment on why pilots of age 55–69 years are mostly involved in LOC-I accidents. It is difficult to collect a consistently accurate count of pilots by different certificates and operations since pilots with the same certificate can fly under different parts. For example, an airline transport pilot can fly both a commercial jet and a private aircraft. The best way to know the accurate count of pilots flying under different operations would be by conducting a nationwide survey.

Figure 4 shows flight crew's total hours of flying experience in the range size of 1,000 at the time of accident. Most pilots (53.01%) had less than 1,000 hours of experience at the time of their accident. Pilots with more experience were less likely to be involved in an accident, as shown in the figure.

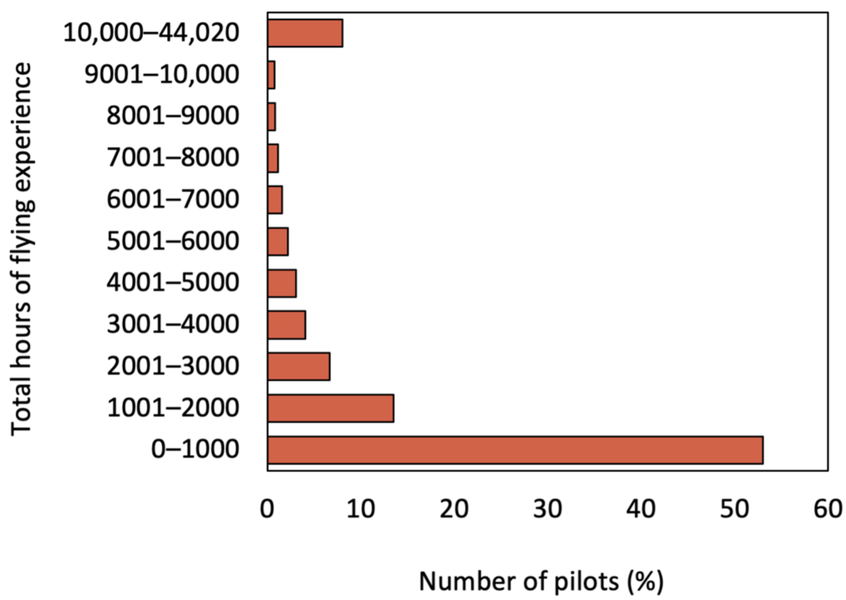

Figure 4: Total hours of flight experience of flight crew at the time of their LOC-I accident.

Figure 5 shows a breakdown of 0–1,000 hours of the flight crew's flying experience at the time of the accident. Most pilots (14.47%) were inexperienced, i.e., had less than 100 hours of flying experience at the time of their accident. Almost half (49%) of the 0–100 hours pilots had less than 40 hours of flying experience. Note that the FAA requires at least 40 hours of flight time for a private pilot certificate (14 CFR part 61) (CFR, 2023).

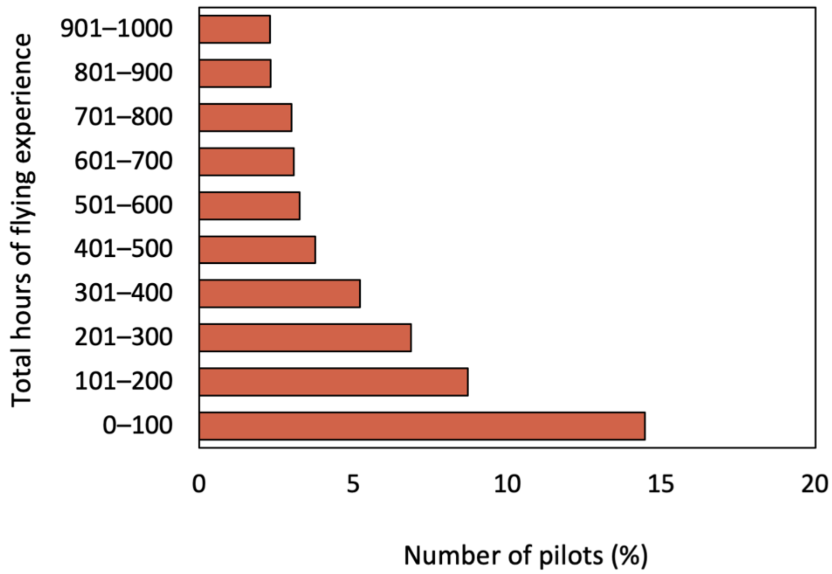

Figure 5: Percentage of total pilots with less than 1000 hours of flying experience at the time of LOC-I accident.

Figure 6 shows pilots' age and total flying experience at the time of LOC-I. Most pilots were 50–60 years with 100–200 hours of flying experience at the time of their LOC-I.

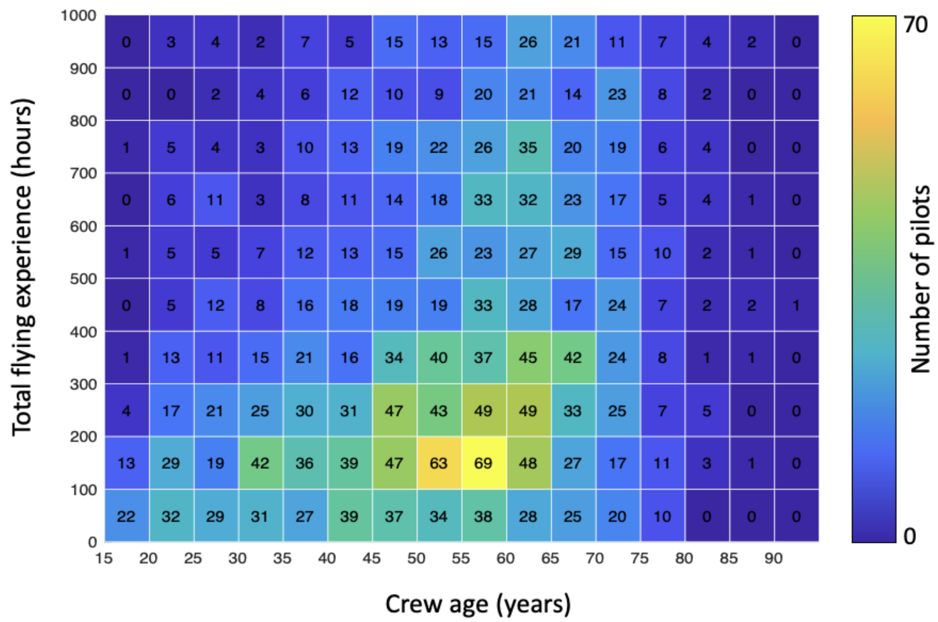

Figure 6: Heat map of pilots' age and total flying experience at the time of LOC-I.

Figure 7 shows the total hours of flying experience of flight crew in the accident aircraft make at the time of accident. 91.51% of the pilots had less than 1000 hours of flying experience in the accident aircraft make at the time of their accident. More than half (55.47%) of the pilots had less than 100 flying hours in the aircraft make. 8.47% of pilots had 1,000–15,990 flying hours in the aircraft make at the time of their LOC-I.

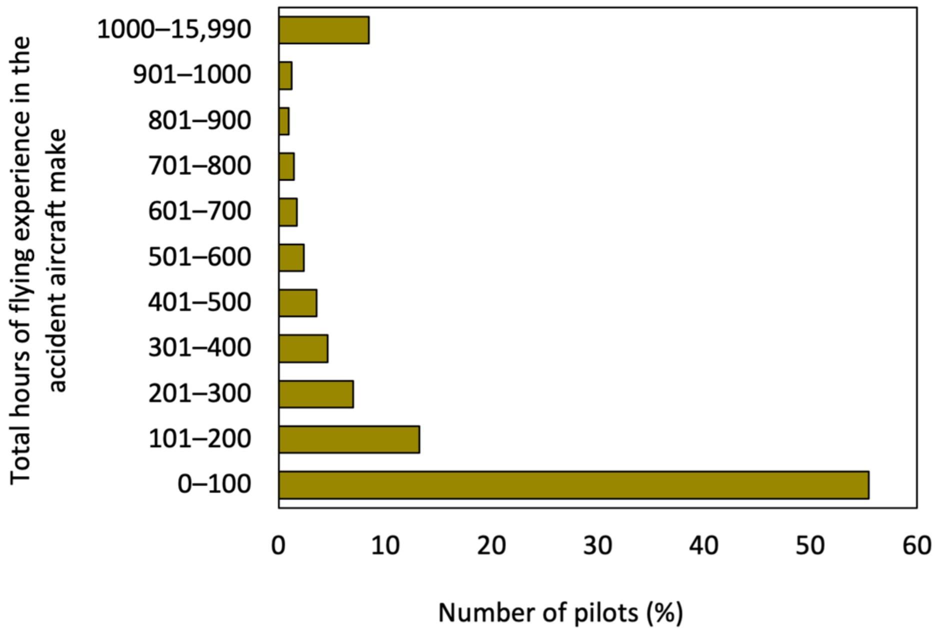

Figure 7: Percentage of pilots with flying experience in accident aircraft make at the time of LOC-I.

Figure 8 shows pilots' age and total hours of flying experience in accident aircraft make at the time of LOC-I. Most pilots were 60–70 years and had flown less than 10 hours in the accident aircraft make at the time of their LOC-I.

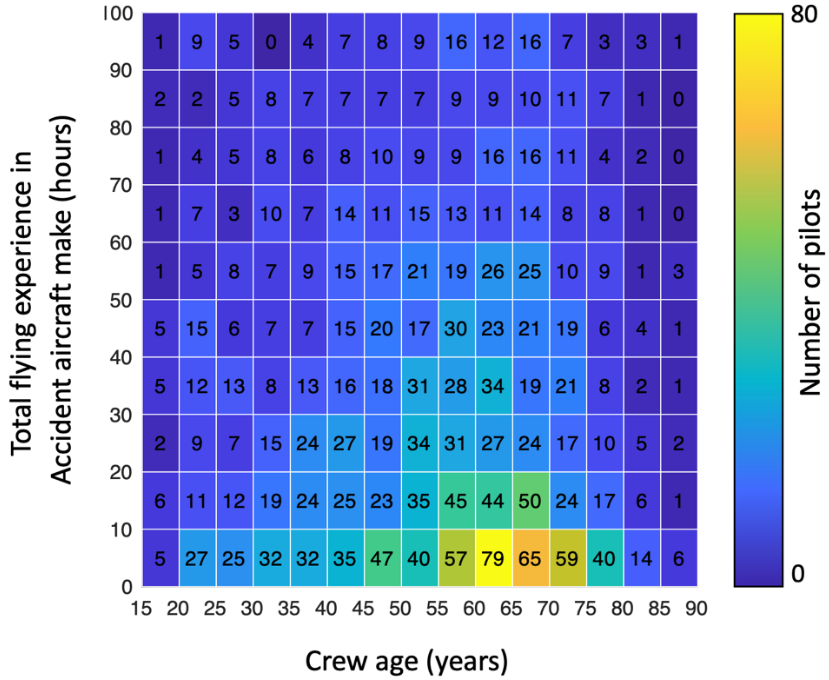

Figure 8: Heat map of pilots' age and flying experience in accident aircraft make.

Figure 9 shows the total hours of flying experience of flight crew (not necessarily in the same aircraft make) in the last 90 days before the accident. Most (41.55%) pilots had less than ten flying hours in the last 90 days before accident. 1.82% of pilots flew more than 100 hours in the last 90 days.

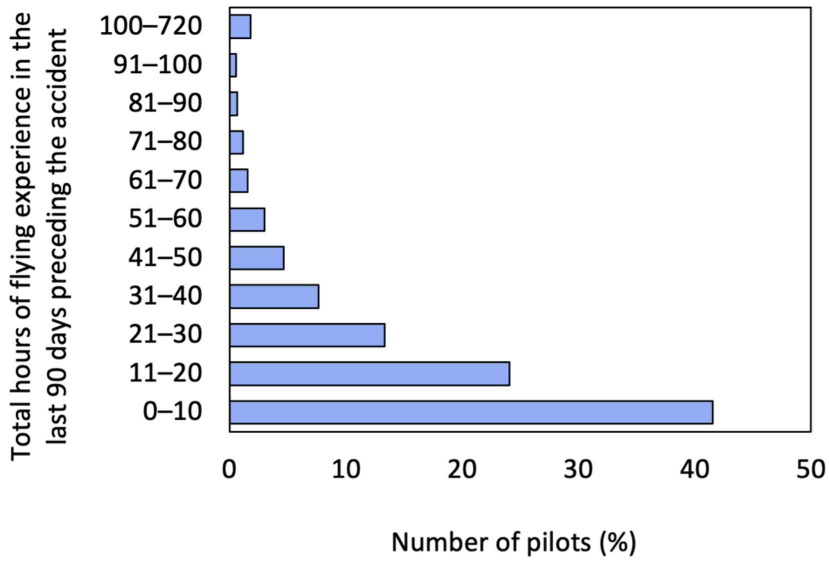

Figure 9: Percentage of pilots with flying experience in the last 90 days preceding the accident.

Figure 10 shows pilots' age and flying experience in the last 90 days before accident. Most pilots were 55–75 years and had flown less than 10 hours in the last 90 days before their LOC-I. Mostly, 60–65 years old pilots less than 30 hours of flying were most involved in an LOC-I.

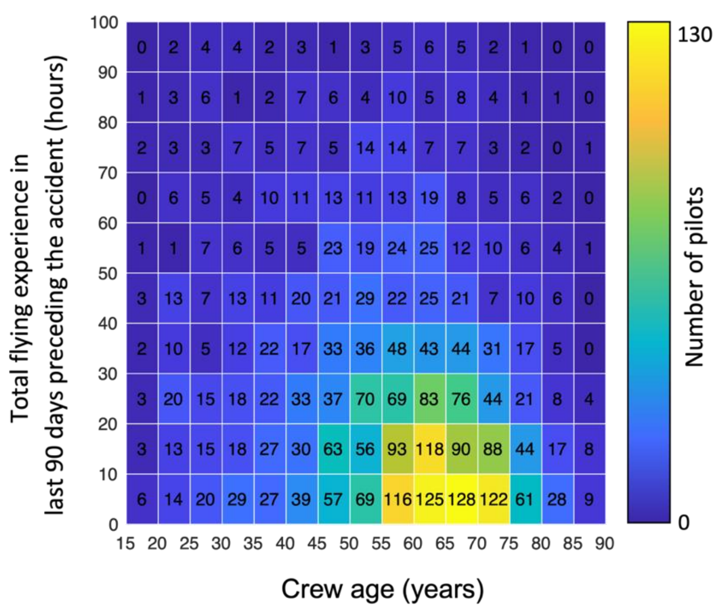

Figure 10: Heat map of pilots' age and flying experience in last 90 days before accident.

Overall, the NTSB accident data shows that Cessna 172 was the most common aircraft involved in LOC-I accidents, followed by Piper PA28, and Cessna 182, 180, and 152 models. Most accidents involved pilots aged 55–69 years. Most pilots had less than 100 hours of total flying experience. The heat maps of pilots' age versus hours analysis show that pilots of age 50–75 with especially low (less than 10 hours) flying experience in the last 90 days and in the aircraft make were mostly involved in a LOC-I.

3. A STATE-BASED APPROACH TO MODEL FIXED-WING AIRCRAFT ACCIDENTS

Portions of this chapter were published in Majumdar, N., Marais, K., & Rao, A. (2021). Analysis of General Aviation fixed-wing aircraft accidents involving inflight loss of control using a state-based approach. Aviation, 25(4), 283-294.

This chapter is based on the state-based approach that I developed to model fixed-wing aircraft accidents in my master's work (Majumdar, 2019). In section 3.1, I describe my method of categorizing the NTSB codes into states and triggers. Next, in section 3.2, I describe the method of creating sequencing rules for the states and triggers. In section 3.3, I demonstrate the modeling of an example accident using the state-based approach. Section 3.4 discusses the results of the state-based analysis of inflight loss of control accidents using the NTSB database. Sections 3.1 and 3.3 and some parts of Section 3.4 are based on my master's work and the paper published in the Aviation journal (Majumdar, 2019 and Majumdar et al., 2021).

In my master's work, I augmented the state-based approach developed by Rao and Marais (2020) to model fixed-wing aircraft accidents (Majumdar, 2019). The state-based model consists of two core concepts: accidents are modelled as a series of states and triggers; and, states and triggers (the dictionary) are ordered and linked by rules (the sequencing), as shown in Figure 11.

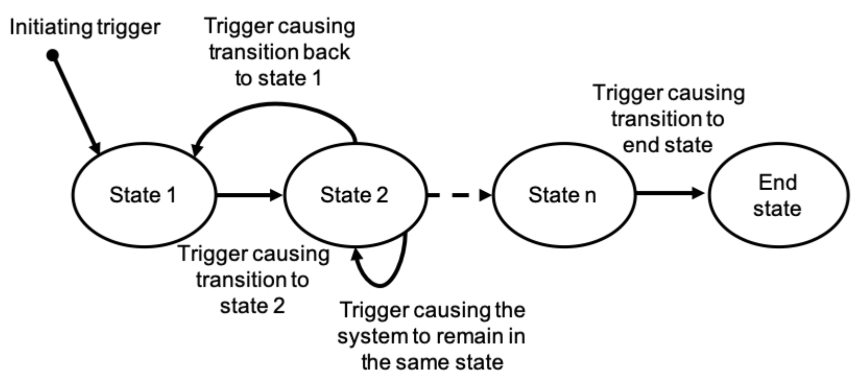

Figure 11: State-based representation of a notional system.

The state and trigger definitions are based on codes in the NTSB database system (occurrence codes, finding codes, modifier codes, and phase of flight codes). The system comprises the aircraft and pilot(s) operating the aircraft. A state is a segment of time wherein a system exhibits a particular behavior. The nodes in Figure 11 represent states of a notional system where the first state represents the default or start state of the system and the last (end) state represents the system's behavior in the final segment of time in the accident. A system can be in only one state at any given point of time. There are two types of states: nominal and hazardous. A **nominal state** is a state of a system that is generally accepted as sufficiently safe by the applicable stakeholders. "Sufficiently safe" depends on the particular context and stakeholders. For example, safe states are those where the aircraft is operating in good weather with all systems functioning and with a competent and fit-to-fly pilot. A system is in a nominal state only when both the pilot and aircraft are in nominal states. A nominal state cannot lead directly to an accident state—it must be directly preceded by a hazardous state.

A **hazardous state** is an off-nominal state that may lead to an accident or an incident. For example, a pilot's poor physiological condition is a "pilot hazardous state", and loss of engine power is an "aircraft hazardous state." A system is in a hazardous state if either the pilot(s), the aircraft, or both the pilot(s) and aircraft are in hazardous states, as shown in Figure 12.

I categorize hazardous states based on when they occur in an accident sequence. A **preflight hazardous state** is a hazardous state that exists before a flight starts, for example, preflight mechanical issue. An **intermediary hazardous state** occurs between a preflight state and an end state (in this case, an accident), for example, inflight loss of control. Each flight terminates in an **end state**, which can be nominal (e.g., safe landing), an incident (e.g., bounced landing), or an accident (e.g., midair collision). Figure 12 shows four possible scenarios of states used in accident modeling: (a) nominal pilot state and hazardous aircraft state; (b) hazardous pilot state and nominal aircraft state; (c) both pilot and aircraft in hazardous state; and (d) end state (accident state).

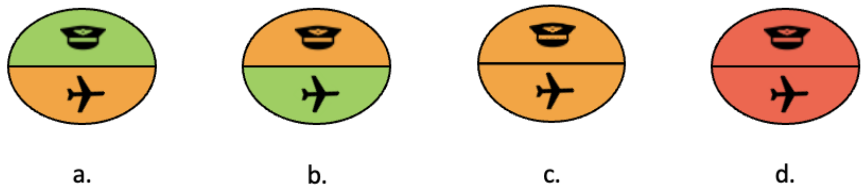

Figure 12: Illustration of four possible scenarios where a system is in hazardous state. Examples of these states are: (a) loss of engine power; (b) pilot's poor physiological condition; (c) pilot's poor physiological condition during a loss of engine power; and (d) on-ground collision with terrain/object end state.

A **trigger** is an event that occurs at a precise instant of time, causing either the aircraft, pilot(s), or both the aircraft and pilot(s) to transition between states or remain in the same state. For example, failure of an engine can cause a system to transition from a nominal state to a hazardous state. The links connecting to each state in Figure 11 represent triggers to each state. The *initiating trigger*, points to the default or start state of the system.

3.1 Fixed-wing Aircraft Dictionary of Hazardous States, Triggers, and Additional Information

Building off on the rotorcraft data dictionary that had 84 state definitions and 182 trigger definitions, I extended the data dictionary to fixed-wing aircraft accidents. In my master's work, I created 108 states and 226 triggers (Majumdar, 2019 and Majumdar et al., 2021). Additionally, I categorized codes which can neither be considered as a state nor a trigger as *additional information*. After several iterations of re-defining and re-categorizing the states, triggers, and additional information, the data dictionary now has 108 states, 194 triggers, and a total of seven additional information. In my Ph.D. work, I also created sequencing rules for states and triggers, as described in Section 3.2.

The following sub-sections describe the process of my data dictionary definitions. Appendix D shows the descriptions for the states, triggers, and additional information. The coded definitions for the states, triggers, and additional information can be found in my master's thesis (Majumdar, 2019).

3.1.1 Fixed-wing state definitions

I grouped the NTSB codes that have similar meanings into states and triggers. For example, I grouped the codes 24518: Altitude and 24519: Proper altitude both indicate that the pilot did not maintain the correct altitude into improper altitude state. Table 4 shows a summary of the fixed-wing aircraft states as compared to rotorcraft states. Fixed-wing aircraft differ from rotorcraft in four ways relevant to accident modelling: (1) Maneuvering. Rotorcraft and fixed-wing aircraft have different maneuvering capabilities due to different flight mechanics. For example, rotorcraft, unlike fixed-wing aircraft, can perform maneuvers such as hovering, and can autorotate in the event of losing engine power. So, these rotorcraft states are not applicable to fixed-wing aircraft. (2) Control surfaces. Fixed wing aircraft, unlike rotorcraft, have ailerons, a rudder, and an elevator for aerodynamic stability. For example, fixed wing aircraft have flaps, unlike rotorcraft. Therefore, I created a new state for improper flaps extended speed (VFE). (3) Takeoff and landing characteristics. Advanced rotorcraft with wheels that can perform running takeoffs, hover taxi, and air taxi, are relatively rare in civil aviation, and therefore rotorcraft accidents associated with these maneuvers are also rare (there were no such accidents in the 1982–2015 accidents covered in Rao and Marais' 2020 analysis). I therefore created new fixed-wing states such as improper takeoff, improper taxi speed, water loop/swerve, and aircraft hydroplaning. (4) Airspeed factors. Fixed-wing aircraft have additional airspeeds to rotorcraft. For example, fixed wing aircraft have five different airspeeds that convey takeoff or rotation speed: lift-off speed (VLOF), takeoff safety speed (V2), minimum takeoff speed (V2MIN), rotation speed (VR), and maximum speed from which the airplane can stop within the accelerate-stop distance (V1).

Table 4: Summary of the states for rotorcraft and fixed-wing aircraft

	Rotorcraft States	**Fixed-wing States**	**State Example**
States applicable only to rotorcraft	13	N/A	Improper autorotation only occurs in rotorcraft.
Rotorcraft states applicable to both rotorcraft and fixed-wing aircraft	54		Both rotorcraft and fixed-wing aircraft can experience hard landings.
Rotorcraft states re-coded for fixed-wing aircraft	17		Fixed-wing aircraft have additional airspeed types, compared to rotorcraft such as minimum takeoff speed (V_{2MIN}).
New states defined for fixed-wing aircraft only	N/A	37	Rotorcraft do not have flaps, unlike fixed-wing aircraft, so I created improper flaps extended speed (V_{FE}) state for fixed-wing aircraft.
Total states	**84**	**108**	

Finally, I added several states that may also apply to rotorcraft but did not appear in any of the rotorcraft accidents in the database. For example, Rao and Marais (2020) defined two LOC states for rotorcraft: inflight loss of control (LOC-I) and on-ground loss of control (LOC-G). Because the database does not always specify whether the LOC was inflight or on the ground, I created an unknown phase LOC state (LOC-U). Table 5 shows the definition and coding for the LOC-I state. Table 5 also shows the Boolean logic for the LOC-I state, which serves as input to my translation code in MATLAB.

Table 5: Inflight loss of control (LOC-I) state definition for fixed- wing aircraft accidents includes a combination of occurrence, phase of flight, and subject/finding and modifier codes from the NTSB database. I excluded the codes that do not specify the phase during which loss of control happens or convey loss of control on the ground.

NTSB Codes (Pre-2008)	**Description**
250	Loss of control – in flight
110	Altitude deviation, uncontrolled
553	Descent – uncontrolled phase
24524 AND (3140)	Descent AND (“Uncontrolled”)
24525 AND (3140)	Proper descent rate AND (“Uncontrolled”)
NTSB Codes (Post-2008)	**Description**
240	Loss of control in flight
650	Uncontrolled Descent
01062022	Pitch control
01062023	Lateral/bank control

3.1.2 Fixed-wing trigger definitions

Using the NTSB codes used for fixed-wing aircraft accidents, and combining codes that convey the same meaning, I defined 194 triggers (see Table 6). Similar to hazardous states, I accounted for the differences between helicopters and fixed-wing aircraft when augmenting and creating new triggers for fixed-wing aircraft. For example, based on different speed characteristics of fixed-wing aircraft, I re-coded the rotorcraft trigger improper aborted landing/takeoff for fixed-wing aircraft by adding a subject code 24503 Abort above V1 with its modifiers. V1 is the takeoff decision speed, beyond which a flight can continue to take off even in case of an engine failure.

Table 6: Breakdown of rotorcraft and fixed-wing aircraft triggers

	Rotorcraft Triggers	Fixed-wing Triggers	Trigger Example
Triggers applicable only to rotorcraft	43	N/A	Rotor system failure can occur only in rotorcraft.
Rotorcraft triggers applicable to both rotorcraft and fixed-wing aircraft	76		Both fixed-wing and rotorcraft can experience improper engine shutdown.
Rotorcraft triggers re-coded for fixed-wing aircraft	63		Both rotorcraft and fixed-wing aircraft can experience improper aborted landing/takeoff, but there are additional NTSB codes that apply for fixed-wing aircraft.
New triggers defined for fixed-wing aircraft	N/A	55	Rotorcraft have rotors and not propellers, so they do not have a propeller control failure trigger.
Total triggers	**182**	**194**	

3.1.3 Additional information

I categorized the codes which can neither be considered as a state nor a trigger as *additional information*. There are two types of additional information: (1) Pre-existing condition; and (2) Information code.

Pre-existing condition is a condition in the aircraft's environment that remains true or applicable throughout a flight and is neither a state nor a trigger. I created four pre-existing conditions: (1) unsuitable airport facilities; (2) unsuitable runway; (3) unsuitable terrain; and (4) unsuitable physical environment.

Information code is detail about a system that is neither a state, a trigger, nor a pre-existing condition. Information codes describe additional information about the accident. I created three information codes: (1) information about object that the accident aircraft collided with during accident (e.g., trees); (2) information about terrain (e.g., mountainous) and (3) information about accident event (e.g., aircraft missing after crash).

3.2 Creating Sequencing Rules for States and Triggers

I created sequencing (or grammar) rules to sequence states and triggers to represent accident models. Sequencing the states means assigning states that can come immediately before, after, or both before and after a particular state. For triggers, I created rules that define which triggers can immediately lead to a particular state. Sequencing states and triggers may help us better understand the proximate causes of LOC-I and other states leading to an LOC-I.

In my master's work, I created sequencing rules for twelve states. In my Ph.D. work, I created sequencing rules for all 108 states and 194 triggers. I wrote a MATLAB code that extracted accidents citing certain two states, and outputted all states used in those accidents. Then, I read narratives of the extracted accidents and evaluated the sequence of states used in those accidents. I referred to the books published by the FAA such as the Airplane Flying Handbook (AFH) and the Pilot's Handbook of Aeronautical Knowledge (PHAK) and used my knowledge from private pilot training to decide the sequencing for one state with another (FAA, 2021 and FAA, 2016a). I created a spreadsheet with all the 108 states in columns and rows. Inspired by the graph theory approach, I assigned values for each type of relationship of one state with another.

Figure 13 shows a snippet of the spreadsheet that includes relationship of each state to another. For example, consider *Intentional/inadvertent flight through poor weather* state that represents pilot flying through a poor weather such as an instrument meteorological condition (IMC). States that immediately follow flight through poor weather are *loss of engine power* and *loss of lift* (assigned value 1). *Low coolant* (which a pre-flight state) can immediately precede *flight through poor weather* (assigned value –1). *Low fuel* state can either immediately come after (if pilot deviates their course in poor weather) or before flight through poor weather (if pilot starts with a low fuel) (assigned value 0). Flight through poor weather can also transition to itself with some triggers, e.g., lack of action by pilot (assigned value 3). There is no direct relationship of flight through poor weather with *on-ground collision with terrain/object* state in the accident reports. That means there must be intermediate states in between these two states, such as inflight loss of control state and on-ground loss of control states.

States	Intentional/ Inadvertent Flight Through Poor Weather State	Loss of Engine Power State	Loss of Lift State	Low Coolant State	Low Fuel State
Intentional/ Inadvertent Flight Through Poor Weather	3	-1	-1	1	0
Loss of Engine Power State	1	3	-1	1	1
Loss of Lift State	1	1	3	8	8
Low Coolant State	-1	-1	8	3	-1
Low Fuel State	0	-1	8	1	3
On-ground Collision with Terrain/Object End State	8	8	8	8	8
On-ground Loss of Control State	1	1	1	8	8

Figure 13: A snippet of sequencing rules for states with different values assigned to each cell. 1: The state mentioned in the row can immediately follow the state mentioned in the column; –1: The state mentioned in the row can immediately precede the state mentioned in the column; 0: The state mentioned in the row can appear either immediately before or after the state mentioned in the column; 3: Relationship of the state with itself—the state can transition to itself with a specific trigger(s); and 8: No direct relationship of the states mentioned in the corresponding row and column.

I used a similar approach to create rules for the 194 triggers with the 108 states. I ran a MATLAB code that extracted accidents (and all their codes) that had a particular trigger and a state together. Then, I read narratives of the extracted accidents and referred to other resources such as the FAA's AFH and PHAK to decide whether a particular trigger could lead to a state. I created another spreadsheet with the rows having all the 194 triggers and the columns with the 108 states.

Figure 14 shows a snippet of the spreadsheet that includes relationship of each trigger to a state. For example, consider the triggers for *inflight loss of control (LOC-I)* state. From the narratives, I found that the *improper runway alignment* trigger can either lead to the LOC-I state or exit from the LOC-I state (assigned value 3). Triggers such as *improper touch-and-go*, *improper use of aerial application/external load equipment*, *improper use of aircraft systems component*, and *improper use of autopilot system* can lead to an LOC-I state (assigned value 1). *Improper touchdown* trigger can exit from the LOC-I state (assigned value 2), that means, an LOC-I can cause an aircraft to improperly touch down on the runway. I found no relationship between the triggers *improper towing/taxiing* and the LOC-I state.

I use these sequencing rules as a basis to model LOC-I accidents from the NTSB database.

States / Triggers	Inflight Loss of Control State	On-ground collision with Terrain/ Object End State	Runway Overshoot/ Excursion State	Runway Undershoot State	Wake Turbulence State
Improper Runway Alignment Trigger	3	1	1	8	8
Improper Touch-and-go Trigger	1	1	8	8	8
Improper Touchdown Trigger	2	1	1	1	8
Improper Towing/Taxiing Trigger	8	1	8	8	8
Improper Use of Aerial Application/External Load Equipment Trigger	1	8	8	8	8
Improper Use of Autopilot System Trigger	1	8	8	8	8

Figure 14: A snippet of sequencing rules for triggers to the states with values. 1: The trigger mentioned in the row can go into the state mentioned in the column; 2: The trigger mentioned in the row can come out of the state mentioned in the column; 3: The trigger mentioned in the row can either go into or come out of the state mentioned in the column; and 8: No relationship of the trigger found with the given state.

3.3 Modeling Accidents Using the State-Based Approach

Here, I demonstrate the working of state and trigger definitions and the sequencing rules using an accident (NTSB Number: LAX99FA077) that happened in January 1999 in Chino, California involving a Beech F35. A non-instrument rated pilot's intentional flight into known instrumental meteorological conditions (IMC) in hilly terrain led to a spatial disorientation. The pilot's failure to maintain aircraft control led to a crash. The pilot and the three passengers were fatally injured. The first two columns of Table 7 show the resulting NTSB codes for the accident report. I model the accident in five steps:

1. **Identify states and triggers from the accident data:** I mapped the finding codes and occurrence codes from the database with corresponding states and triggers as shown in Table 7. Figure 15 shows the states and triggers. Since there are no codes indicating that the pilot was impaired or not fit to fly at the start of the flight, I indicated pilot's state as nominal (in green). I also indicated the pre-existing condition as unsuitable terrain and information about terrain as mountainous/hilly (using the NTSB codes in Table 7).

2. **Identify preflight, intermediary, and end states:** Next, I identified the preflight, intermediary and end states, as shown in the last column of Table 7.

3. **Sequence hazardous states:** I applied the sequencing rules to sequence hazardous states. Sequencing rules are based on flight physics and the sequence that the NTSB used to report an accident.

4. **Link states and triggers:** Using the sequencing rules, I linked triggers to the sequenced states, as shown in Figure 15.

5. **Infer triggers and states based on sequencing rules:** Three states did not have entering triggers, because the accident report does not mention any applicable trigger related codes. The NTSB codes for an accident may not be sufficient to identify all states and triggers in that accident. So, I used the sequencing rules to infer some of the missing information, e.g., no/failed recovery after loss of control trigger. I infer this trigger whenever an end state succeeds a loss of control state in an accident, and the accident does not include any codes related to remedial action trigger (Loss of control state AND (end state) AND NOT (Remedial action trigger).

Table 7: NTSB codes and corresponding states or triggers (NTSB Number: LAX99FA077)

Finding code	Modifier code	Corresponding State/Trigger	Preflight/ intermediary/end state
20100: Light condition 20000: Weather condition	2305: Dark night 2204: Clouds 2240: Drizzle/mist	Prevailing weather and light state	Preflight
24022: Weather evaluation	3115: Inadequate	Improper weather evaluation trigger	NA
24010: inflight planning/decision	3115: Inadequate	Improper inflight planning/decision-making trigger	NA
24015: VFR flight into IMC	3114: Intentional	Flight through poor weather state	Intermediary
24566: Aircraft control	3127: Not maintained	Inflight loss of control state	Intermediary
33400: Spatial disorientation	0: No modifier	Disoriented/ lacking awareness state	Intermediary
19200: Terrain condition	2416: Mountainous/hilly	Unsuitable terrain pre-existing condition Information about terrain: Mountainous/hilly	NA
Occurrence code	**Phase code**	**Corresponding State/Trigger**	**Preflight/intermediary/ end state**
240: In flight encounter with weather	531: Climb to cruise	Flight through poor weather state	Intermediary
250: Loss of control inflight	531: Climb to cruise	Inflight loss of control state	Intermediary
230: In flight collision with terrain/ water	553: Descent-uncontrolled	Inflight collision with terrain/water/object state	End

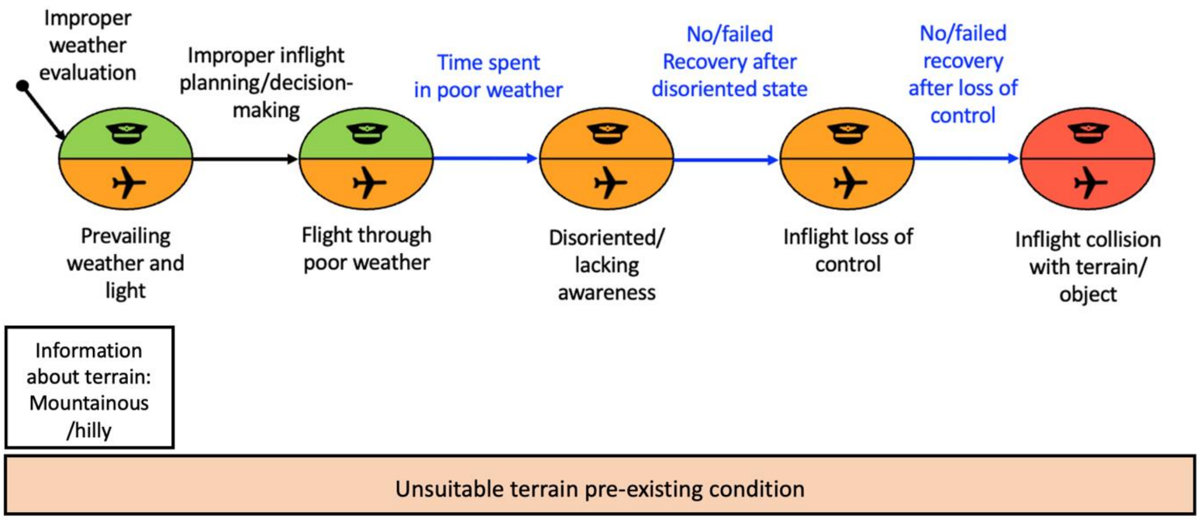

Figure 15: State-based representation of the accident. Using the sequencing rules, I inferred missing triggers to the states. The arrows (and text) in blue are the inferred triggers.

3.4 Top Hazardous States and Triggers in Inflight Loss of Control (LOC-I) Accidents

I identified LOC-I accidents in 2009–2017 by mapping the LOC-I state to the NTSB codes in accidents (Majumdar et al., 2021). I calculated the presence of hazardous states and triggers in the LOC-I accidents using Equation (1).

$$\text{presence}\left(\text{Cause}_j \middle| \text{Accident}\right) = \frac{\sum_{i=1}^{n_{\text{accidents}}} \text{TRUE}\left(\text{Cause}_j \geq 1 \middle| \text{Accident}_i\right)}{\text{Total Accidents}}. \tag{1}$$

Figure 16 shows the top hazardous states for LOC-I accidents in 2009–2017. 77.74% of accidents resulted in an *inflight collision with terrain, water, or object*. *Prevailing/existing weather conditions*, followed by *improper airspeed* were the topmost causes in LOC-I accidents. I identified new findings such as *preflight mechanical issue* and *insufficient qualification/training/ training/experience* as new insights into LOC-I, with a presence of 8.13% and 10.15% respectively in 2009–2017 accidents. Preflight mechanical issue involves scenarios such as improper weight and balance calculations by pilot and operating an aircraft with known deficiencies. Insufficient qualification/training/experience/ familiarity includes lack of experience in a type of aircraft, night or instrument flying, inadequate flight training, and the pilot not being current in their certification. I also inferred *preflight aircraft hazardous state* in 7.46% of accidents whenever an accident report did not cite any codes related to aircraft preflight hazardous state (such as preflight mechanical issue state and preflight low engine fluids states). I inferred this state by using other trigger codes that implied that the aircraft was in a hazardous state before starting the flight.

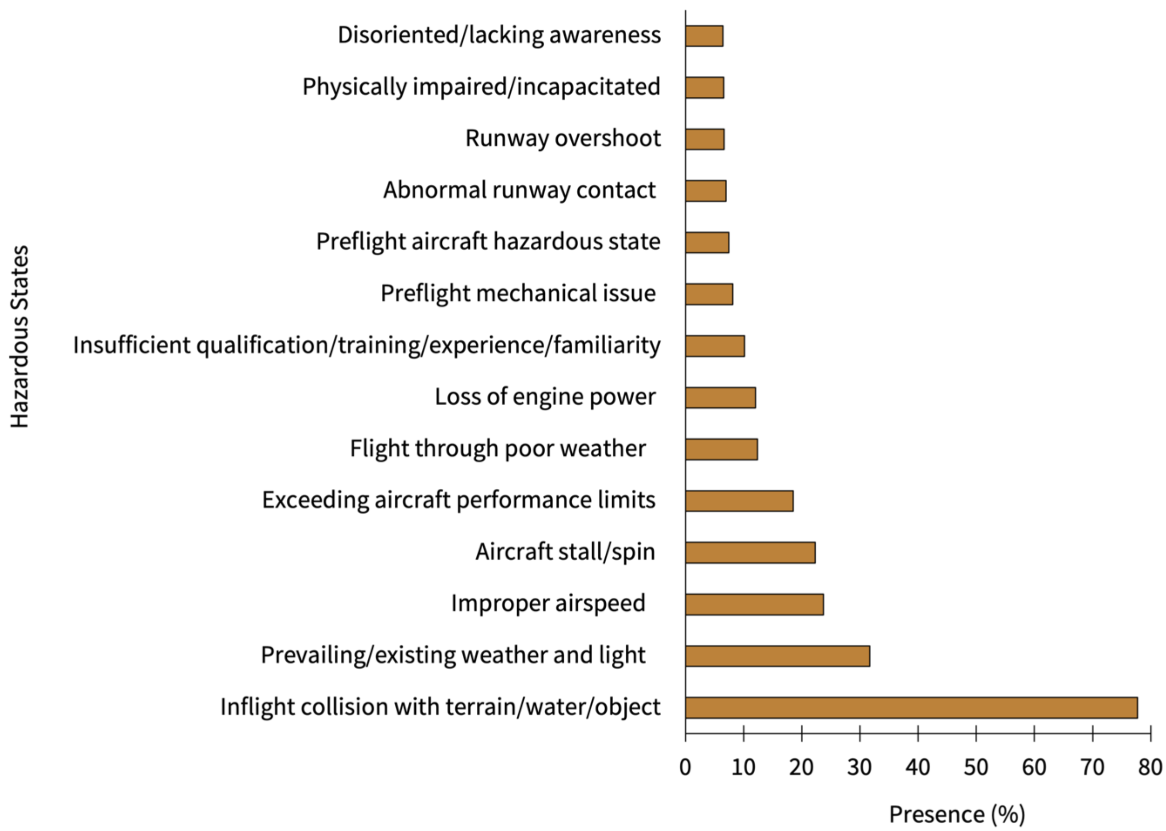

Figure 16: Top hazardous states in 2009–2017 LOC-I accidents

Figure 17 shows the top triggers in LOC-I accidents. I found additional findings such as *improper inflight planning/decision-making, improper maintenance, improper preflight planning*, and *improper use of procedure or directives* that were not identifiable in previous studies (Majumdar et al., 2021). Improper inflight planning/decision-making was most frequent cause (17.34%) in LOC-I accidents. Improper maintenance and preflight planning put a flight in a hazardous state (such as an unsafe to fly aircraft or severe weather conditions) even before it starts.

I also inferred triggers such as *no/failed recovery after loss of control* (94.8%) and *no/failed recovery after disoriented state* (6.29%) when the NTSB does not cite any codes related to improper remedial action with LOC-I and disoriented states respectively. In 19.59% of LOC-I accidents, aircraft clipped (hit) terrain or object and continued the flight, i.e., *clipping of object/terrain* trigger. I inferred *time spent in poor weather* (4.79%) as a trigger to pilot's disoriented state when the NTSB cites prevailing weather/light or a flight through poor weather as the immediate former state with no related trigger information.

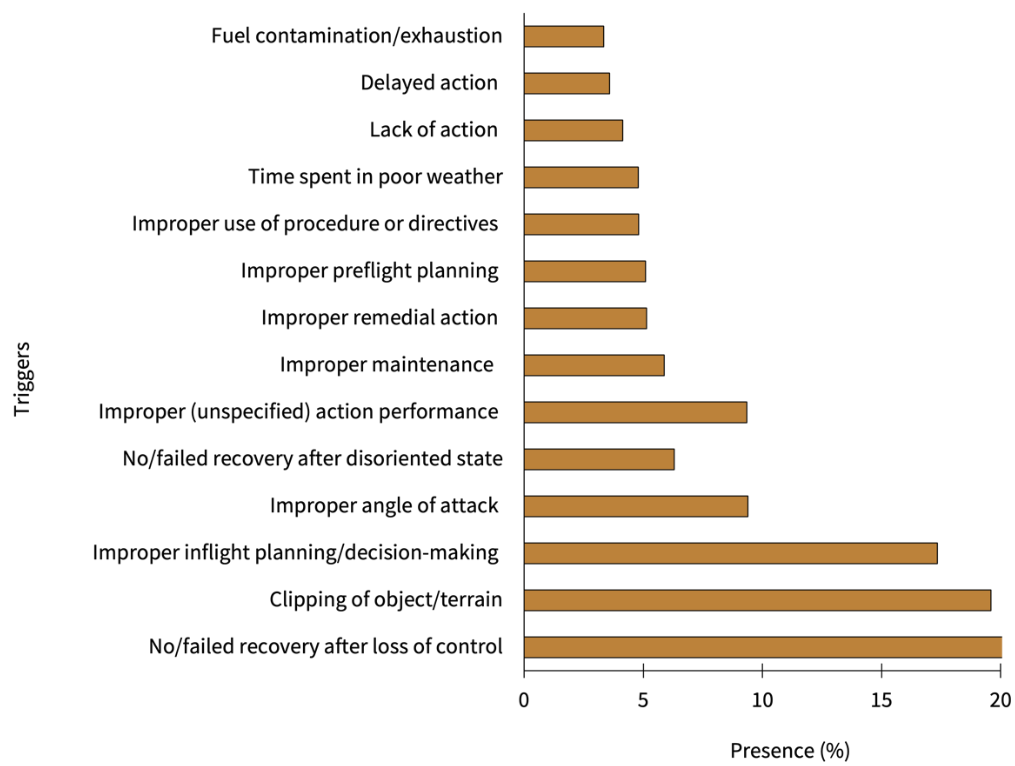

Figure 17: Top triggers involved in 2009–2017 LOC-I accidents

Figures 18 and 19 compare hazardous states and triggers in fatal and non-fatal LOC-I accidents. Figure 18 shows states that are more prevalent in fatal accidents as compared to non-fatal accidents. Fatal accident reports cited pilots' *insufficient qualification/training/experience/ familiarity*, *physically impaired/incapacitated* and *disoriented/ lacking awareness* states more often than in non-fatal accidents. *Exceeding aircraft performance limits* and *aircraft structure failure* were also more involved in fatal accidents.

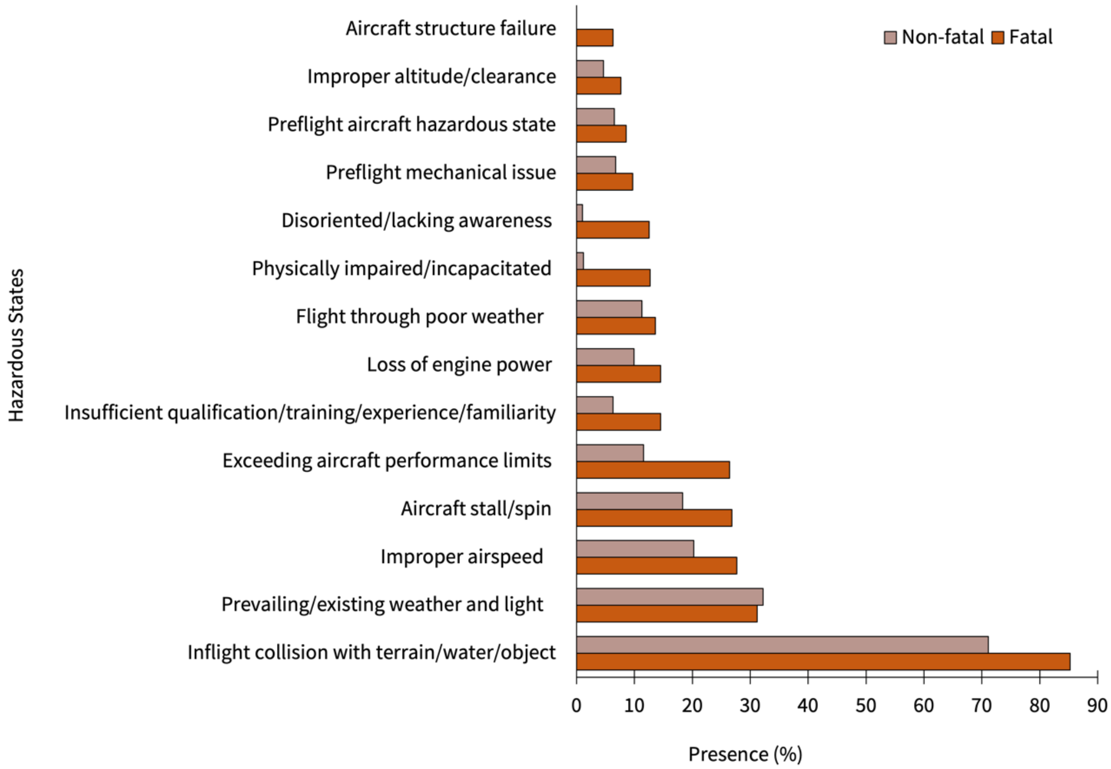

Figure 18: Comparison of top hazardous states in fatal and non-fatal LOC-I accidents

Figure 19 compares top triggers in fatal and non-fatal LOC-I accidents. Fatal accidents involved pilots' *improper inflight planning/decision-making* more often than non-fatal accidents. Since pilot disoriented state was more prevalent in fatal accidents, I inferred *no/failed recovery after disoriented state* and *time spent in poor weather* triggers more often in fatal accidents. Pilots *maneuvering improperly* (such as low altitude buzzing) tended to be more involved in fatal accidents. *Engine assembly failure* and *fuel system failure/contamination* was only present in fatal accidents.

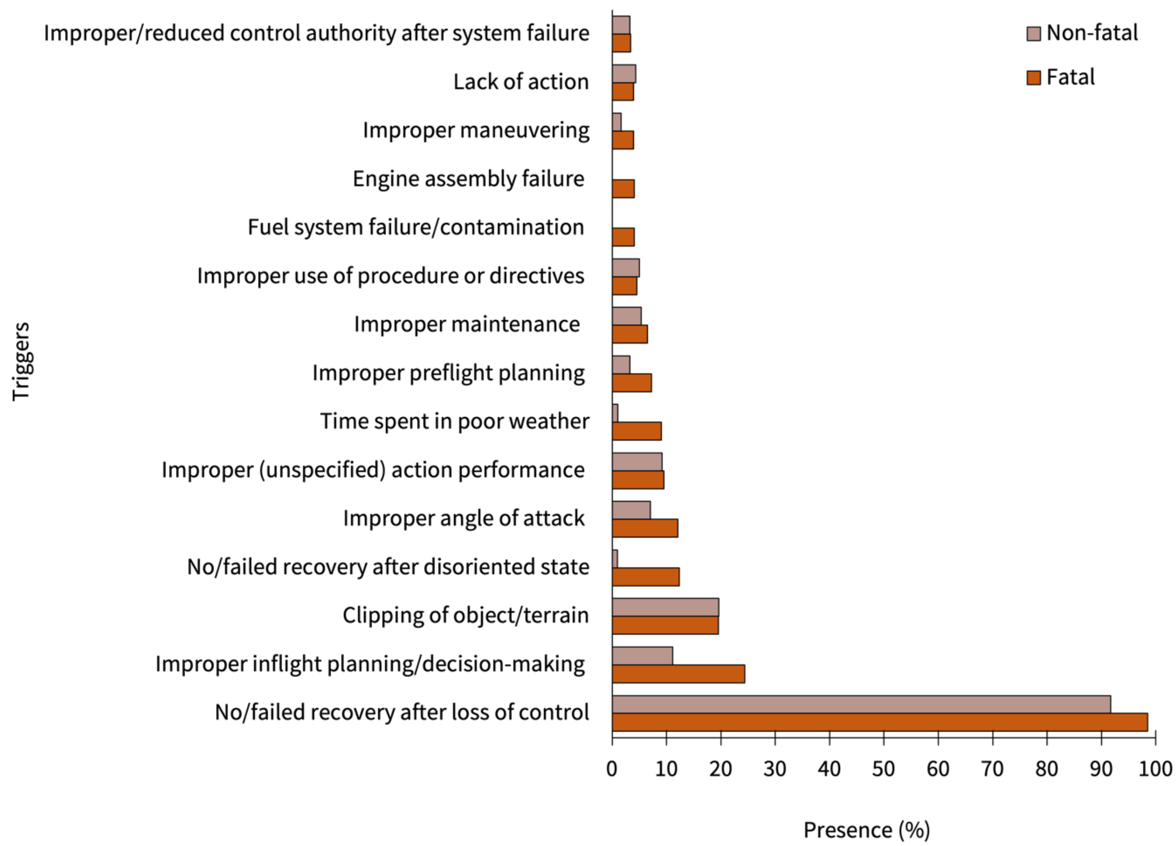

Figure 19: Comparison of top triggers in fatal and non-fatal LOC-I accidents

4. COMPARING FINDINGS USING THE NTSB CODES AND NARRATIVES IN ACCIDENT REPORTS

This section provides motivation for the question: *Can we find additional causes from accident reports that are not coded?* To determine whether the NTSB narratives have additional information as compared to the codes, I analyzed a set of accident reports by studying its narratives and counting the codes used in the accidents. Then, I compared the findings from both the analysis.

4.1 Selecting Accidents for Analysis

The General Aviation Joint Safety Committee (GAJSC) considered a subset of 175 LOC-I accidents from the NTSB database and evaluated their causes and possible preventive measures in detail (GAJSC, 2014). I used their accident subset as a starting point for studying the narratives and analyzing the codes. Since the GAJSC considered only fatal accidents and some of the accidents involved highly advanced aircraft, I considered another subset of 25 fatal and 25 non-fatal accidents that involved traditional training aircraft such as Cessna 172 and Piper PA-28 Cherokee.

Since all the accidents chosen by the GAJSC were fatal, I randomly selected additional 25 fatal and 25 non-fatal accidents in 2001–2017 involving FAR Part 91. I first applied a query on the MS Access NTSB database sheet to filter accidents that were operating under Part 91, happened between 2001 and 2017, and had the LOC-I occurrence code (*250* for accidents before 2008 and *240* for accidents starting 2008). Then, I randomly selected 25 accident IDs that were fatal and 25 accident IDs that were non-fatal. After selecting the accident IDs, I extracted their detailed information such as the codes used in the accidents and their narratives.

4.2 Analysis Method

I analyzed accident reports by running the NTSB-coded information through the state-based algorithm that I built in my master's work (implemented in MATLAB) and then manually reading the accident narratives to identify hazardous states and triggers. I compiled case study sheets to record details about accidents from the NTSB reports: NTSB No. and date, aircraft model, personnel involved and certificates, information from the factual, brief, and probable cause reports, and finding codes as shown in Figure 20. For each accident, I identified and recorded the issues mentioned in the accident. Then, I mapped the identified issues to the state and trigger definitions from the state-based approach data dictionary. I also created new states and triggers if there was no corresponding state or trigger in the data dictionary that could be mapped to a certain issue.

NTSB_ID	Aircraft model	Personnel	Keywords		
Year			Factual	Brief	Cause
ERA13LA279	Cessna 172M	Private pilot	The pilot reported that the altitude of the occurrence was about "200 feet [above ground level]." Review of radar data provided by the Federal Aviation Administration (FAA) revealed the airplane was performing takeoff and landings to runway 33 at LOU. The airplane impacted the ground about 430 feet from the departure end of the runway in a right wing low, nose down attitude.	The pilot could not recall any information about the accident except that the airplane had ascended to about 200 ft above ground level. According to Federal Aviation Administration radar data, the airplane had performed three takeoffs and landings, and the accident occurred during the initial climb after the fourth takeoff. The airplane impacted the ground in a right-wing, nose-down attitude about 430 ft from the departure end of the runway.	The pilot's failure to set the correct flap position before takeoff and his inadequate preflight planning, which resulted in the operation of the airplane over the maximum allowable gross weight, both of which led to an aerodynamic stall at too low an altitude at which to recover.
Jun-13		3 Passengers		Postaccident examination of the airplane revealed that the flaps were set at 30 degrees. According to the Pilot's Operating Handbook, the flaps should be up for normal and obstacle-clearance takeoffs, and flap settings greater than 10 degrees are not recommended at any time for takeoff. Further, calculations of the airplane's weight and balance revealed that the airplane was over the maximum allowable takeoff weight by 114 pounds before the airplane's initial departure. The exact weight at the time of the accident could not be determined; however, it is likely that the airplane was still operating above the maximum allowable weight. Although the airplane had taken off and landed three times while overweight without incident, it is likely that the improper flap setting increased the drag and, in combination with the airplane's overweight condition, degraded the airplane's climb performance, which resulted in the airplane experiencing an aerodynamic stall at a low altitude.	

Figure 20: Snippet of Spreadsheet with details mentioned in the NTSB accident reports.

4.3 Accident Case Studies

Consider a fatal accident that happened in December 2006 (ATL07FA029). Table 8 shows the method of analyzing this accident. The report stated, "The pilot then responded that he would be landing on runway 18, and was advised by the employee that there was no "runway 18." The pilot then stated that he would land on runway 27, and shortly thereafter said that he would land on runway 22." I deduced that the pilot was not familiar with the airport and lacked related runway information. I mapped this issue with the state *insufficient qualification/training/experience or familiarity*. I include all findings from the narratives in the second column. The second column includes the corresponding codes cited in the report. The last column includes my mapping of the findings from the narratives and codes to respective states, triggers, or pre-existing conditions. The text in orange represents that the report did not use codes corresponding to those states. The narrative also did not mention the water terrain condition or how it may have contributed to the accident.

Table 8: Narrative Analysis of an Example Accident (NTSB Number: ATL07FA029). The report did not use corresponding codes for the states in orange text (e.g., runway overshoot, improper turn, and improper airspeed). The narrative also did not mention anything about water terrain condition and how it contributed to the accident.

	Findings from Narratives	**Corresponding Codes Cited**	**Corresponding State/Trigger/Pre-existing Condition**
NTSB No. Month & Year of Accident	ATL07FA029 December 2006		
Aircraft Model	Cessna 340A		
Personnel (Injury)	Private pilot 3 Passengers (All fatally injured)		
Factual Information (History of Flight)	Lack of destination airport information		Insufficient qualification/training/ experience or familiarity state
	Did not take a prompt decision of choosing a landing runway		Improper inflight planning/decision making trigger
	Overshot the runway		Runway overshoot state
Brief Analysis	Tight low right turn during approach		Improper turn state
	Stalled during approach	24552-3113: Inadvertent stall/spin	Aircraft stall/spin state

Table 8: Narrative Analysis of an Example Accident (NTSB Number: ATL07FA029). The report did not use corresponding codes for the states in orange text (e.g., runway overshoot, improper turn, and improper airspeed). The narrative also did not mention anything about water terrain condition and how it contributed to the accident.

	Findings from Narratives	**Corresponding Codes Cited**	**Corresponding State/Trigger/Pre-existing Condition**
	Lost control	250: LOC-I 230: Inflight collision with terrain/water	LOC-I state Inflight collision with terrain/water/object state
Probable Cause and Findings	Failure to maintain airspeed during a turn from base to final		Improper airspeed state
	Impairment of the pilot due to use of combination of drugs	33140: Impairment (drugs)	Physically impaired state
	No related information mentioned in the narratives	19200-2430: Terrain condition (water)	Unsuitable terrain condition pre-existing condition

Here, I give two example accidents that demonstrate inconsistent translation of information in the narratives to accident codes. Consider a fatal accident (NTSB Number: CEN10FA028) that happened in October 2009 where a private pilot flying a Beech B100 with three passengers crashed after encountering sever weather enroute the flight. The NTSB recorded five different codes for the accident: 0303301084: Thunderstorm—decision related to condition; 0204103044: Lack of action by pilot; 0204103044: Lack of action by air traffic control (ATC) personnel; 402390: Enroute-cruise—Windshear or thunderstorm; and 402240: Enroute-cruise—Loss of control in flight. The two codes (0204103044 and 0204103044) used by the NTSB to explain pilot and ATC personnel actions are broad and do not provide specific detail about the actions. The narratives mention pilot's and ATC personnel's actions in detail, i.e., the pilot's failure to avoid severe weather and the controller's failure to provide adverse weather avoidance assistance that led to an encounter with a severe thunderstorm and subsequent loss of control and inflight breakup of the aircraft.

Consider another non-fatal accident (NTSB Number: ERA13LA279) that happened in June 2013 where a pilot with three passengers received serious injuries and a substantial damage of a Cessna 172M. The NTSB listed six codes: 0106201711: Incorrect use/operation of aircraft configuration; 0106103508: Maximum weight capability exceeded; 0204152044: Decision making/judgment by pilot; 0206301544: Use of equipment/system by pilot; 0302000091: Environmental issues; and 0206101544: Weight/balance calculations by pilot. The NTSB determined that the pilot's failure to set the correct flap position before takeoff and his inadequate preflight planning resulted in the aircraft operating over the maximum allowable gross weight, and subsequent stall at a significantly low altitude at which to recover. In the report, the NTSB does not include codes related to an aerodynamic stall, improper takeoff, and a low altitude.

4.4 Comparison of Findings Using the NTSB Codes and Narratives

My analysis showed that pilot-related issues were mentioned in more detail in the narratives than in the codes. Table 9 shows a comparison of the findings using the NTSB codes and narratives. 100 out of 225 reports cited improper airspeed in their narratives, whereas 79 out of the 225 reports mentioned it in their codes. There were 21 accidents that involved improper airspeed (and had mentioned it in their narratives) but had not cited airspeed in their codes. Similarly, I found 42 out of 225 additional accident reports that mentioned a low or high altitude in their narratives, but not in their codes.

Only four accidents mentioned improper preflight planning or inspection in their codes, whereas 27 accidents mentioned preflight planning or inspection in their narratives. 42 reports mentioned improper turns (such as steep angle while turning) in their narratives. No codes related to improper turns were cited in the reports. Similarly, although 13 accident narratives mentioned the pilot's failure to maintain control during aborted landing, there were no related codes cited in the reports. Twelve reports cited codes related to the pilot's incorrect action, lack of action, incorrect sequence of actions, and delayed actions. But none of these codes explain further the type of actions or the phase of flight when these issues happened. In some cases, the NTSB system does not have any codes to explain some issues. For example, there are no codes in the NTSB system that can explain pilot induced oscillations or porpoising. Therefore, the codes-only analysis provides an incorrect and sometimes an incomplete count of causes in accidents.

Table 9: Comparison of Findings Using Accident Narratives vs Accident Codes for 225 LOC-I Accidents

<table>
<tr><th>Hazardous conditions</th><th>No. of accidents using NTSB codes analysis</th><th>No. of accidents using narratives analysis</th></tr>
<tr><td>Improper airspeed</td><td>79</td><td>100</td></tr>
<tr><td>Low/high altitude</td><td>22</td><td>64</td></tr>
<tr><td>Lack of experience/currency</td><td rowspan="2">19</td><td>13</td></tr>
<tr><td>Lack of experience in IMC</td><td>13</td></tr>
<tr><td>Impairment due to drugs/alcohol</td><td rowspan="2">17</td><td>15</td></tr>
<tr><td>Hypoxia</td><td>2</td></tr>
<tr><td>Spatial disorientation</td><td>15</td><td>21</td></tr>
<tr><td>Incorrect/lack of action by pilot</td><td>12</td><td>5</td></tr>
<tr><td>Diverted attention</td><td>7</td><td rowspan="2">9</td></tr>
<tr><td>Pilot's obstructed vision/lack of visual lookout</td><td>2</td></tr>
<tr><td>Improper inflight planning</td><td>6</td><td>24</td></tr>
<tr><td>Improper missed approach/go-around</td><td>5</td><td>16</td></tr>
<tr><td>Improper supervision</td><td>5</td><td>7</td></tr>
<tr><td>Runway overshoot/undershoot</td><td>5</td><td>6</td></tr>
<tr><td>Improper preflight planning/inspection</td><td>4</td><td>27</td></tr>
<tr><td>Improper use of flight controls</td><td>4</td><td>7</td></tr>
<tr><td>Improper landing procedure</td><td>4</td><td>8</td></tr>
<tr><td>Fatigued pilot</td><td>4</td><td>4</td></tr>
</table>

Table 9: Comparison of Findings Using Accident Narratives vs Accident Codes for 225 LOC-I Accidents

Hazardous conditions	No. of accidents using NTSB codes analysis	No. of accidents using narratives analysis
Climb/descent at a steep angle	3	25
Shallow climb		1
Improper (aerobatic) maneuvering	2	4
Ostentatious display/complacency	2	3
Improper turn	0	41
Improper weather assistance or briefing	1	3
Improper emergency procedure	1	1
Improper circling approach	1	2
Failure to maintain control during aborted landing	0	13
Failure to abort takeoff	0	3
Unstabilized flight/porpoising	0	2

The analysis of narratives and comparison with the codes clearly suggest that we can potentially extract more pilot-related information (with more specific detail) from studying the accident narratives as compared to only a code-analysis.

5. MODELING ACCIDENTS BY EXTRACTING INFORMATION FROM REPORTS USING NATURAL LANGUAGE PROCESSING

The NTSB accident reports provide an abundance of information in the form of narratives. Not all the information written in the narratives necessarily gets translated to the codes. Because most previous studies use only the NTSB codes to analyze accident causation, the incomplete causation in the form of codes leads to partial information extraction and therefore incomplete understanding of accident causation. Using all the available information in reports including narratives may help provide a better understanding of accident causation.

5.1 Motivation

To demonstrate the usefulness of accident narrative analysis, consider an accident that happened in 2006 in Charleston, South Carolina (NTSB Number: ATL07FA029). The private pilot and three passengers were fatally injured, and the airplane sustained substantial damage. The NTSB determined the probable cause of the accident to be “the pilot's failure to maintain airspeed during a turn from base to final, resulting in an inadvertent stall/spin. Contributing to the accident was the impairment of the pilot due to the combination of drugs found in his toxicological report.” Table 10 shows the findings and their corresponding states and triggers recorded in the NTSB report. Figure 21 shows the state-based model for the accident based on the NTSB codes.

Table 10: Accident findings recorded in the NTSB report with their corresponding states, triggers, and additional information.

Finding codes	Modifier code	State/Trigger/Additional Information
24552: Stall/spin	3113: Inadvertent	Aircraft stall/spin state
33140: Impairment (drugs)	0: No modifier	Pilot Physically impaired state
19200: Terrain condition	2430: Water	Unsuitable terrain pre-existing condition

Table 10: Accident findings recorded in the NTSB report with their corresponding states, triggers, and additional information.

Event codes	Phase code	State/Trigger/Additional Information
250: Inflight loss of control	563: Approach - VFR pattern - base leg/base to final	LOC-I state
230: Inflight collision with terrain/water	553: Descent - uncontrolled	Inflight collision with terrain/object state

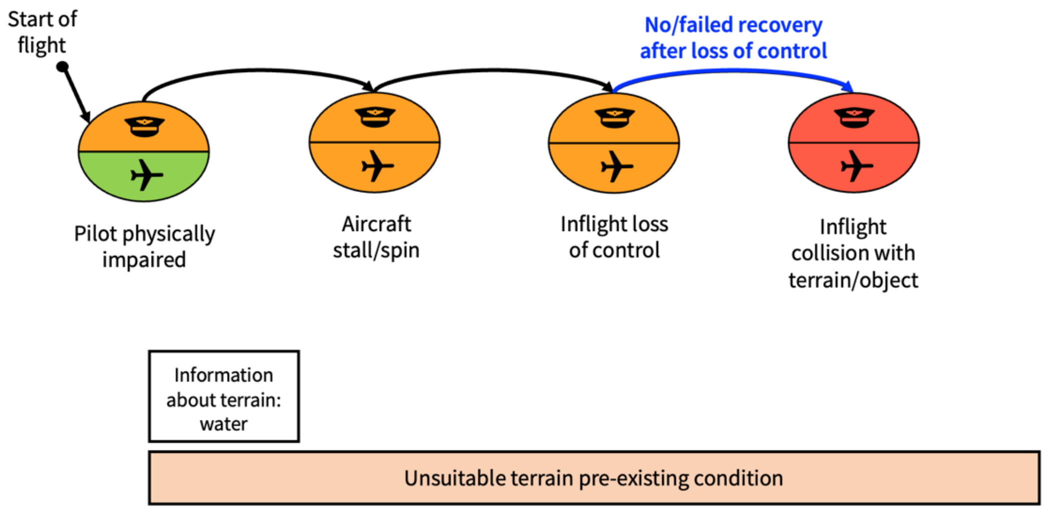

Figure 21: State-based representation of the accident using the NTSB codes (NTSB Number: ATL07FA029). The blue arrow represents the trigger that I inferred using the sequencing rules.

Figure 22 shows the narrative of the accident report. The highlighted text is the findings that were not recorded by the NTSB for this accident in the form of codes.

According to an airport employee at the Charleston Executive Airport (JZI), Charleston, South Carolina, the pilot contacted the JZI UNICOM radio frequency to request an airport advisory. The airport employee informed the pilot that the "winds were from 180 at 12 knots gusting to 17." The pilot then responded that he would be landing on runway 18, and was advised by the employee that there was no "runway 18." The pilot then stated that he would land on runway 27, and shortly thereafter said that he would land on runway 22. The employee said that out of curiosity he stepped outside to witness the approach of the airplane. He said that the airplane was southwest of the airport moving northeast perpendicular to runway 22, at an altitude of approximately 500 feet. He watched as the airplane was on a left base for runway 22. He said that the airplane overshot the runway and began a "tight, low right turn" away from the airport. Shortly thereafter, the airplane stalled and completed two revolutions before it was lost from his sight. Examination of the airframe, flight controls, engine assemblies and accessories revealed no evidence of a pre-crash mechanical failure or malfunction. A forensic toxicology test was performed on specimens from the pilot by the FAA Bioaeronautical Sciences Research Laboratory, Oklahoma City, Oklahoma. The specimens contained, Tramadol (also known by the trade name Ultram), which is used for the management of moderate to severe pain. The level of Tramadol found in the pilot's blood on post-mortem toxicology testing was at least twice that of maximal regular doses of the substance. Single doses have been shown to cause mild impairment of psychomotor abilities in healthy volunteers. Diphenhydramine was also found in the blood of the pilot. The pilot may have been impaired, at that time, due to the use of Tramadol or Diphenhydramine or both.

The National Transportation Safety Board determines the probable cause(s) of this accident to be: The pilot's failure to maintain airspeed during a turn from base to final, resulting in an inadvertent stall/spin. Contributing to the accident was the impairment of the pilot due to the combination of drugs found in his toxicological report.

Figure 22: NTSB report narrative for the accident (NTSB Number: ATL07FA029). The highlighted text are additional findings identified from the narrative that were not recorded by the NTSB in the form of codes.

I mapped these additional findings that I found from the narrative to the state and trigger definitions and therefore identified four more states and one additional trigger, as shown in Table 11.

Table 11: Highlighted findings from the narratives with their corresponding states and triggers

Narrative findings	State/Trigger/Additional Information
"The pilot then responded that he would be landing on runway 18 and was advised by the employee that there was no "runway 18."	Insufficient Qualification/Training/Experience or Familiarity State
"… he would land on runway 27, and shortly thereafter said that he would land on runway 22."	Improper inflight planning/decision making trigger
"… the airplane overshot the runway…"	Runway Overshoot/Excursion State
"… and began a tight, low turn."	Improper Turn/Bank State
"… failure to maintain airspeed…"	Improper Airspeed State

After analyzing the narrative, the accident has total eight states (four from the NTSB codes and four from the narrative) and two triggers (one inferred from the NTSB codes and other from the narrative). Figure 23 represents the enhanced state-based model for the accident based on these eight states and two triggers.

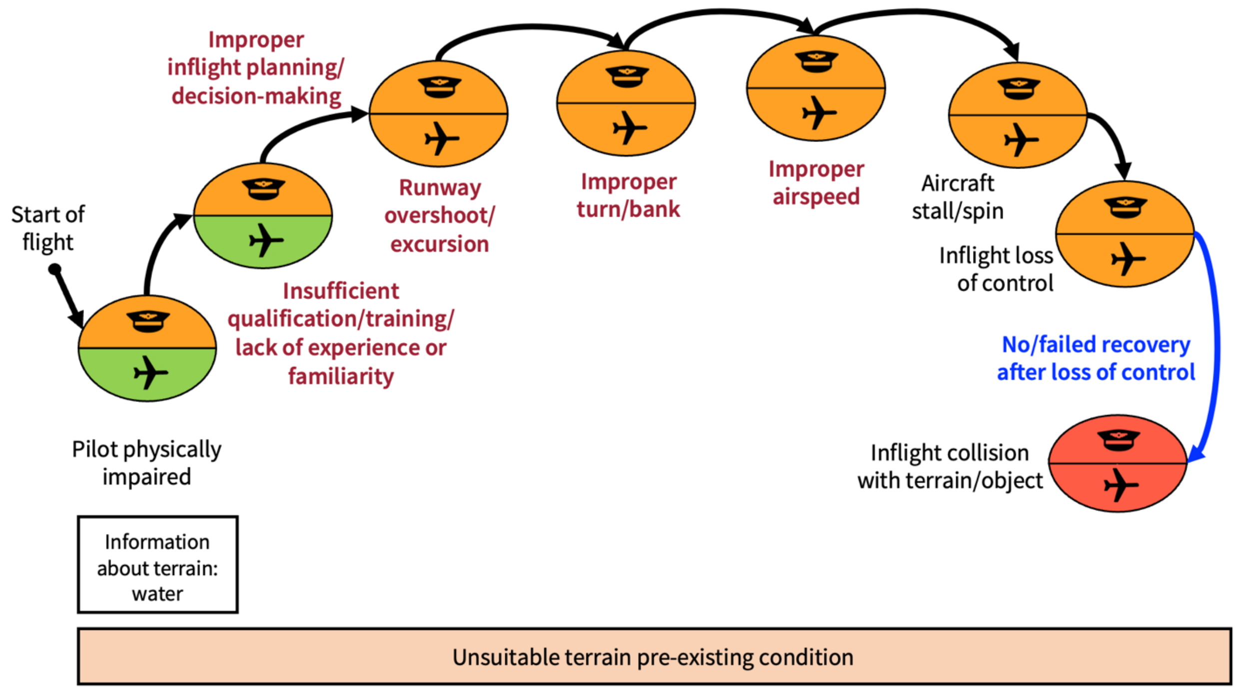

Figure 23: State-based representation of the accident using both the NTSB codes and the narrative (NTSB Number: ATL07FA029). The blue arrow represents the trigger that I inferred using the sequencing rules. The red text represents the additional findings that I identified using the narrative.

This enhanced state-based accident model clearly provides more complete understanding about accident causation. Because of the pilot's lack of familiarity of the airport, he overshot the runway, which made him make a "tight and low turn" (improper turn) to get back to the runway, which caused an improper airspeed, leading to a stall, and eventually a collision with the terrain.

In Chapter 4, I manually read 225 such accident narratives to reveal additional insights about LOC-I causation that were not identifiable only from the NTSB codes. For large volumes of data such as thousands of accident reports, it is time consuming and labor intensive to manually read such unstructured accident reports and manually code the data to map to the 309 states, triggers, and additional information. Artificial Intelligence (AI) such as Natural language processing (NLP) uses computational techniques and machine learning algorithms to allow a faster automated data analysis, hence reducing human workload associated with data analysis. Machine learning is a branch of artificial intelligence (AI) and computer science that helps retrieve hidden patterns within the data (data mining) to classify or predict event(s) from the data.

5.2 Literature review

Many researchers have applied text mining tools on aviation incident reports and found that NLP can generate meaningful information from unstructured data in accident reports (Young et al., 2019). I conducted a literature review, as shown in Table 12, to evaluate different methods used in previous studies and their application.

Table 12: Literature review of text mining tools used to analyze aviation accident reports.

Method	Type of Results	Publications	Dataset
Unsupervised ML: Word frequency & Bag-of-Words (BoW)	Top factors (word frequency)	Huang (2020)	NTSB (2013–2018)
	Typical words used in reports	Nakata (2017)	ASRS (2013)
Unsupervised ML: Clustering	Major clusters and sub-clusters (k-means)	Rose et al. (2020)	ASRS (2010–2020)
	Categorized primary cause in reports (k-means)	Robinson et al. (2015)	ASRS (2011–2013)
	Top clusters (k-means)	Liu et al. (2020)	Chinese Civil Aviation reports (2017)
Unsupervised ML: Topic Modeling	Correlation between topics, n-grams (LDA)	Kuhn (2018)	ASRS (2010–2015)
	Top topics (LDA)	Robinson (2019)	ASRS (1995–2004)
	Top topics with terms (LSA)	Irwin et al. (2017)	ASRS (2010–2014)
Supervised ML: Clustering	Multi-label classification (k-NN)	Ahmed et al. (2010)	ASRS (10,000 reports)

Table 12: Literature review of text mining tools used to analyze aviation accident reports.

Method	Type of Results	Publications	Dataset
Text mining Software	Top clusters (Statistica™ software)	Anderson & Smith (2017)	NTSB (2004–2011)
	Association between contributing factors (IBM® SPSS® Modeler 13)	Andrzejczak et al. (2014)	ASRS (1980–2010)
<u>Deep learning:</u> Neural networks	Key indicators of accident causes (SVM)	Hu et al. (2019)	NTSB (1982–2017)
	Primary and contributing factors (Attention-based long short-term memory (LSTM) model)	Dong et al. (2021)	ASRS (1988–2020)
	Multi-label classification (BERT model)	Zhao et al. (2022)	NTSB (1982–2008)
	Top events (RoBERTA)	Kierszbaum et al. (2022)	ASRS (2009–2018)

Researchers have applied different text mining tools such as unsupervised and supervised machine learning algorithms to identify aviation accident causation. Unsupervised machine learning uses algorithms to analyze and cluster unlabeled datasets without the need for human intervention. Supervised learning algorithms use training data with labeled datasets that the machine learns to predict newer data. While supervised learning algorithms tend to be more accurate than unsupervised learning models, they require upfront human intervention to label the data appropriately (Alloghani et al., 2020).

Previous efforts have used several unsupervised learning algorithms, such as word frequency and bag-of-words. Huang (2020) used word frequency to identify the top contributing factors and causes using the NTSB GA reports for accidents that happened during takeoff. Nakata (2017) used a modified bag-of-words (BoW) model to detect typical pairs of words used in the starting, middle, and beginning of ASRS reports. The study found three typical flows of accident story related to

(1) machine troubles (aircraft issues); (2) near miss on runway at airport; and (3) near miss during cruising.

Researchers have also widely used methods like clustering and topic modeling on accident reports. Both topic modeling and clustering are unsupervised methods which yield different kinds of outputs. The goal of topic modeling is to discover latent topics or themes in the data. These topics are represented as a set of words that frequently co-occur in the text. Clustering is a technique used to group similar data points together based on their attributes or intrinsic characteristics. The goal of clustering is to identify groups or clusters of data points that are similar to each other and dissimilar to other clusters. The clustering algorithm partitions a dataset into groups, or clusters, of data points that have similar features or patterns. Previous studies on clustering focused on ASRS reports and aviation reports from other countries to identify the top clusters in accidents. Rose et al. (2020) categorized ASRS reports using k-means clustering to reveal trends from clusters such as issues during navigation and ground operations, that were not evident explicitly from the reports. Similarly, Robinson et al. (2015) and Liu et al. (2020) also used k-means clustering to identify top causes in incident and accident reports.

Topic modeling on the ASRS reports helped researchers discover themes in accident causation. Kuhn (2018) and Robinson (2019) used the Latent Dirichlet Allocation (LDA) model to find the most prevalent topics and correlation between the topics in ASRS reports. Irwin et al. (2017) studied ASRS reports using Latent Semantic analysis (LSA) method to identify topics such as environment, phase of flight, and ATC interaction.

Ahmed et al. (2010) proposed a multi-label classification method using supervised machine learning approach, Hierarchical Semi-supervised Impurity based Subspace Clustering (H-SISC) with k-NN clustering, to analyze ASRS reports. Multi-label classification is a type of classification where each instance (accident) can have multiple labels (causes). Other researchers used text mining tools such as Statistica™ and IBM® SPSS® Modeler 13 for identifying top clusters and association between contributing factors in accidents (Anderson & Smith, 2017; Andrzejczak et al., 2014).

Researchers have also used deep learning algorithms to analyze accident causation. Deep learning is a subset of machine learning that uses multiple artificial neural networks to process and learn from large amounts of data (Chassagnon et al., 2020). Deep learning algorithms can learn to recognize patterns in data without being explicitly programmed to do so. Hu et al. (2019) and Dong et al. (2021) used Support Vector Machines (SVM) and deep neural networks for multi-label classification of accident causes. Dong et al. (2021) used an attention-based long short-term memory (LSTM) model to identify primary and contributing factors in ASRS reports. Zhao et al. (2022) and Kierszbaum et al. (2022) used transformer-based language models such as Bidirectional Encoder Representations from Transformers (BERT) and Robustly Optimized BERT Pretraining Approach (RoBERTA) on NTSB and ASRS reports for multi-label classification of accident causation.

Unsupervised machine learning is the most common and least time-consuming method. Clustering using k-means may be helpful when the research objective is to partition number of observations (in our case, reports) into k clusters. Word frequency, n-grams, and topic modeling may help to reveal latent themes in accidents that are not identifiable explicitly through the NTSB codes. I first started with an exploratory analysis where I used the two most common types of unsupervised machine learning methods: n-grams and topic modeling to identify the most prevalent word-combinations and themes in reports. Appendix A discusses the results from the n-grams analysis and topic modeling.

5.3 Multi-Label Text Classification

Although the findings from the exploratory analysis of unsupervised machine learning may be useful for an overall quick thematic analysis for large volumes of data, unsupervised machine learning classifies text in its own way and not in the form of pre-defined labels (in our case, states, and triggers) which may limit our understanding of state and trigger sequences in accidents. Since each accident can have multiple findings (states and triggers), my research objective is more suited to a "multi-label classification" which is a type of text classification where multiple labels are assigned to each instance. In our case, labels are states and triggers and instances are accident reports. Supervised machine learning methods and deep learning algorithms allow models to learn from multiple-labeled data to predict unlabeled data. Previous studies with deep learning models and neural networks showed promise in multi-label classification of accident and incident reports (Hu et al., 2019; Dong et al., 2021; Zhao et al., 2022; and Kierszbaum et al., 2022).

Zhao et al. (2022) and Kierszbaum et al. (2022) used transformer neural network architecture models such as BERT and RoBERTA to apply multi-label classification on accident reports and showed better performance as compared to traditional architecture models such as LSTM and SVM. Transformers rely on self-attention mechanisms to learn contextual relationships between words in a sentence, allowing for more efficient parallel computation (Vaswani et al, 2017). Self-attention allows the model to encode the relative importance of each input token with respect to others by assigning different weights to different elements of the input sequence. This mechanism helps in capturing long-range dependencies and relationships between elements in the sequence.

BERT (Bidirectional Encoder Representations from Transformers) is a type of pre-trained language model developed by Google researchers in 2018 (Google, 2018). One of the key innovations of BERT is its bidirectional training, which allows it to consider the entire context of a word or sentence, rather than just the left or right context as in previous models. So, BERT can capture more complex relationships between words and sentences and improve performance on natural language processing tasks (Devlin et al., 2018).

5.4 Experimental Setup

I chose Longformer which is a transformer neural network model because transformer models have previously proved to be successful on multi-label classification of aviation reports (Zhao et al., 2022 and Kierszbaum et al., 2022). Figure 24 shows a flowchart for a deep learning model. We first import an accident dataset, pre-process the data, and split it into three different datasets for three stages (1) training; (2) validation; and (3) testing.

1. **Training:** The model uses labeled data to learn patterns and relationships in the data by optimizing its weights and biases through multiple iterations. Goal is to minimize the loss or error between the model's predictions and the actual labels, so that the model can make accurate predictions on unseen data. Training Dataset is the largest subset which is used to train the deep learning model. It contains labeled examples that the model uses to learn

patterns and relationships in the data. The model is trained on this dataset through multiple iterations of forward and backward passes to optimize its weights and biases.

2. **Validating:** The validation stage is used to tune the hyperparameters of the model and to perform model selection. Hyperparameters are parameters that control the behavior of the model, such as learning rate and batch size. The model's performance on the validation dataset, which is separate from the training dataset, is used to evaluate different hyperparameter settings and model architectures to give the best performance. Validation Dataset is separate from the training dataset and is used to evaluate the model's performance during training and to make decisions about hyperparameter settings and model architecture.

3. **Testing:** The testing stage is used to evaluate the final performance of the trained deep learning model after it has been optimized and fine-tuned using the training and validation datasets. The testing dataset is an unseen sample of data used to assess how well the model generalizes to the unseen data and evaluate the final performance of the trained deep learning model after it has been optimized and fine-tuned using the training and validation datasets.

The next step is to design the architecture of the neural network such as selecting the number of layers and configuring the hyperparameters. Then, we train the model on a preprocessed training data and validate it on a validation data to evaluate its performance. Based on the model performance, we fine tune the model to get an optimal performance. After achieving good performance, we test the model on an unseen accident dataset to predict more states and triggers.

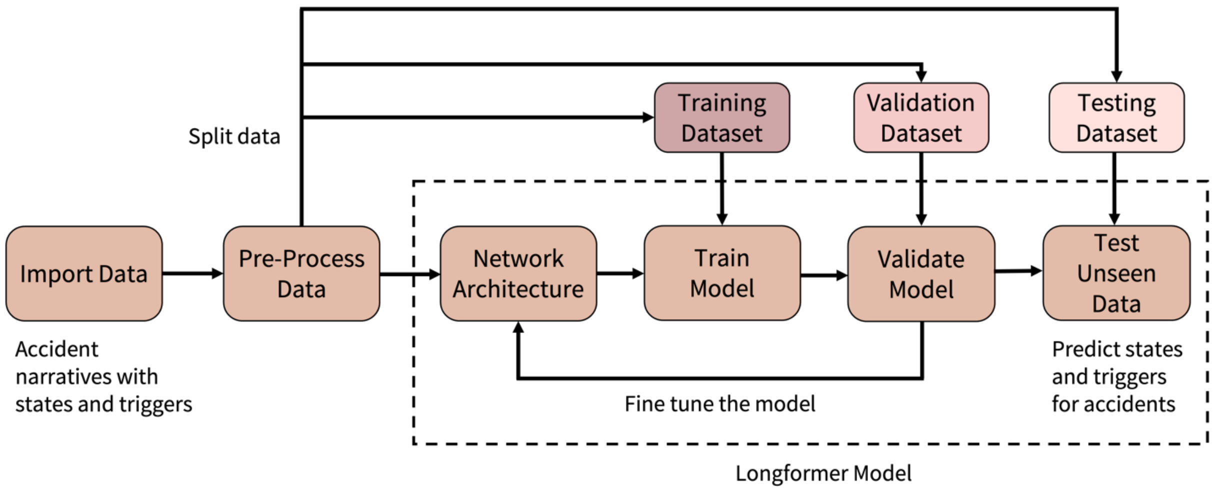

Figure 24: Flowchart for a deep learning model

In the following sub-sections, I will describe the experimental setup of generating the dataset, inter-rater reliability (IRR) for the manually coded dataset, selecting the model, preprocessing the dataset, and implementing the model.

5.4.1 Preparing the Dataset

I collected data using two methods: (1) NTSB coded accidents; and (2) manually coded accidents.

1. NTSB coded accidents

I identified all accidents from the NTSB database that involved a LOC-I state (see Chapter 3 Table 5). I extracted total 16,029 LOC-I accidents in 1982–2019. Using my MATLAB code, I retrieved state-based models (corresponding states, triggers, and additional information) for all the accidents based on their NTSB codes.

2. Manually coded accidents

Since the NTSB codes do not always completely represent all findings mentioned in accidents (see Section 1.1: Background and Motivation and Section 5.1: Motivation), I created a separate dataset of 90 accidents to be manually read and coded by raters. I retrieved the accidents from the GAJSC's subset of LOC-I accidents (GAJSC, 2014). I created a spreadsheet with the 90 accident narratives in rows and corresponding blank columns for the corresponding 309 states, triggers, and additional information for each accident. I assigned the spreadsheets to two raters. Both raters were undergraduate students with private pilot certificates. Each rater analyzed the reports independent of the other. They had access to the state-based data dictionary definitions but did not have access to the NTSB codes listed in the accident reports. The final spreadsheet after analysis was a collection of binary codes (0s and 1s). Raters entered a "1" for a corresponding state or trigger if it was present in an accident. Raters put a "0" for all other states and triggers that were not present in the accident.

3. Inter-rater reliability (IRR) of manually coded dataset

To validate the measure of consistency between the two raters, I evaluated the inter-rater reliability (IRR) for the manually coded dataset. Inter-rater reliability is a measure of the degree of agreement or consistency between multiple raters for a given dataset. A higher IRR value indicates greater agreement and coding consistency between the raters. A low IRR value means that there is a low level of agreement or consistency among the raters in their evaluations. There are multiple methods for evaluating IRR such as percentage agreement, Cohen's kappa, and Fleiss' kappa statistics (Hallgren, 2012). There is limited guidance in literature on what IRR method is best suited for which type of data. Further, each method has its own limitations. For example, percent agreement method, that gives the average percentage of agreement between raters, does not account for agreements that occur by chance or if a rater codes instances randomly (Belur et al., 2021). Percentage agreement also considers only absolute agreement instead of the degree of agreement. For example, on a scale of 1–5, two raters scoring 4 and 5 is much better than scores of 1 and 5. Although Cohen's kappa statistic factors in the role of chance when evaluating inter-rater reliability, it can show no agreement among raters even if the observed agreement is high (Eugenio & Glass, 2004). Further, Cohen's kappa does not consider the weight of categories in IRR calculations. It assumes that all categories have the same importance or weight, and therefore, each disagreement is treated equally. Weighted kappa statistic considers weights of ratings when categories have different levels of importance or when some disagreements are more important than others (Hallgren, 2012).

Since the accident dataset has only binary outcomes (i.e., 0s and 1s) and all ratings for states and triggers are considered to have the same level of importance, weighted statistical methods are not needed for IRR calculations. Further, because both raters had sufficient airplane flying knowledge (note that both are pilots) and had access to all state and trigger definitions, there is a low probability of raters randomly coding the accidents. So, I chose the percentage agreement method for the IRR analysis. Figure 25 shows a snippet of both the raters' coding for the accidents.

NTSB ID	Inflight loss of control		Improper airspeed	
	Rater 1	Rater 2	Rater 1	Rater 2
FTW03FA054	0	1	1	1
ATL02FA160	1	1	1	0
CHI07FA182	0	0	0	0
…				
…				

Figure 25: Snippet of raters' coding for accidents. The shaded boxes represent the four IRR cases. Case C0 (teal), C1 (green), C2 (red), and C3 (orange).

I considered four cases for the IRR calculation. Case C0 (shown in teal-colored cells in the figure) is when both the raters did not select a state or trigger. Case C1 (green) is when both the raters identified a particular state or trigger. Case C2 (red) is when rater 1 identified a state or trigger, but rater 2 did not. And Case C3 (orange) is when rater 2 identified a state or trigger, but rater 2 did not. I counted the average number of instances for each case for all 90 accidents and all 309 states, triggers, and additional information. Table 13 shows the average percentage for each case between the two raters.

Table 13: Four cases for IRR calculation between the raters

Case #	Rater 1	Rater 2	Percentage
C0	0	0	96.7%
C1	1	1	1.4%
C2	1	0	0.7%
C3	0	1	1.3%

There was an overall 98.1% agreement between the raters (C0 and C1). On average, rater 1 identified 6.3 states and triggers per accident and rater 2 identified 8.2 states and triggers per accident. Both the raters identified a total of 109 states and triggers (Rater 1 = 1 OR Rater 2 = 1) for all the 90 accidents. Because both the raters did not identify the remaining 101 of total 309 states and triggers, so C0 (Rater 1 = 0 AND Rater 2 = 0) dominates the results. Table 14 shows the percentage agreement for the three cases where at least one of the raters identified a state or trigger.

Table 14: Percentage agreement in cases where at least one rater identified a state or trigger.

Case #	Rater 1	Rater 2	Percentage
C1	1	1	41.39%
C2	1	0	19.72%
C3	0	1	38.89%

Of the identified states and triggers, both raters agreed 41.39% times. Overall, there was a 58.61% disagreement where one rater identified a state or trigger and the other did not. To resolve the disagreements between Rater 1 and 2, I re-evaluated the accident coding by re-considering the coding for the states and triggers which had a disagreement, i.e., cases C1 and C2. After reading the accident narratives, I re-coded the states and triggers with the disagreements. In this study, I call myself Rater 3.

I also evaluated how closely all three raters' coding matched with the NTSB coding. Table 15 shows the different cases that I considered for this evaluation. Case A represents an agreement between the NTSB and the raters, i.e., when the raters' code matches the NTSB's coding for the corresponding state or trigger. Case B is when the raters' code does not match the NTSB's coding for the corresponding state or trigger. For example, when the NTSB has cited LOC-I state for an accident, and rater also identified LOC-I state for the accident, then it is attributed as Case A (NTSB = 1 AND Rater = 1). For case A, I calculated the average percentage of number of states and triggers per accident that were present in both the NTSB and raters' coding. For case B, I calculated the average percentage of number of states and triggers per accident that the rater missed the NTSB code. I calculated the percentage of the two cases separately for each rater using Equations 2 and 3. n represents total number of accidents in the dataset (i.e., 90). L represents total states and triggers (i.e., 309). $NTSB_i^j$ stands for the NTSB's coding for the j^{th} state or trigger and i^{th} accident. $Rater_i^j$ is the rater's code for the j^{th} state or trigger and i^{th} accident.

$$Case\ A = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\sum_{j=1}^{L}\left(NTSB_i^j\ = 1\ AND\ Rater_i^j\ = 1\right)}{\sum_{j=1}^{L}\left(NTSB_i^j\ = 1\right)}\right) \tag{2}$$

$$Case\ B = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\sum_{j=1}^{L}\left(NTSB_i^j\ = 1\ AND\ Rater_i^j\ = 0\right)}{\sum_{j=1}^{L}\left(NTSB_i^j\ = 1\right)}\right) \tag{3}$$

Table 15: Three cases for comparing raters' coding with the NTSB coding

Case #	NTSB Code	Raters' Code	Rater 1	Rater 2	Rater 3
A	1	1	44%	70%	75%
B	1	0	56%	30%	25%

On average, Rater 1 correctly identified 44% of the NTSB codes, and Rater 2 identified 70% of the codes. Rater 1 missed 56% of the NTSB codes while Rater 2 missed 30% of the codes. I (i.e., Rater 3) identified 75% of the NTSB codes and missed 25% of the codes. Note that I had higher scores than both the raters because during my re-evaluation of accident coding, I only re-considered the coding for the states and triggers that had disagreements.

Additionally, I calculated the average number of additional states and triggers that the raters identified that were not cited in NTSB codes, as shown in Equation 4:

$$\frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{L}\left(NTSB_i^j = 0\ AND\ Rater_i^j = 1\right) \tag{4}$$

On average, Rater 1 identified 3.4 more states and triggers per accident, Rater 2 identified 3.6 more states and triggers per accident, and Rater 3 identified 4.3 more states and triggers per accident. These additional states and triggers may suggest more findings that the NTSB did not cite in the accident codes. I used Rater 3's manual coding for the DistilBERT model since it resolved the disagreements between Rater 1 and 2. For the final dataset, I took the union of Rater 3's manual coding and the NTSB coding to generate a near-complete and richer coding of the 90 accidents.

5.4.2 Selecting the Model

I first considered the DistilBERT model for the multi-label classification task. DistilBERT is a small, fast, cheap (to pre-train), and light version of the BERT model, developed by Hugging Face in 2019 (Hugging Face, n.d.-a). It is designed to provide similar performance to the original BERT model while requiring significantly fewer resources, making it more accessible for applications with limited computing power or memory (Sanh et al., 2019). DistilBERT has 40% fewer parameters than the BERT model and runs 60% faster while retaining 97% of BERT's language understanding capabilities.

One main limitation of DistilBERT, BERT, and RoBERTA is that these models have a maximum sequence length of 512 tokens, which may impact the model performance badly on long context sequences. The maximum sequence length of 512 tokens refers to the length of the input sequence after tokenization. Tokenization is the process of breaking up the input text into individual tokens or words, based on pre-defined vocabulary, that are used as input to the model. In the context of accident reports, 36% of the 1982–2019 LOC-I reports have more than 512 words.

The mean word count for these 16,029 accidents is 748 words. So, DistilBERT's maximum length limitation of 512 tokens when applied to accident reports may negatively impact the model performance.

Longformer is another transformer-based language model introduced by Allen Institute for Artificial Intelligence (AI2) in 2020. It is an extension of the BERT architecture designed to handle text of up to 4,096 sequence length. Longformer uses a self-attention operation that scales linearly with the sequence length and supports sequences of length up to 4,096. Longformer has proved to consistently outperform RoBERTa in previous studies (Beltagy et al., 2020). So, I converted the pretrained DistilBERT model to use the pre-trained Longformer self-attention model (Beltagy et al., 2020).

5.4.3 Pre-Processing the Data

I imported the accident reports in a raw data .dat file format and tokenized them with the pre-trained Longformer tokenizer. Longformer tokenizer uses a combination of Byte-Pair Encoding (BPE) tokenization (GPT-2 BPE derived from the GPT-2 language model) and pre-processing methods, such as lowercasing the text and normalizing whitespaces and punctuation, to convert the input text into tokens (Hugging Face, n.d.-b). BPE is a sub-word tokenization algorithm that breaks down words into smaller sub-word units based on the frequency of their occurrences in the corpus. The tokenizer allows the model to handle out-of-vocabulary (OOV) words and to generalize better to unseen words.

Additionally, I created a corresponding binary coded dataset for the 16,029 NTSB and 90 manually coded accidents with 309 labels (states, triggers, and additional information). As the number of labels increases, the complexity of the problem also increases, and the model may require more data and computational resources to learn the correlations between the inputs and the multiple labels (Tarekegn et al., 2021). Moreover, if the distribution of the labels is imbalanced, i.e., some labels are more frequent than others, the model may struggle to learn the less frequent labels and may be biased towards the more frequent ones. So, I selected the ten of the most frequently cited states and triggers in LOC-I accidents for implementing multi-label classification in the model. Table 16 shows the presence (number of times a state/trigger was cited at least once in an accident) of the ten states and triggers in 1982–2019 LOC-I accidents.

Table 16: Presence of states and triggers in LOC-I accidents

State/Trigger	**Presence**
No/failed recovery after loss of control	94.39%
Aircraft stall/spin	37.42%
Improper airspeed	24.05%
Loss of engine power	15.21%
Insufficient qualification/training/experience	14.38%
Improper inflight planning/decision-making	13.53%
Improper altitude/clearance	13.30%
Flight through poor weather	12.97%
Time spent in poor weather	8.08%
Disoriented/lacking awareness	7.75%

I separated the dataset into two parts: (1) 14,529 NTSB and 70 manually coded accidents for model training and validation (total 14,599 accidents); and (2) 1,500 NTSB and 20 manually coded accidents for testing the unseen dataset. The model randomly split the 14,599 training and validation data into 90% for training and 10% for testing. Figure 26 shows the split of the dataset for training, validation, and testing.

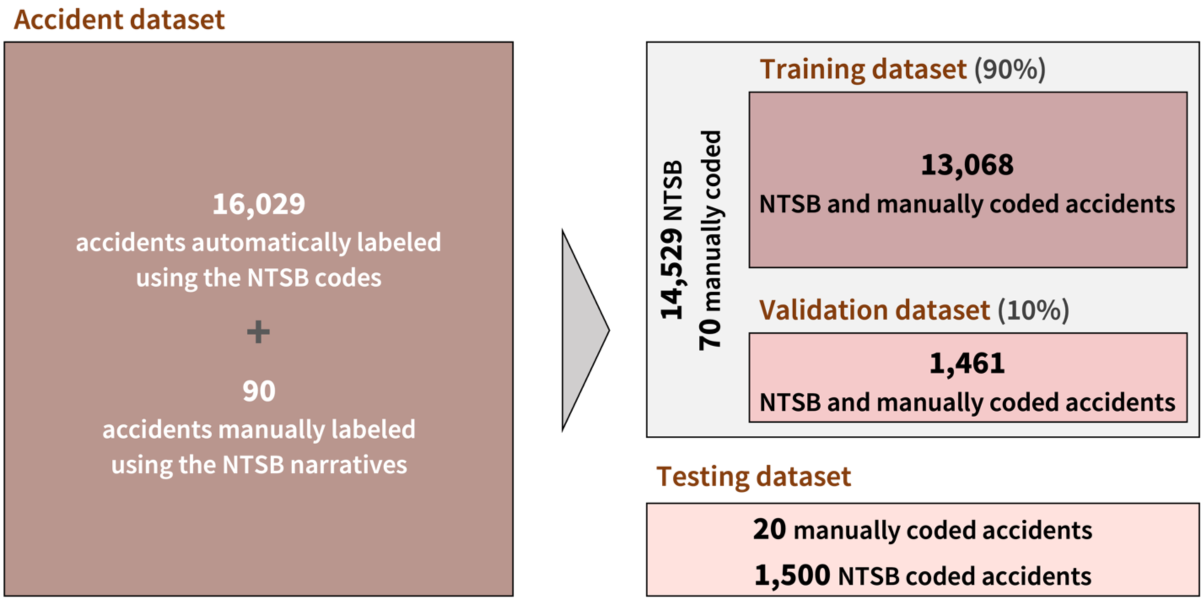

Figure 26: Spilt of the accident dataset into training, validation, and testing

5.4.4 Implementing the Longformer Model

I used the "allenai/longformer-base-4096" pre-trained Longformer self-attention model. I fine-tuned the model by tuning/optimizing the hyperparameters. Hyperparameters are the variables that determine the network structure and how the network is trained. Hyperparameters are set before training and optimized to achieve optimal model performance. Although the Longformer has a maximum length of 4,096 tokens, the memory and computational requirements of self-attention (in Longformer) grow quadratically with sequence length, making it infeasible (or very expensive) to process long sequences (Beltagy et al., 2020). Since 75% of all LOC-I accident reports have less than 1,024 words, I set the maximum sequence length to 1,024.

The "allenai/longformer-base-4096" model has 12 transformer layers. A transformer layer consists of two sub-layers: a multi-head self-attention mechanism and a feedforward neural network (Singh & Mahmood, 2021). Each transformer layer has 16 attention heads with a hidden size of 768 (Hugging Face, 2020). I used the default Adam optimizer and learning rate of $1e-05$. I set the dropout rate as 0.3. Dropout rate is a regularization technique used to prevent overfitting in neural networks. Overfitting occurs when a model is too complex and learns to fit the training data too well, leading to poor performance on new unseen data (Li et al., 2019). A dropout rate of 0.3 means that 30% of the neurons in a layer will be randomly dropped during training. Training and validation batch size was set to 5. Batch size is the number of samples passed to the neural network before the model weights are updated. I used 12 epochs for training the data. An epoch is the total number of iterations of all the training data in one cycle for training the model. The model had a linear transformation "pre_classifier" layer that has an input feature vector of size 768 and input tensor of size [5, 768] (where 5 is the batch size). The layer applies a linear transformation to this input tensor, mapping it to a tensor of size [5, 384]. The purpose of this layer is to reduce the dimensionality of the input feature vector from 768 to 384, which can help to reduce the number of parameters in the model and improve its efficiency. I conducted the experiments with PyTorch library on Google Collab Graphical Processing Unit (GPU) hardware accelerator.

5.5 Model Performance Evaluation

In the following sub-sections, I will describe the evaluation metrics for model performance and the results for model performance evaluation.

5.5.1 Evaluation Metrics

To evaluate the model performance on the validation dataset, I applied the traditional evaluation metrics for a multi-label classification: (1) accuracy and (2) hamming loss.

For the testing dataset, I also calculated the F1 score for each state and trigger. F1 score is the harmonic mean of precision and recall. F1 score evaluates the overall effectiveness of a model in making correct positive predictions for each label. Additionally, I visualized the model performance using confusion matrices for the testing dataset. Equations 5–9 show how to calculate each metric. A confusion matrix is a matrix of actual labels versus predicted labels. Table 17 summarizes the four possible outcomes in a confusion matrix:

1. True Positive (TP): case where the model predicted a positive label, and the actual label was also positive.

2. False Positive (FP): case where the model predicted a positive label, but the actual label was negative.
3. True Negative (TN): case where the model predicted a negative label, and the actual label was also negative.
4. False Negative (FN): case where the model predicted a negative label, but the actual label was positive.

Table 17: Four possible outcomes of a confusion matrix

Outcome	Actual Label	Predicted Label
True Positive (TP)	1	1
False Positive (FP)	0	1
True Negative (TN)	0	0
False Negative (FN)	1	0

$$Accuracy = \frac{Number\ of\ correct\ positive\ predictions}{Total\ number\ of\ predictions} = \frac{1}{n}\sum_{i=1}^{n}\frac{TP + TN}{TP + TN + FP + FN} = \frac{1}{nL}\sum_{i=1}^{n}\sum_{j=1}^{L}\left[I(Y_j^{(i)} = Z_j^{(i)})\right] \tag{5}$$

$$Hamming\ loss = \frac{Number\ of\ wrong\ predictions}{Total\ number\ of\ predictions} = \frac{1}{n}\sum_{i=1}^{n}\frac{FP + FN}{TP + TN + FP + FN} = \frac{1}{nL}\sum_{i=1}^{n}\sum_{j=1}^{L}\left[I(Y_j^{(i)} \neq Z_j^{(i)})\right] \tag{6}$$

$$F1\ score = \frac{2\ \times\ Precision\ \times\ Recall}{Precision\ +\ Recall} = \frac{TN}{TN + FP} = \frac{1}{n}\sum_{i=1}^{n}\frac{2\left|Y^{(i)} \wedge Z^{(i)}\right|}{|Y^{(i)}| + |\ Z^{(i)}|} \tag{7}$$

$$Precision = \frac{Number\ of\ correct\ positive\ predictions}{Total\ number\ of\ positive\ predictions} = \frac{TP}{TP+FP} = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|Y^{(i)} \wedge Z^{(i)}\right|}{\left|Z^{(i)}\right|} \qquad (8)$$

$$Recall = \frac{Number\ of\ correct\ positive\ predictions}{Total\ number\ of\ actual\ positive\ labels} = \frac{TP}{TP+FN} = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|Y^{(i)} \wedge Z^{(i)}\right|}{\left|Y^{(i)}\right|} \qquad (9)$$

$n =$ number of accidents in training set

$\wedge =$ logical AND operator

$Y^{(i)}$ = true states and triggers for ith accident in training set

$Z^{(i)}$ = predicted set of states and triggers for ith accident

$L =$ set of states and triggers

$I =$ Indicator function; $I(x) := \begin{cases} 1 & \text{if } x \in Y_i \\ 0 & \text{if } x \notin Y_i \end{cases}$

$Y_j^{(i)}$ = true label for ith accident and jth state/trigger in training set

$Z_j^{(i)}$ = predicted label for ith accident and jth state/trigger in training set

5.5.2 Model Performance

1. Validating the Model

For the validation dataset of 1,461 accidents, the model predicted 92.9% of the states and triggers. Hamming loss was 0.071. Table 18 shows the performance for the validation dataset.

Table 18: Performance of Longformer on validation dataset

Evaluation Metric	Actual Label
Accuracy	92.9%
Hamming Loss	0.071

1. Testing and Predicting Unseen Data

To evaluate the testing performance, I separated the 20 manually coded accidents and 1,500 NTSB coded accidents for evaluating the model prediction and performance for the testing data. The best evaluation method for the model is to compare the model's predictions with the manually coded accidents. I found the union of the NTSB codes and manual codes for the 90 accidents to ensure that all possible findings are included for those accidents. To the best of our knowledge, the union of the NTSB and manually coding for the 90 accidents are as complete as possible in the context of the findings.

a. Predicting 20 Manually Coded Accidents

Table 19 shows the testing performance for the 20 manually coded accidents. The model could predict 97.5% of the states and triggers for the 20 unseen manually coded accidents. Table 20 shows the F1 scores for each state and trigger for the 20 accidents. Seven of the ten states and triggers had an F1 score of 1. The model also accurately predicted the inferred triggers, time spent in poor weather and no/failed recovery action after loss of control, with F1 scores of 1. Time spent in poor weather is inferred trigger that is based on sequencing rules (see Majumdar et al., 2021). No/failed recovery We infer this trigger when a pilot spent too much time in poor weather and became disoriented. If an accident has a flight through poor weather and disoriented, then we infer time spent in poor weather trigger to the disoriented state. We infer no/failed recovery action after loss of control if an accident does not specify pilot's remedial action.

Table 19: Performance of Longformer on 20 manually coded accidents

Evaluation Metric	Actual Label
Accuracy	97.5%
Hamming Loss	0.025

Table 20: F1 scores for states and triggers for the 20 manually coded accidents

State/Trigger	F1-Score
No/failed recovery after loss of control	1.0
Loss of engine power	1.0
Disoriented/lacking awareness	1.0
Improper airspeed	1.0
Time spent in poor weather	1.0
Improper inflight planning/decision-making	1.0
Flight through poor weather	1.0
Aircraft stall/spin	0.9
Insufficient qualification/training/experience	0.7
Improper altitude/clearance	0.7

Figure 27 shows the confusion matrices for the ten states and triggers. The model could predict almost all states and triggers correctly. There were two false negatives each for aircraft stall/spin and improper altitude/clearance states. The model missed one accident with insufficient qualification/training/experience state.

The model predicted five of 20 accidents incorrectly. For the two accidents with false negatives for *aircraft stall/spin*, one accident cited stall only in the NTSB code but did not mention stall or any relevant keywords (e.g., such as “stall”, “spin”, and “nose drop”) in its report (NTSB Number: CHI02FA215). For the second accident, the report mentioned “The airplane was observed by a witness entering a spin and continued spinning down...” (NTSB Number: DFW05LA012). The model did not capture the keyword “spin” as aircraft stall/spin.

For the third accident, the model did not predict *insufficient qualification/training/experience*, i.e., a false negative (NTSB Number: LAX06FA289). The report mentioned "… the non-instrument rated pilot's decision to continue flight into instrument meteorological conditions..."

For the remaining two accidents, the model did not predict *improper altitude/clearance* i.e., two cases of false negatives. On reading the accident narrative, I found that the reports mentioned about low altitude flying. One accident mentioned "a witness stated that he… noticed a low flying airplane buzzing the City of Hartselle and lining up to land at a local airport" (NTSB Number: ATL06LA110). The other accident mentioned "The airline transport rated pilot was maneuvering the airplane at low altitude over a sugar cane field for the purpose of scaring birds out of the field." (NTSB Number: MIA03FA077).

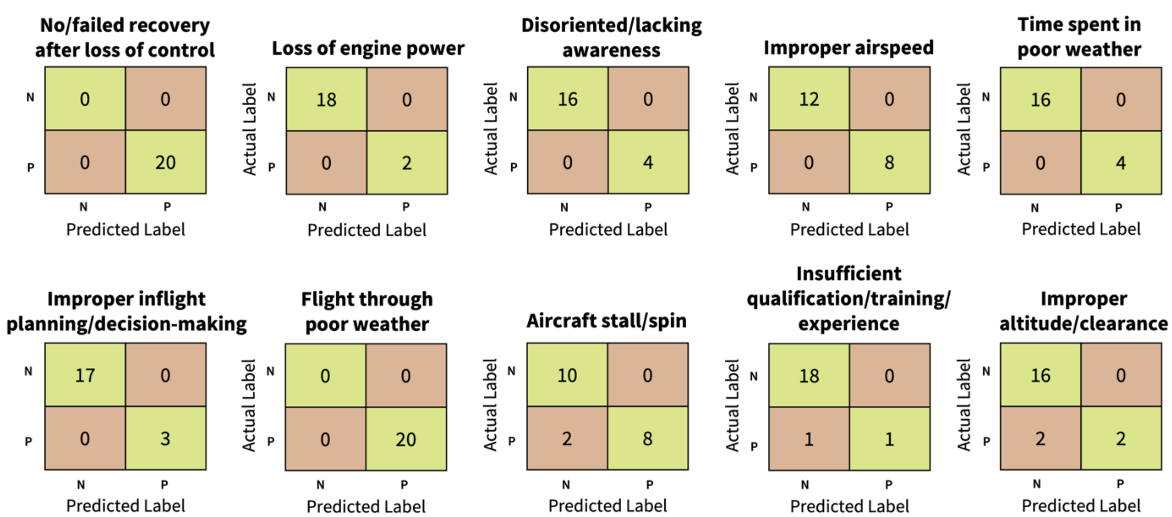

Figure 27: Confusion matrices for ten states and triggers for 20 manually coded accidents

b. Predicting a different set of 20 Manually Coded Accidents

To evaluate the consistency of model performance, I ran the model a second time to predict a different set of 20 manually coded accidents. For the second run, I separated the 90 manually coded accidents into a different set of 70 accidents for training (in addition to the 14,529 NTSB coded accidents) and the model predicted states and triggers for a different set of 20 accidents.

During the validation, the model had an accuracy of 93.1% and a loss of 0.068 for the 1,461 accidents. Table 21 shows the testing performance for these different 20 accidents. The model predicted 96.5% of the states and triggers with a loss of 0.035.

Table 21: Performance of Longformer on a different set of 20 manually coded accidents

Evaluation Metric	Actual Label
Accuracy	96.5%
Hamming Loss	0.035

Table 22 shows the F1 scores for the ten states and triggers. Four states and triggers had an F1 score of 1. Improper airspeed had the lowest F1 score because of there were only two accidents that had this state. Out of the two accidents, the model predicted one correctly.

Table 22: F1 scores for states and triggers for a different set of 20 manually coded accidents

State/Trigger	F1-Score
No/failed recovery after loss of control	1.0
Loss of engine power	1.0
Disoriented/lacking awareness	0.8
Improper airspeed	1.0
Time spent in poor weather	0.8
Improper inflight planning/decision-making	1.0
Flight through poor weather	0.9
Aircraft stall/spin	0.9
Insufficient qualification/training/experience	0.8
Improper altitude/clearance	0.7

Figure 28 shows the confusion matrices for the ten states and triggers. The model could predict almost all states and triggers correctly. There were five false negatives, one each for disoriented/lacking awareness, time spent in poor weather, aircraft stall/spin, insufficient qualification/training/experience, and improper altitude/clearance. The model missed one accident with insufficient qualification/training/experience and another with flight through poor weather state. The model could not predict five out of 20 accidents.

For the first accident, the model could not predict three states and triggers: *insufficient qualification/training/experience, Disoriented/lacking awareness*, and *time spent in poor weather*. On reading the report, I found that the narrative mentioned the following that corresponds to insufficient experience: "the non-instrument rated pilot's continued flight into instrument meteorological conditions." The report did not mention about the disoriented state and only cited it in the NTSB code. Therefore, the model did not capture disoriented and time spent in poor weather from the narrative.

For the second accident where the model missed *improper altitude/clearance,* the report specified about low altitude flying by mentioning, "the pilot's failure to maintain adequate airspeed while performing a low-level pass, which resulted in an uncontrolled descent and collision with terrain." For the third accident, the model missed *aircraft stall/spin* state although the report mentioned the following: "the non-certificated pilot's failure to maintain airspeed, which resulted in an inadvertent stall and a subsequent impact with the ground."

One of the two false positive cases where the model predicted *insufficient qualification/training/experience,* the report mentioned about pilot's low instrument hours: "a review of the logbook indicated that the pilot had logged… 4.6 hours in simulated instrument meteorological conditions." The second accident where the model predicted *flight in poor weather,* the report mentioned about fog: "the pilot's loss of control while performing an instrument approach. A contributing factor was the prevailing fog." Both these accidents did not cite the corresponding states in the NTSB codes. The model's performance and almost correct predictions for the 20 accidents suggests that it has the potential to predict the states and triggers quite accurately for accidents in general.

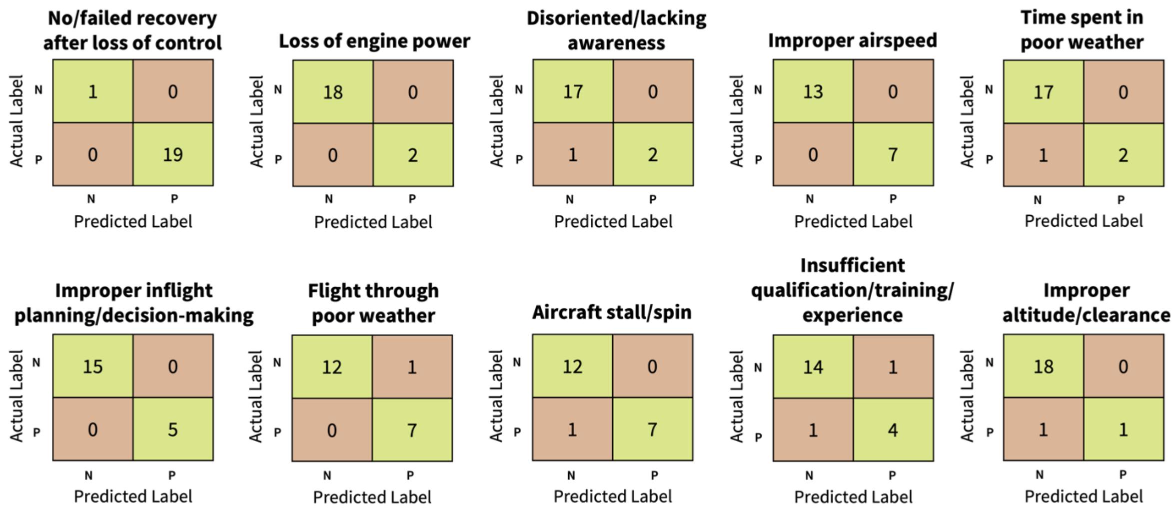

Figure 28: Confusion matrices for ten states and triggers for a different set of 20 accidents

c. Predicting 1,500 NTSB Coded Accidents

Table 23 shows the testing performance for the 1,500 manually coded accidents. The model could predict 93.2% of the states and triggers for the 1,500 unseen manually coded accidents. Table 24 shows the F1 scores for each state and trigger for the 1,500 accidents. Note that the evaluation metrics for the 1,500 accidents may not reflect the model's true performance because these accidents are coded only using the NTSB codes and may have incomplete coding of states and triggers because of no manual intervention.

Table 23: Performance of Longformer on 1,500 NTSB coded accidents

Evaluation Metric	Actual Label
Accuracy	93.2%
Hamming Loss	0.068

Table 24: F1 scores for states and triggers for 1,500 NTSB coded accidents

State/Trigger	F1-Score
No/failed recovery after loss of control	0.94
Loss of engine power	0.87
Disoriented/lacking awareness	0.86
Improper airspeed	0.78
Time spent in poor weather	0.77
Improper inflight planning/decision-making	0.76
Flight through poor weather	0.67
Aircraft stall/spin	0.69
Insufficient qualification/training/experience	0.66
Improper altitude/clearance	0.60

Six of the ten states and triggers have F1 scores above 0.7. Since the F1 score evaluates the model's overall effectiveness in making correct positive predictions, the F1 scores for the last four states are less than 0.7. Even though the model could correctly predict improper altitude/clearance 95.7% of the times, it still has a low F1 score because F1 is based on true positive values (which is the lowest for this state).

Figure 29 shows the confusion matrices for the ten states and triggers. The model could not predict 4.2% of all states and triggers. The false positives may suggest additional findings in the accidents and may imply under-reporting of codes for the accidents. If the model can predict more states and triggers which were originally not cited by the NTSB, then that would improve accident modeling and provide a richer understanding of accident causation.

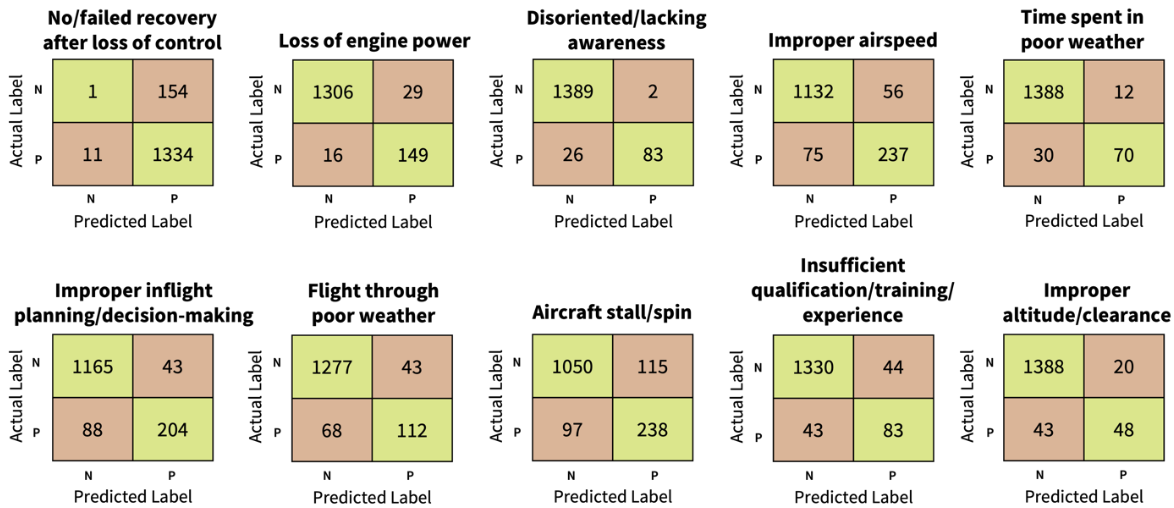

Figure 29: Confusion matrices for ten states and triggers for 1,500 NTSB coded accidents

I studied a few cases with large values for false positive and false negative to evaluate whether the reports mentioned the corresponding states or triggers. *No/failed recovery after loss of control* trigger had 154 cases of false positives. I looked at two accidents with false positive cases for the trigger. Both accidents mentioned pilots' recovery or corrective actions in their reports but not in the codes. First accident report mentioned "… there was insufficient altitude to fully recover from the stall…" (NTSB Number: WPR14FA320). The second accident report mentioned "the pilot made corrective control inputs, but the airplane did not fully respond, bouncing again on the runway" (NTSB Number: WPR14CA365). The issues mentioned in the reports can be mapped to no/failed recovery after loss of control.

Aircraft stall/spin had 115 cases of false positives. Out of the two accidents that I studied, the first accident report mentioned "The pilot's failure to maintain adequate airspeed… which resulted in an aerodynamic stall" (NTSB Number: WPR14FA303). The second accident report mentioned "The pilot's failure to maintain airspeed… resulting in a stall/mush." (NTSB Number: CEN14FA396). Although issues mentioned in both the reports correspond to aircraft stall/spin, their codes did not cite the state. So, the model predicted the state for these two accidents correctly.

I analyzed a few more randomly chosen accidents with false positive cases. For the first accident, the model predicted *improper altitude/clearance* when the NTSB did not cite a corresponding code (NTSB Number: FTW95FA001). I found that although the report did not cite any altitude related codes, the narrative mentioned "an inadvertent pilot-induced stall at too low an altitude to affect a safe recovery." The narrative correctly suggests improper altitude and the model accurately predicted the state.

For another accident, the model predicted *improper airspeed* when the NTSB cited improper stall speed (Vs) only in its codes (NTSB Number: LAX94FA193). Improper stall speed is categorized as improper stall speed as per the state definitions. The narrative for this accident mentioned "… a failure of the pilot to maintain adequate airspeed which resulted in an inadvertent stall." Hence, the model predicted the improper airspeed correctly based on the narrative.

For a false negative case, the model did not predict *aircraft stall/spin* in an accident even when the NTSB had cited the code (NTSB Number: NYC94FA064). The report did not mention any stall or spin related keywords in its narrative (such as "stall", "spin", and "nose drop"). The absence of the keyword in narrative suggests that the model in fact did not miss the state incorrectly.

5.6 Discussion and Conclusion

Overall, the model performed well in predicting states and triggers from reports. Since accidents may have incomplete translation of findings in codes and narratives, some of the false negatives may mean that certain issues were only cited in the codes and not the narratives. Some of the false positives may mean that certain issues were only cited in the narratives and not in the codes. The predictions on the 1,500 accidents may suggest new findings that were not cited in the NTSB codes and may be able to infer missing states and triggers, e.g., time spent in poor weather (leading to a disorientation). Further, most accidents do not have any finding mentioned that explains what triggered the LOC-I to cause an accident. The predictions may suggest that most accidents involve no/failed recovery after loss of control. The model predicted improper airspeed in many accidents when the NTSB had not cited it in 56 out of 1,500 accidents. Based on the accurate prediction of improper airspeed on the 20 accidents, we can speculate that some of those 56 accidents could have been under-cited in their NTSB coding.

For future work, we can configure the model to predict more than ten states and triggers. However, there could be potential challenges in including more states and triggers. One such issue is with imbalanced multi-classification datasets that contain an uneven distribution of labels across instances and may increase the problem complexity in training the model. For example, for the 1982–2019 accidents, aircraft stall/spin state is present in 36.42% of accidents whereas improper takeoff state is present in 1.73% of accidents. The model may perform poorly in predicting the less occurred states such as improper takeoff because of a lack of representative samples of accidents involving the state. Some methods to address such an issue are (1) oversampling minority states and triggers to balance the distribution; (2) augmenting the data to generate synthetic data for minority labels; (3) using custom loss functions to assign higher weights to minority labels during optimization; and (4) fine-tuning the model, e.g., increasing the output layer nodes. Increasing number of output nodes allows the network to capture more fine-grained information and produce more detailed predictions for each class or label. More output nodes means that the neural network will be able to produce predictions for more labels.

Additionally, the results from the model need to be evaluated and verified by subject matter experts before applying the findings in planning future safety studies (Kuhn, 2018 and Young et al., 2019).

Some of the practical applications of automatically classifying information from accident reports are to:

1. Provide an automatic analysis of reports regardless of their NTSB coding that may help in identifying additional findings and therefore a richer accident causation analysis.
2. Improve reliability of coding and facilitate accident coding for the NTSB reporters based on the automatic analysis of written narratives.
3. Use grammar rules from the state-based approach to infer missing information in accident reports and increase the quality of accident coding.

6. ANALYZING LESSONS LEARNED ARTICLES INVOLVING INFLIGHT LOSS OF CONTROL

To understand LOC-I causation from pilots' perspectives, it is helpful to study sources other than the NTSB accident reports. More than 300 pilots have shared their LOC-I related stories in AOPA Pilot magazine's "Never Again" series over the past 27 years, since the series was made online in 1994 (AOPA, n.d.). By studying these LOC-I stories, we may understand pilots' perspective of what unsafe conditions and pilot actions lead to a LOC-I and how pilots prevent a potential LOC-I.

The Pilot magazine's "Never Again" series provides a forum for pilots to share their experiences of unsafe flying conditions and discuss probable causes and factors that led to the unsafe condition, their instinctive reaction to these conditions, corrective actions to mitigate the unsafe condition, and lessons learned from their mistakes. The National Transportation Safety Board (NTSB) has also investigated some of these incidents. For example, the NTSB investigated a near collision between a Cessna 185 and a Boeing 737 that happened in 1994 (NTSB Number: ANC94IA075B) and that was reported in the "Never Again: Close Call" article by Kramer (2020).

6.1 Identifying Articles with LOC-I Incidents

I studied 132 articles from the 2009–2020 (May 2020) Never Again" archives of the AOPA's Pilot magazine. In these articles, pilots share their experiences of unsafe flying conditions and discuss probable causes and factors that led to the unsafe condition, their instinctive reaction to these conditions, corrective actions to mitigate the unsafe condition, and lessons learned from their mistakes. I documented all the articles in 2009–2019 that mentioned near LOC-I experiences or conditions that could have caused LOC-I if corrective action was not taken by the pilot. Some of these conditions mentioned in the articles are severe weather conditions, fuel starvation, and engine/aircraft control failure. I found 21 such LOC-related articles in the AOPA archives. Here, I present causal factors from those incidents, as mentioned in the articles. Additionally, I discuss lessons learned from pilots' LOC-I experiences as mentioned in the AOPA Never Again archives and provide insights and emerging themes from these archives.

6.2 Identifying Causal Factors, Corrective Actions, and Lessons Learned

Consider the March 2020 article that discusses a 1994 incident where the Cessna 185 pilot experienced partial loss of control due to a near miss with a Boeing 737 during the initial climb near the restricted airspace in Merrill Field, Alaska (Kramer, 2020; NTSB Number: ANC94IA075B). The NTSB recorded the Cessna pilot's failure to maintain adequate visual separation from the Boeing and the ATC personnel's failure to adjust the flightpath of both the aircraft as the only two probable causes of the incident. The NTSB report does not mention any other findings or contributing factors. The AOPA article discusses the Cessna pilot's perspective on the incident. In the article, the pilot states "… my failure to be more aware of my surroundings played a significant role in what could have been an unthinkable tragedy for all involved." He also mentions "I learned a valuable lesson with regard to complacency and situational awareness that evening." I used such phrases from the articles to identify pilot mistakes and unsafe events/conditions. For example, based on the article, I determined an unsafe event such as near miss, a condition such as wake turbulence, and pilot mistakes such as lack of situational awareness and complacency as contributing factors to the partial loss of control. Similarly, I summarized articles to identify corrective actions taken by the pilot to mitigate loss of control and lessons learned. For example, in this incident, when the pilot encountered wake turbulence, he lowered the power to idle and pushed the yoke forward for a downward pitch. In the article, the pilot discusses that from this incident, he learned to be more aware and look around especially when entering restricted airspace and immediately react to the training scenarios and execute a sequence of correct actions.

After identifying the causal factors for all the articles, I grouped them into categories based on similar themes. For example, I found two incidents that involved wake turbulence. So, I created a category called wake turbulence. Further, pilots mentioned in two articles that they were not situationally aware. So, I created lack of situational awareness as another category. I used a similar method to create themes of corrective actions taken by pilots and lessons learned from the incidents.

6.3 Causal Factors of LOC-I Incidents

I created 24 categories that described causal factors in the incidents and counted the number of times each category was cited in the articles. Figure 30 shows all the 24 categories that I created from the findings from the 21 articles.

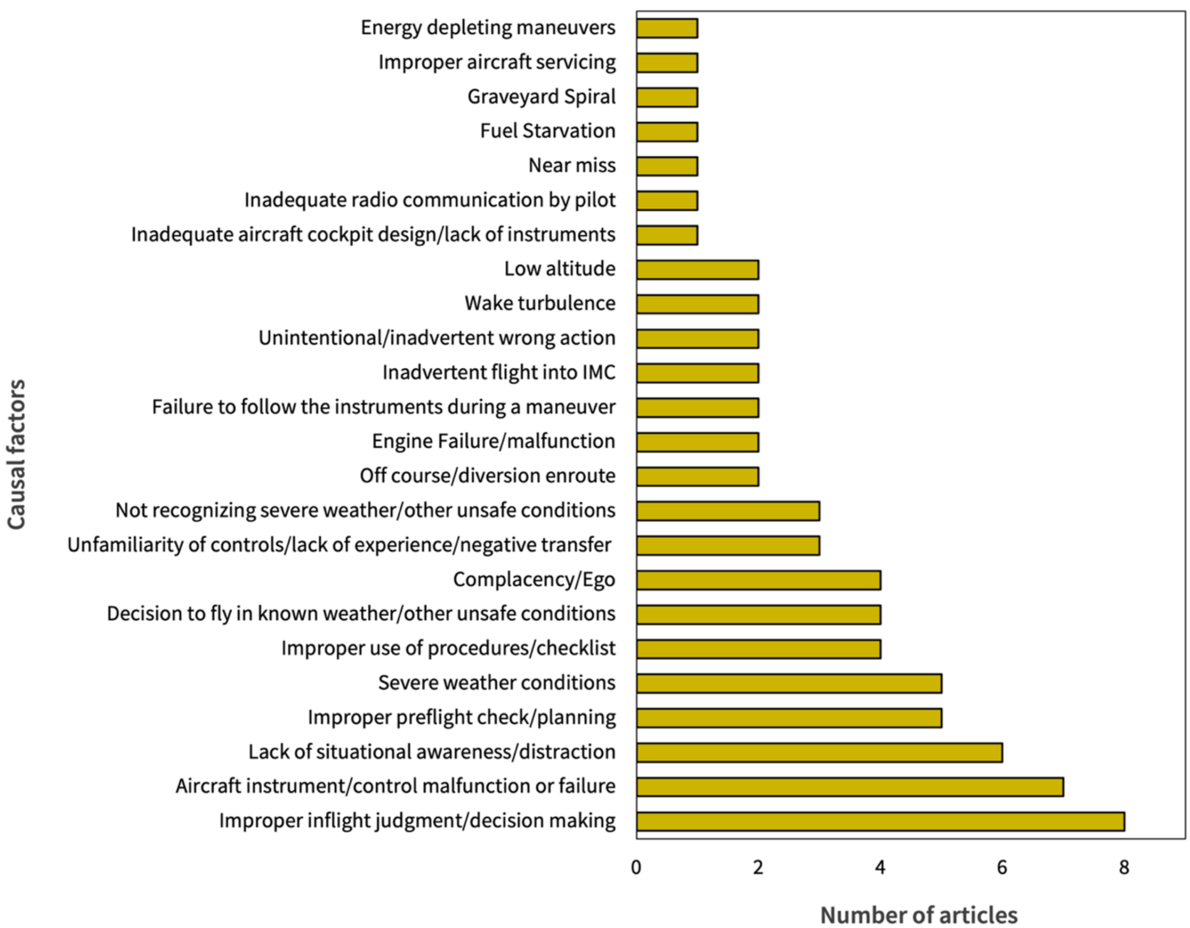

Figure 30: 24 categories of causal factors leading to LOC-I, as mentioned in the articles.

Pilot conditions and actions were the most common factors in these LOC-I incidents. Figure 31 shows the most prevalent theme in the incidents.

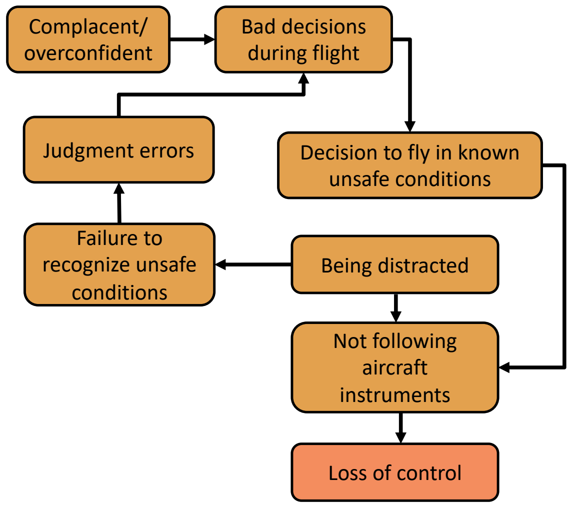

Figure 31: Theme of how pilot conditions and actions led to LOC-I incidents.

I found that pilots most frequently (four articles) cited being complacent or overconfident in their own abilities during the flight as the sources of bad decisions (such as improper judgment) that contributed to potential loss of control incidents. Additionally, the articles most frequently cited the pilot's decision to fly in known severe weather/wind conditions or other unsafe conditions such as low altitude or with foreign object debris (FOD) in the cockpit. The articles also suggest that failure to recognize severe weather/wind/other unsafe conditions mostly caused pilots to make judgment errors about weather/wind conditions, which led to a decision to fly in the known unsafe conditions. Further, being distracted and not following the instruments were other frequently cited factors that led to a loss of control. One such incident involved a pilot who got distracted while scud running (Herman, 2013). Scud running is a practice where pilots lower their altitude to avoid clouds or instrument meteorological conditions (IMC) to stay clear of weather to maintain visual contact with the terrain. The pilot did not follow the instruments which led to a loss in altitude and a failure to maintain aircraft control. The pilot mentioned that he remained calm and applied back pressure with full power to regain control.

Two articles mentioned pilots running out of fuel because they had diverted from their planned routes. Consider the incident where the pilot decided to fly in a headwind, diverted enroute, and misinterpreted the remaining fuel level which led to fuel starvation (Houghton, 2020). By deciding to land at a nearby airport for refueling, the pilot was able to prevent a potential loss of control.

6.4 Corrective Actions Taken by Pilots

One reason that these incidents did not turn into accidents is because the pilots took corrective actions at the appropriate time to mitigate a potential LOC-I. Apart from analyzing pilot mistakes and unsafe conditions, it is also important to analyze the set of corrective actions that helped pilots to come out of the unsafe conditions. I identified corrective actions taken by pilots in each incident and categorized them into 18 themes, as shown in Figure 32.

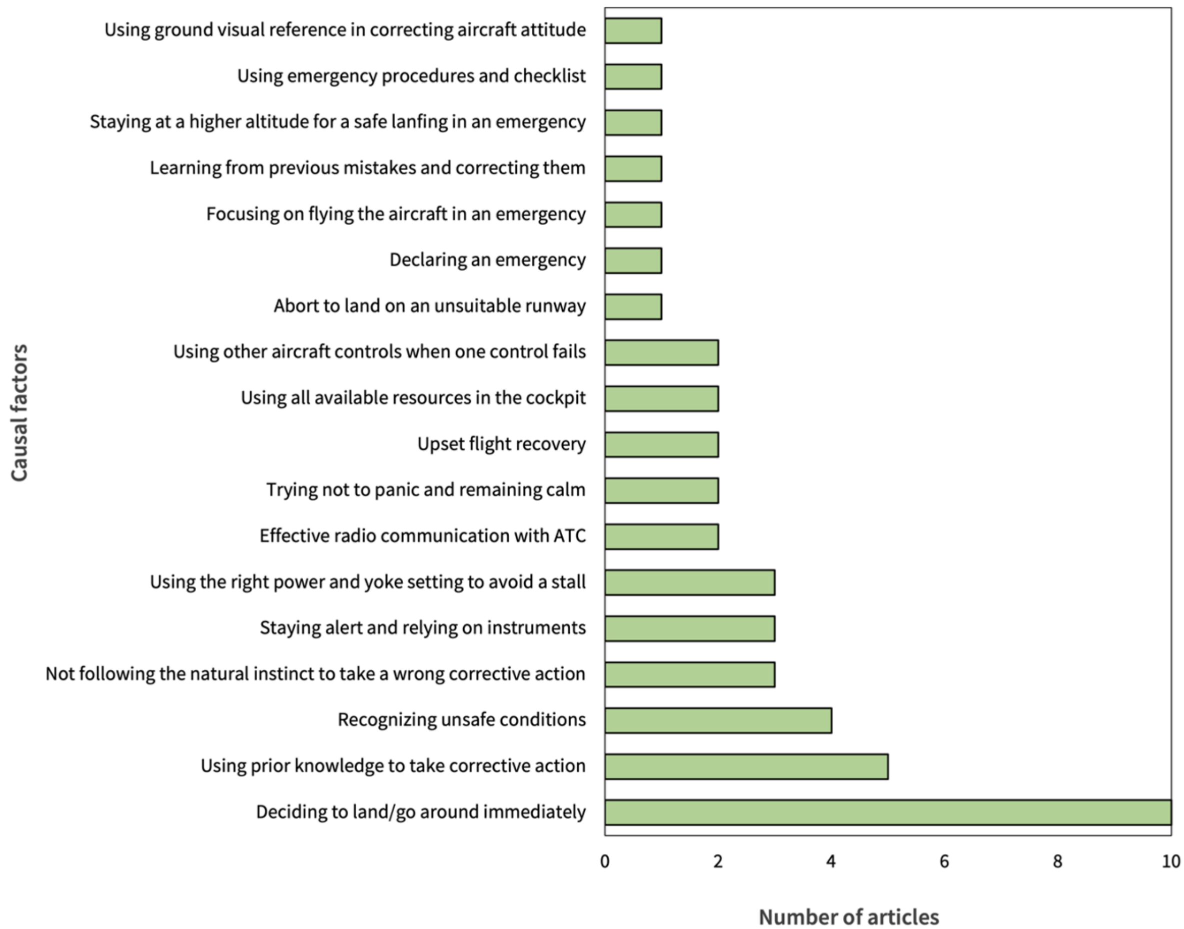

Figure 32: 18 themes of corrective actions that pilots took to mitigate or prevent an LOC-I

Figure 33 summarizes the most prevalent theme of corrective actions taken by pilots that helped them prevent an LOC-I. The findings suggest that effective training and regular maneuver practices may help pilots prevent a potential LOC-I.

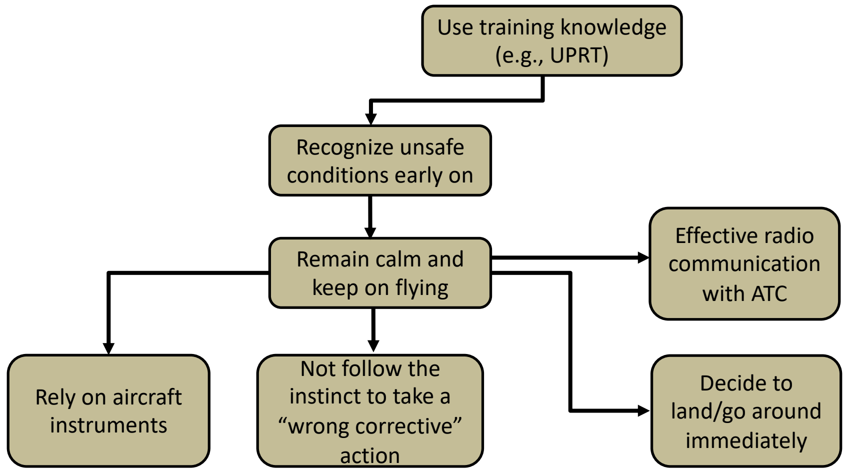

Figure 33: How pilots' corrective actions helped them prevent or recover from LOC-I

In five articles, pilots mentioned that their prior training knowledge (such as upset prevention and recovery training and aerobatics knowledge) helped them recognize an unsafe or hazardous condition and take a corrective action. One such article described an incident that involved an upset[1] condition in a Zenith 601 due to wake turbulence from a Boeing 737 (Thomas, 2017). The pilot used his aerobatics training to recover from the upset state. NTSB accident reports suggest that not being able to recognize unsafe conditions generally leads to hazardous conditions culminating in an accident (NTSB, 2023). Four of the 21 articles that I studied mention that the pilot's ability to recognize unsafe conditions helped them take early preventive measures to mitigate LOC-I accidents. In ten articles, pilots decided to land immediately (at a nearby airport or conduct forced landing) or go around whenever they encountered hazardous conditions such as adverse weather conditions, IMC (instrumental meteorological conditions), or malfunctioning aircraft controls. The articles also suggest that pilots tend to follow the instinct to take a wrong corrective action such as pulling the yoke during a spiral or when rolling over. Three such articles

[1] The FAA defines an upset as an event that unintentionally exceeds the parameters normally experienced in flight or training. These parameters are:

- Pitch attitude greater than 25 degrees, nose up
- Pitch attitude greater than 10 degrees, nose down
- Bank angle greater than 45 degrees
- Within the above parameters but flying at airspeeds inappropriate for the conditions.

mentioned that recognizing and not following the instinct to take the wrong corrective action helped them prevent a hazardous condition and prevent a potential LOC-I accident.

6.5 Lessons learned from the LOC-I Incidents

Pilots in the articles discussed the lessons that they learned from the incidents that may help to prevent a LOC-I incident in the future. I identified more than 50 lessons learned for the 21 LOC-I-related articles and categorized them into 13 themes, as shown in Table 25.

Table 25: I found 13 themes of lessons learned, as mentioned by the pilots in the LOC-I articles

Lessons Learned Themes	No. of articles
Stay situationally aware and cautious of cockpit and flight surroundings such as instruments, altitude, and traffic.	6
Plan ahead for flights and make sure all pre-flight checklist items are met.	9
Gain adequate proficiency in aircraft type and model, and its systems.	5
Consider aircraft and runway capabilities before making in-flight judgments.	3
During emergencies, keep flying the aircraft instead of giving up. Maintain calm and do not panic to make correct judgments and decisions.	5
Estimate how different flight conditions and maneuvers can affect fuel usage.	2
Learn from previous mistakes, read accident and incident reports, and be prepared for different possible scenarios.	3
Use other functioning controls and all back-up instruments and cockpit resources (such as passengers' help) during control/instrument failure.	3
Pilots who recognized unsafe flight conditions early on had more time to make correct decisions and actions.	4
Rely on aircraft instruments while conducting maneuvers or an IMC flight.	3
Don't hesitate to use services such as flight following and declaring an emergency to the ATC.	3
When in doubt, go around.	2

Table 25: I found 13 themes of lessons learned, as mentioned by the pilots in the LOC-I articles

Lessons Learned Themes	**No. of articles**
Regularly practice maneuvers and upset recovery training to immediately respond to unsafe flight scenarios. Training may also help pilots to not follow the natural but wrong corrective action by the help of re-enforcement.	5

In five articles, pilots mentioned that not panicking and maintaining calm helped in making a correct judgment in a hazardous scenario. The pilots continued flying the aircraft instead of giving up. Pilots in two articles suggested keeping the fuel tanks full for long distance flights and correctly estimating the fuel usage in headwinds and enroute diversions. Pilots state that refueling enroute even when the destination is close helps in avoiding risks of loss of control. One such article involved an incident where the pilot decided to fly in a headwind, diverted enroute, and was running out of fuel (Houghton, 2020). The pilot immediately landed at a nearby airport for refueling and avoided a potential LOC-I. Learning from previous mistakes, reading NTSB accident and incident reports, and constant practice to gain proficiency in aircraft type and model help to immediately react to training scenarios and perform a sequence of corrective actions.

The findings of this study helped us to identify specific pilot errors contributing to LOC-I that were not mentioned in the NTSB reports.

7. SURVEY OF PILOTS' INFLIGHT LOSS OF CONTROL EXPERIENCES AND TRAINING

The contents of this chapter were published in Majumdar, N., & Marais, K. (2022). A Survey of Pilots' Experiences of Inflight Loss of Control Incidents and Training. In AIAA AVIATION 2022 Forum (p. 3778).

To gain a better understanding of pilots' perspective and how pilot actions and other unsafe conditions lead to LOC-I, I conducted a survey of pilots who have experienced LOC-I. The target population for this study was pilots from all sectors of aviation who have experienced a partial inadvertent LOC-I or prevented a potential inadvertent LOC-I. Inadvertent means that the LOC-I was not intentional (such as an intentional stall maneuver during training). A stall is a loss of lift and increase in drag that occurs when smooth airflow over the aircraft's wing is disrupted at an exceeded critical angle of attack (AOA).

I focused only on inadvertent LOC-I experiences where a pilot was not prepared for the LOC event to happen (i.e., I did not consider cases where a pilot practiced stall, spin, or other LOC-I related maneuvers and successfully recovered from the unsafe condition). Participants were eligible to participate in the study if they were at least 18 years old, a student pilot or a certified pilot, and must have experienced an inadvertent LOC-I or prevented a potential LOC-I.

The following sections are based on the paper presented at the 2022 AIAA AVIATION Forum (Majumdar & Marais, 2022).

7.1 The Human Factors Analysis and Classification System (HFACS) Framework

Inspired by Reason's (Reason, 1990) Swiss Cheese model, (Wiegmann & Shappell, 2001) developed a Human Factors Analysis and Classification System (HFACS) framework that defines the holes in the Swiss Cheese Model and describes different kinds of active and latent failures, as shown in Figure 34. The HFACS framework includes most aspects of human errors and latent conditions such as operator conditions, unsafe supervision, environmental factors, and organizational influences. The taxonomic nature of the HFACS framework provides a systematic approach for analyzing accidents. HFACS has been widely applied in the aviation industry and other industries such as rail, shipping, and marine and has gained wide acceptance as a tool to classify human factors in accidents and incidents (Xi et al., 2010; Zarei et al., 2019; Celik & Cebi, 2009; and Chen, et al., 2013).

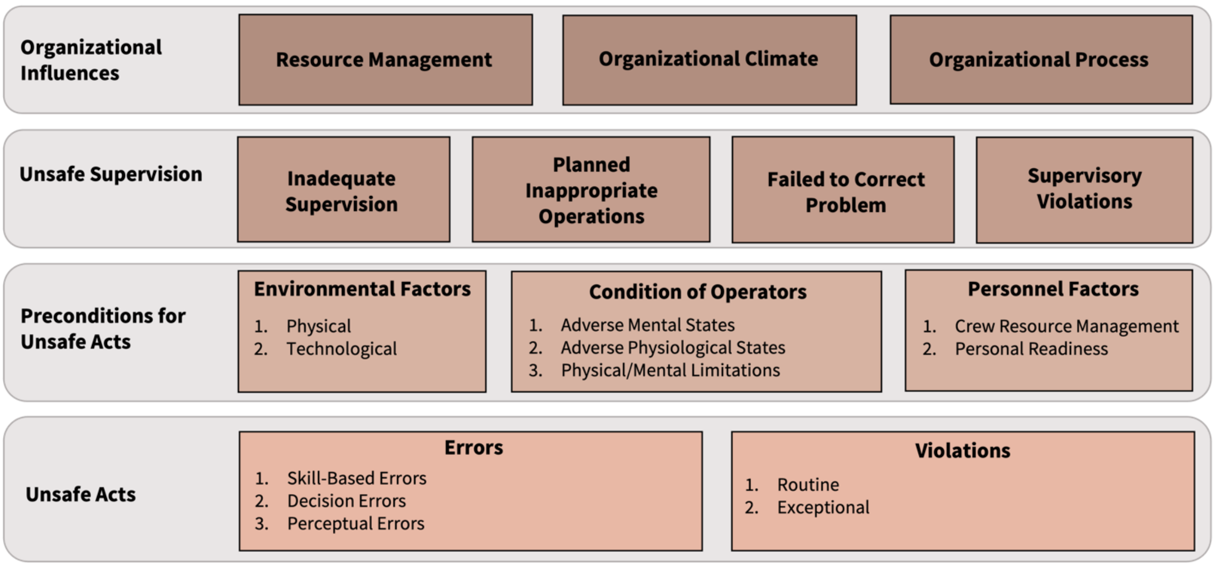

Figure 34: The HFACS Framework [adapted from (Wiegmann & Shappell, 2003)]

The HFACS framework classifies human error at four levels:

1. **Organizational Influences** include (a) *resource management* (management, allocation, and maintenance of organizational resources such as human resources, monetary assets, equipment, and facilities); (b) *organizational climate* (working atmosphere, management culture, and policies); and (c) *organizational process* (formal processes, e.g., time pressures and schedules; procedures, e.g., documentation and performance standards; and oversight within the organization, e.g., risk management and safety programs).

2. **Unsafe Supervision** includes (a) *inadequate supervision* (failures in supervision such as inadequate training and/or professional guidance); (b) *planned inappropriate operations* (aspects of improper crew scheduling and operational planning such as crew pairing and crew rest); (c) *failure to correct problem* (when a supervisor knows the deficiencies among

individuals, equipment, training, or other related safety concerns, and still chooses to not correct the issue); and (d) *supervisory violations* (instances when a supervisor willfully disregards the existing rules and regulations).

3. **Preconditions for Unsafe Acts** address the latent failures that lead to active failures or unsafe events and include (a) *environmental factors* (*physical environment*, e.g., weather, altitude, and lighting; and *technological environment*, e.g., design of equipment and controls, display/interface characteristics, checklist layouts, and automation); (b) *conditions of operators* (*adverse mental states*, e.g., loss of situational awareness, complacency, and task saturation; *adverse physiological states*, e.g., medical illness, hypoxia, and physical fatigue; *physical or mental limitations*, e.g., visual limitations, incompatible physical capabilities, and information overload); and (c) *personnel factors* (*crew resource management*, e.g., poor communication or coordination with the crew, air traffic control (ATC), etc.; and *personal readiness*, e.g., inadequate training and certification).

4. **Unsafe Acts** are active failures and are either (a) errors or (b) violations.
   Errors represent the mental or physical activities that fail to achieve their intended outcome (Wiegmann & Shappell, 2003). There are three basic types of errors. *Skill-based* errors refer to errors that involve flight skills that occur without significant conscious thought and can be classified into attention failures (e.g., lack of visual lookout and distraction), memory failures (e.g., omissions in checklist items or steps), and technique errors (e.g., improper use of flight controls). *Decision errors* represent "honest mistakes" that happen due to inadequate knowledge or just poor decisions. Decision errors can be classified into three broad categories: procedural errors (rule-based mistakes e.g., inappropriate maneuver or procedure); poor choices (knowledge-based mistakes e.g., improper preflight or inflight planning); and problem-solving errors (e.g., wrong response to an emergency). *Perceptual errors* occur when one's perception of the world differs from reality. These types of errors happen when sensory input is either degraded or unusual such as during visual illusions, spatial disorientation, or vertigo (e.g., not being able to recognize hazardous conditions or not relying on instruments when flying at night or in instrument meteorological conditions).

Violations refer to the willful disregard for the rules and regulations that govern the safety of flight (Wiegmann & Shappell, 2003). Routine violations are habitual by nature and often tolerated by a governing authority (e.g., inadequate briefing for flight and failure to use ATC radar advisories). Exceptional violations appear as isolated departures from an authority, neither typical of the individual nor condoned by management (e.g., unauthorized acrobatic maneuver and not current/qualified for flight) (Reason, 1990).

7.2 Research Instrument and Procedures

I developed a web-based survey based on HFACS to gain insight into how and why pilots lose control in flight. The survey has two sections: (a) 27 questions about pilots' inadvertent LOC-I experiences and the training that they received to prevent or recover from an LOC-I; and (b) seven demographic questions. I asked questions from each category of the HFACS framework except the categories that could likely involve a punishable offence—violations and adverse physiological conditions (e.g., drug use). The survey format gave respondents an option to discuss one or more LOC-I experiences before responding to demographic questions. Appendix B includes the consent form and survey questions.

After the study was approved by Purdue's Institutional Review Board, I disseminated the survey via various aviation groups, newsletters, and mailing lists such as the General Aviation News and Curt Lewis and Associates, LLC. I also used various social media messaging systems to send out the survey link. I contacted organizations such as the Purdue Pilots Incorporation, the Partnership to Enhance General Aviation Safety, Accessibility, and Sustainability (PEGASAS), the Ninety Nines, and Women in Aviation International to forward the survey to their members. I also encouraged snowball sampling by generating a constant survey link that respondents could forward to other pilots. Snowball sampling resulted in the survey being forwarded to additional flying clubs and pilots. After keeping the survey open for 45 days, I closed the survey and collected the responses.

7.3 Data Analysis

638 individuals opened the survey and 308 consented to begin the survey. 203 respondents then selected that they had experienced an inadvertent LOC-I or prevented a potential LOC-I and were thus eligible to continue with the survey. 187 respondents went on to share their first LOC-I experience. Twelve pilots shared two LOC-I experiences and two pilots shared three LOC-I experiences. Overall, 128 pilots responded to all survey and demographic questions, and 75 gave partial responses.

I first cleaned the data by removing outliers, repetitive answers, or nonsensical responses. For example, one participant said that they had 5,000 years of flying experience.

7.3.1 Demographic Data Analysis

Most (50) responses were from pilots 65 years and older. Figure 35 shows the current age of the pilots who participated in the survey. 115 male pilots and 13 female pilots shared their loss of control experiences. Two participants did not specify their gender.

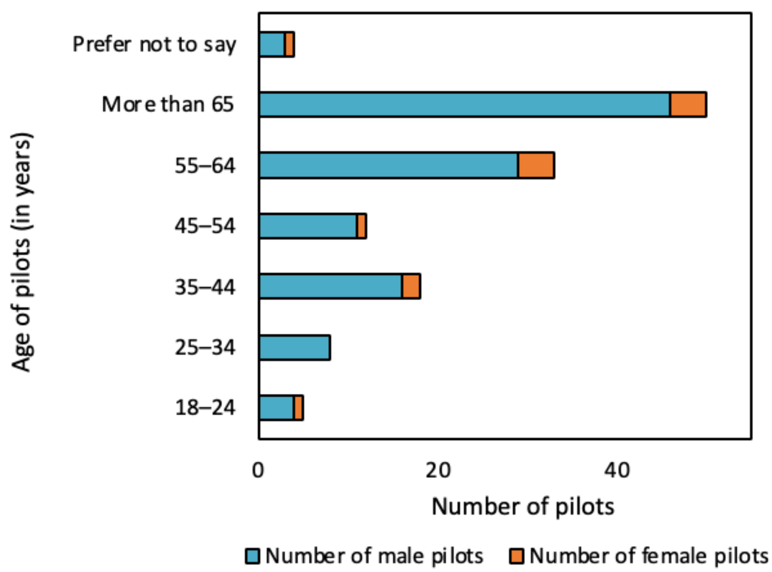

Figure 35: Age group of pilots who have shared their loss of control experiences.

Figure 36 shows the number of years of flying experience pilots had when they took the survey. The mean total flying years is 29.36. Figure 37 shows the number of flying hours of pilots. The mean total flying hours is 5,000.

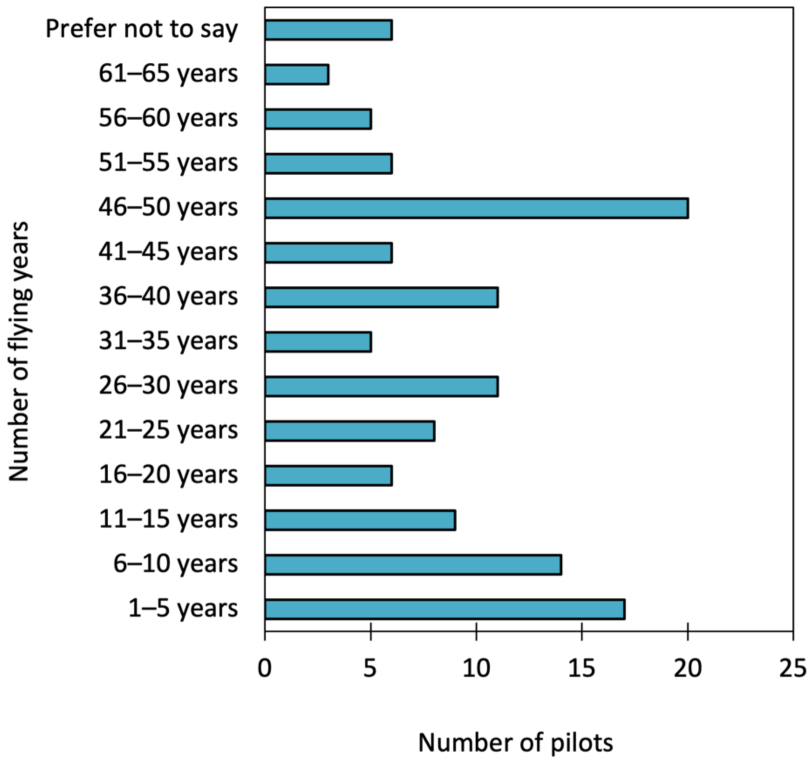

Figure 36: Number of years of flying experience. Six pilots did not answer.

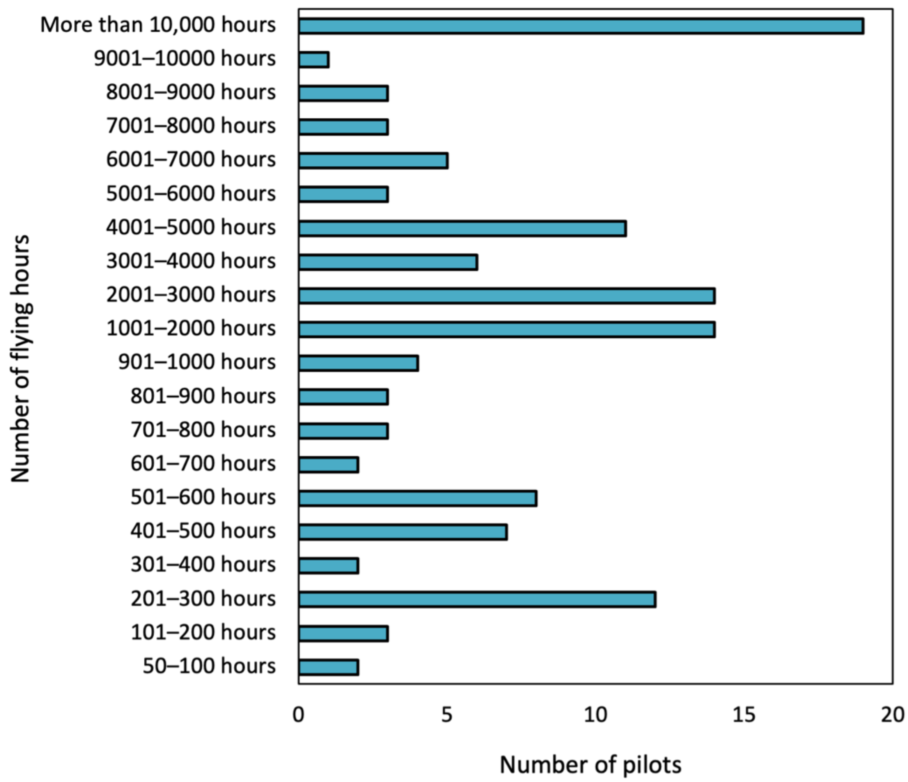

Figure 37: Number of flying hours of pilots. Five pilots did not answer.

The topmost grades of pilot certificates of the participants are private (54), commercial (47), and airline transport (36). Figure 38 shows the count for each grade of the pilot certificate. Eight participants chose "other" as an option and specified their pilot certificates as Certified Flight Instructor (CFI), Certified Flight Instructor-Instrument (CFII), Certificated Flight Instructor-Multiengine (CFIME), or military.

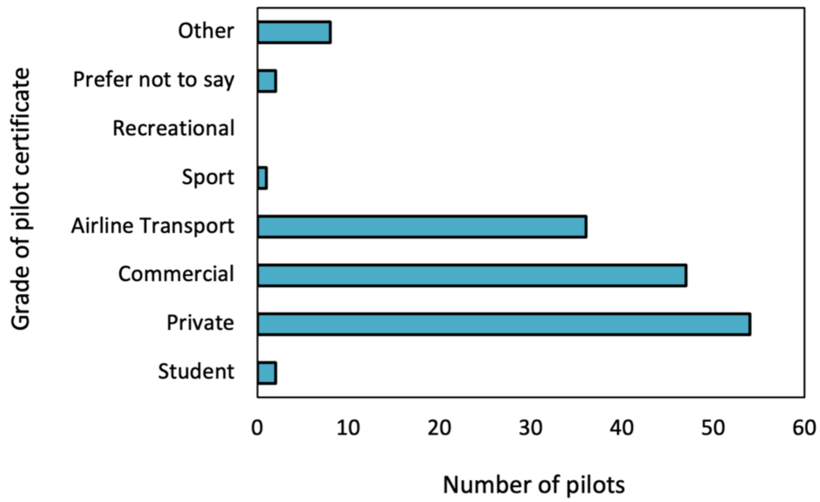

Figure 38: Grade of pilot certificates of the participants. Eight participants chose other as an option and specified their pilot certificates as CFI, CFII, CFIME, or military. Two pilots chose "prefer not to say." Some pilots had more than one type of rating.

Figure 39 shows the types of ratings or endorsements for the pilots. 130 pilots have a single-engine land rating and 95 have an instrument rating. The ten pilots who selected "other" specified ratings such as basic ground instructor, flight, or rotorcraft instructor, and aerobatic.

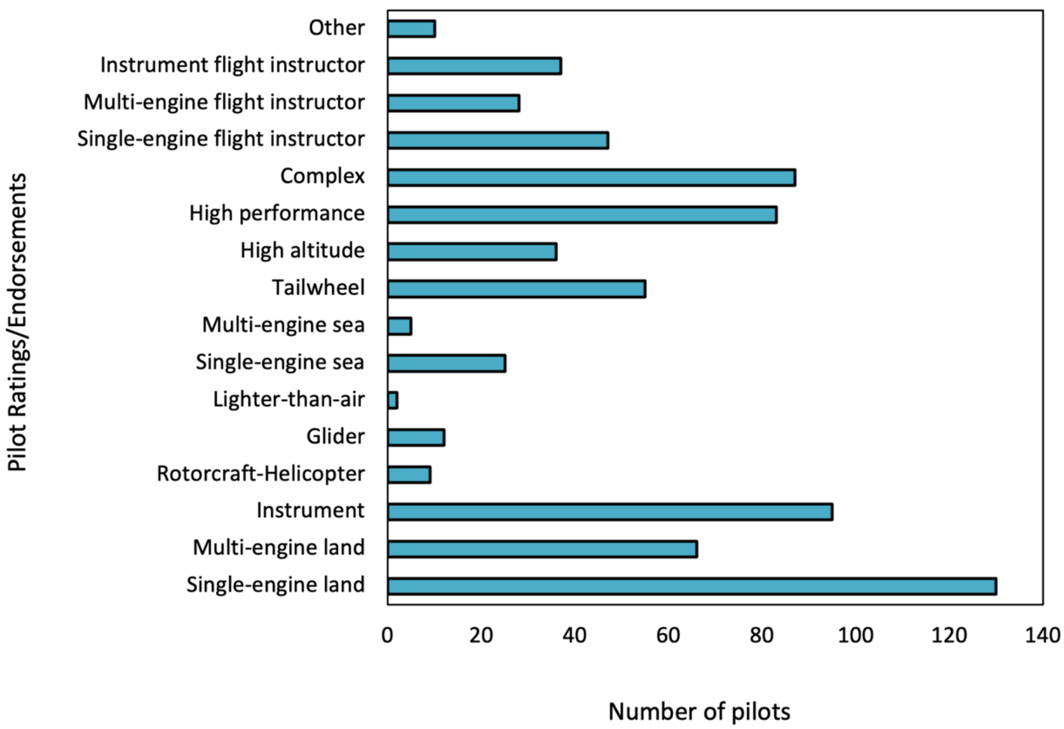

Figure 39: Pilot ratings and endorsements for the participants who have shared their loss of control experiences. Two participants did not respond.

Figure 40 shows the number of days of flying per month for pilots. Most pilots (43 pilots) fly 2–7 days a week and 37 pilots fly once a week.

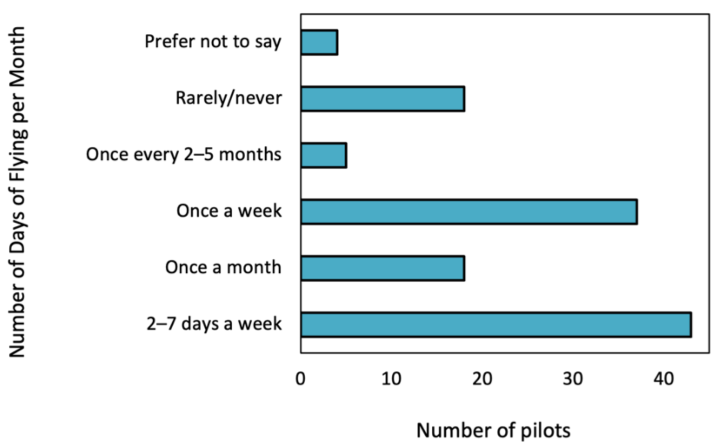

Figure 40: Approximate number of days of flying per month. Four pilots did not answer.

7.3.2 Causes of LOC-I Incidents

155 participants were certified pilots and 32 were student pilots at the time of their first LOC-I flight. Sixteen of these responses were from instructors and Designated Pilot Examiners (DPEs) who were not acting as a pilot-in-command (PIC) in the LOC-I flight. Thirteen student pilots were flying with an instructor and 18 student pilots (all with fewer than 70 flying hours) were flying solo. One student pilot did not indicate whether they were flying solo or with someone. Figure 41 shows the number of flying hours of pilots at the time of their LOC-I experiences. The mean number of flying hours at the time of the LOC-I is 2207.9. Most pilots (20.8%) had fewer than 100 hours of experience when their LOC-I happened.

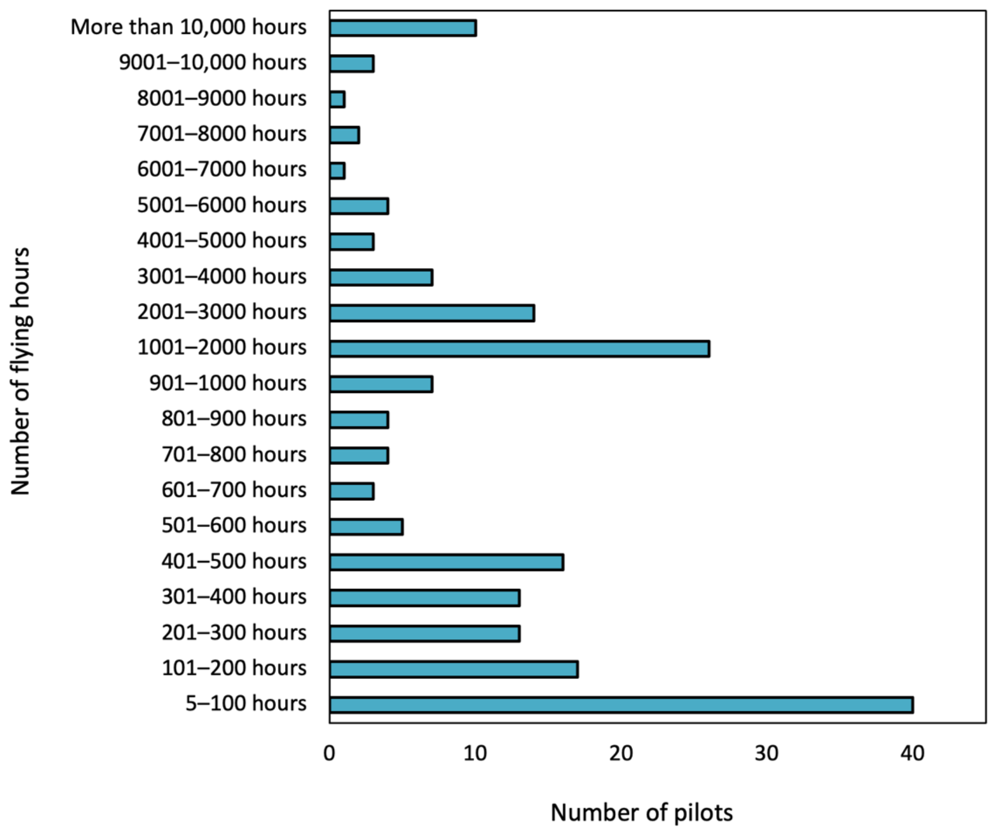

Figure 41: Number of flying hours of pilots at the time of their first LOC-I experience. Eight pilots did not respond.

Table 26 shows who the pilots were flying with during their LOC-I flights. Most pilots (87) were flying solo during their first LOC-I. 17 of 87 pilots were students flying solo.

Table 26: Number of Pilots Flying Solo or With Someone During LOC-I Flight

Pilots Flying	**Number of pilots**
Flying solo	87
Flying with an instructor	21
Flying with passenger(s)	58
Flying with a certified pilot	38
Prefer not to say	6

Table 27 shows the kind of organization that they were flying with during their LOC-I flights. Most pilots (38.22%) were not flying with any organization. The twelve who selected "other" specified that they were flying or instructing in a personally owned airplane, rental aircraft, or were flying with an airplane flight test program, new aircraft development company, or the military. Seven out of thirteen pilots with two LOC-I experiences stated that they were flying with the same organization as before when the second LOC-I happened.

Table 27: Type of Organization Pilots were Flying with

Type of Organization	**Number of Pilots**
Flying Club	19
Flight School	56
Professional Company	21
Volunteer Organization	6
None	73
Other (such as a rental company, military)	12
Prefer not to say	4

Pilots chose error-based options (such as inadequate pre-flight check and deciding to fly in known unsafe conditions) as a factor in their LOC-I most often. Out of 166 LOC-I events shared by pilots, 132 events involved some kind of pilot error (skill-based, decision, or perceptual), 69 events involved environmental factors (such as bad weather, light, or wind conditions), and 35 events had aircraft system or mechanical issue. Other factors that contributed to their LOC-I were instructor's improper supervision (nineteen events), pilot-related conditions (such as adverse mental or physiological state) (twelve events), and personnel factors (such as personal readiness and insufficient crew coordination) (twenty events). Figure 42 shows the issues identified in survey responses in the context of HFACS failure categories.

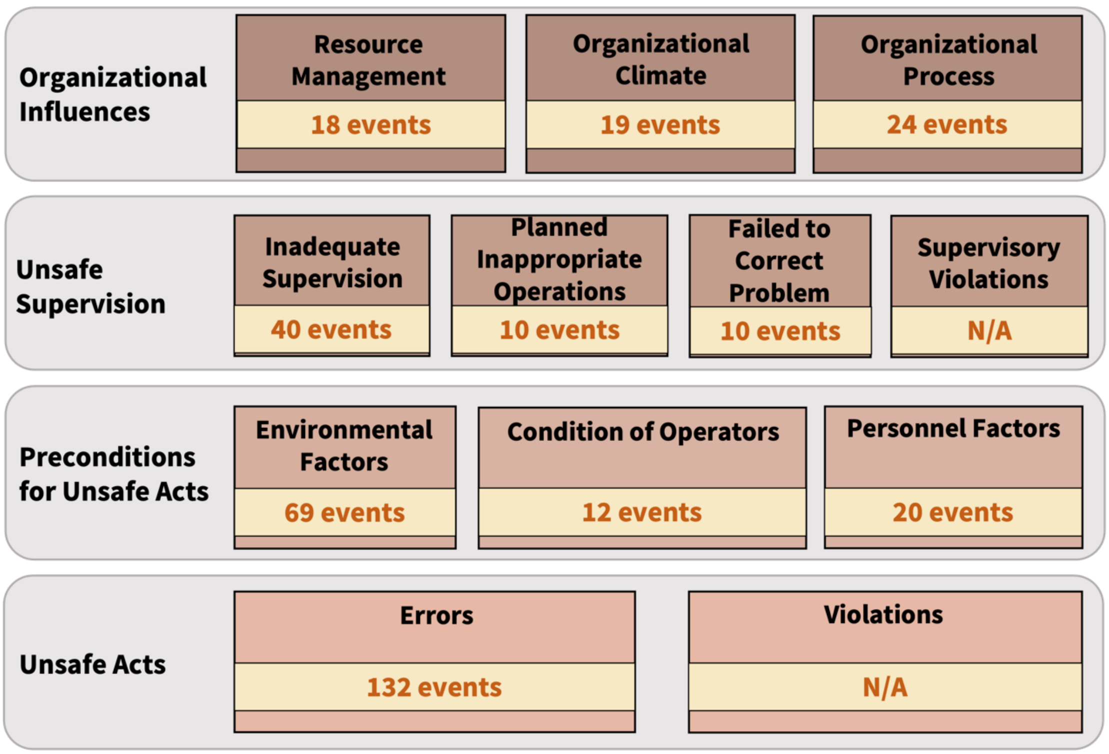

Figure 42: Issues in the context of HFACS categories, as found in 166 LOC-I events.

Pilots who chose the "other" option specified issues ranging from organizational influences to skill-based errors. Organizational issues (such as relevant safety-critical information withheld during pre-test briefing, and missing step(s) from the Pilot Operating Handbook (POH) or checklist), physical environment (such as turbulence, wind shear, strong winds, poor visibility, icing conditions, and dark night), and aircraft issues (such as an improperly rigged instrument, equipment failure, autopilot failure, engine failure, insufficient instructions in aircraft manual, and propeller failure) contributed to the LOC-I. Pilots also mentioned how inadequate supervision such as not receiving adequate training in avoidance maneuvers or spin recovery contributed to the LOC-I. Pilot-related conditions such as fatigue from long shifts, overconfidence, arrogance, complacence, inadequate training or knowledge, lack of aircraft experience, and distraction from unsafe conditions also contributed to the LOC-I. Some of the errors that pilots mentioned frequently were not being able to engage/disengage the autopilot, failure to secure all items, improper preflight check, not following the ATC instructions properly, improper use of flight controls, not recognizing the risk of unsafe conditions, getting distracted while handling other tasks, improper maneuver practices, and pilot induced oscillations (e.g., due to overcontrol in severe weather).

The findings indicate that the most prevalent themes were pilot error, poor weather or wind conditions, aircraft systems or mechanical malfunction, inadequate supervision, and organizational influences such as inadequate organizational processes.

The next sub-sections discuss how failures in different HFACS categories contributed to pilots' LOC-I experiences, based on the responses.

1. Organizational Influences

25 pilots mentioned that they had observed improper working conditions or management in their organization before or during the LOC-I flight, and 77 pilots denied observing improper working or management conditions. Nine pilots chose that they were unsure about observing any such conditions.

Pilots who indicated that they had observed improper conditions or chose the "unsure" option were directed to a set of multiple-choice questions that asked more specific organizational influences related questions. Out of the 166 LOC-I events shared by pilots, 24 pilots mentioned issues with their organization's process, nineteen mentioned issues related to their organization's climate, and eighteen mentioned resource management issues.

Figure 43 shows a theme of pilot responses for the six organization-related questions. Seventeen pilots who selected the "other" option specified more issues in organizational processes (such as operator deferred critical aircraft maintenance and standards for performance exceeded the minimum requirements for FAA approval), and organizational climate (such as withholding safety-critical information from the team and not a robust enough safety program). One pilot responded that the instructors were inexperienced and never taught them how to identify and rectify an LOC-I condition. Another pilot responded that the private airport owner did not correct the runway conditions.

Pilots also added more details about the organizational processes, climate, and resource management. Pilots mentioned improper organizational processes such as not staying updated with new procedures (e.g., stabilized approaches and collision avoidance techniques), disorganized processes within the organization, long hour blocks leaving minimal time for delays or preflight planning, and inadequate discussion or communication of procedures and rules. Organizational climate issues such as an adversarial relationship between management and employees caused employees to feel pressured to hide any errors for fear of overly severe discipline or termination. More such issues included management's attitude to get the job done, using a "divide and conquer" style of management, ignoring the procedures if one had enough experience, and minimal regard for following rules. Pilots also discussed resource management issues such as observing overt and regular sexism, racism, rudeness, cavalier attitude within the management and CFIs, poor aircraft maintenance, inadequate supervision, and task saturation due to work overload.

Organizational Influences

Resource Management

1. Overt and regular sexism, racism, and rude behavior
2. Cavalier attitude
3. Poor aircraft maintenance
4. Task saturation with work overload
5. Inadequate supervision

Organizational Climate

1. Adversarial relationship between management and employees
2. Management's attitude to get the job done
3. Using a "divide and conquer" management style
4. Ignoring procedures
5. Minimal regard for following rules

Organizational Process

1. Deferred critical aircraft maintenance
2. Standards for performance exceeded the minimum requirements for FAA approval
3. Disorganized processes
4. Not keeping up to date with new procedures
5. Disorganized processes
6. Long hour blocks; minimal time for delays or preflight planning
7. Inadequate display or communication of procedures and rules

Figure 43: Theme of pilot responses in the "other" text box about organizational influences

1. Unsafe Supervision

40 pilots mentioned issues related to instructor or organization's supervision. 32 (25.8%) pilots mentioned that their instructor had not prepared them well or taught them methods to recover from an LOC-I. Ten pilots mentioned inappropriate supervisory operations (such as crew scheduling), and ten pilots mentioned that the instructor failed to correct a problem (such as not correcting student's unsafe practices). Although there were no explicit questions regarding supervisory violations, one pilot wrote that their organization had minimal regard for following the rules. 29 pilots who chose the "other" option added further details. Figure 44 shows a theme of pilot responses in the unsafe supervision category.

Pilots mentioned that the instructors were not required to teach spin recognition and recovery during the primary flight training and therefore they did not provide experiences that could lead to unexpected LOC-I scenarios. Additionally, some instructors did not discuss various unsafe conditions with pilots, such as airspeed during unusual attitudes and handling a runaway autopilot. Some pilots also mentioned that their instructors helped them to recover from the LOC-I. Several pilots mentioned how aerobatic training experience helped them to safely mitigate a potential LOC-I.

Unsafe Supervision

Inadequate Supervision	1. No spin recognition and recovery training 2. Inadequate instruction on handling unsafe conditions 3. Instructor unaware of student's progress 4. Inadequate discussion or communication
Planned Inappropriate Operations	1. Inappropriate crew scheduling and operational planning before flight 2. Flights conducted in hour long blocks
Failed to Correct problem	1. Misjudged how quickly aircraft could depart controlled flight 2. Delayed action of instructor to recover from LOC

Figure 44: Theme of pilot responses about unsafe supervision

2. Preconditions for Unsafe Acts

For this category, I asked questions regarding pilots' mental or emotional well-being (mental state), their crew coordination (crew resource management), and their personal readiness on the day of the LOC-I flight. For example, if a pilot chose the option "I was not mentally or physically fit to fly on the day of the LOC-I flight" or the "other" option from the HFACS categories-related question, they were directed to the question regarding their mental or emotional well-being. 69 out of 166 events involved environmental factors (such as poor weather) contributing to the LOC-I, twelve events involved pilot conditions (such as fatigue), and 20 events had issues related to personnel factors (such as flying experience and crew coordination). Figure 45 shows a theme of pilot responses about the preconditions for unsafe acts.

Regarding the pilot conditions, pilots specified that they did not recognize or expect unsafe conditions (e.g., assumed an easy approach, did not expect clear air turbulence, and sudden unpredicted weather change), had a long day of flying, and had many stressors (new plane, low flying hours, low experience with the aircraft, absence of instructor, or inadequate radio communication skills). Some pilots also mentioned that they were well-rested, on high alert, and situationally aware and therefore were able to prevent a potential LOC-I event.

Ten pilots indicated that a lack of crew coordination contributed to their LOC-I and specified details such as their instructor managing tasks poorly, or not using the student pilot as a resource, and miscommunication between instructor and student.

Nine pilots indicated that they were not sufficiently ready, mentioning that they did not have experience in IMC with a specific aircraft configuration, and had low flying hours in the aircraft type.

The survey also had a text response question that asked pilots about the unsafe conditions or events that existed before or during the LOC-I flight. Seven pilots preferred not to say. 124 pilots responded with a text response. Most of these responses overlapped with the previous answers. The responses had themes of **conditions of operators** (e.g., anxiety or under pressure, airsickness, fatigue due to long day or inadequate crew rest, disorientation, mental lapse, lack of experience, distraction due to task overload, and student overconfident or not motivated), **environmental factors** (e.g., inadequate panel lighting, improperly placed instrument, unsuitable airport conditions, poor visibility, poor weather, strong/gusty winds, high density altitude, no lights on ground in a dark night, turbulence, low ceiling, wind shear, wake turbulence, and unforecast icing), **personnel factors** (e.g., not proficient/inexperienced in the aircraft flying, lack of knowledge/experience in recovery maneuvers, lack of knowledge of aircraft systems, and unfamiliarity with the airport flying to), **organizational influences** (improper maintenance, improper design, insufficient standards, withholding safety-critical information), and **aircraft issue** (defective aircraft component, uneven fuel tank levels, engine failure).

Preconditions for Unsafe Acts

Environmental Factors	1. Unexpected turbulence 2. Windshear 3. Strong winds 4. Poor visibility 5. Dark night 6. Improper aircraft lighting/instrument placement
Condition of Operators	1. Feeling pressure to fly 2. Not situationally aware/distracted 3. Overconfidence/complacence 4. Did not recognize or expect unsafe conditions 5. Not current in aircraft, IMC, or at night conditions 6. Did not feel comfortable flying even when current
Personnel Factors	1. Miscommunication between PIC and ATC/ground radio, passengers, or other pilots 2. Miscommunication between instructor and student pilot, did not follow instructor's instructions 3. Instructor managed tasks poorly, did not use student as a resource

Figure 45: Theme of pilot responses about the preconditions for unsafe acts

3. Unsafe Acts

The survey asked pilots questions about their actions before or during the LOC-I flight such as types of errors, unsafe acts, and remedial acts that the pilots took to recover or prevent the LOC-I event.

Out of the 132 LOC-I events that involved pilot error, most events involved skill-based (75 events) and decision errors (72 events). Some of the skill-based errors apart from the given options were the student pilot's poor flying skills, improper use of flight controls, pilot induced oscillations due to overcontrol in IMC, improper preflight or inflight planning, fixation, and omission of an action (e.g., failing to look at an instrument) that contributed to the LOC-I. Figure 46 shows a theme of pilot responses about their unsafe acts.

Pilots were also asked to list their unsafe actions in a chronological order that led to the LOC-I. The most common errors were **low airspeed**, **misjudgment** (e.g., not recognizing risks such as flying in featureless dark night or strong air turbulence, not recognizing that the aircraft was in a spin, unable to recognize spatial disorientation, over-estimating student's capabilities, negative transfer, i.e., flying by "habit"), **improper decision-making** (e.g., attempting takeoff in unsuitable runway conditions with an overweight aircraft, choosing to fly in poor weather/strong wind conditions, continuing flight/landing in unsafe weather or runway conditions, not going-around, failure to use supplemental oxygen), **insufficient radio communication** (e.g., changing frequencies, not calling ATC to renew flight plan, not advising "unable" when pilot could/had not performed a certain action, not requesting a non-circling approach), **becoming distracted** (e.g., diverting excessive attention towards a critical condition, failing to maintain instrument scan, losing visual scan), **improper maneuvering** (e.g., excessive bank, not using proper crosswind landing technique), **improper use of checklist** (e.g., not following maneuver checklist, missing a checklist item), **improper remedial action** (e.g., not following spin recovery technique, improper stall recovery), **improper use of flight controls** (e.g., not recognizing a disengaged autopilot, incorrect use of autopilot, improper aircraft configuration, under or over correction of rudder inputs, pilot induced oscillations), **improper preflight check** (e.g., uneven fuel tank levels, weight and balance check), **uncoordinated flight or unusual aircraft attitude** (e.g., not maintaining coordinated flight while practicing a departure stall, not recognizing uncoordinated attitude during a stall), and **not relying on instruments**.

Unsafe Acts

Errors

1. Improper (low) airspeed
2. Improper preflight/inflight planning (flight in IMC or at dark night)
3. Misjudgment (e.g., not recognizing risks)
4. Improper decision-making (e.g., continuing flight in unsafe weather)
5. Insufficient radio communication (e.g., changing frequencies)
6. Becoming distracted (e.g., fixation)
7. Improper maneuvering (e.g., excessive bank)
8. Improper use of checklist (e.g., missing a checklist item)
9. Improper remedial action (e.g., improper spin recovery)
10. Improper use of flight controls (e.g., incorrect use of autopilot)
11. Improper preflight check (e.g., uneven fuel tanks)
12. Uncoordinated flight (e.g., during a stall practice)
13. Not relying on instruments

Figure 46: Theme of pilot responses about unsafe acts

7.4 Corrective Actions Taken by Pilots

143 pilots specified their corrective actions. Seven out of 143 pilots mentioned that they were unable to recover from LOC-I, four of these pilots crashed (with no fatality), and the remaining three either made a hard landing or somehow naturally flew out of the poor weather. Eight pilots mentioned that their instructor took control of the aircraft and recovered from the LOC-I. 43 pilots mentioned that they used the recovery techniques that they learned for upset, unusual attitude, spin, or spiral. 22 pilots used stall recovery and spin prevention procedures that they learned from their training. Other pilots mentioned that effective radio communication with the ATC (e.g., declaring an emergency), deciding to land/go around immediately, flying out of poor weather (e.g., IMC), proper use of flight controls, staying alert and relying on instruments, and continuing to fly the aircraft helped them prevent a LOC-I. Some pilots also had comments about the use of autopilot. Five pilots mentioned that disengaging the autopilot and manually overriding the aircraft controls helped them prevent or recover from the LOC-I. One pilot mentioned that engaging the autopilot when the pilot was undergoing vertigo gave them time to regain situational awareness.

Pilots also mentioned that during the LOC-I flight, there were certain things that they should/could have done to prevent or recover from the LOC-I. Some of them are to clearly communicate with the ATC and instructor, be more proficient in the aircraft system, be more alert, focus on the airspeed, make better and faster inflight judgment and decisions, divert to another airport or attempted a go around, use appropriate spin recovery method, keep aircraft at a level attitude, use flight controls (rudder) properly, and use cockpit resources effectively (such as a co-pilot or a passenger).

Pilots who did not take corrective actions, blamed issues such as complacency, concern about going around in front of passengers, an urgency to land, distraction from flying the aircraft, fear, inadequate training, anxiety or under pressure, surprise and unfamiliarity with the situation, being unprepared to take proper corrective action, adverse psychological state leading to fixation or omission, pressure from the management, and time pressure. Multiple pilots reported that they could not prevent the LOC-I because of their lack of knowledge of how to recognize or recover from unsafe conditions (such as deteriorating weather or spin).

7.5 Discussion

Pilots mentioned the following preventive measures that may help in avoiding LOC-I: attentive use of autopilot (and knowing how and when to override autopilot), remaining calm in emergencies and flying the aircraft first, constant practice and learning, proper preflight planning, not following the instinct to take wrong corrective action (such as pulling on the yoke instead of pushing it during a roll), securing all items in the cockpit (so that they don't jam the controls), quick decision-making, and alternative use of other flight controls in case one control fails. Pilots mentioned that LOC-I can happen even on the nicest of VFR days and to extremely experienced pilots. A pilot mentioned that there should be more IFR training since VFR into IMC accidents cause significant fatalities. Another pilot suspected from their own experience that a fair number of "pilot error" during base-to-final spin entries could be due to very local disturbances in wind velocity. Another pilot opined that current flight instruction leads to bad flying habits and suggested using concepts of pitch and power rather than airspeed to train pilots.

Several pilots mentioned that they were not taught recovery techniques and suggested including recovery techniques for upset (out of control) conditions such as spins and spirals in training programs. Some pilots suggested learning spin recovery before a solo flight so that they can recognize such unsafe conditions when flying without the instructor. A pilot mentioned that after the LOC-I incident “now I know what a spin feels like in practice, and not in theory.” Another pilot mentioned that pilots should be trained on how to recover from or prevent a spin in a pattern (which could rapidly turn into an accident since there is not enough altitude to recover). A pilot mentioned that they never got a helpful answer from any instructor on how to recover from pilot-induced oscillations. Aerobatics training helped a few pilots to recognize and recover from an LOC-I. A pilot who has experienced two partial LOC-I events mentioned that they could prevent the second LOC-I because of their first experience. A CFI suggested additional training for instructors to help students who have frozen at the controls. Lastly, a pilot wrote “training is the difference between a story and a statistic (death).” Pilots strongly recommend that training should include more recovery techniques and IFR training. Pilots should do more practice of maneuvers and stay current so that they can take immediate remedial actions by muscle memory instead of taking wrong corrective actions.

Most pilots who were able to recover from LOC-I mentioned that they used their knowledge from LOC-I prevention and recovery training. Some pilots who were not able to take a corrective action mentioned factors that precluded their ability to make corrective action. Most of these factors were related to pilot conditions and their readiness such as fear or anxiety, not being able to recognize the situation, unfamiliarity, and lack of knowledge to recover from unsafe conditions.

7.6 Conclusion

The findings from the study helped in identifying specific pilot errors and issues in training that lead to LOC-I, issues that are not mentioned explicitly in the NTSB reports. Pilot error (decision and skill-based) was the topmost issue in most events (80% of total 166 LOC-I events). Most of these errors such as improper maneuvering and a lack of or improper remedial action are direct results of inadequate training. The most frequent chains of unsafe actions or conditions in the reported LOC-I events were (1) improper preflight or infight planning leading to a flight in poor weather; and (2) pilot’s lack of visual lookout or distraction leading to an improper airspeed. 25.8% of pilots mentioned that either their instructor had not prepared them well or taught them methods to recover from LOC-I. Several pilots mentioned that because of their lack of LOC-I recovery training (such as upset, spin, spiral, and stall recovery), they were not able to recover from LOC-I.

Not surprisingly, 41.6% of the LOC-I events involved poor weather or light conditions. This is a consistent statistic from previous studies (Majumdar et al., 2021 and Rao & Marais, 2020). 21% of pilots reported issues in their organization such as a negative attitude within the management, organizational pressures, and inadequate procedures. Organizational pressure whether explicit or implicit is a challenge in most flight training environments (Keller et al., 2019). 19% of the LOC-I events involved pilot conditions and factors such as fatigue, unfamiliarity with the unsafe conditions, and other stressors that contributed to their LOC-I.

By garnering such perspectives directly from pilots, I found rich insights into human factors contributing to LOC-I. This study focused primarily on pilots who had experienced an LOC-I while piloting an aircraft. In the next phase of my research (Chapter 8), I delved deeper into the survey insights by interviewing pilots and instructors to understand their perspectives on LOC-I and the training in practice to prevent LOC-I.

8. INTERVIEWS OF PILOTS AND FLIGHT INSTRUCTORS ABOUT THEIR INFLIGHT LOSS OF CONTROL EXPERIENCES AND TRAINING

To delve deeper into the causes of LOC-I and to understand the LOC-I training in practice, I interviewed pilots and flight instructors about their experiences with LOC-I, if any, and their perspectives about LOC-I training. Building on the survey, in this study, I aimed to delve deeper into human factors issues wherever possible. Participants were eligible to participate in the study if they were at least 18 years old and a pilot who have experienced an LOC-I or a certified flight instructor.

8.1 Research Instrument and Procedures

I conducted virtual semi-structured interviews with pilots asking them about their perspectives on LOC-I, their LOC-I experiences, if any, and the training that they received or provide as an instructor to prevent LOC-I. The interview had a total of 58 standard questions including five demographic questions, along with time for more open-ended responses. Each interview lasted for about an hour. Appendix C includes the consent form and interview questions.

After the study was approved by Purdue's Institutional Review Board, I started identifying the participants who were interested in the study. During the survey study, nine participants had contacted the research team showing an interest in the research. I first contacted those participants to seek their interest to participate in the study. Additionally, I contacted seven more pilots using contacts from other pilots. Out of the 16 pilots that I contacted, nine participated in the study.

I shared the consent form of the study with participants before scheduling an interview with them. I conducted the interviews over Zoom calls. I recorded the calls with participant's verbal consent to participate in the study (a statement mentioned in the consent form).

8.2 Data Analysis

I conducted nine interviews between 21st June 2022 and August 19th, 2022. I first transcribed the interview recordings to text and then destroyed the interview recordings. I used NVivo12, a qualitative data analysis software, to code responses from the interview into different categories.

8.2.1 Demographic Data

Out of the nine pilots I interviewed, there were four airline transport pilots (ATP), four commercial pilots, and one private pilot. Seven pilots were certified flight instructors. Pilots' ages ranged from 44 to 73 years. There were seven male pilots and two female pilots. Pilots had multiple ratings and endorsements as shown in Figure 47. Pilots had a flying experience ranging from 603 to 10,200 hours and 20 to 48 years. Eight pilots had flown more than 1,500 hours.

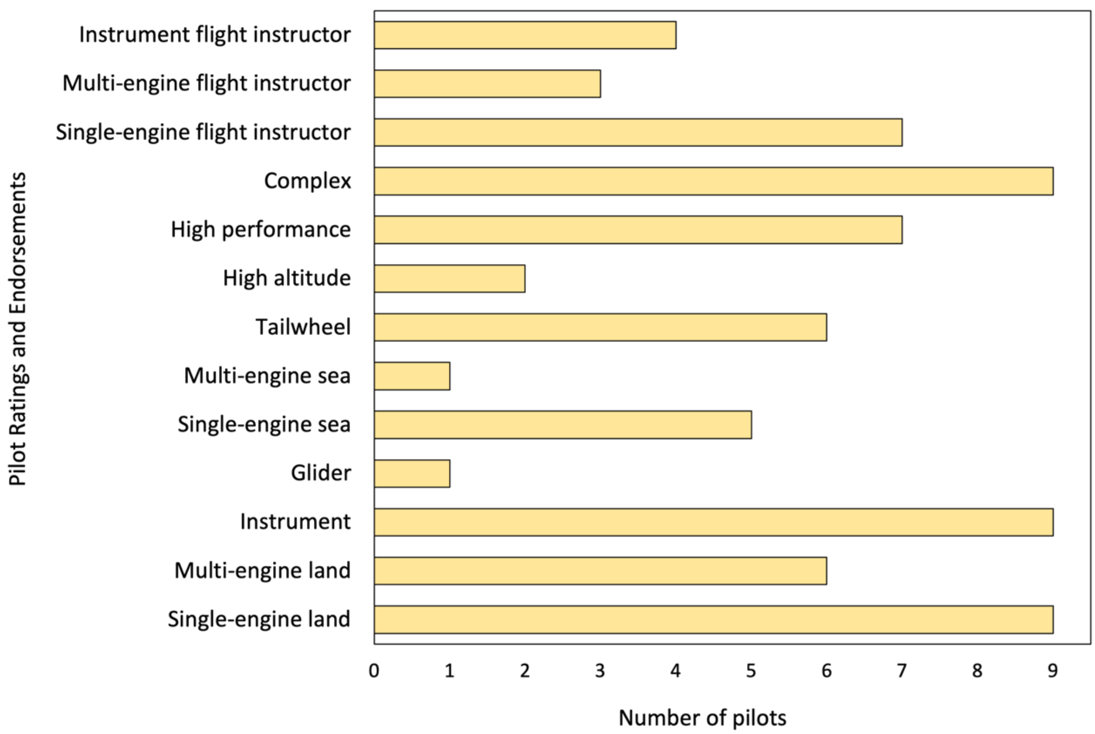

Figure 47: Ratings and endorsements for the nine pilots interviewed.

8.2.2 A summary of the LOC-I Experiences

Six pilots had experienced or prevented an inadvertent LOC-I. One pilot shared two of their incidents. At the time of their LOC-I incident, three pilots had a private certificate, two were commercial pilots, one was an ATP, and another was a student pilot. Out of the seven incidents shared, two resulted from an intentional attempted maneuver (a stall maneuver going wrong). Figure 48 shows the multiple ratings and endorsements at the time of their LOC-I. Table 28 shows the hours and years of flying experience, flying frequency, pilot certificate, aircraft make and model, and who the pilots were flying with at the time of their LOC-I.

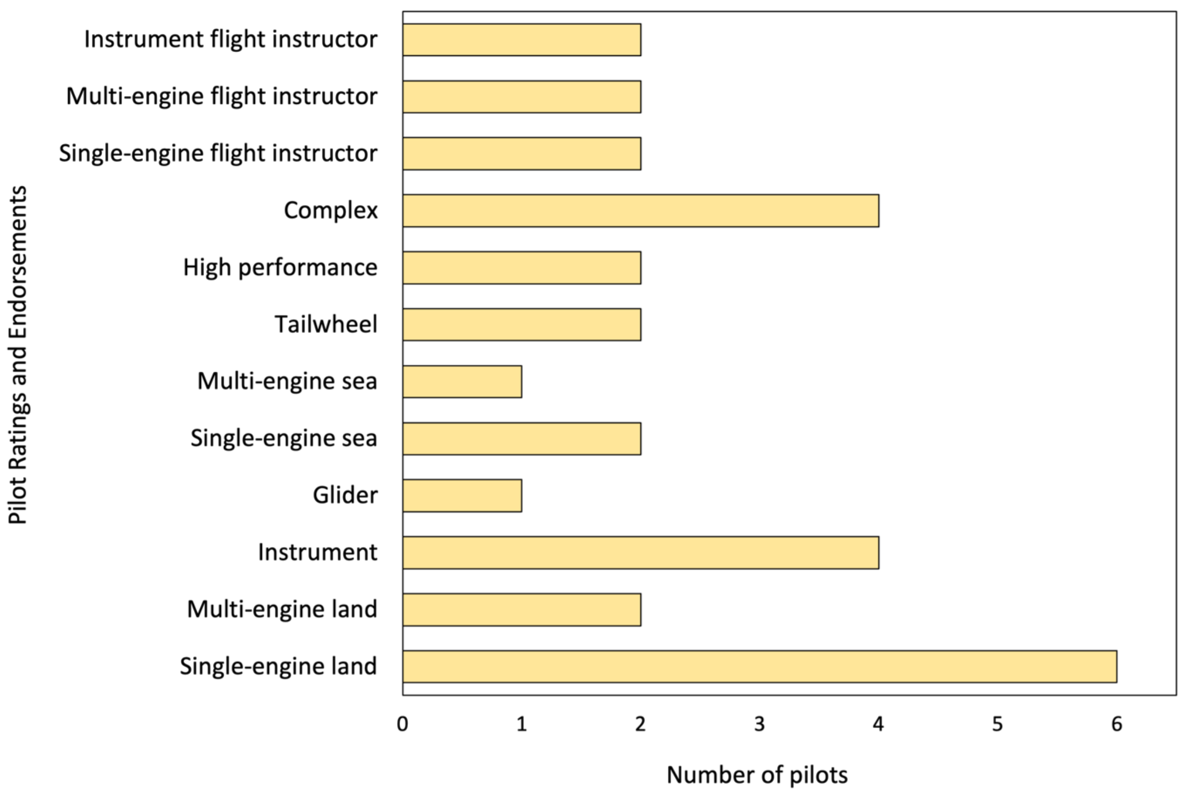

Figure 48: Ratings and endorsements of the pilots at the time of their LOC-I

Table 28: Flying experience, flying frequency, aircraft during the event, and who the pilots were flying with at the time of their LOC-I. The pilot number corresponds to the pilots who shared their LOC-I related incidents. Pilots 4, 6, and 7 did not have LOC-I experiences.

Pilot No.	Flying hours	Flying years	Flying frequency (average days a month)	Grade of pilot certificate	Aircraft make and model	Flying solo or with someone
Pilot 1	2000	25	6	ATP	Cessna 175	Solo
Pilot 2	700	25	2	Private	Cessna 172	Solo
Pilot 3	30	1	20	Student	Cessna 172	Solo
Pilot 5	60	1.5	2	Private	Cessna 172	Two passengers
	750	24	1	Commercial	Cessna R182	One passenger
Pilot 8	1000	10	25	Commercial	Piper Cherokee	Student (who was acting as a passenger)
Pilot 9	60	1	5	Private	Cessna 172	Instructor (for currency)

8.2.3 How did the LOC-I incidents happen?

This section describes each incident as told by the pilots.

Event 1: Pilot 1 was in approach in gusty conditions. During the downwind leg, the aircraft stalled precipitously because of a wind gust. The pilot does not remember whether the stall warning horn came on. They were already at a higher-than-normal approach airspeed because of the gust. After the stall, they immediately added some more power and made sure that the wings were level, so they could recover from the upset.

Event 2: Pilot 2 was prepared for instrument conditions during the flight. The pilot's aircraft had a different heading indicator than what they were used to, and they had never flown in IMC in that aircraft. The pilot intentionally flew into IMC and quickly became disoriented and experienced vertigo. They think they became disoriented because they didn't put their head back against the headrest, which is recommended practice when flying in IMC. When the ATC gave them a heading change, they overcorrected the heading, leading to pilot induced oscillations, and ultimately lost a lot of altitude. The pilot could only recover once they were out of IMC and could use the ground as a reference.

Event 3: Pilot 3 had initiated a go-around late in the landing phase (start of the flare). The aircraft was configured with full flaps and minimal power for landing. The pilot incorrectly retracted the flaps completely instead of one notch at a time and added power during the go around. Due to the incorrect procedure of retracting all the flaps at once, the aircraft immediately lost lift and the nose became very high. A high-pitched nose causes the wings to exceed their critical angle of attack, which can occur at any airspeed, in any attitude, and with any power setting. Exceeding the critical angle of attack can lead to a stall. The aircraft had yet not initiated a climb. The pilot lowered the nose slightly because of the low altitude and made sure to stay coordinated with proper rudder input to establish a controlled climb.

Event 4: Pilot 5 was flying with two passengers and practicing a stall maneuver. The center of gravity was far aft (rearward CG) due to the passengers sitting in the rear seats. If the CG is too far aft, it will be too near the center of lift and the aircraft will become less stable and difficult to recover from a stall (FAA, 2016b). So, during the stall maneuver, the aircraft became unstable and the right wing dropped. The pilot had never seen that behavior in training. They recovered by rolling the wings back to level and pulling back on the yoke.

Event 5: Pilot 5 was in an approach phase during strong crosswind conditions in a Cessna R182. During the landing phase, the pilot thought that the wind had abated and so did not prepare well for landing in the strong crosswind. The Cessna R182 Pilot’s Operating Handbook (POH) states “When landing in a strong crosswind, use the minimum flap setting required for the field length” (Cessna Aircraft Company, 1977). Flaps provides the aircraft with more lift, allowing it to fly at lower airspeeds. However, the lower the airspeed is, the less effective the controls become. In a strong crosswind, using partial flaps increases the final approach speed, and in turn, increases the controls’ effectiveness to make a stabilized approach during crosswind landing. The pilot mistakenly deployed full flaps during landing. Just after touchdown, the aircraft started to tilt to the right, skidded sideways, and bounced. The pilot tried to recover by pulling all the way back on the yoke and rolling opposite to the wind direction. The pilot added that keeping the nose wheel up long enough during the landing prevented the aircraft to flip over. Unfortunately, the pilot could not maintain aircraft control which caused the propeller to strike the ground, and the pilot got injured. The pilot mentioned that they could have prevented the incident by not extending all the flaps and by being more aware of the risks of using improper aircraft configuration during a crosswind landing.

Event 6: Pilot 8 was prepared to fly in VFR at night, as reported by the weather at the airport. However, after a few minutes of climbing, they encountered IMC. The pilot reported that the cockpit panel lights stopped working during the flight, which disoriented them. The pilot got into an unusual attitude and entered a spiral, losing a lot of altitude. They used their phone's flashlight to scan the instruments, used the spiral recovery procedure, and eventually recovered.

Event 7: Pilot 9 was doing a practice stall. During the stall maneuver, the aircraft was in an uncoordinated flight and thus experienced a wing drop. They tried to recover using an opposite aileron rather than the opposite rudder, which exacerbated the wing drop. Then the pilot lowered the nose to unstall the wings and recovered.

8.2.4 What caused the LOC-I incidents?

I identified causes in the LOC-I experiences, as mentioned by the pilots, and classified them into different categories. Figure 49 shows a tree-map of probable causes in the LOC-I experiences. The size of the boxes represents the relative frequency of the causes mentioned in the events. For example, pilot conditions were mentioned in six out of seven events and organizational factors, aircraft system issue, and ATC communication were each mentioned in one event.

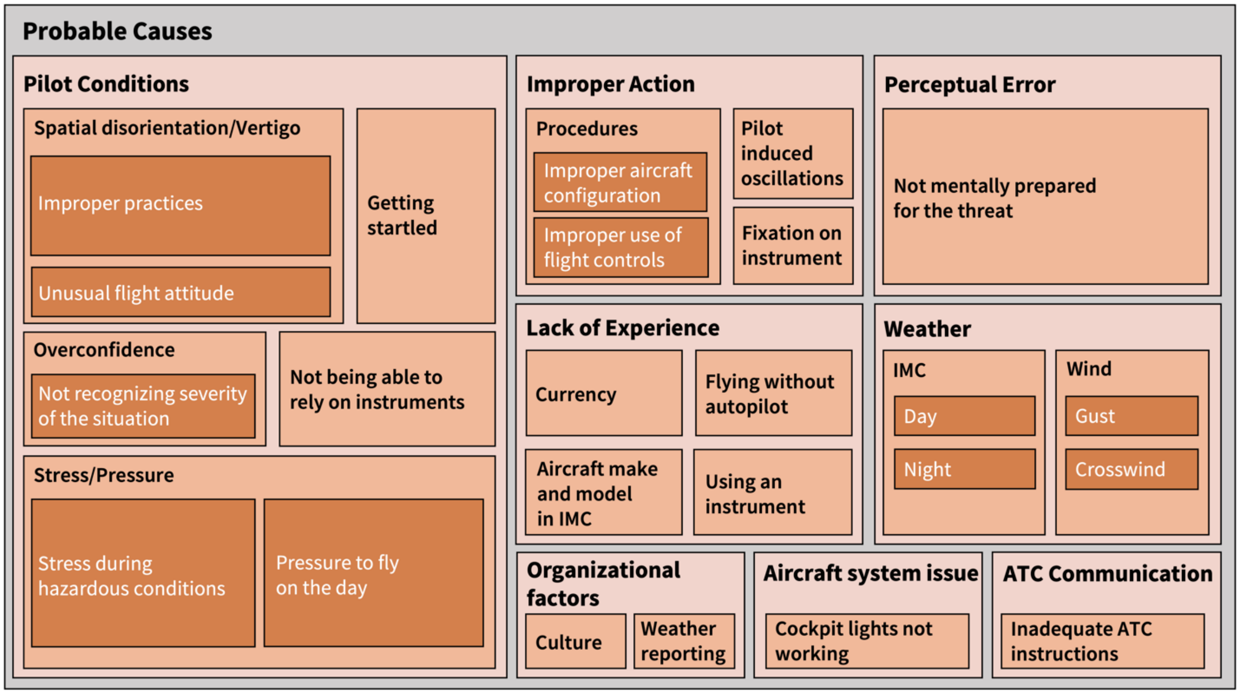

Figure 49: Tree-map of hierarchical categorization of probable causes as found in the LOC-I experiences. The size of the boxes represents the relative frequency of the causes mentioned in the events.

1. Pilot Conditions

a. Spatial disorientation/Vertigo

Pilots underwent conditions such as spatial disorientation and vertigo during IMC conditions due to improper practices (not putting the head back against the headrest during instrument conditions and using improper flight controls) and unusual flight attitude in night IMC. A pilot mentioned that because of their disorientation, even though they knew aerobatics and upset recovery, they could not have regained control of the aircraft, had they not entered IMC to VFR.

b. Overconfidence

A pilot mentioned that the incident happened due to their overconfidence due to which they did not perceive the severity of the situation. The pilot also mentioned that although they had done crosswind landings before, they had not experienced wind conditions of the same intensity as in their LOC event.

c. Not being able to rely on the instruments

A pilot mentioned that they were not able to rely on the instruments in night IMC because the cockpit lights were not working that made them disoriented for a while before they could recover the aircraft control.

d. Getting startled

Getting startled (surprised) is a common phenomenon in unsafe situations. Pilots mentioned that they got surprised and startled for a brief moment, they were able to regain control quickly. One pilot mentioned that the startling effect happened because they never saw that situation in their training (a stall with a wing drop).

e. Stress/Pressure

A pilot underwent stress when they were not able to control the aircraft. Another pilot mentioned that some pilots felt slightly stressed before the flight (during their solo flight as a student and during their refresher flight with an instructor). A pilot mentioned that they had a self-imposed pressure to initiate a go around during their flight which then led to an inflight upset during the initial climb (due to improper aircraft configuration). Another pilot mentioned that they felt pressure to fly on the day even when they felt that they should not because of the weather conditions.

2. Perceptual Error

Perceptual errors occur when one's perception of the world differs from reality (Wiegmann & Shappell, 2003). These types of errors happen when sensory input is either degraded or unusual such as during visual illusions, spatial disorientation, or vertigo (e.g., not being able to recognize hazardous conditions). Pilots mentioned that they had perceived the flight or situation to be easy and doable. They were not mentally prepared for the threat and did not recognize the severity of the situation. One pilot who inadvertently flew into an unexpected IMC mentioned that they were not mentally prepared to fly in those conditions.

3. Weather Conditions

Weather contributed to a LOC-I conditions in four of the seven incidents. Two pilots experienced an upset during approach and LOC-I during landing in gusty weather conditions, and other two pilots experienced a spatial disorientation and LOC-I in day IMC and night IMC respectively.

4. Improper Action

Pilots performed incorrect actions during the flights that caused an upset or a potential LOC-I. The most common types of actions were improper procedures, pilot induced oscillations, and fixation.

a. Procedures

Pilots used improper procedures such as using improper aircraft configuration (improper flaps configuration during a go around and performing a stall maneuver with the CG further aft due to passengers in the aircraft). Improper use of flight controls such as using opposite aileron instead of the opposite rudder during a spin caused a pilot to experience a near LOC-I.

b. Pilot induced oscillations

Pilot-induced oscillations are sustained or uncontrollable oscillations resulting from efforts of the pilot to control the aircraft (Department of Defense, 1997). They occur when the pilot of an aircraft inadvertently commands an often increasing series of corrections in opposite directions, each an attempt to cover the aircraft's reaction to the previous input with an overcorrection in the opposite direction. A pilot during their IMC flight exacerbated the condition due to overcorrecting the heading and altitude, winding up losing a lot of altitude during the process.

c. Fixation

A pilot mentioned that during the aircraft upset, they focused on the airspeed and altitude alone, fixating on the airspeed indicator and the altimeter, and thus ignoring other instruments such as the turn and heading indicator.

5. Lack of Experience

a. Currency

A pilot mentioned that during the incident they were an inexperienced student pilot on their possibly third solo flight. They did not remember their procedures well while performing the go-around maneuver. Another pilot mentioned that because of their reduced number of flying hours, they did not take the correct recovery action, and instead took an instinctive wrong action to recover from a stall with a wing drop.

b. Flying without autopilot

Pilots mentioned that because they were so used to flying with an autopilot, they could not manually maintain control of the aircraft in conditions such as IMC and strong crosswind. A pilot mentioned that they could not control the aircraft (causing pilot induced oscillations) during IMC when they flew an aircraft without an autopilot.

c. Specific aircraft in IMC

A pilot mentioned that this was their first time flying the specific aircraft in IMC, that too without an autopilot. They had flown the aircraft many times but only in VFR conditions.

d. Using an instrument

The aforementioned pilot also stated that the aircraft that they flew during the incident had a different heading indicator than the ones that they had used before which made it difficult to determine and maintain the correct heading.

6. Organizational Factors

I identified issues with the culture at their organization and the weather reporting system in one of the incidents.

a. Culture

A pilot mentioned that when the incident happened, they did not feel comfortable to discuss it with their organization because they feared losing their job. They mentioned that they felt that the culture at the organization was not open enough to hear about the incident. The pilot also mentioned that they did not know about the NASA ASRS database where they could report the incident anonymously. These insights suggest a critical issue at the organizational level where pilots did not feel encouraged to share their incidents and experiences. New pilots feel pressured to maintain a clean record since they cannot afford scrutiny on their record that might result in not getting certifications that they need to further their careers.

b. Weather reporting

A pilot stated that they received an incorrect weather reporting (VFR conditions) before the flight but when they took off, they inadvertently entered IMC at night. The pilot did not feel comfortable discussing the incident with their organization.

7. Aircraft System Issue

During a flight at night IMC, the lights in the cockpit panel went off and the pilot became disoriented and felt they could not rely on their instruments. The pilot hence entered a spiral and lost a lot of altitude before they finally recovered.

8. ATC (Controller's) Communication

A pilot mentioned that they felt stressed communicating with the controller during the incident. The controller sounded stressed and did not communicate calmly which further exacerbated the situation. They added that calling the pilot by the aircraft tail number and eventually handing the pilot to a different controller clouded the communication and the pilot's action even more. The pilot added "When ATC recognizes that a pilot may be in trouble, continuing the standard communication protocols does little, if anything, to solve the problem. In fact, it can make it worse. In my case I already knew I was in trouble. Repeating the desired heading and altitude did nothing to give me the tools to solve my problem. It only increased my stress level. As pilots we are trained to follow ATC commands, basically without question." The pilot recommended calling the pilot by their names in such emergency situations and talking in a more empathetic way could help pilots get out of the threat more easily without creating a panic.

8.2.5 How did the pilots recover from LOC-I?

During private pilot training, students learn recovery techniques for unexpected hazardous scenarios. The FAA specifies recovery techniques like stall recovery and unusual flight attitude recovery in the Airman Certification Standards (ACS) document (FAA, 2018b).

A general way of training for a stall recovery involves the pilot using steady back-pressure on the yoke to raise the nose above the horizon. Raising the nose causes the wings to exceed their critical angle of attack. As airflow is disrupted over the wings, the airplane's stall horn (or light) turns on and the controls start feeling "mushy", i.e., loose and sloppy. The wings stall and the nose drops when airflow over the wings is suitably disrupted and the lift becomes insufficient to keep the wings flying. The pilot recovers by lowering the nose (and hence reducing the angle of attack), applying full power, and leveling the wings, which then increases airspeed and lift (AOPA, 2021).

For unusual attitude recovery training, the instructor puts the student under a view-limiting device, such as a hood, and instructs the student to close their eyes and put their head down. The instructor then puts the aircraft into an abnormal climbing, descending, or steeply banked attitude. The student must then figure out what the aircraft is doing and react accordingly to bring the aircraft to a straight and level flight.

The pilots mentioned using several techniques to recover from their LOC-I incident or to prevent a potential LOC-I:

1. Stall and Spin Recovery Techniques

A spin is an aggravated stall condition that may result after a stall. Mishandling of yaw control during a stall increases the likelihood of a spin entry (FAA, 2021). In a spin, both wings are in a stalled condition but one wing is in a deeper stall than the other, which results in the aircraft rotating around a vertical axis, following a downward corkscrew path. A pilot mentioned using the PARE technique to recover from a spin during a night IMC flight. PARE stands for **P**ower (idle), **A**ilerons (neutral), **R**udder (full opposite to the spin and held in that position), and **E**levator (forward). The pilot mentioned that they could save themselves only because they knew spin recovery from their CFI training. Of all pilot certificates issued in the United States, only the initial CFI certificate requires spin training (14 CFR 61.183) (CFR, 2023). The FAA requires private and commercial pilots to only demonstrate the understanding of spin recovery as "knowledge" and not as a "skill" (FAA, 2018b; FAA, 2018c; and FAA, 2016c). This lack of spin recovery skill caused one of the private pilot's I interviewed to have the instinct for a wrong corrective action. When the private pilot stalled the aircraft with a wing drop, they first tried to recover incorrectly using the opposite aileron instead of the opposite rudder. However, immediately afterwards, they lowered the nose and recovered from the stall by leveling the wings. Another pilot who mistakenly retracted all the flaps immediately during a go-around corrected their action by lowering the nose slightly to regain lift and prevent a stall during takeoff. Some pilots mentioned that their aerobatic training helped them become more aware of the aircraft state to recover properly.

2. Upset Recovery Techniques

One pilot who experienced an aircraft upset during approach added power and ensured level wings to prevent an impending stall. Several pilots also mentioned in the survey that they could recover from a potential LOC-I using upset recovery methods. Some other pilots from the survey also mentioned that they could not recover from LOC-I because they did not know these recovery techniques. The training of these recovery techniques is popularly known as Upset Prevention and Recovery Training (UPRT). UPRT is mandatory only for FAR Part 121 Air Carriers (i.e., airlines, regional air carriers, and all cargo operators) and hence pilots with an Air Transport Pilot (ATP) certificate (FAA, 2015a). UPRT consists of maneuver-based exercises based on different scenarios (such as all-weather upsets, improper airspeed, slow flight, low altitude events, etc.) to ingrain pilots with both flying skills and the mental processes to address human factors such as startle, surprise, and fear and maintain positive aircraft control.

3. Aeronautical Decision Making

Aeronautical decision making (ADM) is a systematic approach to making best decisions to mitigate risk factors. Pilots from the interview mentioned how effective ADM helped them save their lives. For example, a pilot flying with their student mentioned that their student remained calm and followed their instructions to help. Since the cockpit lights were not working in the night flight, they used their phone's flashlight to scan the instruments and recover from a spin. Another pilot mentioned that spending the first few seconds to recognize the hazard before taking preventive actions helped them to prevent a potential LOC-I.

Some pilots who flew into IMC or windy conditions mentioned that they could not take an immediate corrective action. A pilot who got disoriented during their IMC flight could only recover when they entered back into VMC. They used ground reference to level the wings and maintain altitude to finally regain aircraft control. Another pilot recounted that although they pulled back on the yoke and rolled the wing to the crosswind direction during landing, they could not maintain aircraft control, and ended up in a propeller strike.

8.2.6 What could have the pilots done differently to prevent the incidents?

When I asked pilots what they could have done differently to prevent their LOC-I, their responses had a theme around decision-making, planning, and situational awareness. This theme is consistent with the responses from the survey and the AOPA's LOC-I related articles. Pilots who flew in gusty and crosswind conditions mentioned that they should have planned better and should not have flown that day. Pilots often misjudge and overestimate their capabilities and lose the ability to objectively evaluate the weather and the associated risks. A pilot in their interview mentioned that pilots need to evaluate the risks based on the particular day and not based on their prior accomplishments in similar risk conditions. Each flight has the same risk factors. The pilot quoted "…the environment or the airplane doesn't care about your landing last week. It only cares about what's happening now." Another pilot mentioned that if they were more alert and recognized the risks well, they could have been more prepared for the strong crosswind landing. Pilots who were practicing stall maneuvers told that they could have been more aware of maintaining a coordinated flight to prevent a wing drop or could have immediately recovered by using the right recovery techniques.

8.2.7 What did the pilots learn from their LOC-I experiences?

Pilots had several remarks on the lessons that they learned from their experiences. Pilots should always stay prepared for risks such as an inadvertent flight in IMC and spins. Some pilots mentioned that although they were momentarily startled, they could easily regain aircraft control because they were aware of the hazardous conditions and were prepared for the possible scenarios that could happen. VFR flight into IMC is the number one cause of spatial disorientation (AOPA, 2014). Pilots are more susceptible to getting disoriented especially if they are not prepared well and are situationally unaware. A pilot recommended to turn at less than a standard turn rate (i.e., 3° per second turn) in IMC when disoriented. In the process of banking too much, there is a tendency to overturn and experience more vertigo. The pilot also added that one should always plant their head at the headrest during IMC and rely on the instruments to minimize the vertigo symptoms.

Effective ADM can help pilots identify and manage risks and minimize errors. The FAA prescribes several checklists and models for effective ADM, ranging from IMSAFE (Illness, Medication Stress, Alcohol, Fatigue, Emotion), PAVE (Pilot-in-command, Aircraft, environment, External pressures), 3P (Perceive, Process, Perform) to TEAM (Transfer, Eliminate, Accept, Mitigate) (FAA, 2016a). These checklists focus on human factors aspects in preflight and inflight planning.

Crew Resource Management (CRM) is another crucial strategy to effectively use all available cockpit resources and follow procedures. It is critical to follow the prescribed procedures throughout the flight. However, there could be situations where pilots need to use their judgment, going beyond the procedures, to deal with the hazardous scenarios. Many pilots in the interview and survey mentioned that remaining calm and not panicking helped them to recover from LOC-I.

Findings from the AOPA articles, survey, and interviews unanimously suggest that pilots' decision to fly in known poor weather conditions was one of the top factors in LOC-I. Pilots who have relatively less experience in weather conditions and the specific aircraft should evaluate their risks accordingly to make critical decisions such as go or no-go and land or go around. Instrument training helps prepare pilots better to handle the aircraft in inadvertent VFR into IMC scenarios. During instrument training, pilots gain deeper knowledge about weather conditions and related human factors (e.g., vertigo) and learn to control the plane solely by instrument. Pilots also recommended to stay current and familiar with all instruments in different aircraft, maintain manual flying skills (without using an autopilot), and practice various maneuvers to recover from unsafe scenarios.

8.2.8 Pilots' Training in Practice

From the pilots' survey, I found that inadequate training and instructors' improper supervision contributed to loss of control. To gain a deeper understanding of training in practice, I asked all pilots (n = 9) in the interview about how their instructors trained them and specifically asked the CFIs (n = 7) about how they train their students.

All pilots indicated that their instructors taught them maneuvers such as stalls with different aircraft configurations (power on and power off), slow flight, and landings, based on the FAA's requirements for private pilot certification (14 CFR § 61.107) (CFR, 2023). All pilots also learned to maintain aircraft control during unusual attitudes, as required by the FAA. All pilots said that their instructors also trained them in strong winds and marginal weather. Pilots had inconsistent responses about whether their instructors taught them about pilot conditions and errors. While some pilots said that their instructors did not teach them about different conditions and errors, others said that their instructors taught them well. One pilot specifically said that they were never taught about the to-dos for IMC flying, such as putting one's head back against the headrest to avoid disorientation or vertigo. The pilot also mentioned that their instructors did not know about pilot induced oscillations and how to recover from them. The pilot became disoriented and partially lost control in an IMC flight because they did not know to put their head back against the headrest and how to recover from the pilot induced oscillations. Some pilots indicated that their instructors trained them to prevent threats if a maneuver goes wrong, whereas others indicated that they were not trained for the same. One pilot mentioned that they could have potentially recovered from the LOC-I easily if they were trained well for the potential threats.

Some CFIs indicated that they teach maneuvers such as stalls, spins, and spiral recovery. Other instructors mentioned that they do not teach full stall, spin, and spiral recovery since those maneuvers are not part of the FAA's requirement for a private or commercial pilot certificate. Like the non-CFI pilots, all the CFIs also indicated that they train their students in marginal weather and wind conditions. All of them mentioned that they train students about pilot conditions and errors, such as spatial disorientation and distraction. All but one CFI said that they train pilots to prevent threats if a maneuver goes wrong. Table 29 summarizes the agreement and disagreement areas between the pilots and CFIs.

Table 29: Pilots' responses on how their instructors trained them versus CFIs' responses on how they train their students. There were three areas of agreement and two areas of disagreement between pilots' and CFIs' responses.

Training areas	Agreement/disagreement between pilots and CFIs	Notes
Maneuvers, as required by the FAA	Agreement	All pilots and CFIs agreed that their training included all maneuvers like stall and slow flight.
Unusual attitude recovery, as required by the FAA	Agreement	All pilots and CFIs agreed that their training included unusual attitude recovery.
Wind and weather conditions	Agreement	All pilots and CFIs agreed that their training included flights and landings in marginal weather and windy conditions.
Pilot conditions and errors	Disagreement	Some pilots indicated that their instructors did not teach them about different conditions and errors, while others mentioned that their instructors taught them well. All CFIs mentioned that they train students about pilot conditions and errors.
Potential threats	Disagreement	Some pilots indicated that their instructors trained them to prevent threats if a maneuver goes wrong, whereas others indicated that they were not trained for the same. All but one CFI mentioned that they train pilots to prevent threats if a maneuver goes wrong.

8.2.9 Gaps in the Training in Practice

I also asked pilots and CFIs about their perspectives on the current training in practice. I analyzed their responses to find themes for the gaps in training. Pilots also provided recommendations for improving the training. Here, I discuss those gaps and recommendations, as discussed by the pilots and CFIs.

1. **Instrument:** Inadvertent VFR into IMC is one of the topmost contributing factors in LOC-I. The FAA requires three hours of simulated instrument time for a private pilot certificate with an airplane category and single-engine class rating (CFR, 2023). Some pilots mentioned these three hours of simulated instrument training are not sufficient to safely fly out of an inadvertent VFR into IMC. They recommended that students should experience flying in real IMC with instructors or using flight simulators.

2. **Upset Prevention and Recovery Training (UPRT)**: As discussed in Section 8.2.5, UPRT is mandatory only for ATPs who fly under FAR Part 121 (air carriers). There is no mandatory focus on UPRT for pilots under Part 135 (charter-type services) or Part 91 (GA). A pilot recommended to include UPRT training for private pilots in the FAA requirements. Several pilots also indicated in the survey and interviews that they could recover from a potential LOC-I using upset recovery methods. Some other pilots from the survey also mentioned that they could not recover from LOC-I because they did not know those recovery techniques. A pilot recommended high-fidelity simulator training for upset recovery and spin training for GA pilots.

3. **Hypoxia:** Hypoxia is the lack of sufficient oxygen in the body tissues to maintain normal physiological function. It is a physiological condition that can impair pilots due to the effects of decreased oxygen pressure at an altitude (FAA, 2015b). The FAA allows GA pilots to fly without the use of supplemental oxygen up to an altitude of 12,500 feet mean sea level (MSL). However, hypoxia can occur at altitudes as low as 5,000 feet especially at night (Nesthus et al., 1997). The FAA recommends that GA pilots use supplemental oxygen when flying unpressurized above 5,000 ft MSL at night, when the eyes become more sensitive to oxygen deprivation (FAA AC 61-107) (FAA, 2015c). Hypoxia has a range of symptoms and there is

no consistent physical reaction that signals critical impairment. Some of the symptoms include incoordination, tremors, lack of concentration, confusion, memory loss, flexibility, working memory, drowsiness, visual impairment, anxiety, depression, euphoria, shortness of breath, headache, dizziness, nausea, and light-headedness (Neuhaus & Hinkelbein, 2014). Due to the nature (e.g., euphoria) and variety of the symptoms, it is difficult to identify hypoxia when experiencing it, especially if one is not trained to recognize the symptoms. An ATP recommended providing hypoxia awareness training to even GA pilots so they could learn to recognize their personal symptoms and use recovery procedures.

4. **Energy management:** Automation is increasingly popular in small aircraft. Though automation assists pilots in long flights, overreliance on automation may impede pilots' manual flying skills, thus contributing to accidents. Proficiency in stick and rudder skills may help pilots in emergencies, such as an autopilot malfunction or failure. Some CFIs mentioned that current training methods are inadequate to train the stick and rudder skills. They recommended that training should focus on the basic principles of roll, pitch, and yaw for energy management. Energy management is the process of planning, monitoring, and controlling altitude and airspeed targets in relation to the aircraft's energy state (including fuel, engine power, and aerodynamic forces) to: (1) attain and maintain desired vertical flightpath-airspeed profiles; (2) detect, correct, and prevent unintentional altitude-airspeed deviation from the desired energy state; and (3) prevent irreversible deceleration and/or sink rate that results in a crash (FAA, 2021). One CFI mentioned that once pilots understand the concept of energy management, instructors should teach how to apply those concepts in maneuvers, and how to correlate them. This CFI has their own training school where they train private pilots several other maneuvers in addition to the FAA requirements, such as spins, emergency maneuvers, and aerobatics.

5. **Distraction:** A few CFIs mentioned that sometimes pilots tend to make operational errors because they get distracted or are too fixated on their target, e.g., on the runway touchdown point during a base to final turn. When a pilot overshoots a turn, they could decide to go around to make a better approach the next time. Instead, pilots tend to correct the turn by increasing the bank too much which may lead to a spin or a spiral, especially, if the pilot gets distracted

from maintaining the correct airspeed and pitch. A CFI recommended to teach pilots the concept of distractions while performing maneuvers and how to recover from pilot induced oscillations. Repetition and practice may help pilots to make better judgments and prevent errors.

6. **Quality of instructors:** A CFI mentioned that new pilots lack proficiency in their skills due to inadequate instruction quality. Since instructors pass on the skills that they have learned from their instructors, inadequate instructions may lead to inadequate training even for the future generations of pilots. Current training mostly focuses on teaching scenarios rather than on the stick and rudder skills. The CFI suggested regular refresher clinics for flight instructors to keep them updated on effective training methods.

8.2.10 Recommendations of Maneuvers for LOC-I Training

Pilots recommended some useful maneuvers and practices for LOC-I training. A lazy eight is designed to develop the proper coordination of the flight controls across a wide range of airspeeds and attitudes (FAA, 2021). Pilots do not learn this maneuver in their private pilot training. A pilot suggested lazy eight training for private pilots could help them learn better about energy management. Other pilots recommended steep turns (at a bank angle between 45° and 60°), slow flights, and power-on stalls as some helpful maneuvers to learn to maintain coordination, altitude, and speed control. The FAA already requires private pilots to demonstrate these three maneuvers. Some pilots mentioned that full stall demonstrations, spin, and spiral training may help pilots to recognize and recover from potential threats. Pilots should learn how to recover from potential risks in maneuvers if the maneuvers go wrong. For example, instructors should train students to recover from a spiral or spin before endorsing them to for solo practices for a stall.

8.3 Discussion and Conclusion

The findings from the study helped in identifying additional context in LOC-I and provided a deeper perspective into LOC-I causation, recovery methods, and the training in practice. I found LOC-I causes ranging from pilot conditions to organizational factors. Weather contributed to four of the seven LOC-I incidents. Lack of experience or familiarity of specific instrument was another common factor that contributed to LOC-I. Issues with the organizational culture suggests possible reasons why new pilots tend not to share their incidents and experiences. An open and honest working relationship of instructors with their students helped some pilots in debriefing issues clearly. Additionally, ATC’s communication style may contribute to pilots’ stress in emergencies. A pilot recommended calling the pilot by their names instead of aircraft tail numbers in emergency situations and talking in a more empathetic way could help pilots get out of the threat more easily without creating a panic.

Pilots recovered using recovery knowledge such as spin recovery and UPRT. Consistent with the findings from the survey and AOPA lessons learned articles, pilots shared lessons learned such as always practicing maneuvers, staying current, and maintaining flying experience without an autopilot. Pilots also discussed gaps in the training and provided recommendations. A pilot recommended that training should be consistent at all levels from private pilot to ATP. Pilots who transition from GA to airlines end up discarding old training methods and re-learning new training methods. The findings from this study may help pilots improve their operating procedures and focus training methods to prevent LOC-I in the future.

9. CONCLUSION AND RECOMMENDATIONS FOR FUTURE WORK

In this chapter, I summarize the findings from my research, provide recommendations based on the insights from pilot surveys and interviews, and discuss future work.

9.1 Discussion and Conclusion

Despite many efforts, General Aviation accidents continue to occur at unacceptable rates. There has been extensive research into the General Aviation accident causation based on historical data from sources such as the NTSB accident database. The NTSB's accident coding system is based on a chain of events model. But not all aspects of accidents are events. Moreover, unlike commercial aviation, General Aviation reports tend to focus more on environmental and aircraft factors such as bad weather and improper airspeed than pilot factors. The reports provide limited detail about pilot action and conditions. Even when the reports mention pilot factors, the information is vague and broad, e.g., "pilot took a delayed action." Additionally, not all issues mentioned in narratives get translated to codes. Therefore, only relying on the historical data may yield incomplete stories and partial understanding about accident causation. Getting pilots' perspectives using surveys and interviews about their experiences may help in provide a deeper understanding into the role of human factors in accidents. Only a few published studies have investigated General Aviation accident causation using human-subjects research. These studies tend to focus on specific pilot conditions, such as fatigue and hypoxia, rather than providing a comprehensive understanding of pilots' experiences and incidents. Using historical data such as the NTSB database and pilots' perspectives via surveys and interviews may help in providing a richer understanding of accident causation to prevent accidents in the future.

LOC-I continues to be the deadliest cause of General Aviation accidents. Most of these accidents involve pilot-related factors. For my research, I focused on LOC-I accidents. I addressed the following research questions to provide a better understanding of LOC-I accident causation and an enhanced framework for a comprehensive LOC-I causation analysis:

1. *What causes LOC-I?*
    1.1 *Which types of errors do pilots make in LOC-I incidents?*
    1.2 *What causes pilots to make these errors—what is the role of human factors in LOC-I accidents?*

For the first set of research questions, I created a state-based modeling framework by (1) modeling LOC-I accidents in the form of states and triggers and creating sequencing (grammar) rules for 309 states and triggers (Majumdar, 2019; Majumdar et al., 2021; Chapter 3); and (2) providing insights into pilots' perspectives on their experiences and training using lessons learned articles, surveys, and interviews (Majumdar & Marais, 2022).

Aircraft and Demographic Data: To understand the accident aircraft and demographic data for LOC-I, I first analyzed 5,914 LOC-I accidents in 2010–2022 from the NTSB database (Chapter 2). Cessna 172 was the most common aircraft involved in LOC-I accidents. 77% of the accidents were solo flights and 5.95% were instructional. Almost half of the pilots were 55–69 years old at the time of their LOC-I accident. Most pilots had less than 100 hours of total flying experience. Older pilots (50–60 years) had 100–200 hours of flying experience at the time of their LOC-I.

Lessons Learned LOC-I Articles: First, I provided insights into pilots' perspectives on their experiences and training by analyzing pilots' lessons learned articles, surveying, and interviewing pilots with LOC-I experiences (Chapter 6). From the pilots' LOC-I related lessons learned articles, I found pilot factors contributing to LOC-I. Pilots performing energy depleting maneuvers and deciding to fly in known weather or other unsafe conditions were some of the additional insights. Pilots' corrective actions e.g., deciding to land or go around immediately, helped them to prevent or recover from LOC-I. Some of the most common lessons learned were staying situationally aware and adequate pre-flight planning.

Pilots' Survey: The findings from the LOC-I survey helped in identifying specific pilot actions and conditions that contributed to LOC-I, and that are not mentioned explicitly in the NTSB database (Chapter 7). Pilot error (decision-based and skill-based) was the topmost issue in most events (80% of total 166 LOC-I events). Most of these errors such as improper maneuvering and improper remedial action are direct results of inadequate training. 25.8% of pilots mentioned that either their instructor had not prepared them well or did not teach them methods to recover from LOC-I. Pilots could not take a corrective action due to factors, such as fear, fixation, and distraction.

Pilots' Interviews: Interviews with nine pilots provided a deeper perspective into LOC-I causation, recovery methods, and training in practice (Chapter 8). I found causes ranging from pilot conditions to organizational factors. Pilot conditions such as overconfidence were the most prevalent factors contributing to LOC-I. Lack of experience or familiarity of aircraft instrument was another common factor that contributed to LOC-I. I found several gaps in current training methods, such as lack of LOC-I recovery and inadequate simulated instrument training for private pilots. Pilots suggested maintaining flying skills by staying current, practicing maneuvers and manual flying without an autopilot.

2. *How might we find additional causes from accident reports that are not coded?*

   2.1 Can we better model accidents using all the available information in reports to gain a deeper understanding of accident causation?

Comparison of NTSB Codes with Narratives: I first compared the findings of LOC-I accidents from their NTSB codes to their narratives as a motivation to address the second set of research questions (Chapter 4). From my analysis of 225 accident narratives, I found that pilot-related issues were most often mentioned in detail in the narratives rather than in the codes. In some cases, reports had a code cited but not mentioned in their narratives. In other cases, narratives mentioned an issue which did not get translated into a code. This incomplete translation of issues in narratives and codes provides inaccurate representations of accident models. The comparative analysis suggested that narratives may potentially provide additional findings into accident causation.

Natural Language Processing: Next, I applied Natural Language Processing (NLP) and machine learning techniques to automatically extract findings from accident narratives using the state-based approach and multi-label text classification method (Chapter 5). The Longformer model predicted ten states and triggers for 20 manually coded accidents with an accuracy of 97.5%. The model's performance suggests that it has the potential to predict additional states and triggers from accident narratives.

The contributions from my research findings are as follows:

1. The state-based accident approach provides a more complete understanding of how accidents happen. The approach can help in consistent accident coding when reporting accidents. Since multiple codes have a similar meaning, NTSB reporters usually use different codes in different accidents to describe the same issue. For example, *24518: Altitude* and *24519: Proper altitude* both indicate that the pilot did not maintain the correct altitude. By using the state and trigger definitions, reporters can do more consistent coding by just using the states (*improper altitude*, according to the example) or triggers. Therefore, we can have a more accurate count of the top causes in accidents.

2. The enhanced state-based model using Natural Language Processing helps in extracting additional information from accident reports. The model can serve as an "information extraction framework" that can (a) provide an automatic report analysis method to model accidents; and (b) facilitate the NTSB reporters with coding the NTSB reports based on an automatic analysis of the narratives.

3. The human-subjects research identifies the role of human factors in LOC-I and provides a deeper understanding of LOC-I causation and the gaps in training. The findings from my work may help in improving training methods and operating procedures for GA pilots based on the recommendations that I have provided in the next section.

9.2 Safety Recommendations

The findings from the survey and interviews show that human factors ranging from pilot conditions to organizational issues contribute to LOC-I. Figure 50 shows my recommendations based on the survey and interview findings.

Strengthen flying skills

- Constant practice of maneuvers
- Maintain manual flying skills without autopilot
- Build effective aeronautical decision making (ADM) skills

Introduce recovery training

- Aerobatic training
- Upset Prevention and Recovery Training (UPRT)
- Spin, spiral, and stall recovery
- Simulated instrument training for private pilots

Education on pilot conditions

- Vertigo, spatial disorientation, and pilot induced oscillations
- Hypoxia awareness training for GA pilots

Figure 50: Safety recommendations based on insights gained from survey and interviews

1. Strengthen flying skills

Pilots with more flying experience tended to be less involved in LOC-I. Moreover, since most errors happen due to inadequate skills, pilots should strengthen their flying skills by constantly practicing maneuvers, staying current, maintaining flying skills without autopilot, and building judgment skills to recognize hazardous and unsafe scenarios and taking corrective actions promptly. Not having adequate skills caused pilots to become afraid, anxious, feel unfamiliar of the hazards, and unsure of how to recover.

2. Introduce recovery training

Inadequate skills may stem from inadequate training. There are several gaps in training such as lack of recovery training and inadequate simulated instrument training for private pilots. Pilots and CFIs had varied agreements and disagreements on whether instructors use certain training methods (see Table 29). **Aerobatic training** and **recovery techniques** such as UPRT, spin, spiral, and stall may help pilots to recognize unsafe conditions and recover from LOC-I.

Since weather contributes to a large fraction of accidents, more hours of **simulated instrument training** especially for VFR rated pilots may help in preventing VFR into IMC scenarios to turn into accidents. Students should also experience flying in real IMC with instructors or using flight simulators. Further, high-fidelity simulator training may help in instrument, upset recovery, and spin training for GA pilots. There should be additional training emphasis on concepts of **energy management** and applying those concepts to existing certification maneuvers such as slow flight, lazy eights, steep turns, power on, and accelerated stalls. Student pilots were flying solo in 6% of LOC-I accidents (NTSB) and 8% of incidents reported in the survey (see Sections 2.3 and 7.3.2). Instructors should train their students spiral, spin, and stall recovery methods before endorsing them for solo flights. Further, regular refresher clinics for flight instructors may help them stay updated on effective training methods.

3. Education on pilot conditions

Further, pilots should also be educated consistently about different **pilot conditions** such as vertigo, spatial disorientation, and pilot induced oscillations and how to prevent or recover from them. Hypoxia awareness training for GA pilots could help them learn to recognize their personal symptoms and use recovery procedures. Finally, effective aeronautical decision making (ADM) and crew coordination may help pilots recover from LOC-I.

Additionally, some design-related recommendations that could be implemented in the future are as follows:

1. **Incorporate advanced technology to improve aircraft design:** Since stall and spin are major contributors to LOC-I, research into improved stall and spin recovery cockpit technology is needed. The GAJSC loss of control working group found that pilots' lack of awareness with

respect to angle of attack (AOA) is one of the top factors in fatal LOC-I accidents (GAJSC, 2014). The FAA stated that AOA indicators can have the highest possibility of significantly enhancing safety and reducing fatalities in General Aviation (FAA, 2013; FAA, n.d.). Existing GA aircraft should be installed with AOA-based systems such as AOA indicators to increasing pilots' awareness of the aerodynamic effects of AOA and reduce the likelihood of LOC-I. The FAA has promoted AOA-based systems through their policy to streamline design and production approval of such non-required safety enhancing equipment. However, these systems are still not prevalent in the GA fleet (FAA, 2016d). Other advanced avionics systems, such as synthetic vision systems and enhanced ground proximity warning systems provide pilots with real-time information about their surroundings to improve situational awareness. These systems may help pilots avoid hazardous and unsafe states and take corrective actions promptly. Researchers should carefully consider whether and how such technology may help safety by studying their effects on pilot performance so that any associated negative impacts are minimized.

2. **Enhance pilot training using training devices:** In their interviews, CFIs suggested more simulator training for GA pilots. Recently, two former FAA administrators also recommended introducing modern simulator technology to strengthen pilots' flying skills in hazardous scenarios such as weather conditions (Wolfsteller, 2023). Aviation training devices such as flight simulators and virtual reality (VR) can be used to provide pilots with realistic scenarios of hazardous and unsafe states, allowing them to practice their judgment and decision-making skills in a safe and controlled environment. Pilots can also train for their instrument rating and learn recovery techniques such as UPRT, spin, spiral, and stall.

3. **Using the state-based approach to prompt pilots with mitigations:** The state-based approach could be implemented as a "mitigation assistant" system in aircraft operations. The system can be implemented in aircraft design to determine probable hazardous outcomes if a pilot is in an unsafe state. Based on the unsafe state, the system can prompt the pilot to make corrective actions to mitigate the unsafe state. For example, most LOC-I accidents involve improper airspeed followed by a stall or spin. In such a case, if the airspeed is low, pilot can

be prompted to scan the attitude and angle-of-attack indicators to verify the aircraft attitude and the angle of attack. Such a prompt may help pilots prevent an impending stall or spin after improper airspeed.

9.3 Recommendations for Future Work

In this research, I created a state-based framework to maximize data extraction and insight formation from the NTSB accident reports and pilots' perspectives. I propose the following recommendations for future work:

9.3.1 Create Logic Rules to Infer More Missing States and Triggers in Accidents

31.8% of LOC-I accidents do not record any codes relevant to the trigger definitions (Majumdar, 2019). I developed eleven inferred states and trigger definitions using grammar rules e.g., aircraft preflight hazardous inferred state. The grammar rules help infer some of the missing information in accidents. More such grammar rules may help in complete the incomplete sequences in accident models and provide more details about aircraft and pilot conditions in accidents.

9.3.2 Improve the Robustness of the Longformer NLP Model

The Longformer model performed well in predicting the 20 manually coded accidents. But how can we surmise the model's actual performance when predicting the 1,500 NTSB coded accidents? One way to answer this could be by looking at the false negatives and false positives for the predictions. In future, we can manually read narratives for a subset of incorrectly predicted accidents to come to a more informed conclusion about the model's capability to predict states and triggers. Additionally, I used ten states and triggers for my experiment. In future, we could fine tune the model to produce comparable results with more states and triggers.

9.3.3 Modeling Aviation Incidents Using the ASRS Database

There has been extensive study using the NASA ASRS database. However, most studies have identified the most frequent causes and factors in the incidents, thus providing limited knowledge of how incidents started as normal flights and ended as unsafe events. Modeling the top types of incidents, such as loss of control and powerplant failure, from the ASRS database using the state-based modeling framework and the NLP model I developed may provide insights into LOC-I incidents.

9.3.4 Investigate the association between pilot age and inflight loss of control

Most LOC-I accidents recorded in the NTSB database (Chapter 2) involved older pilots (50 years and older). In the LOC-I incidents survey (Chapter 7), most pilots who took the survey were 65 years and older. Although the survey data for LOC-I incidents may be biased due to self-selection, the NTSB LOC-I accidents suggest a potential association between age and LOC-I accidents. Based on the guidance from previous studies, future work could investigate this relationship to determine implications for factors such as technological designs, aircraft re-design, and training (Charness & Bosman, 1992 and Salvendy, 2012).

9.3.5 Study the Effects of Different Training Methods on Pilot Proficiency

Aviation training lays the foundation for learning flight physics and stick-and-rudder skills. Pilots carry those necessary skills throughout their flight careers and use them during emergencies to prevent accidents. However, most accidents involving pilot error, such as improper maneuvering or remedial action, directly result from inadequate training. There is a mismatch between how instructors train pilots and the skills pilots gain from their training to prevent or recover from unsafe events. Based on the findings from my survey and interviews, I recommend studying how do private pilots perceive risk, e.g., poor weather conditions and whether different training methods such as different flight school types affect pilot proficiency. As mentioned in the safety recommendations section earlier, the effect of increased reliance on flight simulators and VR devices on pilot proficiency should be investigated.

9.3.6 Modeling Next Generation Transportation Operations Using the State-based Approach

The next few years are expected to experience a growth in next generation transportation and smart mobility solutions, such as unmanned aerial vehicles (UAVs), autonomous vehicles, and advanced air mobility (AAM). Although there are many benefits of NextGen such as convenience and sustainability, new variables will be introduced in the system due to the difference in operations, mission types, and maneuverability. Extending the state-based approach on these transportation modes may help in understanding the systems better, detecting risks early on, and preventing hazards and incidents.

APPENDIX A. UNSUPERVISED MACHINE LEARNING TECHNIQUES FOR NATURAL LANGUAGE PROCESSING

As a starting point for analyzing the narratives (Chapter 5), I used the probable cause statements of accident narratives that describe the main events, causes, and factors contributing to an accident. I first pre-processed the text by implementing three steps on each report through the Python library Natural Language Toolkit (NLTK Documentation: https://www.nltk.org/): (1) tokenization (split each narrative into words (tokens), lowercase the words, and remove punctuation); (2) stop word removal (disregard words such as “the” or “and” which provide little meaningful insight in narratives); and (3) lemmatization (change words in third person to first person and verbs in past and future tenses into present, e.g., “preparing” will convert to “prepare”). Figure 51 shows the method of pre-processing of data.

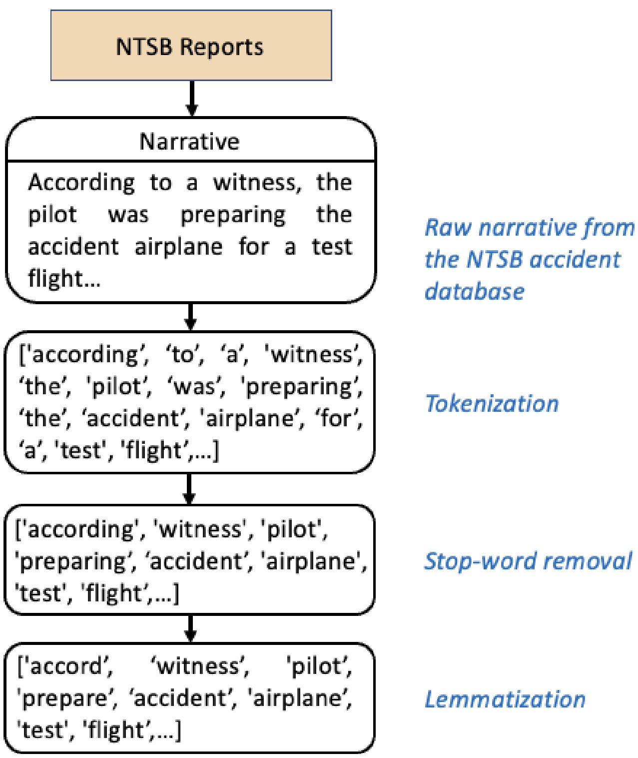

Figure 51: Method of pre-processing the narrative data from the NTSB reports

1. N-Grams Analysis

An N-gram means a contiguous sequence of N items or words. For example, in a sentence "Pilot lost aircraft control", "pilot lost" is a 2-gram (a bigram), "pilot lost aircraft" is a 3-gram (trigram), and "pilot lost aircraft control" is a 4-gram. The same sentence has three sets of bigrams and two sets of trigrams, i.e., "pilot lost aircraft" and "lost aircraft control." N-grams are useful in text analysis because they capture the local context of words or characters within a text. N-grams can be used in accident analysis to analyze and understand patterns in accident data. By extracting N-grams from accident reports or other relevant texts, we can gain insights on common occurrences and contributing factors.

I used the NLTK library in Python to find the most frequent words in the probable cause statements of 5,515 LOC-I accident reports in 2010–2019. Figure 52 shows the most frequent words. Apart from the common words such as pilot, airplane, and control, some of the non-obvious most frequent words were landing, stall, takeoff, engine, and airspeed. This suggests that most LOC-Is are accompanied with aerodynamic stalls.

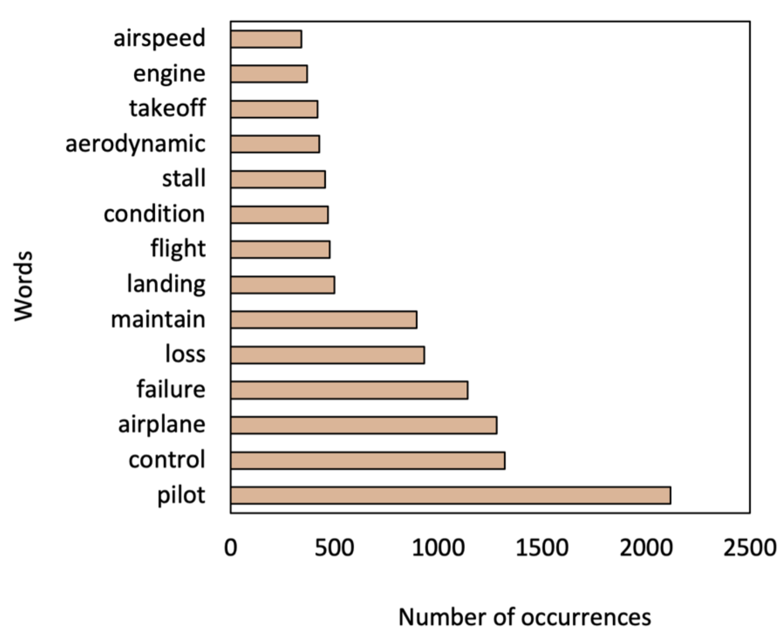

Figure 52: Most frequent words in the probable cause statements in 2010–2019 LOC-I accident reports.

Figure 53 shows the top thirteen 2-grams in the probable cause statements. Apart from airplane control, and aerodynamic control, some of the most frequently used words that are insightful are engine power, adequate airspeed, angle (of) attack, pilot decision, spatial disorientation, and low altitude. We can infer from here that pilot's decision making plays a key role in LOC-I accidents. Additionally, spatial disorientation and low altitude are some of the common events in LOC-I accidents.

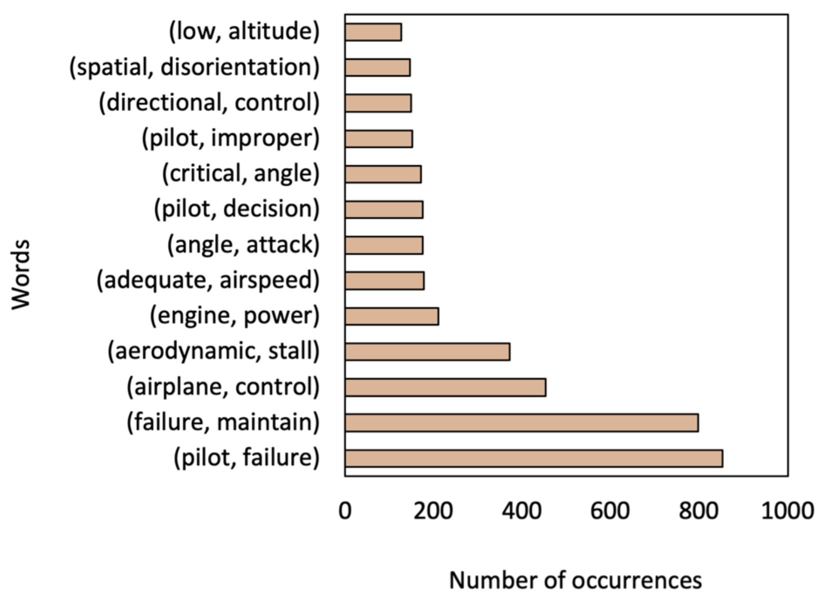

Figure 53: Most frequent 2-grams in probable cause statements in 2010–2019 LOC-I accident reports.

Figure 54 shows the 5-grams in the probable cause statements. The 5-gram analysis reveals some insights. Findings suggest that flight instructor's delayed remedial action is one of the top factors in LOC-I accidents. Loss of engine power is mostly due to fuel starvation in LOC-I accidents. Further, maneuvering at low altitude with an aerodynamic stall is a dangerous combination to end up in an accident. (Exceeding) aircraft's design stress limitation leading to an inflight breakup is another event in LOC-I accidents. Gusting crosswind conditions could lead to an aerodynamic stall causing an LOC-I. Operation of airplane by a non-certificated pilot leads to some of the LOC-I accidents.

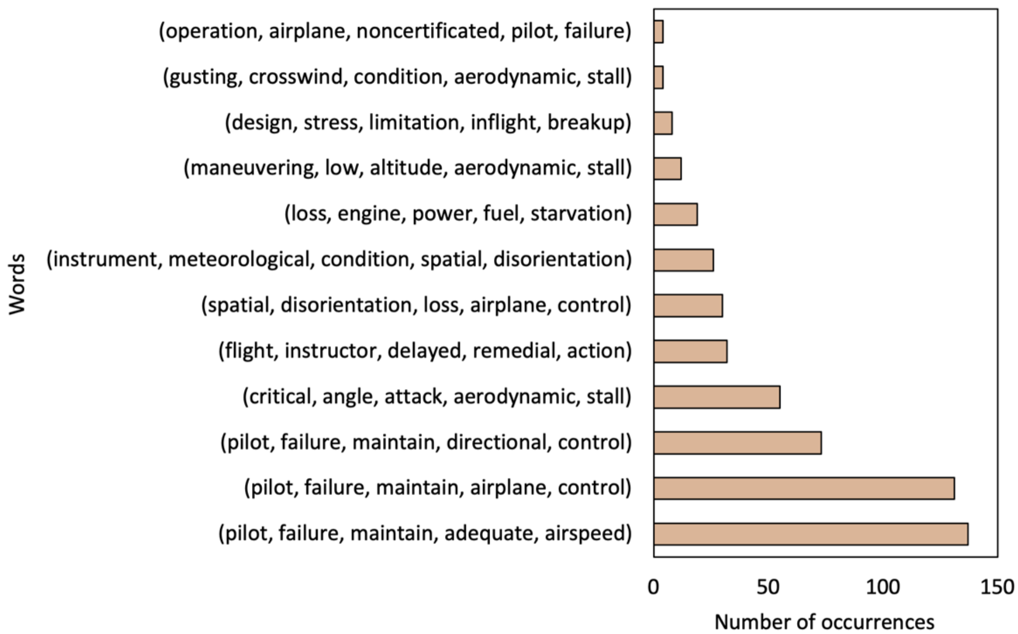

Figure 54: 5-grams in probable cause statements of 2010–2019 LOC-I accident reports.

2. Topic Modeling

Researchers have used topic modeling on ASRS reports to identify themes in the reports (Kuhn, 2018 and Robinson, 2019). Topic modeling is an approach that can identify latent structure within a corpus of documents. Topic modeling is a flexible approach that relies less on subject matter experts than alternative document categorization and clustering methods (Kuhn, 2018). It uses machine learning to automatically identify topics or themes within a collection of documents. With the goal of grouping documents together based on shared topical content, it can uncover hidden or latent topics in a set of incident reports.

I used the WordStat text analysis software to analyze 5,515 accident reports in 2010–2019 for topic modeling. WordState uses the topic extraction feature to uncover the hidden thematic structure of a text collection by applying a combination of natural language processing and statistical analysis method called factor analysis (Provalis Research, 2021). I extracted a total of

200 topics with their keywords and count. Table 30 shows the top topics found in narratives with their keywords. “Engine power total loss” was one of the most frequent topics, followed by “after takeoff shortly.” Pilot’s improper decision contributed to accidents frequently. Accidents also happened due to improper landing flare. Topics also show that student pilots were flying solo often in LOC-I accidents. Improper turns such as “steep left turn” also contributed to accidents.

Table 30: Six of the most frequent topics in accident reports

Topic	Keywords	Count
ENGINE POWER TOTAL LOSS	Loss; Power; Determined; Experienced; Based; Engine; Engine Power; Total Loss; Partial Loss; Left Engine; Power Loss	13,833
AFTER TAKEOFF SHORTLY	After; Shortly; Takeoff; Touchdown; After Takeoff; Shortly After; Shortly After Takeoff; Takeoff Roll	10,639
IMPROPER DECISION CONTRIBUTING	Contributing; Lack; Decision; Accident; Inadequate; Experience; Improper Decision; Inadequate Preflight	9,350
LANDING FLARE IMPROPER	Improper; Flare; Resulted; Subsequent; Hard; Bounced; Inadequate; Loss; Decision; Landing Flare; Improper Landing Flare; Hard Landing; Bounced Landing; Subsequent Loss; Improper Decision; Improper Flare; Subsequent Failure	6,760
STUDENT PILOT SOLO	Solo; Student; Student Pilot; Student Pilot Reported; Solo Flight; Solo Student Pilot Reported; Solo Cross	4,873
LEFT TURN STEEP	Steep; Turn; Turns; Bank; Entered; Degree; Descending; Series; Making; Left Turn; Airplane Entered; Steep Left; Bank Angle; Left Bank; Degree Turn; Descending Turn; Steep Left Turn; Descending Left Turn	4,831

APPENDIX B. SURVEY OF PILOTS' EXPERIENCES OF INFLIGHT LOSS OF CONTROL INCIDENTS AND TRAINING

Survey Flow

Standard: Survey Description (1 Question)
Block: Consent form (1 Question)
Standard: First LOC-I Survey Questions (28 Questions)

Branch: New Branch
If
If * Would you like to discuss another LOC-I or potential LOC-I experience? Yes Is Selected

Block: Second LOC-I Survey Questions (28 Questions)

Branch: New Branch
If
If * Would you like to discuss another LOC-I or potential LOC-I experience? No Is Selected

Block: Demographic Questions (8 Questions)

Branch: New Branch
If
If * Would you like to discuss another LOC-I or potential LOC-I experience? Yes Is Selected

Block: Third LOC-I Survey Questions (28 Questions)

Branch: New Branch
If
If * Would you like to discuss another LOC-I or potential LOC-I experience? No Is Selected

Block: Demographic Questions (8 Questions)

Branch: New Branch
If
If * Would you like to discuss another LOC-I or potential LOC-I experience? Yes Is Selected

Block: Fourth LOC-I Survey Questions (28 Questions)

Branch: New Branch
If
If * Would you like to discuss another LOC-I or potential LOC-I experience? No Is Selected

Block: Demographic Questions (8 Questions)

Branch: New Branch
If
If * Would you like to discuss another LOC-I or potential LOC-I experience? Yes Is Selected

Block: Fifth LOC-I Survey Questions (27 Questions)
Block: Demographic Questions (8 Questions)

Branch: New Branch
If
If * Would you like to discuss another LOC-I or potential LOC-I experience? No Is Selected

Block: Demographic Questions (8 Questions)

Start of Block: Survey Description

The aim of this study is to further understanding of what leads to inadvertent inflight loss of control (LOC-I) in General Aviation. The survey asks questions about inadvertent LOC-I experiences you may have had and the training that you received to prevent an LOC I.

LOC-I means that a pilot was unable to maintain control of the aircraft in flight, resulting in an unrecoverable deviation from the intended flight path. Inadvertent means that the LOC-I was not intentional (e.g., an intentional stall during training).

If you have experienced an inadvertent LOC-I or prevented a potential LOC-I while piloting an aircraft, we ask that you consider participating in our study. If you are interested in potentially participating, please click Next to proceed to the Informed Consent page, which provides details on the study and your role in it.

End of Block: Survey Description

RESEARCH PARTICIPANT CONSENT FORM

Pilots' Experiences of Inflight Loss of Control Incidents and Training

Dr. Karen Marais

School of Aeronautics and Astronautics

Purdue University

IRB No. IRB-2021-757

1. Key Information

Please take time to review this information carefully. This is a research study. Your participation in this study is voluntary which means that you may choose not to participate at any time without penalty or loss of benefits to which you are otherwise entitled. You may ask questions to the researchers about the study whenever you like. If you decide to take part in the study, be sure you understand what you will do and any possible risks or benefits.

This study is a part of the Safety Analysis and General Aviation (SAGA) research project under Partnership to Enhance General Aviation Safety, Accessibility, and Sustainability (PEGASAS) Center of Excellence and funded by the Federal Aviation Administration (FAA). This survey asks questions about your inflight loss of control (LOC-I) experiences and the training that you received to avoid or recover from LOC-I. Our overall goal is to understand the underlying aspects of LOC-I to develop focused training methods that help pilots to avoid LOC-I accidents.

2. What is the purpose of this study?

This study seeks to understand pilots' inadvertent inflight loss of control (LOC-I) experiences during training and solo flights and identify the underlying aspects of LOC-I from a human factors perspective. Through this research, we hope to assist the FAA in developing focused training methods that help pilots avoid LOC-I accidents.

3. What will I do if I choose to be in this study?

We are surveying student pilots and certified pilots from all sectors. If you choose to participate in this survey, you will be asked to answer specific questions related to your LOC-I experience(s) and flight training related to LOC-I knowledge and recovery. You must be at least 18 years old to participate in this survey. As a pilot, you can provide us insights into how LOC-I happens and how pilots are trained to recover from a potential LOC-I. If you indicate that you have had more than one LOC-I experience, we will give you an option to discuss your other LOC-I experiences. We will ask you to list out the conditions and actions that you took that led to the LOC-I. All the text response questions are optional. We encourage you to answer the questions as honestly as possible. At the end of the survey, we will ask you a few demographic questions.

4. How long will I be in the study?

This survey should take you approximately 20–50 minutes to complete; depending on how many LOC-I experiences you choose to share.

5. What are the possible risks or discomforts?

The risk level from participating in this study is minimal, no greater than you would encounter in daily life or during the performance of routine physical or psychological exams or tests. We will not be collecting any personally identifiable information during the study. Breach of confidentiality is always a risk with data, but we will take precautions to minimize this risk as described in the confidentiality section.

6. Are there any potential benefits?

There are no direct benefits to participating in this study. The results of this study may help us make General Aviation safer by implementing better training methods to help pilots prevent LOC-I accidents.

7. Are there costs to me for participation?

There are no anticipated costs to participate in this research.

8. Will information about me and my participation be kept confidential?

This study is funded by the FAA. We have anonymized the responses of this survey which means that the survey will not record participants' IP addresses, location data, or contact information. We will not ask you to reveal any personally identifiable information in the survey. All responses will be reported only in aggregate at the end of the study. We may use direct quotes from the text response, but we will not link any personal identifiers to those quotes. Only the research team will have access to the raw data that we collect and will process and analyze the data at Purdue University. We will use Box, licensed through Purdue, to store data, and share data only among the research team members. We will share our findings and data analysis results in aggregate with our project sponsor (the FAA), and potentially publish the findings in a PhD thesis, peer-reviewed scientific journals, and conference proceedings. The project's research records may be reviewed by departments at Purdue University responsible for regulatory and research oversight.

9. What are my rights if I take part in this study?

You do not have to participate in this research project. Your participation in this study is voluntary. You may choose not to participate, or, if you agree to participate, you can withdraw your participation at any time without penalty or loss of benefits to which you are otherwise entitled. If you decide to stop the survey without finishing, some of your responses may still be useful to the researchers. During the survey, you will be able to go back and forth as you wish within each block of questions. However, once you exit the current block of questions and enter the next one, you won't be able to change your answers to the questions in the previous block. You may choose to not answer some questions and you may stop the survey at any time without any repercussion to you. If you do not wish to complete the survey in one sitting, you may save your progress and return where you left off if you use the same computer to re-access the link. You may ask questions to the researchers about the study whenever you would like.

10. Who can I contact if I have questions about the study?

If you have questions, comments, or concerns about this research project, you can talk to one of the researchers. Please contact Prof. Karen Marais at (765) 494-0063 or kmarais@purdue.edu or Neelakshi Majumdar at nmajumda@purdue.edu.

To report anonymously via Purdue's Hotline, see www.purdue.edu/hotline.

If you have questions about your rights while taking part in the study or have concerns about the treatment of research participants, please call the Human Research Protection Program at (765) 494-5942, email (irb@purdue.edu), or write to:

Human Research Protection Program - Purdue University

Ernest C. Young Hall, Room 1032

155 S. Grant St.,

West Lafayette, IN 47907-2114

11. Document of Informed Consent

I have had the opportunity to read this consent form and have the research study explained. I have had the opportunity to ask questions about the research study, and my questions have been answered. I am prepared to participate in the research study described above. If you wish to keep a PDF copy of the consent form, please click here. If you are 18 years old and above, agree to participate in the study and have reviewed the above information, please select "I consent, begin survey" and click Next to proceed to the survey questions. If you do not consent or do not wish to participate in the survey, please select "I do not consent, end survey" and click Next to exit the survey.

◯ I consent, begin survey (1)

◯ I do not consent, end survey (2)

Skip To: End of Survey If = 2

End of Block: Consent form

Page Break

Start of Block: First LOC-I Survey Questions

QS1.1 * Have you ever experienced an inadvertent inflight loss of control (LOC-I) or prevented a potential LOC-I?

◯ Yes, I have experienced an inadvertent LOC-I or prevented a potential LOC-I (4)

◯ No, I have never experienced or prevented an inadvertent LOC-I (5)

◯ Do not wish to answer (6)

Skip To: End of Survey If QS1.1 = 5

Skip To: End of Survey If QS1.1 = 6

Page Break

QS1.2 * Were you a student pilot or a certified pilot at the time of your LOC-I experience?

◯ Student pilot (1)

◯ Certified pilot (2)

◯ Prefer not to say (3)

QS1.3 * Approximately how many flight hours did you have when you had your LOC-I experience?

◯ Number of flight hours at the time of LOC-I (2)
____

◯ Prefer not to say (3)

QS1.4 * During your LOC-I experience, who were you flying with? Please check all that apply.

- ☐ I was flying solo (4)
- ☐ I was flying with an instructor (1)
- ☐ I was flying with passenger(s) (2)
- ☐ I was flying with a certified pilot (3)
- ☐ Prefer not to say (5)

Page Break

QS1.5 * What kind of organization, if any, were you flying with during the LOC-I flight? Please check all that apply.

- ☐ Flying club (1)
- ☐ Flight school (2)
- ☐ Professional company (3)
- ☐ Volunteer organization (4)
- ☐ None (5)
- ☐ Prefer not to say (7)
- ☐ Other (6) ____

Page Break

Display This Question:

If QS1.5 = 1

Or QS1.5 = 2

Or QS1.5 = 3

Or QS1.5 = 4

Or QS1.5 = 6

Or QS1.5 = 7

QS1.6 * Have you ever observed improper working conditions or management in your organization?

- ◯ Yes (1)
- ◯ Unsure (2)
- ◯ No (3)
- ◯ Prefer not to say (4)

Display This Question:

If QS1.6 = 1

Or QS1.6 = 2

QS1.7 * Which of the following hold(s) true regarding your operator's practices before/during the LOC-I flight? Please check all that apply.

- ▢ The operator did not correct a known deficiency in documents, processes, or procedures (1)
- ▢ The operator did not correct inappropriate or unsafe actions of individuals at the organization (2)
- ▢ Prefer not to say (3)

☐ Other (4) ____

Display This Question:

If QS1.6 = 1

Or QS1.6 = 2

QS1.8 * Have you observed any of these issues in your organization before/during the LOC-I flight?

☐ Improper management of resources in my organization (1)

☐ My organization has/had a poor working atmosphere or culture (2)

☐ The procedures and rules in my organization were inadequate (3)

☐ Inappropriate crew scheduling and operational planning before the flight (5)

☐ Prefer not to say (6)

☐ Other (4) ____

Display This Question:

If QS1.8 = 1

QS1.9 * Would you like to add more details about the management of resources in your organization? Please do not enter any identifying information (e.g., colleague or company name).

○ Response (9) ____

○ Prefer not to say (10)

Display This Question:

If QS1.8 = 2

QS1.10 * Would you like to add more details about the working atmosphere or culture in your organization? Please do not enter any identifying information (e.g., colleague or company name).

◯ Response (4) ____

◯ Prefer not to say (5)

Display This Question:

If QS1.8 = 3

QS1.11 * Would you like to add more details about procedures and rules in your organization? Please do not enter any identifying information (e.g., colleague or company name).

◯ Response (6) ____

◯ Prefer not to say (7)

Display This Question:

If QS1.8 = 5

QS1.12 * Would you like to add more details about crew scheduling and operational planning in your organization? Please do not enter any identifying information (e.g., colleague or company name).

◯ Response (6) ____

◯ Prefer not to say (7)

Page Break

QS1.13 * Which conditions or factors do you think contributed to your LOC-I experience? Please check all that apply

▢ I made decision-based or action-based errors before/during the LOC-I flight (1)

▢ I was not mentally or physically fit to fly on the day of the LOC-I flight. (3)

- There was a lack of coordination between me, the ATC, ground staff, passenger(s), or the instructor before/during the flight. (4)
- I was not certified, prepared, or properly trained for the flight. (5)
- I had not received adequate training from my instructor or the ground school before the LOC-I flight. (6)
- My instructor(s) did not point out or correct unsafe actions/habits before/during the LOC-I flight. (7)
- My instructor did not correct a critical mistake that I made that led to the LOC-I. (8)
- Prefer not to say (11)
- Other (10) ____

QS1.14 * We reviewed last 11 years of LOC-I related incident articles written by pilots in the AOPA's Pilot magazine and found some common issues that frequently caused loss of control. Do any of the following factors hold true for your LOC-I flight?

- There was an aircraft instrument/control failure in my aircraft. (1)
- The flight controls were not responding normally. (2)
- There were inoperative/malfunctioning aircraft instrument(s). (3)
- There was an engine failure/malfunction. (4)
- My pre-flight aircraft check or flight planning was inadequate. (5)
- The aircraft was not serviced or repaired properly. (6)
- I did not follow the aircraft instruments while performing a maneuver. (7)

- [ ] I did not follow the checklist properly. (8)
- [ ] I did not consider the aircraft's capabilities. (9)
- [ ] I did not recognize severe weather/wind/other unsafe flight conditions. (10)
- [ ] I decided to fly in known unsafe weather/wind/other flight conditions. (11)
- [ ] I was using energy depleting maneuvers before the LOC-I. (12)
- [ ] The prevailing weather or light conditions were poor. (13)
- [ ] I diverted or went off-course from my planned route, leading to low fuel/fuel exhaustion. (14)
- [ ] I did not load enough fuel for my planned route, so I was low or out of fuel. (15)
- [ ] I inadvertently entered instrument meteorological conditions (IMC) from visual meteorological conditions (VMC). (16)
- [ ] I was flying at low altitude. (17)
- [ ] Prefer not to say (18)
- [ ] Other (19) ____

Page Break

Display This Question:

If QS1.13 = 10

Or QS1.13 = 3

QS1.15 * Which of the following hold true regarding your mental/emotional well-being on the day of the LOC-I flight? Please check all that apply.

- [ ] I was feeling pressure to fly. (1)

- I was stressed/mentally fatigued before the flight. (2)
- I lacked the motivation to fly. (3)
- I was not situationally aware during the flight. (4)
- I got distracted during the flight. (5)
- I had become overconfident/complacent during/before the flight. (6)
- Prefer not to say (7)
- Other (8) ____

Display This Choice:

If QS1.13 = 10

- Not applicable (9)

Display This Question:

If QS1.13 = 4

Or QS1.13 = 10

QS1.16 * Which of the following hold(s) true regarding coordination during your LOC-I flight? Please check all that apply.

- There was a miscommunication between me and my instructor. (1)
- There was a miscommunication between me and the ATC/ground radio. (2)
- I did not follow my instructor's instructions properly before/during the flight. (3)
- There was a miscommunication between me and the ground staff. (4)
- There was a miscommunication between me and the passenger(s). (5)
- Prefer not to say (6)

☐ Other (7) ____

Display This Choice:

If QS1.13 = 10

☐ Not applicable (8)

Display This Question:

If QS1.13 = 5

Or QS1.13 = 10

QS1.17 * Which of the following hold(s) true regarding your personal readiness for the LOC-I flight? Please check all that apply.

☐ Even though I was current in the aircraft, I did not feel comfortable flying the aircraft. (1)

☐ I realized that I did not have recent experience in flying the aircraft. (2)

☐ Even though I was current in instrument or night conditions, I did not feel comfortable flying at night or in IMC. (3)

☐ I realized that I did not have recent experience flying at night or in IMC. (4)

☐ Prefer not to say (5)

☐ Other (6) ____

Display This Choice:

If QS1.13 = 10

☐ Not applicable (7)

Display This Question:

If QS1.13 != 6

QS1.18 * Which of the following hold(s) true regarding the training you received from your instructor(s) up until the day of your LOC-I flight? Please check all that apply.

☐ My instructor(s) had not prepared me well to recover from LOC-I before my first LOC-I flight. (2)

☐ My instructor(s) had never taught me methods to recover from LOC-I before my first LOC-I flight. (3)

☐ My instructor(s) had provided me adequate guidance on methods to recover from LOC-I before my first LOC-I flight. (1)

☐ Prefer not to say (4)

☐ Other (5) ____

Display This Choice:

If QS1.13 = 10

☐ Not applicable (6)

QS1.19 * Which of the following hold(s) true regarding the training you received from your instructor(s) up until the day of your LOC-I flight? Please check all that apply.

☐ My instructor(s) had not prepared me well to recover from LOC-I before my first LOC-I flight (1)

☐ My instructor(s) had never taught me methods to recover from LOC-I before my first LOC-I flight (2)

☐ Prefer not to say (3)

☐ Other (4) ____

Page Break

Description S1 **Unsafe conditions, events, and actions**

Generally, accidents and incidents happen due to a combination of unsafe flight, weather, pilot-related, or other external conditions and events. Similarly, there can be multiple unsafe acts that lead to an incident or accident.

Consider a case where a pilot experienced a potential LOC-I due to wake turbulence from a bigger aircraft. Before the approach, the pilot had changed his radio frequencies and did not hear any transmissions from the ATC regarding the larger aircraft's approach. Moreover, the pilot was not situationally aware of their surroundings. Due to the wake turbulence, the aircraft rolled almost fully inverted several times. The pilot got disoriented and the plane was in an upset state. The pilot used their aerobatics knowledge to initiate an upset recovery by rolling the aircraft towards the sky and prevented a potential LOC-I.

In this case, the following are the unsafe conditions and events:

1. Wake turbulence
2. The pilot got disoriented.
3. The aircraft was in an upset state.

Unsafe actions:

1. The pilot was not situationally aware during the flight.
2. The pilot did not maintain the correct radio frequency.

Corrective actions:

1. The pilot used their aerobatics knowledge to recover an inverted aircraft.

Now, let's discuss the series of unsafe conditions, events, and actions in your LOC-I experience.

Display This Question:

If QS1.13 = 1

Or QS1.13 = 10

QS1.20 * What kind of errors did you make during your LOC-I flight? Please check all that apply.

- ☐ I made improper decision(s) before/during the LOC-I flight. (1)
- ☐ I took wrong action(s) or did not take correct actions, leading to the LOC-I. (2)
- ☐ I perceived the flight conditions incorrectly and made an incorrect decision based on that misperception. (3)
- ☐ Prefer not to say (4)
- ☐ Other (5) ____

Display This Choice:

If QS1.13 = 10

- ☐ Not applicable (6)

QS1.21 * What unsafe conditions or events existed before/during the LOC-I flight?

- ○ Response (4) ____
- ○ Prefer not to say (5)

QS1.22 * What unsafe actions did you take before and during the LOC-I flight? Please list them in chronological order. If you do not wish to answer, then enter "N/A" or "NA" in the first text box.

- ○ 1st Unsafe action (1) ____
- ○ 2nd unsafe action (2) ____
- ○ 3rd unsafe action (3) ____

○ 4th unsafe action (4) ____

○ 5th unsafe action (5) ____

○ 6th unsafe action (6) ____

○ 7th unsafe action (7) ____

○ 8th unsafe action (8) ____

○ 9th unsafe action (9) ____

○ 10th unsafe action (10) ____

○ 11th unsafe action (11) ____

○ 12th unsafe action (12) ____

○ 13th unsafe action (13) ____

○ 14th unsafe action (14) ____

○ 15th unsafe action (15) ____

○ 16th unsafe action (16) ____

○ 17th unsafe action (17) ____

○ 18th unsafe action (18) ____

○ 19th unsafe action (19) ____

○ 20th unsafe action (20) ____

Page Break

QS1.23 * How did you recover from the LOC-I or prevent a potential LOC-I?

○ Response (4) ____

○ Prefer not to say/Not applicable (5)

Page Break

QS1.24 * If you did not take a corrective action, what do you think you could or should have done?

○ Response (4) ____

○ Prefer not to say/Not applicable (5)

QS1.25 * If you did not take a corrective action, what made you not take an action?

○ Response (4) ____

○ Prefer not to say/Not applicable (5)

Page Break

QS1.26 * Is there anything else that you would like to add about your LOC-I experience?

○ Response (6) ____

○ Prefer not to say (7)

Page Break

QS1.27 * Would you like to discuss another LOC-I or potential LOC-I experience?

○ Yes (1)

○ No (2)

End of Block: First LOC-I Survey Questions

Start of Block: Second LOC-I Survey Questions

QS2.1 * Were you a student pilot or a certified pilot at the time of your LOC-I experience?

○ Student pilot (1)

○ Certified pilot (2)

○ Prefer not to say (3)

QS2.2 * Approximately how many flight hours did you have when you had your LOC-I experience?

○ Number of flight hours at the time of LOC-I (2) ____

○ Prefer not to say (3)

QS2.3 * During your LOC-I experience, who were you flying with? Please check all that apply.

▢ I was flying solo (4)

▢ I was flying with an instructor (1)

▢ I was flying with passenger(s) (2)

▢ I was flying with a certified pilot (3)

▢ Prefer not to say (5)

Page Break

QS2.4 Were you flying with the same organization as before when the second LOC-I happened?

○ Yes (1)

○ No (2)

Display This Question:

If QS2.4 = 2

<< Repeat QS1.5 to QS1.27>>

End of Block: Second LOC-I Survey Questions

Start of Block: Third LOC-I Survey Questions

<< Repeat QS2.1 to QS2.27>>

End of Block: Second LOC-I Survey Questions

Start of Block: Fourth LOC-I Survey Questions

<< Repeat QS2.1 to QS2.27>>

End of Block: Second LOC-I Survey Questions

Start of Block: Fifth LOC-I Survey Questions

<< Repeat QS2.1 to QS2.27>>

End of Block: Second LOC-I Survey Questions

Start of Block: Demographic Questions

QD1 * How old are you?

- ○ 18–24 years (1)
- ○ 25–34 years (2)
- ○ 35–44 years (3)
- ○ 45–54 years (4)
- ○ 55–64 years (5)
- ○ 65 or older (6)
- ○ Prefer not to say (7)

QD2 * What gender do you identify with?

○ Male (1)

○ Female (2)

○ Non-binary/third gender (3)

○ Prefer not to say (4)

Page Break

QD3 * What grade of pilot certificate do you currently have? Please click all that apply.

▢ No certificate (1)

▢ Student (2)

▢ Private (3)

▢ Commercial (4)

▢ Airline Transport (5)

▢ Sport (6)

▢ Recreational (7)

▢ Prefer not to say (8)

▢ Other (9) ____

QD4 * Which ratings or endorsements do you currently have? Please click all that apply.

▢ Single-engine land (1)

▢ Multi-engine land (2)

- Instrument (3)
- Rotorcraft-Helicopter (4)
- Glider (5)
- Lighter-than-air (6)
- Single-engine sea (7)
- Multi-engine sea (8)
- Tailwheel (9)
- High altitude (10)
- High performance (11)
- Complex (12)
- Single-engine flight instructor (13)
- Multi-engine flight instructor (14)
- Instrument flight instructor (15)
- None (16)
- Prefer not to say (17)
- Other (18) ____

Page Break

QD5 * Approximately how many years of flying experience do you have?

- Number of flying years (1) ____
- Prefer not to say (2)

QD6 * Approximately how many flight hours do you have logged?

- Number of flying hours (1) ____
- Prefer not to say (4)

QD7 * Approximately how many days a month do you fly, on average?

- 2–7 days a week (1)
- Once a week (2)
- Once a month (3)
- Once every 2–5 months (4)
- Rarely/never (5)
- Prefer not to say (6)

Page Break

QSurveyEnd You have reached the end of the survey. To finish the survey, please click Submit.

End of Block: Demographic Questions

APPENDIX C. INTERVIEW OF PILOTS' EXPERIENCES OF INFLIGHT LOSS OF CONTROL INCIDENTS AND TRAINING

RESEARCH PARTICIPANT CONSENT FORM

Interview of Pilots' Experiences of Inflight Loss of Control Incidents and Training

Dr. Karen Marais

School of Aeronautics and Astronautics

Purdue University

IRB No. IRB-2022-73

1. Key Information

Please take time to review this information carefully. This is a research study. Your participation in this study is voluntary which means that you may choose not to participate at any time without penalty or loss of benefits to which you are otherwise entitled. You may ask questions to the researchers about the study whenever you like. If you decide to take part in the study, be sure you understand what you will do and any possible risks or benefits.

This study is a part of the Safety Analysis and General Aviation (SAGA) research project under Partnership to Enhance General Aviation Safety, Accessibility, and Sustainability (PEGASAS) Center of Excellence and funded by the Federal Aviation Administration (FAA). This research study is being conducted by Neelakshi Majumdar, a Ph.D. candidate in the School of Aeronautics and Astronautics at Purdue University, under the guidance of Dr. Karen Marais. Our overall goal is to understand what leads to inadvertent inflight loss of control (LOC-I) and how pilots are trained to prevent or recover from LOC-I. LOC-I means that a pilot was unable to maintain control of the aircraft in flight, resulting in an unintended departure of an aircraft from controlled flight regime. Inadvertent means that the LOC-I was not intentional (e.g., an intentional stall during training). Through this study, we aim to develop focused training methods that may help pilots to avoid

LOC-I accidents. In this study, we will ask you questions about your LOC-I experience(s) and the training that you received or provide as an instructor to prevent or recover from LOC-I.

2. What is the purpose of this study?

This study seeks to gain insight into what causes inadvertent inflight loss of control (LOC-I) and how training may prepare or fail to prepare pilots to avoid LOC-I. We are seeking both pilot and flight instructor perspectives. We hope to enroll about 10 participants in our study. We aim to identify the underlying causes of LOC-I from a human factors perspective. Through this research, we hope to assist the FAA in developing focused training methods that help pilots avoid LOC-I accidents.

3. What will I do if I choose to be in this study?

This study follows a semi-structured interview format. A semi-structured interview is a type of interview in which the interviewer asks only a few predetermined questions while the rest of the questions are not planned in advance. If you choose to participate in this study, we will ask you to answer some open-ended and specific questions related to LOC-I in general, the training you received (or give, if you are an instructor) as well as any LOC-I experience(s) you may have had. As a pilot, you can provide us insights into how LOC-I happens and how pilots are trained to prevent or recover from a potential LOC-I. If you indicate that you have had more than one LOC-I experience, we will give you an option to discuss your other LOC-I experiences. All the questions are optional, and you may stop the interview at any time without any repercussion to you. We encourage you to answer the questions as honestly as possible. You must be at least 18 years old to participate in this study.

4. How long will I be in the study?

This interview should take approximately an hour to complete; depending on the depth of your responses and the number of LOC-I experiences you choose to share.

5. What are the possible risks or discomforts?

The risk level from participating in this study is minimal, no greater than you would encounter in daily life or during the performance of routine physical or psychological exams or tests. We will not be collecting any personally identifiable information during the study. We will be recording the interview so that we can transcribe the recording into text and can analyze your responses. Only Neelakshi Majumdar will have access to the recording file. After transcription, we will destroy the recording file. Only the research team will have access to the transcribed text. This research is anonymous. Anonymous means that we will not record any information about you that could identify you. There will be no linkage between your identity and your response in the research. If you or the interviewer inadvertently reveal any direct identifiers during the interview, we will remove them from the transcribed text. Breach of confidentiality is always a risk with data, but we will take precautions to minimize this risk as described in the confidentiality section.

6. Are there any potential benefits?

There are no direct benefits to participating in this study. The results of this study may help us make General Aviation safer by implementing better training methods to help pilots prevent LOC-I accidents.

7. Are there costs to me for participation?

There are no anticipated costs to participate in this research.

8. Will information about me and my participation be kept confidential?

This research is anonymous. Anonymous means that we will not record any information about you that could identify you. There will be no linkage between your identity and your response in the research. This means that we will not record your name, address, phone number, date of birth, etc. in the transcribed response file. We will remove any such identifiers from the transcribed text. After transcription, we will destroy the recording file. All responses will be reported only in aggregate at the end of the study. We may use direct quotes from the responses, but we will not link any personal identifiers to those quotes. Only the research team will have access to the raw data (transcribed responses) and will process and analyze the data at Purdue University. We will use Box, licensed through Purdue, to store data, and share data only among the research team members. We will share our findings and data analysis results in aggregate with our project sponsor (the FAA), and potentially publish the findings in a PhD thesis, peer-reviewed scientific journals, and conference proceedings. The project's research records may be reviewed by departments at Purdue University responsible for regulatory and research oversight.

9. What are my rights if I take part in this study?

You do not have to participate in this research project. Your participation in this study is voluntary. You may choose not to participate, or, if you agree to participate, you can withdraw your participation at any time without penalty or loss of benefits to which you are otherwise entitled. If you decide to stop the interview without finishing, some of your responses may still be useful to the researchers. You may choose to not answer some questions and you may stop the interview at any time without any repercussion to you. You may ask questions to the researchers about the study whenever you would like.

10. Who can I contact if I have questions about the study?

If you have questions, comments, or concerns about this research project, you can talk to one of the researchers. Please contact Prof. Karen Marais at (765) 494-0063 or kmarais@purdue.edu or Neelakshi Majumdar at nmajumda@purdue.edu.

To report anonymously via Purdue's Hotline, see www.purdue.edu/hotline.

If you have questions about your rights while taking part in the study or have concerns about the treatment of research participants, please call the Human Research Protection Program at (765) 494-5942, email (irb@purdue.edu), or write to:

Human Research Protection Program - Purdue University
Ernest C. Young Hall, Room 1032
155 S. Grant St.,
West Lafayette, IN 47907-2114

11. Document of Informed Consent

If you are 18 years old and above, have reviewed the above information, and agree to participate in the study, we will ask you to verbally acknowledge the following statement before we start the interview:

"I have had the opportunity to read this consent form and have the research study explained. I have had the opportunity to ask questions about the research study, and my questions have been answered. I am prepared to participate in the research study described above."

Semi-structured Interview

Interview of Pilots' Experiences of Inflight Loss of Control Incidents and Training

Objective of the study: To understand pilots' perspectives on their LOC-I experiences and their causes, LOC-I training, and their opinions on LOC-I.

Interview Script:

We are here to talk about your perceptions about LOC-I and the training in practice to prevent or recover from an inflight loss of control. Also, if you have personally experienced an LOC-I or prevented a potential LOC-I and are open to sharing that experience, we will ask you about that. We have prepared a set of standard questions on which we will base our conversation. I will not be asking any questions related to any violations that you may have made during your experiences or training, and if you volunteer such information, we will ask you to stop. I expect that this conversation will last about an hour. I will be recording the interview so that I can transcribe the recording into text and can analyze your responses. Only I will have access to the recording file. After transcription, I will destroy the recording file. Only Prof. Marais and I will have access to the transcribed text.

Before we proceed, could you open the consent form that I sent you via email?
Have you read all the instructions in the consent form, and do you understand them?
Do you have any questions or concerns?
Please let me know if you would like to proceed with the study.

<Continue if the participant says "yes". Stop otherwise.>
Could you please verbally acknowledge the consent statement at the very end of the consent form.
"I have had the opportunity to read this consent form and have the research study explained. I have had the opportunity to ask questions about the research study, and my questions have been answered. I am prepared to participate in the research study described above."

Great, thank you. I will now begin recording.

<Start recording>

I will first start by asking you a few basic demographic questions. If you prefer not to answer a question, please just say “skip”.

General/Demographic Questions

1. What grade(s) of pilot certificate do you currently have (Student, Private, Commercial, Airline Transport, Sport, Recreational, Other)?

   ▢ No certificate

   ▢ Student

   ▢ Private

   ▢ Commercial, CFI

   ▢ Airline Transport

   ▢ Sport

   ▢ Recreational

   ▢ Prefer not to say

   ▢ Other___________

2. Which ratings or endorsements do you currently have (Single/Multi-engine land, Single/Multi-engine sea, Instrument, Rotorcraft-Helicopter, Glider, Lighter-than-air, Tailwheel, High altitude, High performance, Complex, Single/Multi-engine/Instrument flight instructor)?

   ▢ Single-engine land

   ▢ Multi-engine land

   ▢ Instrument

   ▢ Rotorcraft-Helicopter

   ▢ Glider

   ▢ Lighter-than-air

- ▢ Single-engine sea
- ▢ Multi-engine sea
- ▢ Tailwheel
- ▢ High altitude
- ▢ High performance
- ▢ Complex
- ▢ Single-engine flight instructor
- ▢ Multi-engine flight instructor
- ▢ Instrument flight instructor
- ▢ None
- ▢ Prefer not to say
- ▢ Other___________

3. As a <u>student pilot</u>, what FAA part did you fly under? Part 61 or 141?
4. Approximately how many <u>hours and years of flying experience</u> do you have?
   Hours: ______
   Years: ______
5. How <u>old</u> are you now?
6. Have you ever <u>experienced</u> an inadvertent inflight loss of control or prevented a potential LOC-I?

<If participant is a CFI and has not experienced an LOC-I themselves>

Have you ever experienced an LOC-I with a student?

Or did any of your students had an LOC-I experience while you were training them?

<If the participant is a <u>CFI and has NOT experienced an LOC-I incident</u>, skip to Q40–53>

<If the participant has experienced an LOC-I incident (irrespective of whether they are a CFI or not), go over all the questions below Q6–53>

7. Are you willing to discuss your LOC-I experience?
8. How many times did you experience an LOC?
9. <If the participant had multiple LOC-I experiences> Is there a particular LOC incident that you would like to talk about?

   Would you mind telling a few more details about your LOC-I experience.
10. How old were you at the time of the LOC flight?
11. What grade(s) of pilot certificate did you have at the time of the LOC flight?

   ▢ No certificate

   ▢ Student

   ▢ Private

   ▢ Commercial

   ▢ Airline Transport

   ▢ Sport

   ▢ Recreational

   ▢ Prefer not to say

   ▢ Other____________

12. Which ratings or endorsements did you have at the time of the LOC?

   ▢ Single-engine land

   ▢ Multi-engine land

   ▢ Instrument

   ▢ Rotorcraft-Helicopter

   ▢ Glider

▢ Lighter-than-air

▢ Single-engine sea

▢ Multi-engine sea

▢ Tailwheel

▢ High altitude

▢ High performance

▢ Complex

▢ Single-engine flight instructor

▢ Multi-engine flight instructor

▢ Instrument flight instructor

▢ None

▢ Prefer not to say

▢ Other____________

13. How many hours and years of flying experience did you have at the time of the LOC?

    Hours: ____

    Years: ____

14. Approximately how many days a month on average were you flying at that time?

15. Were you flying solo or with someone during the LOC flight?

16. If a student pilot, what FAA part were you flying under? Part 61 or 141?

    <If flying with someone> who were you flying with? For example, a passenger, fellow-student or instructor.

    Were you flying as a CFI during this LOC experience (or any other LOC experiences)?

17. <If the participant mentioned in Q16 that they were flying as a CFI with a student> Was it an instructional flight? Was your student acting as the PIC (pilot in control) when you both lost control?

18. Did the LOC result from an attempted intentional maneuver that went wrong (e.g., during LOC-I training)?

19. Can you tell me what happened on the day you experienced LOC?

Checklist Questions

<Ask these questions if the participant hasn't included these points in their answer for Q19>

20. ☐ What was the purpose of the flight? What kind of flying were you doing?

21. ☐ What kind of aircraft were you flying in?

22. ☐ What airport were you flying from and where to?

23. ☐ What were the terrain conditions during the flight?

24. ☐ What airspace were you flying through?

25. ☐ Were you explicitly communicating with a tower or were you flying in an un-towered field?

26. ☐ When did you become aware that you were losing or had lost control?

27. ☐ Let's talk about that particular day, how were the weather conditions (specifically ceiling, IMC, wind) on that day? What time of the day was it? Day or night?

28. ☐ Do you think the weather or wind conditions contributed to the LOC?

29. ☐ Did you feel stressed or under any external or internal pressure to fly on the LOC day?

30. ☐ Were you exhausted or overtired that day?

<If the participant was flying as a CFI with a student during an instructional flight>

31. ☐ Do you remember how your student was feeling, if they were stressed, under any pressure, or fatigued, and whether they shared that before or during the flight?

32. ☐ Can you describe your sequence of actions and the maneuvers that you conducted to recover from the LOC or to prevent a potential LOC?

    What would have made it worse?

    <If the participant was flying as a CFI with a student during an instructional flight>

33. Can you describe your and your student's sequence of actions and the maneuvers that were taken to recover from the LOC or to prevent a potential LOC?

    ☐ <If the participant did NOT take a corrective action>

34. Why do you think you did not or could not take a corrective action?

    <If the participant was flying as a CFI with a student during an instructional flight>

35. ☐ Why do you think your student did not or could not take a corrective action?

36. ☐ What could you have done differently to prevent or recover from the LOC?

Perceptual Errors and Training Questions

I would like to now focus on whether you had made any kind of errors (i.e., wrong actions, lack of actions, or bad decisions) based on inaccurate perceptions of people, situations, or objects during the LOC-I flight. These kinds of errors are called perceptual errors. Perceptual errors often result from the pre-conceived ideas that people hold about other people, objects, and situations. For example, in the context of driving, sometimes one cannot see critical information while driving because it is dark, or a pedestrian's clothes have low contrast, i.e., they assume there is no critical information, when in reality there is some information. Perceptual errors may also happen when you rely on previous experiences to make decisions. For example, deciding to drive in a storm because the last time you drove in a storm, you got to your destination safely.

37. Do you remember making any such perceptual errors during the LOC-I flight?

    <If the participant was flying as a CFI with a student during an instructional flight>

38. Do you remember your student making any such perceptual errors during the LOC-I flight?

39. Have you ever formally reported or otherwise documented this incident?

<If "yes"> where did you document it? Do you mind sharing the incident number or link to the article? Why do you think you did not document it?

<If participant was not flying as a CFI during LOC>	<If participant is a CFI (irrespective whether they had an LOC-I)>
Thinking back to the training you had before the LOC-I flight…	<If CFI has experienced LOC-I with a student during an instructional flight> Let's talk about pilot training before the LOC-I flight. <If CFI has experienced LOC-I but NOT during an instructional flight or has NOT experienced LOC-I at all> Let's talk about LOC-I related pilot training in practice.
40. What kind of maneuvers or other practices did you learn to prevent or recover from a potential LOC-I?	40. <Ask all CFI whether they experienced LOC or not> a) What kind of maneuvers or other practices did you learn to prevent or recover from a potential LOC? b) What kind of maneuvers or other practices do you teach your student to prevent or recover from a potential LOC-I? <If CFI has experienced LOC-I with a student during an instructional flight > What kind of maneuvers or other practices did you teach your student to prevent or recover from a potential LOC-I?
41. Did your instructor teach you how to prevent and recover from potential threats if a maneuver goes wrong (e.g., a stall maneuver could lead to a spin)?	41. Do you teach your student how to recover from potential threats if a maneuver goes wrong (e.g., a stall maneuver could lead to a spin)? <If CFI has experienced LOC-I with a student during an instructional flight> Did you teach your student how to recover from potential threats if a maneuver goes wrong (e.g., a stall maneuver could lead to a spin)?

<If participant was not flying as a CFI during LOC>	<If participant is a CFI (irrespective whether they had an LOC-I)>
42. Do you think that student pilots should be trained maneuvers if they don't yet know how to recover if the maneuver goes wrong (like we discussed about a stall maneuver leading to a spin)? Why or why not?	42. <Ask all CFI whether they experienced LOC-I or not> Do you think that student pilots should be trained maneuvers if they don't yet know how to recover if the maneuver goes wrong (e.g., a stall maneuver could lead to a spin)? Why or why not?
43. Were you trained well for controlling the aircraft during weather conditions (such as gusty winds, mountain wave, crosswinds)?	43. How do you train your student for controlling the aircraft during weather conditions (such as gusty winds)? <If CFI has experienced LOC-I with a student during an instructional flight > How did you train your student for controlling the aircraft during weather conditions (such as gusty winds)?
44. Did your flight instructor, flight school, or ground school teach you about pilot conditions (such as fatigue, hypoxia, spatial disorientation) and errors (such as distraction or just freezing over controls) that may contribute to an LOC-I?	44. Do you train your student about pilot conditions (such as fatigue, hypoxia) and errors (such as distraction or just freezing over controls) that may contribute to an LOC-I? <If CFI has experienced LOC-I with a student during an instructional flight > Did you train your student about pilot conditions (such as fatigue, hypoxia) and errors (such as distraction or just freezing over controls) that may contribute to an LOC-I?
45. <If the participant answered a "YES" to the previous questions> Did your instructor train you how to prevent or mitigate these conditions and errors?	45. <If the CFI answered a "yes" to the previous questions> How do you train your student on how to prevent or mitigate these conditions and errors? <If CFI has experienced LOC-I with a student during an instructional flight> How do you train your student on how to prevent or mitigate these conditions and errors?

<table>
<tr><th><If participant was not flying as a CFI during LOC></th><th><If participant is a CFI (irrespective whether they had an LOC-I)></th></tr>
<tr><td>46. Do you think you were well-prepared in terms of maneuver training and LOC-I recovery training before the LOC-I event?</td><td>46. Do you think you prepare your students well in terms of training to prevent and recover from an LOC-I?

<If CFI has experienced LOC-I with a student during an instructional flight>
Do you think you had prepared your student well in terms of training to prevent and recover from an LOC-I, before the incident?</td></tr>
<tr><td>47. <If the participant answered a “no” to the previous questions> How do you think you could have been prepared better to prevent or recover from the LOC-I?</td><td>47. <If the CFI answered a “no” to the previous questions>

What can you do differently to prepare your student to prevent or recover from an LOC-I?

Do you want to add your opinions on LOC-I incidents and pilot training to prevent LOC-I?

<If CFI has experienced LOC-I with a student during an instructional flight> What could you have done differently to prepare your student to prevent or recover from the LOC-I?</td></tr>
</table>

48. What did you learn from your LOC-I experience?

49. Is there anything else that you would like to add about your experience?

50. What kind of maneuvers should the pilots be taught for PPL?

51. What kind of maneuvers are not good enough in the current curriculum?

52. If you had the authority to modify the training, what would you have modified?

53. Do you want to add your opinions on LOC-I incidents and pilot training to prevent LOC-I?

APPENDIX D. STATES, TRIGGERS, AND ADDITIONAL INFORMATION

This section includes descriptions for the 108 states, 194 triggers, and seven additional information, as described in Chapter 3.

1. State Descriptions

Table 31: Descriptions for hazardous states

No.	State	Description
1	Inflight Loss of Control State	A hazardous state that involves an unintended departure of an aircraft from controlled flight regime (FAA, 2016).
2	Improper RPM State	Hazardous state where the propeller RPM is either too low or too high.
3	Improper Altitude/Clearance State	Hazardous state where the aircraft is operating too close to the ground, terrain, water, or object.
4	Improper Climb State	Hazardous state where the aircraft's climb was incorrect/climb capability was exceeded/climb rate was incorrect.
5	Improper Distance State	Hazardous state where the distance from the runway/landing site/object/aircraft is incorrect.
6	Improper Heading State	Hazardous state where the pilot failed to maintain heading/course.
7	Improper Airspeed State	Hazardous state where the pilot fails to maintain correct airspeed during the flight.
8	Improper Descent State	Hazardous state where the aircraft's descent was incorrect/descent rate was incorrect.

Table 31: Descriptions for hazardous states

No.	State	Description
9	Intentional/Inadvertent flight through poor weather State	Hazardous state where the pilot intentionally or inadvertently flew into poor weather conditions.
10	Flight in Prevailing Poor Weather and Light State	Hazardous weather state that existed during the start of flight.
11	Preflight Mechanical Issue State	Hazardous state where the flight begins with a pre-existing mechanical problem with the aircraft
12	Preflight Pilot Hazardous Inferred State	**Inferred using grammar rules:** Hazardous preflight state of the pilot inferred when NTSB does not mention relevant state codes for an accident.
13	Physically Impaired/Incapacitated State	Hazardous preflight state where the pilot was impaired or incapacitated
14	Overconfidence/ Lack of confidence State	Hazardous state where the pilot demonstrated lack of/overconfidence in his/her/aircraft's ability.
15	Insufficient Qualification/Training/Lack of Experience or Familiarity State	Hazardous state where the pilot did not meet the qualification/training requirements to perform the flight
16	Fatigued/Overworked State	Hazardous state where the pilot was fatigued/overworked prior to flight.
17	Anxiety/Under Pressure State	Hazardous state where the pilot was anxious or under pressure while operating the aircraft
18	Poor Psychological State	Hazardous state where the pilot was in poor state of mind prior to the flight.
19	Low Fuel State	Hazardous state where the aircraft was operating with low fuel level.

Table 31: Descriptions for hazardous states

No.	State	Description
20	Low Oil State	Hazardous state where the aircraft was operating with low or improperly maintained/serviced oil level.
21	Low Hydraulic Fluid State	Hazardous state where the aircraft was operating with low or improperly maintained/serviced hydraulic fluid level.
22	Improper Supervision State	Hazardous state where the instructor failed to correctly supervise the student pilot.
23	Mental Overload State	Hazardous state where the pilot’s abilities are limited as he/she is overwhelmed mentally.
24	Unattended Aircraft State	Hazardous state where the aircraft is left unattended with the engines running.
25	Low Coolant State	Hazardous state where the aircraft was operating with low coolant level.
26	Low Grease State	Hazardous state where the aircraft was operating with low or improperly maintained/serviced grease level.
27	Poor Interpersonal Relations State	Hazardous state where the pilot has poor relations with his co-pilot/crew.
28	Controlled Flight into Terrain/ Object End State	Hazardous state where which an airworthy aircraft (under pilot control) is inadvertently flown into terrain, water, or an object.
29	Inflight Collision with Terrain/ Object End State	Hazardous state where the aircraft collided with terrain/water/object during flight.
30	Hard Landing End State	Hazardous state where the aircraft landing gear impacted the ground with great force.

Table 31: Descriptions for hazardous states

No.	State	Description
31	Forced/Emergency Descent/Precautionary Landing State	Hazardous state where the pilot is unable to choose the landing site and is forced to perform an emergency landing.
32	On-ground collision with Terrain/ Object End State	Hazardous state where the aircraft collided with terrain/water/object while operating on the ground.
33	Propeller Contact to Person End State	Hazardous state where rotating propeller blades contact a person, resulting in injuries.
34	Dragged wing End State	Hazardous state where the aircraft's wing is dragged along the ground/water.
35	Nose Down/Over End State	Hazardous state where the aircraft's nose contacts the ground/water/runway surface:
36	Midair Collision End State	Hazardous state where two or more aircraft collide during flight.
37	Ditching End State	Hazardous state where the crew makes a planned emergency landing in water.
38	Ground Resonance State	Hazardous state where the primary frequency of the main rotor is amplified by the stiffness (and frequency) of the landing gear, resulting in violent vibration of the helicopter.
39	Fire/Explosion End State	Hazardous state where the aircraft explodes or catches fire after impact with terrain/object.
40	Abnormal Runway Contact State	Hazardous state where the pilot failed to execute a correct landing (other than hard landing).
41	Pilot Incapacitated Inflight/Vision Clouded Inferred State	**Inferred using grammar rules:** This state represents when pilot's vision gets clouded or pilot is incapacitated inflight due to other hazardous states. This state generally leads to LOC state.

Table 31: Descriptions for hazardous states

No.	State	Description
42	Rollover End State	Hazardous state where the aircraft landing gear pivots about an object and exceeds the critical roll angle.
43	Disoriented/Lacking Awareness State	Hazardous state where the pilot fails to maintain the correct altitude/clearance from terrain or objects.
44	Wake Turbulence State	Hazardous state where the aircraft flew through the wake vortices of another aircraft.
45	Exceeding Aircraft Yaw Performance State	Hazardous state where the aircraft is operated beyond its design yaw performance capabilities.
46	Improper Turn/Bank State	Hazardous state where the aircraft exceeds its banking/roll performance during flight
47	Loss of Engine Power State	Hazardous state where an aircraft's engine loses its power.
48	System Failure State	Hazardous state where an aircraft's system(s)/component(s) have failed/malfunctioned.
49	Aircraft Stall/Spin State	Hazardous state where the lifting surfaces of an aircraft (i.e., wings or rotor blades) exceed a critical angle of attack they experience a loss of lift, and enter a stalled state
50	Lack of Visual Lookout/Distracted State	Hazardous state where the pilot failed to maintain visual lookout for terrain/other aircraft or was distracted.
51	On-ground Poor Weather State	Hazardous state where the pilot intentionally/inadvertently flew through poor weather on the ground.
52	Improper Go-around State	Hazardous state where the pilot did not perform a correct go-around.

Table 31: Descriptions for hazardous states

No.	State	Description
53	Exceeding Aircraft Performance Limits State	Hazardous state where the aircraft is operated beyond its design performance capabilities.
54	Exceeding Aircraft Takeoff Performance State	Hazardous state where the aircraft is operated beyond its design performance capabilities.
55	Exceeding Aircraft Landing Performance State	Hazardous state where the aircraft exceeds its design landing performance.
56	Exceeding Aircraft Crosswind Performance State	Hazardous state where the aircraft is operated beyond its design crosswind performance capabilities.
57	Wheels-up Landing State	Hazardous state where the pilot performs a landing without extending the landing gear.
58	Runway Undershoot State	Hazardous state where the aircraft landed short of the runway.
59	Runway Incursion State	Hazardous state where the aircraft entered runway incorrectly/without clearance
60	On-ground Loss of Control State	Hazardous state where the pilot fails to maintain control of aircraft heading and attitude when on the ground.
61	Improper Level-off State	Hazardous state where the pilot fails to bring the airplane to a level attitude (usually in preparation for a landing).
62	Improper Run-on Landing State	Hazardous state where the aircraft (rotorcraft) did not transition correctly from forward flight to landing.
63	Exceeding Design Stress Limits State	Hazardous state where aerodynamic loads on the aircraft exceed the design stress limits.

Table 31: Descriptions for hazardous states

No.	State	Description
64	Exceeding Aircraft Engine-out Capability State	Hazardous state where the aircraft is operated beyond its performance capabilities after the loss of engine power.
65	Runway Overshoot/Excursion State	Hazardous state where the aircraft departed the runway surface during takeoff or landing.
66	Improper power-on landing State	Hazardous state where the pilot performs an improper landing by maintaining the power to the engine during the descent and landing as opposed to cutting power to idle during the descent. Power-on landing is typically used for scenarios that need higher approach speed such as short-field or crosswind landing.
67	Severity of Accident/Pilot Injuries Inferred State	**Inferred using grammar rules:** This state represents pilot injuries or fatality or aircraft damage due to inadequate rescue or risk mitigating services. This is an end state.
68	Improper Spiral State	Hazardous state where the aircraft is in a steep descending turn in an excessively nose-down attitude and with the airspeed increasing rapidly.
69	Improper Takeoff State	Hazardous state where the pilot did not perform a correct takeoff.
70	Decompression State	Hazardous state where the pressure in the aircraft (cabin) decreases suddenly. Generally, this state happens with small aircraft at very high altitudes.
71	Personnel Physical Characteristics Limitation State	Hazardous state where the physical characteristics of the pilot/personnel hinders the flight performance
72	Personnel Sensory Ability/ Limitation State	Hazardous state where the sensory ability of the pilot/personnel hinders the flight performance

Table 31: Descriptions for hazardous states

No.	State	Description
73	Improper/ Incorrect Use of Braking Capability State	Hazardous state where the aircraft is operated with an improper braking capability or the pilot uses the braking incorrectly
74	Incorrect Use of Instrument Flight Capability State	Hazardous state where the instrument flight capability is incorrectly used
75	Improper Aircraft Configuration State	Hazardous state where configuration of aircraft is improper
76	Improper Circling Approach State	Hazardous state where the pilot initiates an improper circling approach
77	Exceeding Dynamic Load Capability State	Hazardous state where the dynamic load capability exceeded
78	Improper Landing Flare State	Hazardous state where the landing flare was improper
79	Loss of Tail Rotor Effectiveness (LTE) State	Hazardous state where the helicopter tail rotor does not provide the requisite thrust to maintain directional control.
80	Improper Physical Workspace State	Hazardous state where the physical workspace is improper or not suitable for proper functioning of the flight
81	Inadequate Operating Environment State	Hazardous state where the operating environment is not suitable for a safe flight
82	Aircraft Hydroplaning State	Hazardous state in which standing water, slush, or snow, causes the moving wheel of an aircraft to lose contact with the load bearing surface on which it is rolling with the result that braking action on the wheel is not effective in reducing the ground speed of the aircraft.

Table 31: Descriptions for hazardous states

No.	State	Description
83	Correcting Lenses not Worn State	Hazardous state where pilot has not used/worn correcting lenses as stated in the medical certificate
84	Vortex Ring State	Hazardous state where a rapidly descending helicopter’s main rotor blades are engulfed by a doughnut-shaped vortex, resulting in a loss of lift.
85	Emotional Reaction State	Hazardous state where pilot is not able to manage his/her emotional reactions in a particular situation
86	Expectancy State	Hazardous state where pilot made unjustifiable expectancy, the state of thinking or hoping that something, especially something pleasant, will happen or be the case.
87	Inflight Upset State	Hazardous state where the aircraft shows abnormal attitudes and/or over/under speed conditions. It mostly leads to a loss of control. (FAA: AC120-111) An airplane in flight unintentionally exceeding the parameters normally experienced in line operations or training: • Pitch attitude greater than 25 degrees nose up; • Pitch attitude greater than 10 degrees nose down; • Bank angle greater than 45 degrees; or • Within the above parameters, but flying at airspeeds inappropriate for the conditions.
88	Aircraft Structure Failure State	Hazardous state where the aircraft structure gets damaged, separates, or fails.
89	Improper Missed Approach State	Hazardous state where the pilot did not perform a correct missed approach
90	Water Loop/ Swerve State	Hazardous state where the aircraft underwent a water loop or a swerve

Table 31: Descriptions for hazardous states

No.	State	Description
91	Wheels-down Landing in Water State	Hazardous state where the aircraft landed with wheels down
92	Porpoising/ Pilot Induced Oscillation State	Hazardous state where sustained or uncontrollable oscillations occur resulting from efforts of the pilot to control the aircraft
93	Improper Formation Flying State	Hazardous state where a disciplined flight of two or more aircraft is operated improperly
94	Improper Taxi Speed State	Hazardous state where the aircraft has an improper taxi speed
95	Near Collision Between Aircraft State	Hazardous state where two aircraft almost avoided the collision with each other, also known as "near-miss"
96	Loss of Lift State	Hazardous state where the aircraft is unable to maintain the lift and stalls.
97	Improper Autorotation State	This state represents improper autorotation such as delayed autorotation.
98	Preflight Aircraft Hazardous Inferred State	**Inferred using grammar rules:** Hazardous preflight state of the aircraft inferred when NTSB does not mention relevant state codes for an accident.
99	Unknown Phase Loss of Control State	A hazardous state that involves an unintended departure of an aircraft from controlled flight regime (FAA, 2016).
100	Poor Physical Health/Fitness State	Hazardous state where the pilot is not physically fit or healthy to fly.
101	Improper Takeoff/Rotation Speed State	Hazardous state where the pilot fails to maintain correct takeoff/rotation speed during the flight.

Table 31: Descriptions for hazardous states

No.	State	Description
102	Improper Stall Speed State	Hazardous state where the pilot fails to maintain correct speed during the flight to avoid a stall.
103	Improper Climb Speed State	Hazardous state where the pilot fails to maintain correct speed during the climb.
104	Improper Landing Gear Operating/Extended Speed	Hazardous state where the pilot fails to maintain correct speed with landing gear extended.
105	Improper Minimum Control Speed with Critical Engine Inoperative State	Hazardous state where the pilot fails to maintain minimum speed when the critical engine malfunctions.
106	Improper Approach/Landing Speed State	Hazardous state where the pilot fails to maintain correct speed during approach or landing phase.
107	Improper Flaps Extended Speed State	Hazardous state where the pilot fails to maintain correct speed when the flaps are extended.
108	Improper Structural Speed Limits Exceeded State	Hazardous state where the pilot fails to maintain speed within the aircraft structural limits.

2. Trigger Descriptions

Table 32: Descriptions for triggers

No.	Trigger Name	Description
1	Improper Preflight Planning/Inspection Trigger	This trigger represents incorrect or insufficient planning or inspection by the pilot(s) before flight.
2	Inflight fire/explosion Trigger	This trigger represents fire/explosion that occurred during flight (before impact). Trigger defined after sequencing states.
3	Engine Shutdown Trigger	This trigger represents incorrect shutdown of an engine.
4	Inadequate Communication in Organization Trigger	This trigger represents improper or ineffective communication within the management.
5	Time spent in poor weather Trigger	**Inferred using grammar rules:** This trigger causes the system to move from a poor weather state to a disoriented/lack of awareness state.
6	Improper Compensation for Winds Trigger	This trigger represents the pilot’s improper compensation for winds during flight.
7	Improper Inflight Planning/Decision-making Trigger	This trigger represents incorrect planning or decisions taken by the pilot(s) during flight
8	Improper Maneuvering Trigger	This trigger represents sudden or incorrect maneuvering by the pilot during flight.
9	Improper Aircraft Handling Trigger	This trigger represents incorrect handling of the aircraft by the pilot, maintenance, or passenger.
10	Improper Use of Flight Controls Trigger	This trigger represents the improper use of flight controls by the pilot.

Table 32: Descriptions for triggers

No.	Trigger Name	Description
11	Insufficient Flight Advisories/ATC Services Trigger	This trigger represents insufficient flight advisories/ATC services by the ATC controller.
12	Improper Load Jettison Trigger	This trigger represents an improper jettison of external load by the pilot.
13	Failure of Aerial Application/External Load Equipment Trigger	This trigger represents the failure of external load equipment.
14	Control interference Trigger	This trigger impedes the pilot from controlling the aircraft.
15	Clipping of Object/Terrain Trigger	**Inferred using grammar rules:** This trigger represents clipping of an object or terrain during flight. I defined this trigger after sequencing states.
16	Clipping of Wing Trigger	**Inferred using grammar rules:** This trigger represents clipping of wing during flight that doesn't result in an end state (fire/ explosion). Trigger defined after sequencing states.
17	Clipping in Midair Trigger	**Inferred using grammar rules:** This trigger represents clipping of another aircraft during flight. Trigger defined after sequencing states.
18	Failure to Remove Aircraft Tie-down Trigger	This trigger represents failure of ground personnel or pilot(s) to remove a tie-down before flight.
19	Relinquishing Control Trigger	This trigger represents when the pilot gives up control of the aircraft.
20	Disturbance by Passenger Trigger	This trigger represents a disturbance/disruptive event for the crew/pilot.
21	Remedial Action Trigger	This trigger represents an improper or proper corrective action by the pilot.

Table 32: Descriptions for triggers

No.	Trigger Name	Description
22	Incorrect Action Selection Trigger	This trigger represents an incorrect choice made by the pilot to perform a particular action.
23	Improper Action (Unspecified) Performed Trigger	This trigger represents an unspecified incorrect action is performed by the pilot.
24	Incorrect Sequence of Actions Trigger	This trigger represents an incorrect sequence of actions taken by the pilot/maintenance personnel.
25	Delayed Action Trigger	This trigger represents delayed action by the pilot.
26	Lack of Action Trigger	This trigger represents no action taken by the pilot/maintenance personnel.
27	Forgotten Action/Omission Trigger	This trigger represents a missed/forgotten action by the pilot/maintenance personnel.
28	Incomplete Action Trigger	This trigger represents an action that the pilot/maintenance personnel failed to complete.
29	Unnecessary Action Trigger	This trigger represents an action that the pilot/maintenance personnel took an unnecessary action.
30	Improper Use of Procedure or Directives Trigger	This trigger represents situation where the pilot/maintenance personnel failed to follow or disregarded the specified procedure
31	Improper Use of Throttle/Powerplant Controls Trigger	This trigger represents incorrect use of throttle/powerplant controls by the pilot.
32	Impossible/reduced control authority after system failure Trigger	This trigger represents the situations where the pilot has limited or no control over the aircraft after the failure of critical flight control components

Table 32: Descriptions for triggers

No.	Trigger Name	Description
33	None/Failed Recovery Action after Loss of Control Trigger	**Inferred using grammar rules:** This trigger represents no action/failed attempt by the pilot to recover from an loss of control, and triggers an end state.
34	Improper Use of Weather/Wind Information Trigger	This trigger represents improper advisory of the weather/wind before or during the flight by ATC or dispatcher or improper use of the same by flight crew.
35	Fuel Contamination/ Exhaustion Trigger	This trigger represents fuel contamination or exhaustion
36	Door/Window Not secured/Damaged Trigger	This trigger represents the failure of doors/windows, and contamination of windows
37	Aircraft Powerplant Failure Trigger	This trigger represents the failure of aircraft powerplant and its components
38	Engine Failure Trigger	This trigger represents the failure of engine(s)
39	Improper Use of Aerial Application/External Load Equipment Trigger	This trigger represents the improper use of external load equipment.
40	Ignition System Failure Trigger	This trigger represents the failure of the ignition system
41	Engine Exhaust System Failure Trigger	This trigger represents the failure of the egine exhaust system
42	Improper Use of Aircraft Systems Component Trigger	This trigger represents when the pilot/flight crew improperly uses an aircraft systems component.
43	Reduction Gear Assembly Failure Trigger	This trigger represents the failure of the reduction gear assembly

Table 32: Descriptions for triggers

No.	Trigger Name	Description
44	Induction Air System Contamination/Failure Trigger	This trigger represents the failure or contamination of the induction air system
45	Oil System Failure Trigger	This trigger represents the failure of the oil system.
46	Compressor Assembly Failure Trigger	This trigger represents the failure of the compressor assembly
47	Combustion Assembly Failure Trigger	This trigger represents the failure of the combustion assembly
48	Turbine Assembly Failure Trigger	This trigger represents the failure of the turbine assembly
49	Accessory Drive Assembly Failure Trigger	This trigger represents the failure of the accessory drive assembly
50	Fuselage Failure Trigger	This trigger represents the failure of the fuselage and its components
51	Wing Damaged/Failure Trigger	This trigger represents the damage/failure of the wing and its components
52	Nacelle Failure Trigger	This trigger represents the failure of the nacelle and its components
53	Flight Control Surfaces/ Attachments Failure Trigger	This trigger represents the failure of fuselage/wing components.
54	Failure of Landing Gear Trigger	This trigger represents the failure of the landing gear and its components
55	Flight Control System Failure Trigger	This trigger represents the failure of the flight control system and its components
56	Stabilizer System Failure Trigger	This trigger represents the failure of the flight stabilizer system and its components

Table 32: Descriptions for triggers

No.	Trigger Name	Description
57	Electrical System Failure Trigger	This trigger represents the failure of electrical system components
58	Hydraulic System Failure Trigger	This trigger represents the failure of hydraulic system components
59	Navigation/Communication Instrument Failure Trigger	This trigger represents the failure of navigation or communication instruments
60	Failure of Deicing System Trigger	This trigger represents the failure of the deicing system
61	Fire Warning/Protection System Failure Trigger	This trigger represents the failure of the fire warning system.
62	Oxygen System Failure Trigger	This trigger represents the failure of the oxygen system.
63	Improper Use of Radar/Air Navigation Aids (NAVAID) Trigger	This trigger represents the improper use of the Radar/Air navigation aids (NAVAID) components
64	Insufficient Information/Steps Defined Trigger	This trigger represents the inadequate information or step taken by the pilot
65	Auto Flight System Failure Trigger	This trigger represents the failure of the autopilot/ flight system components
66	Air conditioning System Failure Trigger	This trigger represents the failure of the air conditioning system.
67	Indicating/ Recording System Failure Trigger	This trigger represents the failure of the indicating/ recording system.
68	Engine Assembly Failure Trigger	This trigger represents the failure of engine assembly components

Table 32: Descriptions for triggers

No.	Trigger Name	Description
69	Propeller System Failure Trigger	This trigger represents the failure of the propeller
70	Constant Speed Drive System Failure Trigger	This trigger represents the failure of the constant speed drive system
71	Engine Accessories Failure Trigger	This trigger represents the failure of engine accessories
72	Bleed Air System Failure Trigger	This trigger represents the failure of the bleed air system
73	Fuel System Failure/Contamination Trigger	This trigger represents the failure/contamination of the fuel system
74	Lubricating System Failure/Contamination Trigger	This trigger represents the failure/contamination of the lubricating system
75	Engine Installation Failure Trigger	This trigger represents the failure of the engine installation
76	Improper Functioning/Failure of Engine Instruments Trigger	This trigger represents the failure or improper readings from engine instruments
77	Cooling System Failure Trigger	This trigger represents the failure of the engine cooling system
78	Thrust Reverser Failure Trigger	This trigger represents the failure of the thrust reverser components
79	Turboshaft Engine Component Failure Trigger	This trigger represents the failure of turboshaft engine components
80	Improper Functioning of Meteorological Services Trigger	This trigger represents the improper functioning of meteorological services

Table 32: Descriptions for triggers

No.	Trigger Name	Description
81	Mixture Control Failure Trigger	This trigger represents the failure of the mixture cooling system
82	Oil Cooler Control Failure Trigger	This trigger represents the failure of the oil cooling system
83	Improper Functioning of Approach Aids Trigger	This represents the improper functioning or failure of approach aids
84	Failure of Air Navigation Aids (NAVAID) Trigger	This trigger represents the failure of the Air navigation aids (NAVAID) components
85	Aircraft Light Not Available/Failure Trigger	This trigger represents the unavailability or failure of aircraft lights
86	Failure of Radar Services Trigger	This trigger represents the unavailability or failure of radar services or coverage
87	Improper Use of Meteorological Services Trigger	This trigger represents the improper use of meteorological services
88	Improper Aircraft Rescue and Fire Fighting Service (ARFF) Trigger	This trigger represents the improper functioning or failure of ARFF services
89	Improper/ Lack of Anti-ice Additive Trigger	This trigger represents improper/ lack of anti-ice additive
90	Insufficient Synthetic Oil Trigger	This trigger represents starvation/ lack of synthetic oil
91	Improper Fuel Grade Trigger	This trigger represents incorrect type/ grade of the fuel
92	Improper Oil Grade Trigger	This trigger represents incorrect type/ grade of the oil

Table 32: Descriptions for triggers

No.	Trigger Name	Description
93	Exhaustion/Contamination of Aircraft Fluid Trigger	This trigger represents the improper use of miscellaneous fluids such as fuel additive, oil additive, anti-ice/de-ice, lavatory fluid.
94	Improper Maintenance Trigger	This trigger represents maintenance-related errors or violation
95	Vacuum System Failure Trigger	This trigger represents the failure of vacuum system
96	Pneumatic System Failure Trigger	This trigger represents the failure of pneumatic system
97	Water and Waste System Failure Trigger	This trigger represents the failure of water and waste system
98	Insufficient Procedure, Directives, or Resources Trigger	This trigger represents situations where the pilot(s) or maintenance personnel had procedures, directives, or manuals/resources that did not have requisite information.
99	Improper Use of Landing Gear Trigger	This trigger represents failure of the pilot extend/retract the landing gear.
100	Improper Use of Brakes Trigger	This trigger represents improper use of brakes of the aircraft
101	Improper Use of Fuel System Trigger	This trigger represents the improper use of the fuel system
102	Improper Use of Electrical System Trigger	This trigger represents the improper use of the electrical system
103	Improper Use of Deicing System Trigger	This trigger represents the improper use of the deicing system
104	Improper Use of Autopilot System Trigger	This trigger represents the improper use of the autopilot system

Table 32: Descriptions for triggers

No.	Trigger Name	Description
105	Improper Use of Emergency Equipment Trigger	This trigger represents the improper use of emergency equipment
106	Improper Use of Flight/ Communication/Navigation Instruments Trigger	This trigger represents the improper use of flight/ navigation instruments
107	Improper Weather Observation/Evaluation Trigger	This trigger represents improper observation of the weather by flight crew, ATC, or other personnel
108	Failure of Engine Starting Trigger	This trigger represents the improper use of engine starting or its failure
109	Failure of Turbocharging Trigger	This trigger represents the improper use or failure of turbocharging
110	Improper Aborted Landing/ Take off Trigger	This trigger represents the improper aborted landing or takeoff
111	Inadequate Facilities Provided by Organization Trigger	This trigger represents the inadequate facilities provided by the organization
112	Improper Design and Development of Aircraft Trigger	This trigger represents the inadequate design of an aircraft
113	Inadequate Information/ Conditions/Steps Listed Trigger	This trigger represents the inadequate information or conditions available to the pilot
114	Inadequate Aircraft Design Material Trigger	This trigger represents the inadequate design material of an aircraft
115	Inadequate Oversight/ Surveillance by Management/ Regulator Trigger	This trigger represents the lack of oversight by the management

Table 32: Descriptions for triggers

No.	Trigger Name	Description
116	Insufficient Standards/ Requirement Trigger	This trigger represents insufficient standards or requirements of aircraft or operator by the regulator or other organization
117	Inadequate Certification by Regulator Trigger	This trigger represents inadequate certification by the regulator or other organization
118	Inadequate Documentation/ Record-Keeping Trigger	This trigger represents the lack of record-keeping by the management
119	Cowl Flap Control Failure Trigger	This trigger represents the failure of the cowl flap control
120	Remedial Action Taken Inferred Trigger	**Inferred using grammar rules:** When the pilot takes a remedial action to get out of a hazardous state (recover from a hazardous situation)
121	Failure of Miscellaneous Airframe Component/ Hardware Trigger	This trigger represents the failure of miscellaneous hardware or airframe component
122	Miscellaneous Intentional Act Trigger	This trigger represents an unspecified intentional act by the pilot
123	Improper Communication Trigger	This trigger represents incorrect communication by the pilot/crew or ATC
124	Improper Air Traffic/ Operating Procedure Trigger	This trigger represents Improper Air Traffic/ Operating Procedure
125	Inadequate Pilot Training Trigger	This trigger represents inadequate pilot training.
126	Improper Enforcement by Organization Trigger	This trigger represents an organizational issue where enforcement such as regulatory requirements were improper by the organization

Table 32: Descriptions for triggers

No.	Trigger Name	Description
127	Inadequate Safety Program Trigger	This trigger represents an inadequate safety program by the FAA/ Regulator or Operator
128	Inadequate Management Culture Trigger	This trigger represents an inadequate work culture such as safety and operating practices by the management.
129	Inadequate Scheduling by Management Trigger	This trigger represents an inadequate task scheduling/ workload by the manufacturer of the aircraft
130	Unspecified Improper Task Performance Trigger	This trigger represents an improper task performance that is unspecified, by the ground/ flight crew, passenger, maintenance, or any other personnel
131	Failure of Accessory Gear Boxes Trigger	This trigger represents an improper use or wear/ corrosion or failure of accessory gear boxes of aircraft power plant
132	Unavailable Fire Protection System Trigger	This trigger represents where fire protection system is not installed or unavailable
133	Failure/Malfunction of Aircraft System Component Trigger	This trigger represents where a component of aircraft systems is not functioning properly
134	Engine Compartment Failure Trigger	This trigger represents the failure of the engine compartment
135	Pitot-static System Failure Trigger	This trigger represents the failure of the pitot-static system.
136	Warning/Safety System Failure Trigger	This trigger represents failure of the warning/ safety system
137	Mast Bumping Trigger	This trigger represents mast bumping (Rotorcraft)

Table 32: Descriptions for triggers

No.	Trigger Name	Description
138	Improper Canopy Jettison Trigger	This trigger represents improper canopy jettison.
139	Improper Use of Auxiliary Power Unit (APU) Trigger	This trigger represents the improper use/failure of the auxiliary power unit.
140	Improper Use of Miscellaneous Airframe Component/ Hardware Trigger	This trigger represents the improper use of Miscellaneous Equipment/ furnishings
141	Carburetor Heat Control Failure Trigger	This trigger represents the failure of the carburetor heat control
142	Malfunction of Cargo Compartment Trigger	This trigger represents malfunction of cargo compartment of aircraft
143	Tail strike Trigger	This trigger represents the tail striking an object or terrain.
144	Protective Gear/ Clothing Not Used Trigger	This trigger represents where the pilot does not use protective gear or clothing.
145	Improper Loading/Securing of Cargo Trigger	This trigger represents incorrect loading or securing of cargo by the pilot or ground personnel.
146	Leak/ Explosion of Hazardous Material (HAZMAT) Trigger	This trigger represents the fire/ leak or explosion of HAZMAT
147	Engine Tearaway Trigger	The trigger represents an occurrence in which one or more engines are torn away from an aircraft, but not due to contact with an external object.
148	Improper DF (direction-finding) Steer Trigger	This trigger represents improper direction-finding steer in the aircraft.
149	Not Recognizing Hazardous Condition Trigger	This trigger represents the crew not recognizing or heeding a hazardous condition/warning.

Table 32: Descriptions for triggers

No.	Trigger Name	Description
150	Improper Crew/Passenger Briefing Trigger	This trigger represents improper crew or passenger briefing.
151	Improper Crew Coordination Trigger	This trigger represents improper crew coordination.
152	Improper Use of Oxygen System Trigger	This trigger represents the improper use of oxygen system
153	Improper Use of Aircraft Lights Trigger	This trigger represents incorrect use of navigation lights by the pilot
154	Improper Ice/Frost Removal Trigger	This trigger represents the failure to remove ice/defrost components before flight
155	Pilot Assistance not Used/not Available Trigger	This trigger represents situations where the pilot does not seek proper assistance or did not have access to assistance
156	Improper Fuel Calculation Trigger	This trigger represents situations where the pilot does not correctly calculate the rate of fuel consumption during the mission
157	Improper Use of NOTAMs Trigger	This trigger represents situations where the pilot is not given sufficient NOTAMs or the pilot does not use NOTAMs correctly
158	Improper Use of Performance Data Trigger	This trigger represents improper use of the aircraft's performance capabilities data
159	Improper Refueling Trigger	This trigger represents improper refueling of the aircraft prior to flight
160	Flight to Alternate/ New Destination Trigger	This trigger represents when the pilot decided or disregarded to fly to an alternate destination

Table 32: Descriptions for triggers

No.	Trigger Name	Description
161	Poor Choice of Landing/Takeoff Area Trigger	This trigger represents a poor choice of landing/takeoff/taxi area by the pilot
162	Improperly Planned Approach Trigger	This trigger represents a poorly planned approach by the pilot
163	Improper Use of Available Runway Trigger	This trigger represents an improper use of runway
164	Unstabilized Approach Trigger	This trigger represents an unstabilized approach performed by the pilot
165	Use of Wrong Taxi Route Trigger	This trigger represents use of wrong taxi route
166	Use of Inappropriate Medication/ Drugs Trigger	This trigger represents use of inappropriate medication or drugs
167	Encounter with Jet/Propeller Blast Trigger	This trigger represents encounter with jet/ propeller blast
168	Improper Rescue/Search/ Evacuation Trigger	This trigger represents improper rescue, search and/ or evacuation.
169	Sabotage Trigger	This trigger represents sabotage before or during flight.
170	Improper Use of Inflight Briefing Service Trigger	This trigger represents the improper use of briefs/information received during flight
171	Inadequate Updating of Recorded Weather Information Trigger	This trigger represents the inadequate updating of recorded weather information by the pilot
172	Improper Decision Height Trigger	This trigger represents improper decision height judged by the pilot

Table 32: Descriptions for triggers

No.	Trigger Name	Description
173	Improper Minimum descent altitude (MDA) Trigger	This trigger represents where pilot does not maintain a minimum descent altitude
174	Improper Runway Alignment Trigger	This trigger represents improper runway alignment of the plane by the pilot
175	Central Maintenance Computer Failure Trigger	This trigger represents the failure of central maintenance computer
176	Improper Pull-up Trigger	This trigger represents an improper pull-up by the pilot.
177	Improper Recovery from Bounced Landing Trigger	This trigger represents an improper recovery from a bounced landing.
178	Improper Touch-and-go Trigger	This trigger represents an improper touch-and-go.
179	Improper Touchdown Trigger	This trigger represents an improper touchdown by the pilot.
180	Incorrect Unicom/ Not Selected Trigger	This trigger represents an incorrect unicom being operated or no selection of a unicom by the pilot.
181	Hot Start Trigger	This trigger represents when the aircraft exceeds the manufacturer defined limiting temperature for starting the engine.
182	Excessive Torque/P-Factor Trigger	This trigger represents when the torque or p-factor is excessive and is not corrected.
183	Inadequate/ Improper Reading of Visual Approach Slop Indicator Trigger	This trigger represents when the VASI system is inadequate or is misread by the pilot.
184	Improper Use of Flight Advisories/ATC Services Trigger	This trigger represents improper use or inadequate flight advisories.

Table 32: Descriptions for triggers

No.	Trigger Name	Description
185	No/Failed Recovery Action from Disoriented state Trigger	**Inferred using grammar rules:** This trigger represents no action/failed attempt by the pilot to recover from a disoriented state before a loss of control state.
186	Habit Interference Trigger	Trigger where pilot displays habit interference, that is new skills interacts with "old learning" or behaviors from past learning.
187	Improper Angle of Attack Trigger	Trigger where the angle of attack was improper
188	Improper Towing/Taxiing Trigger	Trigger where towing or taxiing of aircraft was improper
189	APU System Failure Trigger	This trigger represents failure of airborne APU system in aircraft systems
190	Engine Indicating System Failure Trigger	This trigger represents failure of engine indicating system
191	Water Injection System Failure Trigger	This trigger represents failure of water injection system
192	Aircraft Part Separated Trigger	This trigger represents when an aircraft part(s) separates from the aircraft before the end state of accident.
193	Terrain/Collision/Stall Warn Alert Trigger	This trigger represents when aircraft system alerts about terrain/collision avoidance or stall warning
194	Rotorcraft Flight Control System Failure Trigger	This trigger represents failure of rotorcraft flight control system or parts

3. Additional Information Descriptions

Table 33: Descriptions for information and pre-existing conditions

No.	Information/ Pre-existing Condition	Description
1	Unsuitable Airport Facilities Pre-Existing Condition	Pre-existing condition where the unsuitable airport and its facilities contributes to an accident.
2	Unsuitable Runway Pre-existing Condition	Pre-existing condition where the unsuitable runway condition contributes to an accident.
3	Unsuitable Terrain Pre-existing Condition	Pre-existing condition where the unsuitable terrain condition contributes to the accident.
4	Unsuitable Physical Environnent Pre-existing Condition	Pre-existing condition representing unsuitable physical environment for the flight.
5	Information about Object	This code contains detailed information about the specific objects that aircraft collided with during flight.
6	Information about accident event	This information provides more information about the accident event.
7	Information about terrain	This information provides details about the terrain where the aircraft was flying.

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VITA

Neelakshi Majumdar received her undergraduate degree in Electronics and Communication Engineering from Chitkara University, India, in 2014. After working as a programmer analyst at Cognizant for two years, she came to the U.S. to pursue higher education.

Neelakshi worked at the VRSS (Value through Reliability, Safety, and Sustainability) Lab at Purdue University under the guidance of Prof. Karen Marais for six years while pursuing her master's and doctoral degrees, with a concentration in aerospace systems and a minor in autonomy and control. Neelakshi's work on the role of human factors in aviation accidents and how training methods for General Aviation pilots can be improved was sponsored by the Federal Aviation Administration through the PEGASAS Center of Excellence.

Neelakshi also worked as an instructor of record for six years at Purdue University, where she taught two undergraduate-level courses, Design Thinking in Technology and Introduction to Aerospace Design. Neelakshi has been recognized for her research, teaching, and mentoring efforts through various awards, such as the FAA PEGASAS Outstanding Graduate Student Researcher Award, the Rising Stars in Aerospace, Purdue's School of Aeronautics and Astronautics Teaching Fellowship, and the Estus H. and Vashti L. Magoon Award for Excellence in Teaching.

During her six years at Purdue University, she has served in multiple organizations, such as the Purdue Summer Undergraduate Research Fellowship as a research mentor, Purdue Space Day, Aero Assist, and the Women in Engineering Program. Neelakshi is currently a student pilot with 71 flying hours. She plans to join academia to continue her passion for teaching and aerospace safety research.

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