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Abstract

TITLE: Analysis of Factors to Distinguish between Passenger and Cargo Air Carrier Accidents

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The purpose of the current study was to analyze a set of factors for their ability to distinguish between passenger and cargo air carrier accidents. This study utilized a historical dataset of air carrier accidents that occurred between 2002 and 2019 and identified common factors that were able to be categorized according to the theoretical SHELO model. This model, commonly used for analyzing human factors-related causation of aircraft accidents, was utilized to categorize accident factors in levels of the SHELO model, consisting of Software, Hardware, Environment, and Organizational Influences. Data analysis in the form of several logistic regressions revealed a significant effect for all four of these levels to be able to distinguish between passenger and cargo air carrier accidents. These significant factors helped to explain important causal differences between the accidents of these two types of operators, as well as provided a practical use for the SHELO model in analyzing air carrier accidents. The results of this study helped fill gaps within related literature on commercial aviation safety as well as identified areas for future research and recommendations for the air carrier industry.

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List of Abbreviations

ALPA: Air Line Pilots Association

ASN: Aviation Safety Network

ATC: Air Traffic Control

ATCA: Air Traffic Controllers Association

B737: Boeing 737

CAA: Civil Aviation Authority

CFIT: Controlled Flight into Terrain

CIS: Commonwealth of Independent States

FAA: Federal Aviation Administration

FMS: Flight Management System

GDP: Gross Domestic Product

HFACS: Human Factors Analysis and Classification System

IATA: International Air Transport Association

ICAO: International Civil Aviation Organization

IIC: Investigator-in-Charge

IRB: Institutional Review Board

LA: Latin America

LL: Log Likelihood

LOC: Loss of Control

ME: Middle East

NA: North America

NTSB: National Transportation Safety Board

SMS: Safety Management System

SOP Standard Operating Procedure

SARPS: Standards and Recommended Practices

Chapter 1

Introduction

Background and Purpose

Background

On August 14, 2013, a cargo air carrier flight operated by UPS Airlines crashed while on approach to landing in Birmingham, Alabama. The aircraft was destroyed upon impact with the ground, fatally injuring the captain and the first officer (NTSB, 2014). UPS Airlines Flight 1354 was the fourth fatal aircraft accident for a cargo air carrier in the United States between 2009 and 2013. Over the same time period, only one fatal commercial passenger air carrier accident occurred (Levin et al., 2013; NTSB, 2014). A similar disparity exists between accidents for global passenger and cargo air carriers. The Civil Aviation Authority (CAA) of the United Kingdom conducted a study that measured the rate of fatal accidents of several types of air carriers. Between 2002 and 2011, cargo air carriers suffered 8 times as many fatal accidents as passenger air carriers (CAA, 2013). Definitive reasons for the disparity in accident rates was not immediately apparent, but a comparison of the operations of passenger and cargo air carriers identified key differences that could have contributed to the frequency of fatal accidents. According to Levin et al. (2013), cargo air carriers fly into more dangerous airports than passenger air carriers do. The danger of these airports is in reference to the lack of safety equipment or infrastructure due to poor socioeconomic conditions. However, the crash of UPS Flight 1354 into Birmingham was not into a third world country, and the Birmingham Shuttlesworth International Airport was equipped with modern systems to help aircraft navigate to the airport even in unsafe weather conditions.

Levin et al. (2013) suggested that pilot fatigue was likely a causal factor in the accident of UPS Airlines Flight 1354. On December 21, 2011, approximately 2 years before this accident, a new set of regulations was drafted by the Federal Aviation Administration (FAA) to address the issue of pilot fatigue for air carrier operations. These regulations located under 14 C.F.R. §117 (2020) are worded so that they only address flight crew members and certificate holders of passenger operations. The FAA (2020) requires passenger air carriers to follow fatigue risk management, education, and awareness training programs. Flight crew members of passenger air carriers must undergo training on the effects of fatigue on pilot performance and countermeasures to prevent the onset of fatigue from interfering with the safe operation of an aircraft. If the pilot of a passenger air carrier has reported himself or herself as too fatigued to continue the assigned flight duty, the certificate holder must reassign another pilot to this flight. Flight crew members are also limited as to the length of the total flight time of an operation and have mandatory rest periods between operations. For example, flight crew members have a rest period of 30 consecutive hours within any 7-day scheduled work period.

Cargo air carriers are not mentioned within 14 C.F.R. §117 and therefore do not have to abide by these guidelines that protect against flight crew fatigue. The Air Line Pilots Association (ALPA) issued a statement that compared fundamentals of passenger to cargo air carrier operations. “Cargo pilots fly the same airplanes, over the same routes, in the same airspace, and into the same airports as passenger airlines. It’s time to apply these science–based rules to all airline pilots.” (ALPA, n.d.). ALPA continued by stating that 16 cargo air carrier accidents since the year 2000 were directly attributed to pilot fatigue.

Approximately 7 years before the UPS accident in Birmingham, Lacagnina (2006) published an article that compared the occupational safety of passenger to cargo air carrier operations. Over a 10–year period ranging from the mid–1990s to the mid–2000s, cargo air carrier operations were responsible for 14% of all air carrier operations that occurred within the United States. During a similar time period, cargo operations accounted for 21% of the air carrier accidents that resulted in at least one fatality (NTSB, 2010). Lacagnina identified key differences between the operations of passenger and cargo air carriers, beginning with the time of day in which the flights are conducted. Specifically, most passenger air carrier operations to take place in the daytime; however, cargo air carrier operations are conducted primarily at night. This can lead to issues with low–light conditions, which can be exasperated if the destination is an airport with inadequate safety and navigation systems. Cargo air carriers also, on average, conduct longer flights than passenger air carriers. This, combined with nighttime operations, can lead to a fatigued flight crew (Levin et al., 2013).

Lacagnina (2006) compared other operational differences between passenger and cargo air carriers. Cargo air carriers typically fly older aircraft, some of which have been converted from passenger to cargo aircraft. An older fleet of aircraft can lead to mechanical and reliability issues, as well as the need for a different type of maintenance program. Further, the aircraft used by cargo air carriers are designed to carry diverse types of payloads that can vary in size, weight, and loading requirements. Lacagnina described how cargo that has been improperly loaded without the knowledge of the flight crew can render an aircraft uncontrollable if this cargo were to shift too far forwards or backwards during the flight.

The growing body of aviation safety literature is largely void of any direct comparison of passenger and cargo air carrier accidents. In fact, only two studies have been identified that make this direct comparison, with only one of the two studies dedicated to understanding the factors that seem to distinguish the two types of air carriers. Kharoufah et al. (2018) conducted a review of the human-factors causations found in a set of commercial air transport accidents and incidents from 2000 to 2016. Kharoufah et al. classified the details of each event into 13 categories in order to analyze the relationship of the factors and accident or incident frequency. One of these 13 classifications compared cargo air carriers to other types of operations. The results of the study concluded that cargo air carriers suffer a disproportionally higher number of accidents and incidents than expected when considering the number of annual cargo flights. Kharoufah et al.'s findings suggest that cargo air carrier safety is still a concern in the modern aviation industry.

The only other study to focus on the comparison of passenger to cargo air carrier operations was Roelen et al. (2000). With the objective of quantifying the safety record of different cargo operations, Roelen et al. was able to compare the safety of passenger to cargo air carrier flights based on factors such as aircraft manufacturer, type of accident, and the phase of flight in which the accident occurred. Roelen et al. was one of the only studies to use location as a factor to compare the safety of passenger air carriers to cargo air carriers. Location was split into two categories: the global region in which an accident occurred and the state in which the air carrier was based. Although these findings helped differentiate passenger and cargo air carrier accidents, the most recent data within this study was from the year 2000. More recent air carrier accident data needs to be used to investigate modern passenger and cargo accidents and to see if the gap between these types of operations still exists.

A large gap exists in aviation safety literature regarding the comparison of passenger to cargo air carrier accidents. Only one academic study has been identified that focuses on the comparison of these two carriers, and this study is now over 20-years-old. In order to fill the gap identified within the literature, the current study expanded upon Roelen et al. (2000) and Kharoufah et al. (2018) by utilizing a more recent dataset of air carrier accidents and a more rigorous statistical analysis.

One strength of Roelen et al. (2000) that was incorporated into the current study was consideration of numerous factors that have been identified as potentially leading to the occurrence of an air carrier accident. Roelen et al. discussed many similarities and differences between passenger and cargo air carriers and discussed the possibility of each factor leading to an air carrier accident. These factors included aircraft manufacturer, phase of flight, and type of accident. However, Roelen et al. relied heavily on descriptive statistics associated with air carrier accidents, which lacked any type of rigorous inferential statistical analysis.

Kharoufah et al. (2018) did use a more rigorous statistical analysis to compare the accident rates of several types of operators to one another, including passenger and cargo air carriers. However, the comparison of the type of operator was one of several factors included within this study. Therefore, Kharoufah et al. did not focus on the factors that differentiate between passenger and cargo air carrier accidents.

The current study combined the substantial number of factors identified by Roelen et al. (2000) and the statistical rigor of Kharoufah et al. (2018). It should be noted that in neither of these studies were the flight crew of each air carrier accident the focus of the analyses. Analyzing the actions taken by the flight crew can be complicated and subjective due to the nature of investigating the human factors behind an aviation accident. This requires a researcher to infer what the flight crew's knowledge, perception, and understanding of the conditions of the flight leading up to the accident itself. Although past studies do exist that investigate the human-factors factors behind air-carrier accidents, this often requires complex coding and qualitative data analyses that was determined to be out of scope for the current study.

Instead, the focus of the current study was on the objective data from air-carrier accidents. Objective data includes details of the aircraft itself, the phase of flight in which the accident took place, the type of accident that occurred, and the location of the accident, amongst other factors. All factors identified within each air carrier accident was grounded in theory and categorized based upon a derivative of the SHEL model, established by Edwards (1972). This model has been used within aviation research before and was incorporated into the proposed study in a more modern form.

In summary, the discrepancy between the accident rates for passenger and cargo air carriers still exists within the commercial aviation industry but has not been extensively investigated. The current study is now among the limited number of studies in the field of aviation safety that focuses on identifying the factors that differentiate passenger and cargo air carrier accidents.

Purpose

The purpose of the current study was to identify factors that distinguish passenger from cargo air carrier accidents. A commercial air carrier is a company or organization that uses aircraft to transport passengers or freight. Most travelers are familiar with passenger air carriers as these are the airlines used for business and leisure travel. However, there are dedicated cargo air carriers that transport large quantities of freight or over–sized payloads. Passenger and cargo air carriers differ in key areas of their operations, such as the type of aircraft they fly and the time of day in which most of their flights are scheduled. Cargo air carriers have a disproportionally high rate of accidents per flight when compared to passenger air carriers (Lacagnina, 2006). The proposed study will analyze a set of targeted factors obtained from a dataset of air-carrier accidents to determine which factors can differentiate between passenger and cargo air-carrier accidents.

Definition of Terms

Key terms and phrases that were important to the current study are operationally defined as follows:

1. *Air carrier* is defined as an entity who undertakes directly by lease, or other arrangement, to engage in air transportation. Examples of an air carrier include an individual, corporation, company, or governmental entity (14 C.F.R. § 1.1, 2020).
2. *Air carrier aircraft* is defined as an aircraft that is being operated by an air carrier and is categorized as determined by the aircraft type certificate issued by a competent civil aviation authority (14 C.F.R. § 1.1, 2020).
3. *Aircraft accident* is defined as an aviation event in which a person is fatally or seriously injured, an aircraft sustains damage or structural failure requiring repair, or an aircraft is classified as being missing (ICAO, 2020). This term should not be confused with *aircraft incident* which is defined as any aviation event in which the safety of operations was affected; however,

does not meet the three aforementioned attributes of an accident. Aircraft incidents are considered out of scope for the purpose of the proposed study.

4. *Aircraft generation* is a categorical organization of aircraft based on technological advances in their design. There are four generations: first, second, third, and fourth, and each generation advances in engine performance and cockpit automation. First generation aircraft introduced the jet engine to air carrier travel and had limited cockpit automation. Second generation aircraft made slight improvements to both engine operation and cockpit automation. Third generation aircraft introduced electronic flight instruments into the cockpit in place of partial or full mechanical instruments. Fourth generation aircraft use sophisticated fly–by–wire technology in place of older, mechanical flight controls. (Tarnowski & Speyer, 1997; Airbus, 2019).
5. *Aircraft manufacturer* is defined as the company that originally produced an airplane used in air carrier operations. For example, Boeing and Airbus are the two leading aircraft manufacturers of air carrier aircraft used for the carriage of both passengers and cargo.
6. *Cargo air carrier* is defined as a commercial operation carried out by dedicated cargo aircraft, which by design or configuration, are operating exclusively for the transportation of cargo (IATA, 2020). An example of a cargo air carrier based within the United States is FedEx Express.

7. *Factors* are defined as major unplanned or unintended contributors to an accident. Often, they are a negative events or undesirable conditions that, if eliminated, could have prevented the accident, or reduced its severity, frequency, or likelihood of occurrence (AICHE, 2020). Examples of factors of an aircraft accident are low–light conditions and flight crew fatigue due to a flight being conducted at night.
8. *Controlled flight into terrain* (CFIT) is defined as the occurrence of an airworthy aircraft that is flown under positive control into an obstacle, the ground, or water with inadequate awareness from the flight crew (FAA, 2003).
9. *Domestic air carrier* is defined as an air carrier with a base of operations located within the United States of America. A domestic air carrier is not limited to conducting flights solely within the United States. The origin or destination of a domestic air carrier can be a location in another country.
10. *Environment* is defined as internal and external factors in relation to an aircraft. Example external factors include the weather and time of day; example internal factors include levels of noise and vibration.
11. *Hardware* is defined as physical attributes of a machine, equipment, or facilities used by employees (Edwards, 1972). Attributes of an aircraft include the manufacturer, age, and aircraft generation.
12. *International air carrier* is defined as an air carrier that has a base of operations located in any country other than the United States of America.

An international air carrier can conduct a flight that either originates or terminates within the United States.

13. *Location of accident* is defined as the geographic location in which an air carrier accident takes place.
14. *Location of operator* is defined as the geographic location in which an air carrier is based. Whether an air carrier conducts an operation domestically or globally, each carrier has only one main base of operations where the headquarters of their company is located.
15. *Loss of control* (LOC) is defined as an emergency in which an aircraft departs from normal flight but does not return to a normal flight attitude (FAA, n.d.). For example, an aircraft taking off could experience a situation where the cargo on board breaks free from its restraints and shifts towards the rear of the aircraft. This would cause the nose of the aircraft to pitch upwards, beyond the control of the pilots, and the aircraft could become uncontrollable as it rapidly loses speed and falls to the ground.
16. *Mechanical failure* is defined as the improper function or physical damage of an aircraft component, system, or structure during a flight (Roelen et al., 2000). If physical damage occurs, it is due to the failure of the aircraft part itself and not an external force.
17. *Organizational influences* are defined as factors that exist within the structure or operations of a company (Chang & Wang, 2009). Although the flight crew are front–line personnel that make decisions that can

immediately impact the safety of a flight, they are trained and influenced by upper management. Examples of organizational influences are regulations that govern the operation of an air carrier and the socioeconomic status of the country in which an air carrier is based.

18. *Passenger air carrier* is defined as a commercial operation carried out by dedicated passenger aircraft, which by design or configuration, are operating mainly for the transportation of passengers, but may transport a limited amount of cargo (IATA, 2020). An example of a passenger air carrier based within the United States is Delta Airlines.
19. *Phase of flight* is defined as one of the segments into which an air carrier operation can be split including takeoff, climb, cruise, descent, approach, landing, and ground operations (ICAO, 2004).
20. *Software* is defined as a supporting system that is available to employees. Components of this system include computer programs, checklists, manuals, publications, and standard operating procedures (Edwards, 1972).
21. *Time of Day* is defined as the time of day in which air carrier operations take place, specifically either during the daytime or nighttime. The FAA (2020) defines night as the time between the end of evening civil twilight and the beginning of morning civil twilight.
22. *Weight Factor* is defined as a condition in which freight is improperly loaded onto an air carrier aircraft or the freight comes lose during a flight and affects the aircraft's integrity or controllability (Roelen et al., 2000).

Research Questions and Hypotheses

Research Questions

The research questions that guided the current study are as follows:

RQ1. To what extent does the variable set related to the software level of the SHELO model distinguish between passenger and cargo air carrier accidents?

RQ2. To what extent does the variable set related to the hardware level of the SHELO model distinguish between passenger and cargo air carrier accidents?

RQ3. To what extent does the variable set related to the environment level of the SHELO model distinguish between passenger and cargo air carrier accidents?

RQ4. To what extent does the variable set related to the organizational influences level of the SHELO model distinguish between passenger and cargo air carrier accidents?

Research Hypotheses

The corresponding research hypotheses are as follows:

H1. When examined from a simultaneous perspective, the variable set related to the software level of the SHELO model is predicted to have a statistically significant influence on group membership in either passenger or cargo air carrier accidents.

H2. When examined from a simultaneous perspective, the variable set related to the hardware level of the SHELO model is predicted to have a statistically significant influence on group membership in either passenger or cargo air carrier accidents.

H3. When examined from a simultaneous perspective, the variable set related to the environment level of the SHELO model is predicted to have a statistically significant influence on group membership in either passenger or cargo air carrier accidents.

H4. When examined from a simultaneous perspective, the variable set related to the organizational influences level of the SHELO model is predicted to have a statistically significant influence on group membership in either passenger or cargo air carrier accidents.

Study Design

The current study utilized a causal-comparative design. This methodology was selected due to the nature of pre-existing air-carrier accident data that was used to identify factors to distinguish between passenger and cargo-carrier accidents. Specifically, a retroactive causal-comparative design was used as the group membership of passenger or cargo was represented in the single criterion variable used in all of the statistical analyses. This particular design was appropriate as the membership of passenger or cargo for each air carrier accident had already occurred.

Significance of the Study

The current study addressed the lack of attention given to the factors that can differentiate passenger and cargo air carrier accidents. Even though there are fewer daily cargo air carrier flights than passenger air-carrier flights, the frequency of cargo accidents is higher than passenger accidents. Although air carrier accidents are a rare occurrence, just a single accident can result in significant loss of human life and a major monetary loss of cargo and the aircraft itself. After any air carrier accident, it is common to see rules and regulations adopted to address the factors and preexisting conditions that contributed to the occurrence and severity of the accident. However, the crash of UPS Airlines Flight 1354 in 2013 only triggered a temporary interest in the disparity between the accident rates of passenger and cargo air carriers. Aviation regulations and operational differences between passenger and cargo air carriers has remained unchanged since this major accident occurred.

The current study also addressed the gap that exists within aviation safety literature. Only two empirical studies have been published that compared the factors of passenger to cargo air carrier accidents. Of the two studies that have been published, Roelen et al. (2000) provided a detailed comparison of the operations and characteristics that differentiate passenger from cargo air carriers. However, Roelen et al. lacked rigorous inferential statistics when comparing differences between these two types of air carriers. Kharoufah et al. (2018) provided a more recent analysis that compared several types of air carrier operations, including passenger and cargo. However, this comparison was made in the presence of several other types of air carriers that are not part of the scope of the proposed study. Kharoufah et al. also analyzed other factors that contribute to aircraft accidents and did not focus on the comparison of passenger and cargo.

The current study used all factors identified by Roelen et al. (2000) and Kharoufah et al. (2018) that were hypothesized to be able to differentiate between passenger and cargo air carrier accidents. This was followed by a rigorous statistical analysis to analyze the relationship between the targeted factors and the group membership criterion variable of passenger and cargo air carrier accidents. The targeted factors were organized according to the SHELO model. It should be noted that this type of theoretical grounding was absent from Roelen et al. and Kharoufah et al. By grounding the proposed study in a human factors theoretical framework like the SHELO model (Chang & Wang, 2009), an explanation of the relationship between the targeted factors and the dichotomous group membership variable supported the results of the statistical analysis.

The current study did not analyze the factors related to the liveware level of the SHELO model. Instead, the focus on software, hardware, environment, and organizational influences determined if there were other possible factors that could differentiate passenger and cargo air carrier accidents. The findings from the current study can be used to guide researchers in how to conduct follow–up research on the statistically significant levels of the SHELO model. Statistically significant factors categorized as software, hardware, environment, or organizational influences that can differentiate between passenger and cargo accidents should be analyzed more closely.

Limitations and Delimitations

Limitations

1. *Data collection method.* The dataset of air carrier accidents that was used within the current study was comprised of historical data. All of the data within this dataset were objective details about the conditions of the aircraft and flight before the accident occurred. However, any mistakes or inconsistencies in data collection after each individual accident occurred remained as errors within the historical dataset. There was no way to tell if an error existed within each final, published accident report.
2. *Missing Data.* Only data from final accident reports were collected for inclusion in the final dataset. However, accident details missing from any final accident report could cause unreliable results. If missing data was discovered, it resulted in an accident being removed from inclusion within the final dataset. Unlike continuous data, using the mean or median of surrounding datapoints is not an option for categorical data.
3. *Generalizability of certain predictor variables*. The data collection process used for the current study was limited to general accident factors available from the ASN database. Some of the accident factors selected, such as operator location, are too general to be easily generalizable to the target population. However, the selection for the predictor variables was

supported by previous studies that had had the same limitations in regard to accident data. For example, the variable, Location of Operator, was organized into geographic locations, each of which were made up of several countries. This variable represents how organizational influences, such as aviation regulations and socioeconomic factors can distinguish between passenger and cargo air carrier accidents. The recommendations based on the statistical significance of this variable cannot be directly generalized to the target population. Instead, recommendations would have to be made for future research to more closely analyze these factors and break them down into more specific variables.

4. *Accidents that occurred over international water.* Between the years 2002 through 2019, five accidents considered in-scope for the current study occurred over the Atlantic Ocean, Indian Ocean, Pacific Ocean, or Mediterranean Sea. These bodies of water are considered international territory, and therefore made it difficult to identify the location of an accident that occurred over these oceans or seas. In the context of the current study, the location of an accident that occurs over international territory will be the country that the aircraft departed from. Due to the extremely low number of accidents that occurred over these regions, the impact on the results of the current study is considered minor.

Delimitations

1. *Selection of the source for air carrier accident data.* The sole source of air carrier accident data selected for the current study was the Aviation Safety Network (ASN). The content, validity, and reliability of this source is described in detail in Chapter 3 of the current study. Although this source was determined to be reliable, valid, and inclusive of most if not all global air carrier accidents, other possible sources of data were excluded, thus limiting the accessible population of air carrier accidents. A passenger or cargo air carrier accident that was not investigated obtained by the ASN was excluded from the dataset used in the current study.
2. *Timeframe of air carrier accidents within the dataset.* The years 2020 and 2021 were excluded from the dataset used in the current study for two reasons. The first reason was that it is unlikely that a final accident report can be published within the same year as the occurrence of an air carrier accident. Although preliminary reports may be available, these can contain speculation as to the causes of the accident. Only final accident reports were used in the current study in order to ensure the validity and reliability of the data. The second reason for excluding air carrier accidents that took place in 2020 and 2021 was due to the unprecedented events of the COVID–19 global pandemic. This historical event caused a downturn in global passenger traffic. Passenger air carriers converted some of their aircraft into temporary cargo aircraft in order to generate as much revenue as possible

given the restrictions on passenger travel (Quayle & Checksfield, 2020). As a result, it would have been difficult to classify some air carrier accidents as passenger or cargo, which would have threatened the validity and reliability of the results.

3. *Selection of factors.* Only select data from each air carrier accident within the dataset were treated as factors for the analyses used in the current study. Certain factors found in final accident reports were excluded from inclusion in the current study due to several possible reasons, including difficulty in classifying the factor according to the SHELO model or a lack of supporting evidence as to how certain factors could have been used to differentiate between passenger and cargo air carrier accidents.
4. *Exclusion of air carrier incidents.* The dataset used within the current study did not contain any reports on air carrier incidents. This was due to the requirements for the investigation of an aircraft incident being different and less strict than those for an aircraft accident. Aircraft incidents do not involve the loss of human life, substantial property or aircraft damage, and a limited financial effect on the air carrier. Therefore, many air carrier incidents occur without a subsequent investigation, making the availability of data on all air carrier incidents scarce.
5. *Removal of liveware factor from SHELO model.* As discussed earlier within this chapter, the liveware component that would represent the actions of the flight crew per air carrier accident, was determined to be out of scope for

the current study. The purpose of the current study was to examine factors that could distinguish between passenger and cargo air carrier accidents that were not directly related to the actions of the flight crew. The removal of the liveware component was decided by the researcher due to the objective and limited data within the dataset that would not have been significant enough to examine a possible relationship between the flight crew and the distinguishing between passenger and cargo air carrier accidents.

6. *Removal of air carrier data based upon type of accident.* The following types of accidents were unsupported from previous studies or related literature on distinguishing between passenger and cargo air carrier accidents: ground operations or collisions (aircraft was standing or taxing), acts of terrorism (sabotage, hijacking, aircraft shoot-down, or attempted takeovers), mid-air collision, pilot error, fuel exhaustion, wildlife strike, fuel contamination, aircraft missing, and runway incursions.
7. *Exclusion of narrative data from the dataset.* All accident reports are written in narrative form. Analyzing all details within the narratives would have required coding and a standardized process for transforming narrative data into quantitative data. Given the availability of objective data for the targeted factors that was already in quantitative form, all narratives were excluded from data collection. Analyzing these detailed narratives would have required a qualitative approach that was out of scope for the methodology of the current study.

Chapter 2

Review of Related Literature

Introduction

This chapter is organized into three sections. The first section grounds the current study in the theoretical SHELO model, first proposed by Edward (1972) as the SHEL model and updated to its current form by Chang and Wang (2009). The second section provides a review of past research whose purpose it was to distinguish between passenger and cargo air carrier accidents. Some of the related studies did not have a purpose of focusing on only passenger and cargo, and instead focused on one specific factor that could be used to distinguish between these passenger and cargo accidents. The third and final section provides a summary of the related literature, as well as a discussion on the implications of the current study.

Overview of Underlying Theory

The proposed study theorized that factors of air carrier accidents can be categorized according to the SHELO model. The SHELO model consists of six levels: software, hardware, environment, liveware, and organizational influences. In the context of the current study, it was hypothesized that these factors, with the exception of liveware, contributed uniquely to the occurrence of an aviation event that results in severe damage or loss of life. Further, it was hypothesized that the SHELO model can be used to distinguish between passenger and cargo air carrier accidents. The following section provides an overview of the underlying theory that was used in the analyses of the factors.

Aviation Human Factors Frameworks

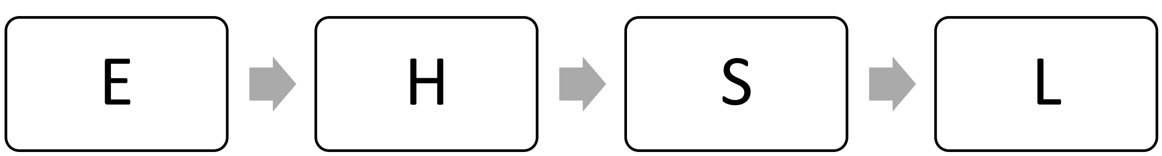
Research into aviation safety frequently focuses on factors that are related to human performance. In order to properly analyze aviation accidents, human error frameworks have been developed from theoretical models to help classify and compare these factors. The SHELL model, adapted from Edward's original EHSL model (1972), provides a framework surrounding an accident which facilitates back tracking from the accident to possible factors that contributed. By analyzing archival air carrier accident data, factors can be identified and classified according to the factors of the SHELL model.

SHELO Model

Edwards (1972) identified four factors that lead to aviation accidents: Environment, Hardware, Software, and Liveware (EHSL). He claimed that during the development of a new system, these factors were considered in a linear form. Each of the four factors directly influenced a single other factor in the following order: Environment, Hardware, Software, and Liveware (See Figure 1).

Figure 1

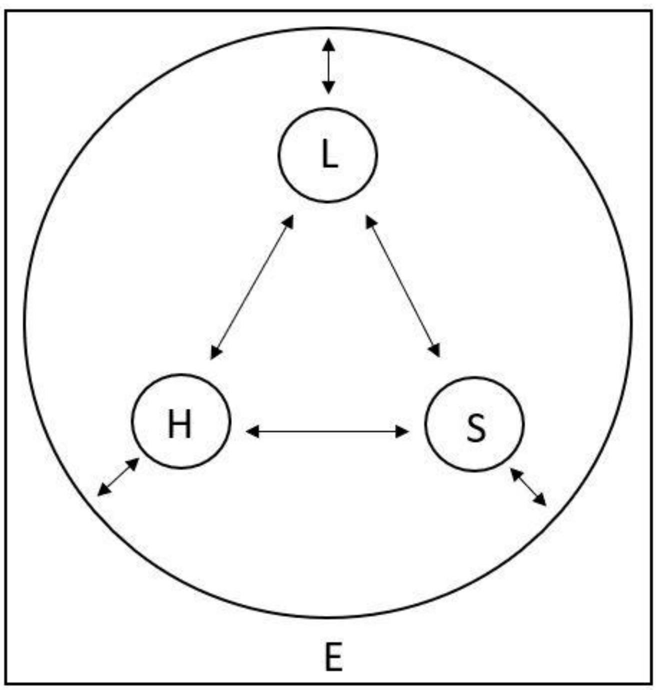
Linear SHEL Model



Edwards believed that this model was not adequate for use in analyzing accidents involving technologically advanced aircraft operating within the modern aviation environment. Instead, Edwards proposed a model with Liveware, Hardware, and Software all interacting with one another within a dynamic environment. This new model theorized that all factors interface with one another, rather than one factor leading to, or causing, another factor in a linear fashion (See Figure 2).

Figure 2

Updated SHEL Model with Interactions



For example, consider an accident in which an airplane runs off the end of a runway during landing. Several factors could be at play, including whether the aircraft was correctly configured for landing (Software), the condition of the brakes and tires (Hardware), the physical and mental conditions of the pilots (Liveware), and visibility based on the time of day (Environment). The linear EHSL model would try to pinpoint the error somewhere within a single factor. However, an analysis using Edward's refined model could categorize an overshoot as having several factors related to Hardware, Software, or Liveware errors. In the context of the aviation industry, Edward's new model became known as the SHEL model.

Edward's SHEL model went through several iterations as it was adapted for various accident investigations and human factors studies. For example, Hawkins (1993) created a variation that modeled the interaction of person–to–person relationships by adding a second Liveware factor. Thus, the SHELL model was used to describe interactions that a human being has in the workplace, including interactions with hardware, software, the environment, and other humans. However, the SHEL and SHELL models were insufficient at studying the effect of organizational influences on safety, which were identified by the International Air Transport Association (IATA) and the International Civil Aviation Organization (ICAO) as risks to the aviation industry. Organizational influences are a crucial factor in aviation safety when studying human performance. Actions taken by the management of a company can influence the safety and culture of all employees (ICAO, 1998). These actions can come in the form of participating in committees or programs that report and share data within the industry, developing rigorous training programs for pilots, and establishing safety management systems (SMS) for every commercial operator. At first, organizational influences were analyzed as a subset of the Environment factor and were not treated as a separate, independent factor (IATA, 2006). However, a recent study has classified organizational threats to safety into its own factor and expanded upon the SHELL model.

During an analysis of human risk factors associated with aircraft maintenance technicians, Chang, and Wang (2009) proposed a variation of the SHELL model that included organizational influences. The rationale behind adding this component was that Chang and Wang believed that errors made at the organizational or managerial level may be difficult for front–line personal to detect or control. An important distinction made by Chang & Wang regarding organizational influences is that managerial, political, and economic constraints could not be captured by the existing SHELL model, and a fifth factor would have to be added in order to analyze the relationship between these influences and a singular human being. By adding organizational influences as a fifth factor to the SHELL model, the SHELLO model became the most recent variation used in safety analysis. In the context of the proposed study, elements of the SHELLO model will be used to analyze historical aviation accident data in order to differentiate between the factors of passenger and cargo air carrier accidents. The components of the SHELLO model are described in more detail in the following sections.

Software. Software, within the context of the SHELLO model, includes supporting systems that are available to employees, such as computer programs, checklists, manuals, publications, initial or recurrent training, and standard operating procedures (SOPs) (ICAO, 1998). Variance in software can lead to human error in the aviation environment, which can ultimately lead to an accident (ICAO, 1998). For example, recency of pilot experience with the Software component, the accuracy of documents that support policy and procedure, and characteristics of these documents, such as format, presentation, vocabulary, symbology, and clarity, are all attributes of both computer programs and paper–based resources found in air carrier cockpits. Several systems in the cockpit, such as flight management systems (FMS), autopilot, fly–by–wire flight controls, and instrument displays require pilots to use a range of tools such as checklists, manuals, SOPs and initial or recurrent training.

There can be interactions between Software and other components in the model that contribute to accidents, such as hardware. Airbus (2019) classified aircraft dating from the 1950s through modern day into four generations, each of which progressed with respect to advances in technology within the cockpit. With each step of incremental progress in cockpit technology, aircraft hardware and software became more intimately linked. For example, in some later–generation aircraft, a computer system mediates the relationship between pilot inputs to the flight controls and the mechanical linkages with the control surfaces, to prevent the pilot from over–controlling the aircraft or creating a hazardous situation. These systems can be credited with helping to reduce human error in many cases; however, some accidents have resulted from a lack of pilot understanding of the functionality of these software systems.

The procedural side of Software is particularly important to the operation of air carrier aircraft. Pilots are trained to rely on checklists when entering separate phases of flight, and manuals or SOPs when faced with an abnormal situation. The National Transportation Safety Board (NTSB, 2001) released a report on an American Airlines accident in which a passenger aircraft overran a runway after the pilots landed in in poor weather. Not only did the pilots deviate from SOPs by deciding to attempt a landing during a thunderstorm, but the flight crew deviated from their before–landing checklist by missing a crucial step that configured the aircraft's spoiler (air brake) system. This accident was not solely caused by human error, but by a deficiency that prompted the airline to revise their company checklists. These types of checklists and SOPs are common among all air carrier operations, including both passenger and cargo. If the same type of aircraft is being operated between a passenger and a cargo air carrier, both will need to comply with similar checklists and SOPs. However, it is possible that the rate of non–compliance with Software elements such as SOPs differs between the two types of air carriers, potentially due to the organizational differences between passenger and cargo air carriers.

Hardware. In the context of the aviation domain, Hardware is often the primary focus in an accident investigation. This could be due to a part of the aircraft experiencing mechanical failure that led to the accident, or an error made by the pilot during an interaction with hardware in the cockpit. ICAO (1998) describes the Hardware component of the SHEL model as the physical attributes of machines, equipment, and facilities used by the employees. After an analysis of an industrial maintenance domain, Metso et al. (2015) added to their description of the Hardware component of the SHELLO model with tools, computers, buildings, or physical infrastructure. These components can contribute to aviation accidents in several ways. For example, Roelen et al. (2000) identified aircraft characteristics like age, manufacturer, and type and number of engines as differentiators between commercial and general aviation aircraft. Although rare, it is possible for Hardware to be the primary cause of an aviation accident. This could be due to a single defective piece of equipment that fails mid–flight, or an older aircraft that has been flown past its operational lifespan. According to Roelen et al., cargo air carriers often fly older aircraft that were retired from passenger service. If the average fleet age for cargo air carriers is higher than passenger air carriers, it is possible that variations in the condition of aircraft equipment could affect safety and lead to an accident.

There can also be interactions between Hardware and Liveware (human) components that contribute to accidents. The FAA (2020) regulates aircraft weighting over 12,500 pounds and aircraft powered by turbo–jet engines, requiring special pilot training and certification to operate these types of aircraft. It is common for a pilot to transfer between several types of aircraft throughout their aviation career, requiring new training every time this transfer occurs. Pilots must be able to adapt to new avionics in the cockpit whenever they are transferred to a new type of airplane. If there is a weakness in their training or they make an operational error while flying due to unfamiliarity with the aircraft's avionics, it is possible that an interaction between the Hardware and the pilots could lead to an air carrier accident. Previously discussed Hardware factors, such as aircraft age, can also interact with other factors of the SHELLO model, such as Environment, and contribute to causing air carrier accidents. Older aircraft are void of modern technologies that help automate processes for the pilot, such as more sophisticated autopilot systems and heads–up displays. The presence of these technologies may provide support for pilots, thereby reducing the risk of an accident. In the context of the proposed study, Hardware factors of air carrier aircraft involved in accidents were identified and utilized to determine their influence on accidents of cargo and passenger air carriers.

Environment. Environment, within the context of the SHELLO model, refers to factors both internal and external to the aircraft (ICAO, 1998). For example, temperature, light, noise, and vibrations are characteristics of an internal environment. Although aircraft hardware and software can vary between air carrier and manufacturer, the cockpit environment is relatively consistent between aircraft. Therefore, external environmental factors are more likely to act as differentiating factors with respect to air carrier accidents. These external factors include factors such as time of day, meteorological conditions, and the infrastructure of foreign airports and facilities.

Time of day is an important factor in aircraft accidents, and a potential differentiator between passenger and cargo air carrier accidents. Roelen et al.

(2000) explained how cargo operations are flown primarily at night, unlike most passenger operations. Flying aircraft at night introduces two concerns regarding the safety of the flight: the condition of the flight crew and the reduced outside visibility. Roelen et al. specified that flying primarily at night introduces physiological challenges to the flight crew. This would mean that most cargo air carrier operations are reliant on their crew members to be able to overcome fatigue and performance limitations associated with operating at night.

Night flying also involves a greater reliance on flight instruments, standardized arrival and approach procedures, and air traffic control (ATC) services. If these instruments are outdated or inoperative (software) or if ATC services are inadequate, it can affect the likelihood of an accident occurring. A lack of services by ATC can be due to a poor infrastructure from underdeveloped countries. Roelen et al. attribute a greater number of operations by cargo in underdeveloped countries as contributing to a poorer safety record compared to passenger air carriers. If a cargo pilot is conducting a nighttime flight into an airport located within mountainous terrain in an underdeveloped country, the pilot may be unable to rely on ATC services or sophisticated instrument procedures to aid him in approach and landing, resulting in a hazardous situation with an increased risk of an accident.

Lastly, hazardous weather is a danger to all types of air carrier operations. This weather can come in the form of reduced visibility, high winds, heavy rain or snow, icing, or other adverse conditions. Advancements in aircraft systems

(Software) and ATC services (Environment) can help pilots avoid flying into weather conditions that increase the likelihood of an accident occurring. For example, weather radar both onboard aircraft and built into airport surfaces can aid the flight crew in avoiding hazardous precipitation and turbulence. This would reduce the likelihood of an aircraft flying into weather that could threaten the safety of the flight. However, the misuse of this technology by an operational error by the flight crew (Liveware) or the absence of the technology due to poor infrastructure (Environment) could cause an aircraft to encounter unanticipated adverse weather.

Organizational Influences. Organizational influences make up the final component of the SHELLO model. After conducting a review of aviation accidents and incidents, Chang, and Wang (2009) found that emphasis of recent literature was placed on organizational–related factors instead of individual factors. Poor safety standards or socioeconomic conditions that influence the organizational or managerial level can affect the performance of front–line workers (McDonald et al., 2000). In the context of the aviation industry, the front–line workers are the flight crew while the organizational level includes the management of each air carrier. The corporate culture within an air carrier is also represented by the Organizational Influences level. Research analyzing an air carrier accident that focuses solely on the flight crew, void of consideration for organizational influences, may produce incomplete results.

In ICAO's Human Factors Handbook (1998), the political and economic constraints under which any aviation system operates were classified under the environment factor of the SHELL model. More specifically, these constraints were considered external environmental factors while the immediate work area (temperature, noise, and air quality) were considered internal environmental factors. Chang and Wang (2009) did not believe that organizational influences were a type of environmental condition and wanted to more accurately analyze these influences in comparison to other factors of the existing SHELL model. Organizational Influences became a new factor, separate from either type of environmental condition, which expanded the SHELL model into the SHELLO model.

When analyzing global air carrier accidents, Organizational Influences will differ between global regions. This is mainly due to differences in socioeconomic factors and aviation regulations. Although an in–depth comparison of aviation safety between individual countries is possible, it would require extensive research into the safety culture, regulatory compliance, and infrastructure of each country. However, it is possible to take a broader approach in comparing the effect of Organizational Influences separated by global region in order to distinguish between passenger and cargo air carriers.

Kharoufah et al. (2018) treated the location of an air carrier as one of the variables of interest in an analysis of aircraft accidents. A list of global regions was taken from a market outlook ranging from 2017–2036 (Boeing, 2017). Although this market outlook was provided by only one aircraft manufacturer, Boeing is the largest producer of air carrier aircraft in the world. Boeing identified seven global regions based on the number of aircraft they operate and the frequency of their operations. These regions included North American (NA), Latin America (LA), the Middle East (ME), Asia, the Commonwealth of Independent States (CIS), Europe, and Africa. Kharoufah et al. used Africa as an example of a global region that suffers from poor socioeconomic conditions with a high rate of air carrier accidents. A list of countries that are categorized under the global regions used in the current study can be found in Appendix A. After accessing data from the African Development Bank Group (2011), it was apparent that Organizational Influences such as lackluster aviation regulations, inadequate pilot training, and long hours for front–line workers were common for air carriers from this region. The African Development Bank Group determined that the safety implementation performance of every region in Africa is twice as low as almost every other global region. This is correlated with data from IATA (2006) where Africa suffered 4.31 aircraft accidents per every one million flights while the global average was as low as 0.65 per every one million flights.

A thorough analysis of all possible Organizational Influences across all global regions in terms of air carrier safety is out of scope for the proposed study. That type of analysis would require extensive data, which is unavailable within the historical air carrier accident dataset. However, much like the dataset used by Kharoufah et al. (2018), the location of the operator for each accident is available. Similarities in socioeconomic status, air carrier management, and aviation regulations are among the common factors between countries within each region.

As supported by Chang & Wang (2009), it would not be effective to analyze the causes of air carrier accidents if Organizational Influences were not considered.

Summary

Based on the purpose of this study as described in Chapter 1, the focus of this literature review is on the following four levels of the SHELO model: Software, Hardware, Environment, and Organizational Influences. The Liveware factor of the SHELLO model was not a focus for the current study, nor was the interaction between Liveware and all other factors. Therefore, the SHELLO model was adapted into the SHELO model. Several statistical analyses helped determine whether predictor variables classified as Software, Hardware, Environment, or Organizational Influences were able to distinguish between passenger and cargo air carrier accidents.

Review of Past Research Studies

The following review of past literature begins with select studies that have focused on significant factors for air carrier accidents. The lack of past research on the specific comparison of cargo to passenger air carrier accidents indicates that this is a gap in the literature. Next, select research on factors related to aviation safety will be reviewed to determine if these factors can distinguish between passenger and cargo air carrier accidents. Each of these factors was organized into the various levels of the SHELO model, followed by a discussion on how this theoretical model helped identify causal distinguish between passenger and cargo air carrier accidents. This section concludes with a summary, as well as implications for how the current study can address gaps found within related literature.

Comparison of Passenger and Cargo Air Carriers

To date, only three studies have been found that examine the difference in factors between passenger and cargo air carrier accidents. Only one of these studies examines, in detail, the safety performance of cargo air carriers. Roelen et al. (2000) quantified the safety record of various categories of cargo air carriers. This study was conducted in order to investigate claims that cargo air carriers suffer a disproportionally high number of accidents in comparison to their passenger counterparts. Roelen et al. collected data from the ICAO, including aircraft accident data beginning in the year 1970 and continuing through the year 2000. This dataset contained 606 accidents related to aircraft powered by jet engines, which make up nearly the entire fleet of passenger and cargo air carriers. The data was categorized based on factors related to the cargo air carrier industry that could explain the claim of a high frequency of accidents. Examples of these factors include average aircraft fleet age, aircraft manufacturer, time of day in which operations take place, geographic region of operations, and flights performed on a non–scheduled basis. Roelen et al. used accident rate as their dependent variable, and this was calculated by analyzing the number of accidents per million flights. Each cargo air carrier factor was analyzed by organizing the data into bar graphs and observing visual differences against a calculated accident rate. For example, if the factor being analyzed was aircraft manufacturer, companies such as Boeing, Airbus, and Antonov were compared on a basis of accidents per million flights. If there was a discernable difference between the levels of each factor, then the factor was identified as a major contributor to differentiating the causes of passenger and cargo air carrier accidents. One major limitation of Roelen et al. was that inferential statistics were not used. Instead, descriptive statistics were reported, with most of the findings being based on visual analysis of graphed distributions. Based on this analysis, Roelen et al. (2000) found that cargo air carriers often fly older aircraft, at nighttime, and with ad–hoc (non–scheduled) operations, which have a particularly high–risk profile. In addition, characteristics of both passenger and cargo air carriers were compared, including accident rates in different global regions, types of accidents, and the phase of flight in which the accident occurs. These categories and associated results will be discussed in more detail later in this review when each category is matched with the appropriate factor from the SHELO model. Several of the categories related to the cargo air carrier industry were used in the current study in order to help differentiate between passenger and cargo accidents. Although Roelen et al. identified several identifying factors between passenger and cargo air carriers, the current study incorporated these factors with newly acquired data. Further, Roelen et al. was limited to data collected through the year 2000. The current study expanded upon the findings of Roelen et al. by analyzing air carrier accident data from 2002 through 2019.

Roelen et al.'s (2000) investigation into cargo air carriers was expanded upon by Lacagnina (2006) who also focused on inconsistencies in the safety between passenger and cargo air carriers. Lacagnina's goal was to identify the major areas of weakness for cargo air carriers and how they compare to their passenger counterparts. This was driven by data that indicated cargo air carriers in the United States have an accident rate of 2–5 times higher than passenger air carriers (Roelen et al., 2000). In order to investigate the cause of this major difference in accident rate, Lacagnina acquired datasets from the FAA and the NTSB. These datasets contained the frequencies of U.S. air carrier accidents from the year 1996 through 2005. Lacagnina then separated the frequency of cargo–only accidents from the total number of accidents in order to determine what the proportion of U.S. air carrier accidents were associated with cargo air carriers. From the year 1996 through 2005, 63 of the 449 accidents (14 percent) involving U.S. air carriers were attributed to cargo air carriers. The remainder (86 percent) were attributed to passenger air carriers. Of these accidents, five of the 24 fatal air carrier accidents (21 percent) were caused by cargo air carriers, while passenger air carriers accounted for 79 percent.

Lacagnina (2006) performed a second analysis on the same dataset acquired from the FAA and NTSB. To achieve this, the data was organized to show the type of accident that had occurred, the type of operation, and whether it was a passenger or cargo air carriers in order to perform a direct comparison. A visual analysis of the graphed distribution of accident frequency organized by phase of flight revealed that cargo air carriers suffer a higher number of accidents during takeoff. The total number of loss of control accidents that occurred during takeoff accounted for 15%

of the total number of air carrier accidents from 1987 through 2000. Of these accidents during takeoff, cargo air carriers accounted for 9% and passenger air carriers accounted for 6%. Lacagnina speculated that this could be due to improperly loaded cargo. Cargo–specific accidents are most common for cargo air carriers compared to their passenger counterparts. Although passenger air carriers do carry a limited amount of cargo, this does not make up most of their payload of passengers and their baggage. Cargo air carriers rely on the carriage of heavy or sometimes dangerous materials that must be properly loaded onto their aircraft. Lacagnina provided several anecdotal examples of cargo air carrier accidents that were caused by non–adherence to cargo loading policies. One such example was the crash of a Fine Air DC-8 in 1997 which suffered a loss of control during takeoff. The crew had properly configured their airplane for takeoff based on how they believed the weight of the cargo onboard the aircraft was distributed. However, the cargo was not loaded according to the air carrier's instructions and the cargo was loaded too far towards the rear of the aircraft. Due to the flight crew not having any way to verify the correct loading procedure of the cargo, there was no way for them to anticipate this accident before the aircraft became airborne.

Lacagnina (2006) also identified aging aircraft as a major difference between passenger and cargo air carriers by providing statistics from ALPA. At the time of the study, 2006, the average age of passenger air carrier aircraft was 7 years, and the average age of cargo air carrier aircraft was 28 years. ALPA also claimed that older aircraft are often plagued by outdated technology, high maintenance requirements, a scarcity of spare parts, and the decline or absence of manufacturer support, all which stem from the operation of older aircraft. With cargo air carriers having average fleet ages significantly higher than passenger air carriers, this is yet another potential distinguishing factor between the two types of operations. All factors identified by Lacagnina (2006) were incorporated into the current study in order to distinguish between passenger and cargo accidents.

A third study was identified that included cargo air carrier operations as a predictor to aircraft incidents or accidents. Cargo air carriers were not the focus, however, Kharoufah et al. (2018), investigated aircraft accidents and incidents over several types of operators. The purpose of this study was to explore why 75% of aviation incidents and accidents can be traced back to human factors causations. Kharoufah et al. theorized that common variables, which can be treated as factors, can be used to identify human factors elements in aviation accidents. Two of Kharoufah et al.'s research questions are relevant to the proposed study: how are (human factors) causes distributed by type of operation in commercial air transport accidents, and how are (human factors) causes distributed by world region (both location of air carrier and location of occurrence) in commercial air transport accidents? Kharoufah et al. did not provide any research hypotheses as to the relationship between these targeted factors and the frequency of aircraft accidents or incidents. Although specific human factors factors were out of scope for the current study, the two factors identified by Kharoufah et al. were of interest.

Kharoufah et al. (2018) randomly selected 200 international air transport accidents in order to identify the principal human factor contributions behind each event and to observe trends within the air transport industry. The 200 accidents were selected from seven different databases, including the NTSB and ASN, which have been selected as the two additional sources of data for the proposed study. Kharoufah et al. read through narratives and details from each event within the dataset and extracted factors that contributed to an aircraft accident or incident. Any common factor across incidents and accidents was coded so that trends related to human factors could be identified. Like Roelen et al. (2000), Kharoufah et al. found aircraft manufacturer, geographic location of accident, and type of operator to be predictive of an aircraft incident or accident.

In order to statistically analyze trends found within the data, Kharoufah et al. (2018) used the Chi Square goodness of fit test. Each accident or incident factor was analyzed with respect to its frequency of involvement in aircraft incidents or accidents that involved human factors to determine if the frequency of aviation accidents or incidents could be explained by another factor. One of the factors identified by Kharoufah et al. (2018) was type of commercial operator. This factor was split into six types of commercial operators: air ambulance, low–cost–carrier, cargo air carrier, passenger charter, regional passenger airline, and full–service network passenger carrier. It was assumed that accident rates would have been evenly distributed between these types of commercial operators. After analyzing the distribution, it was found that cargo air carriers suffered a disproportionally higher accident rate than expected, $\chi 2(5, N = 200) = 194.6$, $p = .05$. Kharoufah et al. was able to reject the null hypothesis of no difference between the types of commercial aviation operations and the frequency of aircraft accidents and incidents. It was expected that cargo air carriers would suffer approximately 10 human factors related incidents or accidents between the years 2000 to 2016. However, cargo accidents suffered approximately 25 incidents or accidents, which is disproportionally higher than the expected frequency based on the number of operations conducted by cargo air carriers.

Kharoufah et al. (2018) provides some explanation of the higher–than–expected frequency count for cargo air carriers, including that cargo air carrier flights primarily occur at night and that cargo carriers lack established safety programs. The proposed study will leverage Kharoufah et al.'s findings by utilizing the variables identified to differentiate cargo air carrier accident factors and expand upon these causes by analyzing additional predictor variables that can differentiate causes of passenger and cargo air carrier accidents. Although "type of commercial operator" was the only factor directly focused on differentiating between passenger and cargo air carriers, other factors within Kharoufah et al.'s study, including global region where the accident took place, phase of flight, aircraft manufacturer, and the type of accident that occurred, were categorized in accordance with the SHELO model and utilized as predictor variables.

Relevant Predictor Variables Categorized by the SHELO Model

The three studies cited above introduced relevant methods and aircraft accident factors that helped define the scope of the current study. These factors included aircraft generation, aircraft manufacturer, global region in which the accident occurred, time of day, phase of flight, and the type of accident. All factors were analyzed for their effect on distinguishing between passenger and cargo air carrier accidents. These factors were grounded in the four selected levels of the SHELO model: software, hardware, environment, and organizational influences. The following section reviews past research that has examined the impact of similar factors within these categories on aviation accidents in order to better understand the current set of factors as well as identify possible additions to the set.

Software. The first factor in the SHELO model is software, and this includes supporting systems that are available to pilots while conducting a flight. Software is a broad and somewhat difficult factor to define, but in the context of the proposed study, any checklist, manual, SOP, or computer program is considered a piece of software. Four variables that are relevant to this study have been identified in related literature to be closely related to software: phase of flight, accidents that were categorized as CFIT, accidents categorized as LOC, and accidents that involved a weight factor. Due to the format of the accident data that was available for the current study, it was not possible to discern if individual accidents were caused by a failure to effectively use checklists, manuals, or SOPs. However, accidents that occurred during certain phases of flight, were categorized as CFIT or LOC, or accidents that involved a weight factor are often the result of a flight or ground crew member not adhering to published procedures, navigational maps and charts, or checklists to ensure the aircraft is properly configured for safe flight (FAA, 2003). Human error caused by failed or improperly used software is discussed in detail below.

Phase of Flight. Any flight, regardless of the type of aircraft or type of operation can be split into major phases. These phases include takeoff, climb, cruise, descent, approach, landing, and ground operations, as defined by ICAO (2004). Each of these phases incorporates varying levels of software to aid the flight crew in conducting a safe flight. Examples of software available to the flight crew include checklists and SOPs to manage aircraft configuration and engine settings, charts, or maps to aid in aircraft navigation, and assistance from air traffic control to further aid in aircraft navigation and separation from other aircraft. Both passenger and cargo air carriers utilize SOPs and checklists to confirm their aircraft is properly configured as it enters a new phase of flight. Navigational charts are also used to ensure the aircraft remains on its approved flight route. Studies, such as Kharoufah et al. (2018), Lacagnina (2006) and Roelen et al. (2000) have shown that passenger and cargo air carriers differ in accident frequency across various phases of flight.

Phase of flight was a factor investigated by Kharoufah et al. (2018) in the study discussed above that examined human factors in aircraft accidents. Two hundred commercial incidents and accidents were analyzed based on the phase of flight in which each event occurred. These phases included takeoff, initial climb, enroute, approach, landing, and taxi. It was assumed that each phase of flight would have an equal number of accidents that have occurred if the flight crew was able to use their software as per their training and company policy. However, the distribution of event frequencies on phases of flight showed a higher number of accidents and incidents occurring in the cruise, approach, and landing phases compared to the takeoff, climb, and taxi phases. A Chi Square test was used to statistically compare the expected distribution of accidents across the major phases of flight verses the observed distribution found within the dataset. Results of the Chi Square test were significant at the 95% confidence level, $\chi 2(5, N = 200) = 292$, $p = .05$, indicating that accidents occurred at different rates within each phase of flight. For example, the cruise phase of flight had fewer accidents compared with the takeoff or landing phases.

Kharoufah et al. then assessed the distribution of accidents within each phase. Any phase of a flight that took place on the ground, such as when an aircraft is taxiing on the surface of an airport, was removed from the analysis. This was due to aircraft speed being relatively low, thus not capable of causing a major accident. The observed frequencies for the takeoff, climb, and cruise phases of flight were higher than the expected frequencies. In contrast, observed frequencies for the approach and landing phases were lower than the expected frequencies. Although Kharoufah et al. did not go into detail as to why differences exist between all phase of flight except for ground operations, it was concluded that the distribution of accidents across the major phases of flight is not uniform. Other studies expanded on this finding by incorporating type of operation into the analysis of accidents occurring within various phases of flight.

In Lacagnina's (2006) investigation of why the accident rate of cargo air carriers was higher than the rate of passenger accidents that was discussed above, the researcher used phase of flight as a factor, but eliminated low–risk events, such as ramp accidents during the ground operations phase, similar to the procedure used by Kharoufah et al. (2018). Descriptive statistics were used to compare the percentage of passenger accidents compared to the percentage of cargo air carrier accidents for each of the major phases. Cargo air carriers had a disproportionally higher percentage of accidents that occurred during takeoff (9% compared to 6% for passenger air carriers), and passenger air carriers had a higher percentage of accidents that occurred during approach and landing (16% compared to 3% for cargo air carriers). No detail was provided as to why accident rates associated with phase of flight varied between passenger and cargo air carriers, but Roelen et al. (2000) provides insight to the accidents that occur within specific phases that can be used to differentiate between types of carriers. The Roelen et al. study discussed above visually analyzed a graphed distribution of several types of accidents and found that cargo air carriers suffer a disproportionally higher number of accidents in the takeoff and climb phase, with one potential cause being the incorrect loading of cargo that disrupts the aircraft's balance during these phases. These findings support the data provided by Lacagnina, who also found that takeoff and climb accidents were more common for cargo air carriers than passenger air carriers. It was unclear as to why passenger air carriers suffered more accidents during approach and landing compared to cargo air carriers. Accident phase of flight was incorporated into the current study as a Software factor to distinguish between passenger and cargo air carrier accidents.

Accidents categorized as CFIT or LOC. CFIT and LOC are two types of accidents that can be the result of similar factors such as a loss of situational awareness or high workload environments. CFIT is defined by the FAA (2003) as occurring when an airworthy aircraft is flown under the control of a qualified pilot or flight crew that results in a collision of terrain, water, or obstacles with inadequate awareness on the part of the pilot as to the impending collision. The FAA (n.d.) references LOC as an emergency when an aircraft departs from normal flight and does not return to a normal flight attitude. Both CFIT and LOC accidents can be traced back to incorrect or inadequate uses of software available to the flight crew (ICAO, 1998). In order to avoid colliding with terrain while the aircraft is at a low altitude, pilots are trained to use aeronautical charts that define where their route of flight should be. If used properly, these charts can help pilots avoid hazards that are sometimes made invisible by low visibility. A LOC accident can occur as a result of flying into adverse weather conditions or when the aircraft is in a state of low energy when close to the ground, such as on takeoff or landing. Aircraft are typically at low airspeeds and do not have enough altitude to recover from an event that renders their aircraft temporarily uncontrollable. The FAA (n.d.)

has required pilots operating under Part 121 to undergo training that would help them avoid or correct actions that could cause their aircraft to lose control, as per a written notice to all U.S. air carriers. These recovery procedures are often created and published by aircraft manufacturers or airlines and are considered supporting software to the flight crew. A failure to adhere to these procedures can result in a LOC situation that ends in an accident.

In Lacagnina's (2006) study discussed above, two accident types were found to have large discrepancies between frequencies of passenger versus cargo air carrier accidents. Lacagnina found that although both passenger and cargo air carriers suffer a high number of LOC accidents, passenger air carriers suffer a higher number of LOC accidents during the approach and landing phases (16% for passenger air carriers compared to 3% for cargo air carriers) and cargo air carriers suffer a higher number of LOC accidents during takeoff (9% for cargo air carriers compared to 3% for passenger air carriers). This is proposed to be due to failure to adhere to SOPs when loading cargo, which is a unique problem for cargo air carriers; a factor that will be discussed later in this review. If an aircraft is not properly configured for each phase according to the checklists and SOPs, this can lead to LOC.

A second type of accident identified by Lacagnina (2006) that can be used to differentiate between passenger and cargo air carriers is CFIT. CFIT occurs when an aircraft that is under proper control of the flight crew impacts level ground, water, or higher–elevation terrain (FAA, 2003). If the aircraft was under proper control before impacting terrain, it is likely that the aircraft became lost or deviated from its intended route of flight. This can be due to a failure to follow proper SOPs, checklists, or instructions by air traffic control. In Lacagnina's analysis of accidents, passenger air carriers suffered a disproportionally higher number of CFIT accidents than cargo air carriers did. No explanation is given as to why this difference exists between carriers, but CFIT was included along with LOC as Software factors to distinguish between passenger and cargo air carrier accidents.

Weight Factor. In the Roelen et al. (2000) study discussed above, one type of accident analyzed was "cargo related." Roelen et al. defines this as any accident caused by cargo coming lose and shifting around inside of an aircraft that led to a loss of control that was not due to pilot complacency, but instead due to the cargo that was loaded improperly. Also, if the cargo onboard an aircraft caused crew incapacitation, it was included under this category. Examples of hazardous cargo can be anything that produces toxic fumes or flammable material that caused an in–flight fire. Cargo air carriers suffered a noticeably higher percentage of cargo–related accidents compared to passenger air carriers. This is expected, as the payload of cargo air carriers is entirely made up of freight or large individual objects. The payload of passenger air carriers can include some smaller cargo or mail, but it is predominantly made up of huma passengers and their personal belongings. Although the higher percentage of cargo related accidents occurring from cargo air carriers is not surprising, other studies have given reasons as to why cargo air carriers suffer these types of accidents in the first place.

Returning to Lacagnina (2006), reasons for cargo related mishaps are given during a discussion on load verification. Ground personnel that load freight and large objects onto cargo aircraft may have to work under adverse and demanding physical conditions while adhering to specific schedules. Lacagnina also lists a lack of licensing requirements for cargo–handling companies and personnel as another cause for cargo–related mishaps. Although the flight crew is ultimately responsible for the proper weight distribution within their aircraft before takeoff, there is no practical way to determine if their airplane is unbalanced. There is also little a flight crew can do from the cockpit if a large piece of cargo gets lose and shifts its location. This could render the aircraft uncontrollable, with “cargo–related factors” given as one of the leading factors that led to the accident. The FAA (2015) has released guidance for cargo air carriers to properly load cargo onto an aircraft and ensure that it is secured in such a way as to prevent an in–flight shift in weight. Advisory Circular 120-85A serves as a guide to all U.S. cargo air carriers and provides information that was unavailable before 2015. The guidance found within this document could help prevent cargo air carrier accidents from occurring due to improperly loaded cargo.

Hardware. In the context of the SHELO model, Hardware is defined as the physical attributes of a machine, equipment, or facilities used by employees. In the context of the proposed study, Hardware pertains to the aircraft involved in an accident and any device or tool used by the pilot on the flight deck.

Several related studies have identified specific examples of hardware failures that have led to an aircraft accident. One example is aircraft generation, which is a categorical variable based upon when certain cockpit technology was implemented into an aircraft's design. With each new generation, aircraft automation has improved while the maintenance costs and reliability has improved compared to older generations (Roelen et al., 2000; Lacagnina, 2006).

Aircraft manufacturer is another important variable when analyzing Hardware. Each manufacturer has their own design and building process for their aircraft, and data supports varying levels of safety and reliability across manufacturers.

The last variable related to Hardware is any accident that was attributed to a mechanical failure. This means that an investigation into an aircraft accident revealed that a mechanical component of the aircraft failed and caused the pilots to lose control or caused catastrophic structural damage to the aircraft. Several related studies were selected based on their analyses of these Hardware variables and how they can be used to differentiate between passenger and cargo air carrier accidents.

Aircraft Generation. The Roelen et al. (2000) study discussed above performed an analysis comparing the accident rate per million flights between passenger and cargo air carriers, across three different aircraft generations. The definitions of the three generations of aircraft were based on a study by Tarnowski

& Speyer (1997), with each successive generation having safety–related technologies within the aircraft becoming more advanced. The first generation of commercial aircraft represented aircraft in which the jet engine was relatively new and cockpit automation was limited. An example of a first–generation aircraft is the Douglas DC-8; an aircraft that is no longer used by most passenger air carriers but is still used as a cargo aircraft. The second generation of aircraft included more advanced engines with improvements to cockpit automation and navigational aids. Examples of these aircraft include the Boeing 737-200 and the Airbus A-300. Neither of these aircraft are widely used by modern passenger air carriers but both continue to serve as cargo aircraft. The third generation introduced electronic flight instrument systems as well as a new focus on human factor aspects within the cockpit. Examples of third–generation aircraft include the Boeing 737NG and the Airbus A320 family. It is common to find third–generation aircraft in both passenger and cargo air carrier fleets.

Roelen et al. compiled air carrier accident data into frequencies based on aircraft generation. The frequencies of the air carrier accidents were measured in the number of accidents per million flights. For example, a frequency of 4.25 would represent just over four air carrier accidents for every one million air carrier flights. Cargo air carriers had a higher frequency of accidents for all three aircraft generations when compared to passenger aircraft in the same generation. First generation aircraft had a much larger discrepancy between cargo air carriers (5.24 accidents per million flights) and passenger air carriers (2.43 accidents per million flights) compared to second generation aircraft (1.53 accidents per million flights for cargo, 1.13 accidents per million flights for passenger) and third generation aircraft (1.41 accidents per million flights for cargo, 0.48 accidents per million flights for passenger). Roelen et al. concluded that the gap between passenger and cargo air carrier accident frequencies is closing with each new generation of aircraft. This is due to technological advancements on newer aircraft that can enhance a pilot's situational awareness and improve safety for both passenger and cargo air carriers. However, the large gap between carriers for first–generation aircraft are likely due to cargo air carriers keeping a higher number of older aircraft in their fleet, increasing the exposure time of these aircraft as they are kept in service longer than an aircraft for passenger operations. The lack of advanced safety equipment in the cockpit, scarcity of spare parts, and decreased manufacturer support for older aircraft may all contribute to a higher accident frequency for these first–generation aircraft.

There has been a new generation of aircraft manufactured since the first three generations identified by Tarnowki & Speyer (1997). The fourth generation, identified by Airbus (2019), introduced fly–by–wire systems to help reduce loss–of–control accidents. Examples of fourth–generation aircraft include the Boeing 787 and Airbus A350. The fourth generation of commercial aircraft was missing from Roelen et al.'s (2000) analysis between passenger and cargo air carriers. Aircraft generation, including the newest fourth generation, was included as a factor in the current study to determine if the difference between passenger and cargo air carrier accidents is distinguished by these successive generations.

Older generation aircraft pose an additional risk to aviation safety outside of pure mechanical issues. Research has indicated that noise and vibration experienced by pilots operating older aircraft may contribute as well. Lee & Kim (2018) conducted a study in order to investigate the issue of flight crew fatigue in all types of commercial operations. Lee & Kim were interested in the effect of crew scheduling on pilot fatigue, which was split into three categories: physical fatigue, mental fatigue, and lack of rest. A study was performed in order to survey pilots on their behavior before and after flights as well as their perception of the environmental condition of the cockpit during their flight. In total, 929 survey responses were collected from airline pilots, approximately 19% of the nationwide airline pilot population in Korea, which enabled Lee & Kim to identify several factors that can lead to flight crew fatigue. Lee & Kim hypothesized that inadequate crew scheduling, which did not allow for proper duration or frequency of rest for flight crews, would result in a negative effect on pilot fatigue.

The results of the surveys showed that approximately 20% of their respondents indicated that they had worked for cargo air carriers in the past while approximately 13% indicated they currently work for cargo air carriers. Lee & Kim (2018) then identified common responses to causes of fatigue within their sample. These became predictor variables that included flight direction, crew scheduling, partnership, aircraft environment, job assignment, and ethnic differences, which together had a statistically significant effect on physical fatigue ($R^2 = 0.223$) and a significant effect on mental fatigue ($R^2 = 0.174$). The issue of crew scheduling is discussed further in factors related to the external environment. However, the condition of the internal cockpit environment is a Hardware factor.

Lee & Kim (2018) included aircraft environment as one of their predictor variables after respondents indicated that high noise or vibration levels in the cockpit can lead to greater amounts of mental and physical fatigue. Some of the outdated technology of early–generation aircraft include less soundproofing to the aircraft's cabin as well as older, louder jet engines. With each successive aircraft generation, engine, and cockpit noise–proofing technologies improve so that noise levels and vibrations are kept to a minimum. The benefits of these advancements include lowering flight crew fatigue and maintaining situational awareness. (Gander et al., 1998). Older generation aircraft, which are commonly used by cargo air carriers, may not have been upgraded to include these technologies. This suggests that the older aircraft more commonly used by cargo air carriers may be more likely to cause crew fatigue than newer generation aircraft more commonly used by passenger air carriers.

Aircraft Manufacturer. Kharoufah et al.'s (2018) study discussed above examined whether aircraft manufacturer was a significant factor. Kharoufah et al. performed a Chi Square test comparing the number of accidents per aircraft manufacture across 13 manufacturers. It was assumed that all aircraft manufacturers would have similar accident rates based on the number of aircraft from each manufacturer currently in operation. For example, Boeing is the world's largest aircraft manufacturer based on how many aircraft are built annually. It is expected that they will have the highest accident frequency based on a high number of Boeing aircraft in operation. A much smaller manufacturer, such as Canadair, would have a lower accident frequency due to a smaller number of annually produced aircraft. The result was a significant difference in accident frequency across manufacturers ($\chi 2(12, N = 200) = 292, p = .05$). In Kharoufah et al.'s analysis, aircraft manufacturers Boeing and Airbus had the highest frequency count of incidents and accidents compared to all other manufacturers. However, the observed frequency of events was much lower than the expected frequency. At first, this can be explained by the fact that Boeing and Airbus are the world's two largest commercial aircraft manufacturers and that their high accident frequencies are due to the high number of their aircraft that are currently in operation compared to other manufacturers. However, the importance of Kharoufah et al.'s findings have to do with the comparison of the number of accidents expected from each manufacturer compared to the number of accidents that have actually occurred. Even though Boeing and Airbus have accident frequencies of approximately 5 times that of the other manufacturers, far fewer accidents have occurred compared to what was expected. This can be attributed to high reliability and quality of Airbus and Boeing aircraft, or excellent maintenance by their operators. In comparison, certain manufacturers based in the CIS or manufacturers that are no longer producing aircraft have higher observed frequencies than expected frequencies.

Kharoufah et al. (2018) provides several reasons as to why a significant difference exists in the safety record of various aircraft manufacturers. The three manufacturers with the largest lead in observed incidents and accidents over expected events are Tupolev, Ilyushin, and Antonov. All three of these manufacturers have produced a fraction of the number of aircraft compared to Airbus and Boeing. A smaller number of aircraft in circulation means a lack of availability of aircraft parts and few destinations where these aircraft can be maintained or upgraded to meet more modern safety standards. Kharoufah et al. states that these types of aircraft are often used in commercial fleets for third world countries, or by various cargo air carriers. The current study categorized aircraft manufacturer based on region and used this variable as a factor in to distinguish between accidents of both types of carriers.

Mechanical Failure. Roelen et al. (2000) also analyzed several types of cargo air carrier accidents and how they compared to the same types found in passenger air carrier accidents. Two of the types of accidents in the sample distribution were “component/system failure” and “structural failure.” Both types of accidents are some forms of mechanical failure of the aircraft itself. This could have been due to the age, or wear–and–tear on the aircraft, or it could have been due to poor maintenance. Roelen et al. found that passenger air carriers have a much higher frequency of component/system failures compared to cargo air carriers. Inversely, cargo air carriers have a much higher frequency of structural failures. Roelen et al. provided no explanation as to why these two types of mechanical failures are different between the two carriers. However, due to the average age of cargo aircraft being higher than passenger aircraft, it is possible that the cargo aircraft suffer long–term corrosion and metal fatigue that can lead to structural failure. It is unclear why passenger air carriers would suffer a higher number of individual component failures. The occurrence of a mechanical failure that led to a passenger or cargo air carrier accident was included as a factor in the final analysis.

In order to better understand how mechanical failure can affect aircraft safety, MacLean et al. (2003) investigated the relationship between aircraft age and the number of failures it experiences throughout its operational life. An aircraft is a complex machine with mechanical and electrical systems, each having its own expected life length. MacLean et al. wanted to create a prediction model of the number of failures an aircraft will experience based on its age. In order to quantify the number of mechanical failures, Maclean et al. tracked the number of unscheduled landings it experienced. It was theorized that if an aircraft suffered a significant mechanical failure in flight, it would have to make an unplanned landing at a time or location that was different than the planned flight.

MacLean et al. (2003) was able to access two databases of air carrier data, provided by AlgoPlus and Avsoft. The AlgoPlus database provided details on unscheduled landings, while the Avsoft database provided records on departures and flying hours for North American air carriers. MacLean et al. limited their study to one particular aircraft: the Boeing 737 (B737). The rationale behind selecting this single aircraft is that it has a large fleet in operation for passenger and cargo air carriers. A total of 142 B737s were selected, and these data points were organized into a time series ranging from the years 1990 through 1992 and analyzed visually through three distribution plots.

The first plot compared aircraft age (ranging from 0 to 15 years) to the number of departures. A visual analysis of the time series plot for aircraft age on the number of departures showed that aircraft were not being used less as they age. The same aircraft are also not kept out of service for repair as they age. MacLean et al. cited the FAA in stating that the decision to operate older aircraft was an economic decision, not a safety issue. However, the prospect of keeping an older aircraft in "like new" condition is not likely as this would require frequent repairs and greater lengths of time out of service for older aircraft.

However, the second time series plot, which compared the average age of aircraft to the number of unscheduled landings had a different distribution. There was a slight increase in the number of unscheduled landings as aircraft age increased. MacLean et al. then fitted a regression model to test the hypothesis that the number of mechanical failures (unscheduled landings) increases with aircraft age. Two targeted predictor variables were used, the number of times that an aircraft is returned to service after any scheduled or unscheduled maintenance while not being repaired to an "as good as new condition" and the age of an aircraft measured between each repair (implying "as good as new" aircraft have an expectation of increasing failures with age). These two predictor variables were tested for predictability against the criterion, the number of mechanical failures (unscheduled landings). The overall model was significant ($F = 28.58$, $p < 0.0001$). This supported the hypothesis that aging aircraft suffer a higher number of mechanical failures (unscheduled landings) than newer aircraft do. MacLean et al. then analyzed the coefficients for the two targeted predictor variables. The number of incomplete repairs increasing with aircraft age was significant ($T = 6.22$, $p < 0.0001$) and the aircraft's condition deteriorating to less than "good as new" between repair cycles was significant ($T = 3.45$, $p < 0.001$).

MacLean et al. (2003) concluded that age has a statistically significant effect on the number of mechanical failures (unscheduled landings) experienced by air carrier aircraft. The aircraft's conditions deteriorate with age even with scheduled preventative maintenance. Older aircraft, even when properly maintained by air carrier maintenance personnel, will suffer a higher frequency of mechanical failures. As discussed earlier in Lacagnina (2006), cargo air carriers have an average fleet age of almost 4 times higher than that of passenger air carriers. Due to the unavailability of data on specific aircraft age and the findings of Roelen et al. (2000), aircraft age was represented as "Aircraft Generation" in the current study. Aircraft generation was used as a predictor in the Hardware level of the SHELO model to distinguish between passenger and cargo air carrier accidents.

Environment. Environmental factors can play a role in causing a commercial aviation accident. These factors come in the form of light, visibility, and the terrain over which an aircraft is flying. Key environmental differences exist between passenger and cargo air carriers. Examples of these differences include time of day and location of occurrence. Flights that occur during nighttime introduce two hazards that are not as common during daytime operations: flight crew fatigue due to abnormal sleep schedules and reduced outside visibility. Location of occurrence refers to the location in which an aircraft accident has occurred. CFIT accidents, which were discussed earlier in this section, are common in areas with hazardous terrain. Whether the terrain was featureless, such as an extended flight over desert or water, or if it was over a mountainous area, airports located in different environments pose various levels of risk to the safety of an aircraft attempting to takeoff or land at these locations.

Time of Day. A differentiating factor between passenger and cargo air carriers is the time of day in which their operations take place. Roelen et al.'s (2000) data on air carrier operations revealed that half of cargo air carrier operations take place at night, compared to only a fifth of passenger operations that occur at night. Roelen et al. also highlighted a possible factor between nighttime flight and the physical conditions of the flight crew. Specifically, operations during early hours can lead to fatigue and being less alert while operating the aircraft. Although Roelen et al. cited evidence that fatal accident rates are doubled at nighttime compared to daytime operations was provided, no distinction was found between passenger and cargo air carriers.

Kharoufah et al.'s (2018) study, discussed above, used data from the Air Line Pilots Association (ALPA) in order to support their findings that the observed rate of cargo air carrier incidents and accidents was higher than the expected rate. According to Kharoufah et al., data collected from various studies and shared with ALPA showed that cargo pilots working night shifts lose about two hours of sleep per day, leading to a total deficiency of greater than eight hours by the end of the week, suggesting pilot fatigue is a potential differentiating factor. This data is supported by a study from NASA that examined the physiological effect of a lack of sleep on the flight crew of cargo airlines.

Gander et al. (1996) from the NASA Research Center examined the psychophysiological responses to overnight cargo operations. This study involved 41 cargo pilots who had their sleep patterns and behaviors analyzed using observation and self–report measures. During each flight, a trained observer from NASA was present in the cockpit and each participating pilot wore a biomedical monitor that measured core body temperature, average heart rate, and average activity of the non–dominant wrist. Participants self–reported habits outside of the cockpit, such as length and quality of sleep, diet, medications, illness, and exercise. The study found that overnight cargo operations involve more physiological disruption than daytime operations due to shorter sleep episodes and sleep patterns that appeared to be more broken. For example, individual sleep episodes on duty days (M = 4.56 hours) were significantly shorter than on no–duty days (M = 8.09 hours; $t = 10.76$, $p < 0.0001$). Pilots who tried to sleep during the daytime in order to accommodate their cargo schedules averaged 3.1 hours less sleep than pilots who slept during the nighttime. This was explained by the fact that nighttime cargo pilots must take rest during daylight hours, which is unnatural compared to the normal sleep habits of most passenger pilots.

A more recent study by Lee & Kim (2018), discussed above, identified factors that affect airline pilot fatigue. These factors included flight direction, crew scheduling, partnership, aircraft environment, job assignment, and ethnic difference had a statistically significant effect on physical fatigue ($R^2 = 0.223$) and a significant effect on mental fatigue ($R^2 = 0.174$). Crew scheduling and job assignment are both closely related to the time of day in which cargo operations take place: predominantly at night, in comparison to the daytime operations of passenger air carriers. The findings from Lee and Kim helped to reinforce the inclusion of time of day as a factor within the current study.

Location of Accident. In the context of the current study, "location of accident" was the global region in which a passenger or cargo air carrier accident takes place. In Kharoufah et al.'s (2018) analysis of human-factors factors in aviation incidents and accidents, the location of each accident or incident was analyzed using a Chi Square test. Seven global regions were identified by Kharoufah et al.: Asia, Africa, CIS, Europe, LA, ME, and NA. An eighth global region, Oceania, was included in the current study due to its usage by the ASN. It was expected that accident rates across these global regions would be consistent when controlling for the frequency of commercial aviation operations. The difference between the expected frequency of incidents and accidents was statistically significant compared to the observed or actual frequency, $\chi 2(5, N = 200) = 34.0$, $p = .05$. Kharoufah et al. was able to reject the null hypothesis of no difference in the location of an accident on the frequency of aircraft accidents or incidents.

The frequency of accidents within a certain global region was not of primary concern to the study, as a higher number of flights within a region would inflate the frequency of incidents and accidents occurring. The more relevant feature within the distribution was the number of expected incidents and accidents compared to the observed (actual) frequency that occurred. Although NA had the highest frequency of accidents occur within its region, the expected frequency was higher than the observed frequency. This comparison was also true for LA, ME, and Asia. Europe's expected and observed incident and accident frequencies were approximately equal. Africa was the only global region with an expected frequency noticeably lower than the observed frequency count. This indicates that more incidents and accidents are occurring within Africa, independent of the fact that fewer flights occur within the region compared to other, larger global regions. The global region in which an air carrier accident has taken place was included as a factor in the proposed study in order to distinguish between passenger and cargo air carrier accidents.

Roelen et al. (2000) conducted a nearly identical analysis of a distribution of commercial aviation accidents across six global regions but compared distributions of passenger to cargo air carrier accidents. Africa, Asia, NA, and South America all suffered higher frequencies of cargo air carrier accidents compared with passenger accidents per million flights for each type of carrier. The highest accident frequencies, by far, were suffered by Africa (16.79 cargo accidents per million flights compared to 3.69 passenger accidents per million flights) and South America (9.02 cargo accidents per million flights compared to 2.12 passenger accidents per million flights). This indicated that these regions may have internal factors related to higher number of accidents. Roelen et al. cited low Gross Domestic Product (GDP) within these regions as a plausible explanation. The competitiveness of the international aviation market can lead to cost–cutting measures that reduce safety to a low priority. This often takes the form of poor airport infrastructure within a country, with air traffic control, operational maintenance and training, and facilities or equipment often being outdated or underdeveloped. Regardless of the nationality of the airline flying into an underdeveloped country, each airline must work with the technology and infrastructure at an airport. While passenger air carriers prefer to fly into larger cities with more developed airport infrastructure, the same cannot be said for all cargo air carriers. Some cargo air carrier flights involve the delivery of cargo to remote areas with little to no passenger traffic. In addition to flights to remote or under–developed areas, cargo air carriers having a higher frequency of nighttime flights compared to passenger air carriers, this further increases the reliance on adequate air traffic control and air navigation facilities (Roelen et al., 2000). A further discussion on GDP is covered later in this review when considering Location of Operator as a factor.

Organizational Influences.

Location of Operator. In the context of the current study, Location of Operator, can be defined as the global region in which a passenger or cargo air carriers is certified. The location of the accident may or may not have occurred within the same state in which the operator is based.

In Kharoufah et al.'s (2018) study, the location of the airline operator for each accident or incident was analyzed with a Chi Square test. The same eight global regions used for to categorize accident location were used to categorize the location of an operator. They hypothesized that frequencies of accidents across these global regions would be consistent when controlled for the number of flights that occur within each region. For example, NA air carriers have some of the highest annual air traffic frequencies, and therefore it is expected that the frequency of air accidents from North American air carriers would also be higher than other global regions. However, NA air carriers are known to have a relatively low accident frequency due to the low average age of their aircraft and the level of aviation regulations and safety standards. The Chi Square test was statistically significant at the 95% confidence level, $\chi 2(6, N = 200) = 36.8$, $p = .05$, for expected versus observed accident counts. Kharoufah et al. was able to reject the null hypothesis of no difference between the state of the commercial operator and the frequency of aircraft accidents and incidents was rejected.

The expected and observed frequencies for NA, LA, Europe, and the CIS were approximately equal. The expected frequency of accidents and incidents for Asian and the ME operators were higher than the observed accident frequency, indicating that both Locations of Operation had a lower frequency count of events than previously thought. However, Africa was the only Location of Operation that had a noticeably higher number of observed accidents and incidents compared to what was expected. Kharoufah et al. (2018) supports the findings with a statement from the African Development Bank Group who stated that below standard aviation safety records since 2000, in combination with week regulations, dangerous working conditions, and long hours lead to more frequent incidents and accidents. In addition to numerous African airlines being banned from flying into certain European countries due to safety concerns, IATA identified Africa as a region in need of infrastructure and technology enhancements to increase the safety records of their airlines (IATA, n.d.).

Other properties of Africa as an operator location of both cargo and passenger air carriers were identified by Enomoto & Geisler (2017). An analysis of plane crashes in 68 countries controlled for the effects of Hofstede's power distance scores, number of flights, GDP, and severe weather conditions. GDP and Hofstede's power distance scores are tools that can be used for the differentiation between passenger and cargo air carrier accidents related to global region. For the purpose of the study in discussion, a power distance score describes how various cultures view relationships between superior and subordinate individuals. A high–power distance score indicates that individuals accept unequal distributions of power, while those with low power distance scores often question authority figures and decisions that affect subordinates (Hofstede, 2001). Enomoto & Geilser identified Africa as one of three global regions where collectivist societies limit individualism and individual achievement. It was also previously discussed that Africa's low GDP can lead to poor maintenance of aircraft and airport infrastructure, as well as lower–quality training and education of the flight crew. The final regression model that incorporated the previously mentioned factors was statistically significant ($R^2 = 0.921$, $p < 0.05$). The results indicated that the number of flights and the accident frequency had a direct relationship. GDP and accident frequency had an inverse relationship, as expected. The lower the GDP, the higher the accident frequency due to flight crew training and the maintenance on aircraft operating within different global regions. Lastly, individualism and accident frequency had an inverse relationship. The lower a country's collective individualism, the higher the accident frequency. The findings from Enomoto & Geilser helped support the inclusion of Location of Operator, being a factor of interest within the current study.

Summary and Study Implications

As discussed in this chapter, only a select number of authors have focused on the safety concerns of cargo air carriers and how they compare to the safety of passenger air carriers. Roelen et al. (2000) conducted the most in–depth comparison of passenger to cargo air carriers. Several comparisons were done between common factors of both types of carriers, such as aircraft manufacturer, aircraft generation, types of accidents, and accident phase of flight. Roelen et al. used descriptive statistics to illustrate to readers that cargo air carriers have an accident rate of 3 times higher than comparative passenger air carriers due to the operation of older aircraft, operations being conducted primarily at nighttime, and differing accident rates amongst key global regions. Lacagnina (2006) also emphasized the key differences that exist between the causations of passenger and cargo air carrier accidents, including identification of nighttime operations and aging aircraft as differentiators. Neither Roelen et al. nor Lacagnina provided inferential statistics to support their conclusions. In comparison, Kharoufah et al. (2018) used inferential statistics to review the human factors causations in commercial air transport accidents and incidents. However, Kharoufah et al. did not focus on the safety of cargo air carriers. Instead, just one of several Chi Square analyses was used to compare cargo to several other types of operations, including passenger air carriers. None of these studies grounded their findings in a theoretical model that could have been used to distinguish between the causations of passenger and cargo air carrier accidents.

The current study addressed these gaps through statistical analyses of the previously discussed factors and their relationship to the group membership variable: passenger or cargo accident. Only two known studies, Roelen et al. (2000)

and Lacagnina (2006) have primarily focused on comparing passenger to cargo air carrier accidents. However, the current study is the only known analysis of the factors of passenger and cargo air carrier accidents that is grounded in a theoretical model. While other studies within the aviation safety domain have classified accident causations under a variation of the SHEL model or the Human Factors Analysis and Classification System (HFACS), no studies have used such a model to distinguish between accidents for these two types of operators. In addition, accident factors related to organizational influences, as previously identified by Wang and Chang (2010) in their analysis of aviation maintenance safety, have not been widely used to analyze aviation accidents.

In addition, robust statistical analyses were used to analyze how the levels of the SHELO model can be used to distinguish between passenger and cargo air carrier accidents. Although robust statistical analyses have been used in similar studies that have focused on aviation safety, none of them were used in the direct comparison the factors for accidents of these two specific operators. By focusing on the Software, Hardware, Environment, and Organizational Influences, the human (Liveware) factor was isolated in order to determine if differences exist between passenger and cargo air carrier accidents.

Chapter 3

Methodology

Population and Sample

Population

The target population for the current study was every commercial passenger or cargo air carrier accident globally. According to the ASN database, 3,806 known aircraft accidents related to airline, corporate, and military operations occurred between 2002 through 2019. Data on the size and makeup of commercial air carriers was obtained from IATA to estimate the percentage of annual aircraft accidents that can be categorized as passenger or cargo air carrier. The main responsibility of IATA is to set technical standards for airlines as well as organize traffic conferences for the purpose of price fixing. IATA assigns a unique identifier to every global airline, and their database contains over 1,100 unique identifiers.

In order to understand the ratio of passenger to cargo air carriers within the target population of 1,100 air carriers, data was obtained from the Air Traffic Controllers Association (ATCA). This data does not focus on just air carrier operations, but all flights within the United States. The ATCA estimates that 87,000 flights are conducted daily within the United States. Only one third, or approximately 29,000 of these flights are commercial air carriers. More specifically, approximately 2,150 commercial air carrier flights are made up of cargo. This equates to a ratio of 92% passenger flights and 8% cargo flights in the United States.

The accessible population for the current study consisted of any commercial passenger or cargo carrier accidents that were investigated and the results of which were published. ICAO (2020) defines an accident as a fatal or serious injury to at least one person, damage or structural failure to the aircraft, or the aircraft itself is missing or unrecoverable. ICAO's Annex 13 (2020) stipulates that the country in which an aviation accident has taken place must launch an investigation into the circumstances of the accident. ICAO also provides guidelines for how accident reports are to be published and distributed in order to share data and findings with other ICAO members and the general public.

Sample

The sample for the current study consisted of all global air carrier accidents that occurred between 2002 and 2019. The source of all the air carrier accident data for the current study was the ASN. As discussed later in this chapter, data for a particular air carrier accident were selected as part of the sample if the accident had a published final accident report, and if the type of operation and the type of accident were considered in-scope. In total, 594 air carrier accidents were considered in-scope and made up the sample for the current study. Of the 594 air carrier accidents, 198 of these accidents involved cargo air carriers while 396 involved passenger air carriers.

Power Analysis

In order to determine if the sample for the current study was large enough to reject a null hypothesis with a reasonable amount of certainty, an a priori power analysis was used to determine minimum sample size. Common values for an a priori power analysis would be $\alpha = 0.05$ and a power of 0.8 (Cohen et al., 2003). Logistic regression was used as the primary statistical analysis in this study. In order to determine an appropriate effect size for logistic regression, we must consider the size of the treatment effect on the odds ratio. If the odds ratio between the two levels of the dichotomous criterion variable is equal to 1, then this would imply that the selected predictor variables have no statistically significant effect on group membership. Given a lack of supporting evidence in related literature and past studies using logistic regression to analyze aviation accidents, a median odds ratio of 1.5 was used in this power analysis.

The population effect size between the causations of passenger and cargo air carrier accidents is currently unknown and has been identified as a gap within related literature. However, the effect size for the binary logistic regression that will be used can be estimated by using maximum likelihood. According to Peduzzi (1996), you can mitigate for low reliability of your estimates due to a sample with a small number of events per variable by obtaining a minimum sample size of 10 times the number of predictor variables within the model. The proposed study contains 10 predictor variables, which would require a minimum sample size of 100 cases.

In order to verify the minimum sample size required for the proposed study, an a priori power analysis was conducted using a power analysis software called G*Power (Faul et al. 2009). A logistic regression test, which is part of the z-test family, was conducted using the following parameters: $\alpha = 0.05$, $1 - \beta = 0.8$, and an odds ratio of 1.5. The resulting minimum sample size was 242 cases. The final sample size of $N = 594$ exceeded the minimum sample size calculated by G*Power.

Instrumentation

Source of Air Carrier Accident Data

The Flight Safety Foundation is an international non–profit organization that is chartered to provide independent guidance and resources for the aviation and aerospace industry (Flight Safety Foundation, 2020). One of the services provided by the Flight Safety Foundation is the ASN. The ASN is a private and independent initiative founded in 1996 with the purpose of organizing international air carrier accidents and safety issues into an online, publicly available database (Aviation Safety Network, 2016). ASN obtains accident report data from several sources, most of which are aviation authorities and safety boards for various countries. The ASN was the sole source of air carrier accident data used within the current study. Examples of the format and data summarized by the ASN is listed in Appendix B.

Validity and Reliability of Historical Data

The air carrier accident data on the ASN was objective and did not require the use of a scale or measurement. Each air carrier accident within the dataset is made up of nominal data that was observed by air crash investigators at the scene of the accident or during the post–accident investigation. Therefore, validity must be determined based on the process the NTSB uses to collect objective data.

Validity is defined as an indicator measuring what it was indented to measure (Abowitz & Toole, 2010). The process used by accident investigators must be standardized to ensure they are collecting data on what they intended to collect. The main source of data accessed by JIMDAT to build their air carrier accident dataset was the NTSB's online database. After any aircraft accident occurs, the NTSB assembles a team that is tasked with dispatching to the accident site to begin the investigation. Certain accident details, such as the location of the accident, the aircraft manufacturer, and the specific air carrier are all able to be quickly determined at the crash site. Each member of this team is a specialist in a certain area, such as air carrier operations, aircraft structure or powerplant mechanics, and human performance (NTSB, n.d.). The investigators will collect and verify data that are specific to their specialty. All investigators report to an Investigator–in–Charge (IIC). The IIC is a senior investigator that requires years of NTSB and industry experience. The IIC will validate data from each specialist before it is included in any preliminary or final accident report. All investigators follow guidelines published in the NTSB Major Investigations Manual (2002). This standardizes the process of data collection and reporting by each investigator to the IIC.

Some of the accident data will also be collected after the initial visit to the crash site. Phase of flight in which the accident occurred and the type of accident that occurred (CFIT, LOC, or weight factor) are all determined during the post–accident investigation. All air carrier aircraft are required to have two special flight recorders on board: a cockpit voice recorder and a flight data recorder. The flight data recorder provides investigators with parameters of the aircraft's performance and orientation leading up to the accident. The cockpit voice recorder provides investigators with recorded audio of the conversations between flight crew members and air traffic control. The analyses of both recorders are also standardized according to the process outlined in the Cockpit Voice Recorder Handbook (2011) and the Flight Data Recorder Handbook (2000). Due to the nature of audio data captured by the cockpit voice recorder, investigators must make certain inferences about the flight crew's thoughts, actions, and emotions. For example, NTSB investigators can infer that a pilot lost situational awareness due to high workload and stress on the flight deck, but there is no objective way to verify this conclusion. This type of data cannot be verified using a video recorder or post–accident interview if the flight crew perishes in the accident. However, all the data within the current dataset are objective and were obtained according to the NTSB's standardized practices. Based on the standardized practices of each investigation team assigned to every air carrier accident and the experience required to be a team member or IIC, data obtained by the NTSB are valid for the use within the proposed study.

Although the NTSB often assists in the investigation of aviation accidents that occur outside of the United States or with an international air carrier, the NTSB counterparts of other countries often lead their own investigations and publish final accident reports. Most of the accidents within the ASN database contain data that was acquired from final accident reports published by entities other than the NTSB. However, most of these countries are members of ICAO, which has developed its own set of standards and recommended practices (SARPS) for accident investigation. All of ICAO's SARPS are published in a series of annexes, and Annex 13 (2020) contains guidance on accident investigation techniques, technologies, reporting, and how recommendations should be made to the international aviation community. With 193 member states that makeup ICAO, the standardization of the methods for reporting aviation accident data provides validity for the NTSB's data collection and reporting methods, as well as the validity of the ASN's online database.

Reliability is defined as the application of uniform measurement rules and uniformity of measurement results over time (Abowitz & Toole, 2010). Within the ASN database, important factors from each accident are summarized in a bulleted format. To determine accident reliability, one air carrier accident per decade was selected at random from the existing dataset. This equates to a total of 18 accidents. All details within these 18 randomly selected accidents were cross checked against final accident reports provided by the ASN. Every single one of the target variables within each accident matched the data on–record within the final accident report. Based on this test of reliability, it is unlikely that errors occurred on behalf of the researcher when populating the current dataset with original air carrier accident data. The reader should be reminded that any air carrier accident absent of a final accident report was out of scope for the current study.

Procedures

Research Design

The current study utilized a causal–comparative research design. In causal–comparative research, an action or event has already taken place. The focus of this type of research is how changes in selected variables can influence group membership (Schenker, 2004). This design is appropriate given that grouping found in the dependent variable, passenger, or cargo air carrier accidents, had already occurred during data collection of the current study. Details of each accident were categorized as predictor variables and grouped according to the levels of the SHELO model.

Causal–comparative studies can use one of two designs based upon whether group membership was on the independent or the dependent variable. Due to the pre–existing group membership of passenger and cargo air carrier accidents in the criterion variable, a retroactive design was used. This design helped determine if the grouping between passenger and cargo air carrier accidents were more likely due to differences in the predictor variables organized into the levels of the SHELO model rather than random chance. One of the issues with a causal–comparative study that must be accounted for is group equivalency, and this is discussed below along with other threats to internal validity.

Institutional Review Board

The current study utilizes a historical, data-analytic methodology acquired from the NTSB, made available by the ASN. The ASN database is publicly available, with identifiable information of the flight crew, passengers, or victims on the ground removed from published reports. The only accident details found in the report than can be connected to individuals that were involved would be the certifications and total flight hours of the flight crew, the total number of injuries and fatalities, and the actions taken by the flight crew before the accident occurred. Due to the public availability of the online database and any personally identifiable information having already been removed, the current study qualified for in Institutional Review Board (IRB) exemption. An application for an IRB exemption was submitted and approved by the Florida Institute of Technology IRB.

Description of Variables

The current study was made up of several targeted predictor variables and one dichotomous, group membership criterion variable. Given that the research design of the current study involved multiple independent variables with a single dependent variable, multiple regression was the appropriate statistical analysis. The criterion variable was Y = passenger or cargo air carrier accident, which was a dichotomous group membership variable. For the purpose of the statistical analysis, passenger air carrier accidents were coded using the number 0 while cargo air carrier accidents were coded using the number 1. Each of the predictor variables were categorized according to the levels of the SHELO model and described in more detail below.

Software. The variable set associated with the Software level of the SHELO model contained four variables. X_1 = Phase of Flight (Takeoff, Climb, Cruise, Approach, and Landing), using dummy coding with Cruise coded as the reference group due to this phase requiring the least frequent aircraft configuration or procedural changes; X_2 = CFIT; X_3 = LOC, and X_4 = Weight Factor.

Hardware. The variable set associated with the Hardware level of the SHELO model contained three variables. X_5 = Aircraft Generation (First, Second, Third, and Fourth), using dummy coding with Generation 1 coded as the reference group; X_6 = Aircraft Manufacturer (categorized by region: Asia, CIS, Europe, LA, and NA), using dummy coding with NA–Manufactured Aircraft coded as the reference group due to Boeing, the largest aircraft manufacturer between 2002 and 2019, being located in NA (Pandey, 2020); and X_7 = Mechanical Failure.

Environment. The variable set associated with the Environmental level of the SHELO model contained two variables. X_8 = Time of Day (day or night); and X_9 = Location of Accident (Africa, Asia, the CIS, Europe, LA, ME, NA, and Oceania) using dummy coding with Africa coded as the reference group due to this region having the largest discrepancy between the frequency of accidents compared to the total number of air carrier flights (Kharoufah et al., 2018).

Organizational Influences. The variable set associated with the Organizational Influences level of the SHELO model contained one variable. X_{10} = Location of Operator (Africa, Asia, the CIS, Europe, LA, ME, NA, and Oceania) using dummy coding with Africa coded as the reference group due to this region having the largest discrepancy between the frequency of accidents compared to the total number of air carrier flights (Kharoufah et al., 2018).

Study Implementation

As mentioned in Chapter 2, the usage of current air carrier accident data to compare passenger and cargo air carrier accidents was identified as a gap within the related literature. The current study utilized the latest accident data available to run a thorough analysis that can be generalized to the current target population of global air carriers. Data collection and integration of entire accident reports from the ASN databases commenced in May 2021 and was completed in November of 2021. The process of determining whether an accident within the ASN database was in–scope or out–of–scope for the current study is provided in Appendix C. The process of populating the study sample and coding nominal data is provided in Appendix D. The collection and organization of data from the ASN database was conducted by a single researcher. Although data collection from such a large dataset by a single researcher was a time-consuming process, this increased the reliability of the data collection process. The statistical analysis of the complete sample took approximately one month to complete.

Threats to Internal Validity

Strong internal validity allowed for the selection of group membership in the criterion variable to be attributed to the differences in the factors that made up the predictor variables. Possible threats to internal validity existed that could have been attributed to selection of group membership in the criterion variable to uncontrolled or unidentified variables. Unfortunately, the analysis of historical data did not allow a researcher control over the environment in which the data was collected. There was also a lack of randomization in terms of which passenger or cargo air carrier accidents were selected for inclusion in the current database.

Due to the nature of air carrier accidents, all available data was included within the current dataset due to the infrequent nature of this type of event. Despite a lack of control over the data itself, possible threats to internal validity were identified and are explained below.

History. Ary et al. (2010) describes history as specific events that could have occurred during the data collection period that can influence the selection of group membership in the criterion variable. Due to the dataset for the current study ranging from 2002 through 2019, certain historical events could have had an influence on the selected factors that distinguish between passenger and cargo air carrier accidents. A historical event that could have had an influence on the criterion variable was the September 11th terrorist attacks. In the United States alone, all civil aircraft were grounded for two days after the September 11th terrorist attacks. The number of annual passenger air carrier operations fell sharply following these attacks due to a decreased demand from air travelers (DOT, 2005). Again, with a decrease in the number of annual passenger air carrier operations, this could have had an impact on the number of air carrier accidents that occurred during that time. The year 2001 was excluded from data collection as only accident data for the years 2002 through the end of 2019 were considered in-scope for the current study. Some of the air carrier accidents that occurred in 2019 may have been too recent for the accident investigation to conclude and for a final accident report to be published. A second historical event that had an impact on the commercial aviation industry was the COVID-19 pandemic, which began in the spring of 2020. The scope of the current study was defined as ending in 2019, which excluded any years that could have been affected by the impact of the pandemic on annual air carrier operations.

Instrumentation. Ary et al. (2010) defines instrumentation threat as changes in how a variable is measured or observed during data collection. In the context of the current study, global aviation accidents were investigated by a variety of government entities, aircraft manufacturers, and the air carriers themselves. Although most investigative branches of federal governments are standardized under ICAO guidelines, it was possible for different aviation accident investigators to come to different conclusions on the causes of aircraft accidents. This was evident after the crash of Egypt Air Flight 990, which was a passenger flight that crashed in October of 1999. Both the NTSB and the Egyptian Civil Aviation Authority were members of the team that investigated the accident for probable cause. Both entities published contradictory final reports. The NTSB concluded that intentional actions of the first officer to deliberately crash the airplane into the ocean was the cause of this accident. The Egyptian Civil Aviation Authority disputed this finding and concluded that the accident was due to a mechanical failure of the aircraft (Egyptian Civil Aviation Authority, 2000). In order to avoid unreliable data in the predictor variables, the proposed study will only use published final accident reports found in the NTSB and the ASN databases. By only using full accident reports instead of preliminary accident reports, only validated accident data was included within the final dataset. Preliminary reports may contain information that has yet to be proven or validated. In addition, by only accessing accident reports found within the ASN database, accidents investigated under the same set of standards were included within the dataset. More specifically, accidents investigated by government entities or organizations from other countries may be biased or inaccurate, as seen with the Egypt Air accident report.

There were two factors per accident within the ASN database that had to be verified or altered before they were coded into the study dataset. The first variable was Time of Day. Within each ASN accident summary, the time when the accident took place was represented as the local time per the departure location of each accident flight based on a 24–hour clock. Within the context of the current study, this variable had to be coded dichotomously (0 = Day, 1 = Night). Therefore, the time of each accident within each ASN summary had to be determined to be day or night using the FAA's definition of nighttime, as defined earlier in this paper, against an online tool that calculates the beginning and end of evening civil twilight (Time and Day A.S., 2022).

The second accident factor in each ASN summary that had to be altered was Accident Location, specifically for accidents that took place over international bodies of water. Out of the entire study sample, only five accidents took place over the Atlantic Ocean, Indian Ocean, Pacific Ocean, or Mediterranean Sea. With only five cases of accidents occurring over international waters, the decision was made to categorize the Accident Location based on the country in which the flight originated. For example, Air France Flight 447 departed from Brazil but crashed while flying over the Atlantic Ocean. Within the current study sample, the Accident Location for this flight was categorized as LA.

Selection Bias. Ary et al. (2010) refers to non–random events that cause bias as to how individuals or cases are assigned to the groups within the criterion variable. In the context of the current study, the criterion variable was limited to two groups: passenger or cargo air carrier accidents. Any aviation accident is a random event that could be caused by many distinct factors. This contrasts with other studies that utilized participants that volunteer or are randomly selected for data collection. The dataset that was used in the current study was not a collection of randomly selected events, but a comprehensive collection of every event that fit ICAO's definition of an aviation accident.

Selection bias was also controlled by only using accidents included within the ASN database. If other accident investigating agencies were utilized for data collection, any difference in their procedures or standards for investigation could have caused some accidents to be excluded from the dataset. It was even possible for aviation events that do not fit ICAO's definition of aviation accident to be listed as an accident by agencies with different protocols. One important characteristic of the criterion variable for the current study was that the ratio of passenger to cargo air carrier accidents was not even. This was due to the frequency of annual passenger air carrier operations outweighing the frequency of cargo air carrier operations. It was important for the ratio of passenger to cargo air carrier operations in the criterion variable to be representative of the target population, and this is discussed in further detail along with the assumptions for logistic regression.

Treatment Verification and Fidelity

The fidelity of the current study was preserved by the researcher ensuring that procedures are followed as outlined in the proposal. Any deviation from the procedures described in a previous section could have threatened the fidelity of the current study. Clear operational definitions of terms used within the current study and the targeted variables were also important to fidelity. The predictor variables, criterion variable, and the selected levels of the SHELO model were defined in Chapters 1 and 3 of this proposal as well as the rationale for the selection of variables included within Chapter 2. The verification of the targeted variables allowed for valid and accurate interpretations of the relationship between the predictor variables and the criterion variable. This strengthened the generalizability of the current study to the targeted population.

Data Analysis

The current study utilized descriptive and inferential statistical analyses to measure the effect of the predictor variables on the criterion variable. The purpose of the descriptive statistical analysis was to provide the reader with a better understanding of the diversity of air carrier accidents that were included within the dataset. Inferential statistics were used to predict how changes in any of the predictor variables influenced group membership in the dichotomous criterion variable: passenger and cargo air carrier accidents.

Descriptive Statistics

The descriptive statistics provided the reader with the final number of air carrier accidents that remained in the dataset before missing data and outlier analysis began. Descriptive statistics also included the total number of passenger and cargo air carrier accidents within the final dataset in order to have a better understanding of the distribution of the dichotomous criterion variable.

Each of the predictor variables were also summarized through descriptive statistics. Due to each of the predictor variables being categorical, it was possible to provide an exact number of the groups within each variable. This included the number of accidents within each Phase of Flight; CFIT, LOC; Weight factor; Aircraft Generation; Aircraft Manufacturer; Mechanical Failure; Time of Day; Location of Accident; and Location of Operator. For every group within the predictor variables, further descriptive statistics were provided to inform the reader of the distribution among passenger air carriers, cargo air carriers, and the total frequency for each variable.

Inferential Statics

Logistic regression was be used to perform the inferential statistical analysis for the current study. This was due to the nature of the dichotomous criterion variable of group membership between passenger and cargo air carrier accidents. Before the primary regression analysis began, data cleaning measures were taken, which included identifying outliers and missing data. Any data missing within the accident summaries provided by the ASN can be located within the final accident report for each accident. However, if accident data is missing from this report, which is treated as the primary source of information for each accident, then this data would not be able to be included within the final dataset. In this instance, the entire accident would be removed from the dataset. Unlike continuous predictor variables, categorical variables cannot use means or medians to provide a replacement for missing data. Instead, the accident would be removed from the dataset and the reader would be informed of such removal.

After data cleaning was completed, all remaining data was reviewed for compliance with the assumptions of logistic regression. Warner (2008) identified the assumptions that must be met for binary logistic regression as well as the need for five events per predictor variable. In the context of the current study, an event was defined as an air carrier accident. Considering all of the predictor variables that were selected for inclusion within the current study, 100 accidents would have been required as the minimum number for a logistic regression analysis. However, the power analysis discussed earlier in this chapter suggested a sample of more than twice this amount. The assumptions of binomial logistic regression are as follows:

1. The criterion variable is dichotomous in nature.
2. The categories of the criterion variable are mutually exclusive and exhaustive.
3. Independence of scores in predictor variables on the criterion variable.

4. Correct specification of the model.

Although not required as assumptions for logistic regression, proper data screening for missing data, outliers, and multicollinearity, was also performed before the primary analysis began. These processes are discussed. in Chapter 4.

The primary analysis began by regressing the single criterion variable on all predictor variables simultaneously. This was followed by four simultaneous logistic regression analyses to evaluate how the variable sets associated with each of the four levels of the SHELO model can distinguish between passenger and cargo air carrier accidents. Select predictor variables were categorized according to the levels of the SHELO model, used most recently used by Chang and Wang (2009). Following each of the four simultaneous analyses, each statistically significant predictor variable was analyzed in terms of the odds of being able to distinguish between the two groups within the criterion variable.

In order to easily interpret the relationship between the predictor variables and the dichotomous criterion variable, MacKinnon and Dwyer (1993) recommend the transformation of any continuous variables into categorical variables. Given the nature of aircraft accident data and the targeted variables within the current study, all predictor variables were categorical. No continuous predictor variables were included within the final dataset for the current study. However, all nominal predictor variables were coded using dummy coding for direct comparisons to a reference group. This recommendation by Tabachnick and Fidell (2013) can be applied to predictor variables that have multiple discrete levels. As explained earlier in this section, all reference groups were selected based upon the absence of a condition (Weight Factor versus the absence of a weight factor in an air carrier crash) or based upon support from related literature (the NA region containing Boeing as the aircraft manufacturer with the highest number of air carrier aircraft in service with the best safety records). The use of dummy coding for all nominal predictor variables allowed for a comparison of the membership in one of the groups on a single predictor variable to the odds of an air carrier accident being passenger or cargo.

Chapter 4

Results

Introduction

The purpose of the current study was to examine the relationship between selected predictor variables and a single, dichotomous criterion variable. The criterion variable (*Y* = *Passenger or Cargo*) is a group membership variable with only two categories. Due to the dichotomous, categorical nature of the criterion variable, the statistical analysis most appropriate for the current study was logistic regression. The single criterion variable was regressed on all predictor variables and tested for statistical significance of the overall model as well as any statistically significant parameters for individual predictor variables.

In order to observe the relationship between the predictor variables and the single criterion variable, several logistic regression analyses were performed. The first analysis was a simultaneous logistic regression with all predictor variables entered into the model at once. The purpose of this analysis was to identify possible significant parameters in the presence of all other predictor variables, as well as the potential gain in the likelihood of being able to differentiate between passenger and cargo air carrier accidents compared to the null model (absent of all predictor variables). After this analysis was performed, four more simultaneous analyses were run according to the levels of the SHELO model: Software, Hardware, Environmental Factors, and Organizational Influences. All of the predictor variables used in the full analysis were categorized into one of the four levels of the

SHELO model, as previously discussed in Chapter 3. Each of these analyses were then used to test the research hypotheses discussed earlier in the current study.

Overview of Predictor Variables

Although logistic regression can be performed with a combination of categorical or continuous predictor variables, all the predictor variables in the current study were nominal in nature. Some of the predictor variables were dichotomous and only contained two groups. Most of these dichotomous predictors were simply coded as "yes" or "no" and included the following variables: LOC, CFIT, Weight Factor, Mechanical Failure, and Time of Day.

The other predictor variables used in the current study contained more than two groups, and therefore could not be coded or analyzed in the same manner as the dichotomous predictor variables. Instead, dummy coding was used for each of these group membership variables. Dummy coding requires the selection of a reference group that is then compared to the rest of the groups on an individual basis. The explanation for the selection of the reference group for each of these variables was explained in Chapter 3. As a reminder to the reader, the reference group is absent from any analysis, but is represented in each of the parameters for the other groups. Each of these parameters is a comparison of one of the groups compared directly to the reference group. As an overview, the first group membership variable with more than two groups was Phase of Flight, and it contained the following groups: Takeoff, Climb, Cruise (the reference group), Approach, and Landing. The second variable with more than two groups was Aircraft Manufacturer categorized according to region: Asia, Europe, CIS, LA, and NA; the reference group). The third variable with more than two groups was Aircraft Generation: Generation 1 (the reference group), Generation 2, Generation 3, and Generation 4. The fourth variable with more than two groups was the Accident Location: Africa (the refence group), Asia, CIS, Europe, LA, ME, NA, and Oceania. The fifth and final variable with more than two groups was Operator Location: Africa (the refence group), Asia, CIS, Europe, LA, ME, NA, and Oceania.

Overview of Dataset

This study collected archival data from the online ASN database, which is organized by year. Any accident on the ASN database that occurred between 2002 through 2019 was analyzed for relevance to the scope of the current study. The ASN database contains 3,806 aircraft accidents that occurred between 2002 and 2019. However, only accidents with publicly available final reports were considered in-scope for the current study. Therefore, any accident listed in the ASN database that did not include a final accident report was considered out of scope and not included within the final dataset.

The purpose of this study was to identify factors that could distinguish between passenger and cargo air carrier accidents. During data collection, the following kinds of operations were considered out of scope and were not included in the final dataset: on-demand/private, executive, military, ferry/positioning, test flight, firefighting, training, ambulance, survey/research, official state flight, illegal flight, parachuting, agricultural, demonstration, aerial work, and any flight categorized as an unknown operation.

Once an accident was determined to be a scheduled passenger or cargo operation, the type of accident was then analyzed for relevance to the scope of the current study. During data collection, the following types of accidents were determined to be out of scope due to a lack of literature that supports them as factors in determining whether an accident was passenger or cargo: ground operation (aircraft stationary, standing or taxi), sabotage or terrorism, hijacking or an attempted takeover, mid-air collision, pilot error, fuel exhaustion, wildlife strike, fuel contamination, shoot-down, aircraft missing, runway incursion, ground collision, inflight fire (unrelated to aircraft systems), and weather-related accidents that did not result in LOC or CFIT.

In total, 594 accidents were considered in-scope for the current study and were included in the final dataset. All of these accidents listed in the ASN database included a final accident report, were either a scheduled passenger or cargo operation, and were a type of accident considered in-scope and supported by literature to differentiate between accident factors. Of the 594 total accidents, 396 were scheduled passenger operations and 198 were scheduled cargo operations.

Descriptive Statistics

The purpose of this study was to determine the relationship between the targeted groups of predictor variables and group membership in the criterion variable. The predictor variables were grouped according to the levels of the

SHELO model: Software, Hardware, Environmental Factors, and Organizational Influences. The group membership in the criterion variable was dichotomous: Passenger or Cargo. The following section provides descriptive statistics for each of the predictor variables grouped according to the SHELO model.

Software

There were five Phases of Flight: Takeoff, Climb, Cruise, Approach, and Landing. Table 1 presents the frequency of accidents that fell in each of these categories for passenger operations, cargo operations, and overall. The most frequent phase of flight in which accidents took place was Landing, with 594 accidents occurring in this phase overall, 225 of which were passenger accidents and 60 of which were cargo accidents.

Table 1

Frequency of Accidents for each Phase of Flight

Flight Phase	***Passenger***	***Cargo***	***Overall***
Takeoff	45	27	72
Climb	20	14	34
Cruise	60	54	114
Approach	46	43	89
Landing	225	60	285
Overall	396	198	594

Each accident in the dataset could have been categorized as either LOC (if the pilot lost control of the aircraft) or CFIT (if the aircraft collided with terrain while under normal control). If an accident wasn't categorized as LOC or CFIT, then it was coded as "neither" in the current dataset. Table 2 presents the frequency of accidents that fell in each of these categories for passenger operations, cargo operations, and overall. The type of accident that occurred most frequently was

LOC, with 385 accidents occurring within this type of accident overall, 265 of which were passenger accidents and 120 of which were cargo accidents.

Table 2

Frequency of Accidents within LOC & CFIT Categories

Type of Accident	***Passenger***	***Cargo***	***Overall***
Loss of Control	265	120	385
Controlled Flight into Terrain	44	33	77
Neither	87	45	132
Overall	396	198	594

Each accident in the dataset could have been categorized as involving a Weight Factor or not involving a Weight Factor. Table 3 presents the frequency of accidents that fell in each of these categories for passenger operations, cargo operations, and overall. Only 13 passenger accidents involved a Weight Factor and only 18 cargo accidents involved a Weight Factor. This totaled to 31 air carrier accidents that involved a Weight Factor and 363 air carrier accidents that did not involve a Weight Factor.

Table 3

Frequency of Accidents Involving a Weight Factor

Type of Accident	***Passenger***	***Cargo***	***Overall***
Weight Factor	13	18	31
No Weight Factor	383	180	363
Overall	396	198	594

Note. The variables Weight Factor and LOC were not mutually exclusive. Of the 31 air carrier accidents that involved a Weight Factor, 23 were categorized as LOC and 8 were not categorized as LOC.

Hardware

Aircraft were categorized into one of four generations: First, Second, Third and Fourth. Table 4 presents the frequency of accidents that fell in each of these categories for passenger operations, cargo operations, and overall. The most frequent Aircraft Generation for which accidents took place was the Fourth Generation, with 372 accidents occurring in this generation overall, 294 of which were passenger accidents and 78 of which were cargo accidents.

Table 4

Frequency of Accidents for each Aircraft Generation

Generation	***Passenger***	***Cargo***	***Overall***
First	8	39	47
Second	37	33	70
Third	57	48	105
Fourth	294	78	372
Overall	396	198	594

There were five regions of aircraft manufacturers, including Asia, the CIS, Europe, LA, and NA. Table 5 presents the frequency of accidents that fell in each of these categories for passenger operations, cargo operations, and overall. The most frequent region of Aircraft Manufacturer involved in air carrier accidents was NA, with 366 accidents occurring from this region of manufacturer overall, 229 of which were passenger accidents and 137 of which were cargo accidents.

Table 5

Frequency of Accidents for each Aircraft Manufacturer Region

Region	*Passenger*	*Cargo*	*Overall*
Asia	4	0	4
Commonwealth of Independent States	14	15	29
Europe	131	38	169
Latin America	18	8	26
North America	229	137	366
Overall	396	198	594

Each accident in the dataset could have been categorized as involving a Mechanical Failure or not involving a Mechanical Failure. Table 6 presents the frequency of accidents that fell in each of these categories for passenger operations, cargo operations, and overall. Only 126 passenger accidents involved a Mechanical Failure and only 67 cargo accidents involved a Mechanical Failure. This totaled to 193 air carrier accidents that involved a Mechanical Failure and 374 air carrier accidents that did not involve a Mechanical Failure.

Table 6

Frequency of Accidents Involving Mechanical Failure

Type of Accident	*Passenger*	*Cargo*	*Overall*
Mechanical Failure	126	67	193
No Mechanical Failure	259	115	374
Overall	396	198	594

Note. The variables Mechanical Failure and LOC were not mutually exclusive. Of the 193 accidents that involved a Mechanical Failure, 61 were categorized as LOC while 132 were not categorized as LOC.

Environmental Factors

Each accident in the dataset was categorized based on Time of Day. Table 7 presents the frequency of accidents that fell in each of these categories for passenger operations, cargo operations, and overall. Of the Daytime air carrier accidents, 287 were categorized as passenger while 105 were categorized as cargo. Of the Nighttime air carrier accidents, 109 were categorized as passenger while 93 were categorized as cargo.

Table 7

Frequency of Accidents by Time of Day

Time of Day	***Passenger***	***Cargo***	***Overall***
Day	287	105	392
Night	109	93	202
Overall	396	198	594

Note. The frequencies of annual passenger and cargo operations are not equal for daytime and nighttime. For example, 42% of cargo operations took place at night within European airspace (Leleu & Marsh, 2009). Less than 10% of passenger operations took place during the day.

The variable, Accident Location, was split into eight global regions: Africa, Asia, the CIS, Europe, LA, the ME, NA, and Oceania. Table 8 presents the frequency of accidents that fell in each of these categories for passenger operations, cargo operations, and overall. The most frequent Accident Location was NA, with 205 air carrier accidents occurring within this region, 104 of which were passenger accidents and 101 of which were cargo accidents.

Table 8

Frequency of Accidents by the Location of the Accident

Region	***Passenger***	***Cargo***	***Overall***
Africa	31	15	46
Asia	81	21	102
Commonwealth of Independent States	22	8	30
Europe	78	17	95
Latin America	50	24	74
Middle East	16	5	21
North America	104	101	205
Oceania	14	7	21
Overall	396	198	594

Note. There were not equal frequencies of operations for these global regions between 2002 and 2019. For example, IATA (2021) reported that the two largest cargo air carriers, UPS and FedEx, are based in NA. Combined, these two operators accounted for 34% of the global cargo air carrier traffic in 2021.

Organizational Influences

The variable, Operator Location, was split into eight global regions: Africa, Asia, the CIS, Europe, LA, the ME, NA, and Oceania. Table 9 presents the frequency of accidents that fell in each of these categories for passenger operations, cargo operations, and overall. The most frequent Operator Location was NA, with 210 accidents occurring with air carriers based within this region, 102 of which were passenger accidents and 108 of which were cargo accidents.

Table 9

Frequency of Accidents by the Location of the Operator

Region	***Passenger***	***Cargo***	***Overall***
Africa	31	16	47
Asia	82	20	102
Commonwealth of Independent States	18	6	24
Europe	82	15	97
Latin America	49	22	71
Middle East	18	4	22
North America	102	108	210
Oceania	14	7	21
Overall	396	198	594

Note. There were not equal frequencies of operations for these global regions between 2002 and 2019. For example, IATA (2021) reported that the two largest cargo air carriers, UPS and FedEx, are based in NA. Combined, these operators accounted for 34% of the global cargo air carrier traffic in 2021.

Inferential Statistics

Preliminary Analysis

Missing Data. Due to the dichotomous group membership in the criterion variable, logistic regression was selected as the statistical analysis for the current study. Before analyzing the hypothesized grouping of the targeted predictor variables according to the levels of the SHELO model, the dataset was examined to determine if any accidents contained missing data. Due to the scope of the current study that required accidents to include a final accident report, missing data was not present for any accident. All of the targeted predictor variables were made up of data that must be included in every final accident report. In addition, accident data published in a final report is collected by a government agency that specializes in aviation accident investigation. The government agency that investigates a specific accident is dependent upon several factors, such as the state in which the accident occurred or the state from which the aircraft operator was based. As discussed in Chapter 3, the final accident report published by a government agency and made publicly available was determined to contain valid accident data. Therefore, the dataset retained all 594 accidents after it was determined that the dataset did not include any invalid missing data.

Outlier Analysis. Part of the preliminary analysis is to analyze the current dataset for potential outliers. An outlier is an extreme data point that is inconsistent with the rest of the dataset. These extreme data points should be examined for their influence on results that are not representative of the relationships between the predictor variables and the criterion variable. Outliers can be identified as one of two types of extreme data points: contaminants or rare cases. In the context of the current study, zero outliers were identified as contaminants. This was likely due to the source of each air carrier accident being publicly available accident reports published by various accident investigation bureaus from various countries. Therefore, the data in these reports deemed accurate and objective. However, one of the predictor variables only contained four data points, and this variable was Aircraft Manufacturers Based in Asia. This low frequency count for a single variable caused instability within the logistic regression and was considered to be a rare case. It was determined that the four accidents that involved an Aircraft

Manufactured in Asia should be removed to avoid missing data and instability within the logistic regression.

Logistic Regression Assumptions

After the dataset was screened for missing or invalid data and outliers, the targeted set of predictor variables were tested for compliance with the assumptions of logistic regression. These assumptions were a dichotomous criterion variable, mutually exclusive categories on the criterion variable, independence of scores on the dependent measure, and the correct specification of the hypothesized model.

Dichotomous Criterion Variable. The nature of the criterion variable used in the current study was a dichotomy of group membership. All accidents were categorized as either a scheduled passenger operation or a scheduled cargo operation. Any accident within the ASN database that did not fit either of these two operations was considered out of scope and not included in the final dataset. Therefore, the assumption of a dichotomous criterion variable was met.

Mutually Exclusive Categories on the Criterion Variable. It is assumed that categories within the criterion variable for logistic regression are exhaustive and mutually exclusive. In terms of the current study, an accident was categorized as either a scheduled passenger or cargo operation based on the kind of operation listed in the final accident report for a specific case. However, an operation could not be categorized as both passenger and cargo. This requirement for an accident to only be categorized as one type of operation met the assumption of mutually exclusive categories on the criterion variable.

Independence of Scores on the Criterion Variable. Tabachnick & Fidel (2013, p. 445) stated that "Logistic regression assumes that responses of different cases are independent of each other. That is, it is assumed that each response comes from a different, unrelated case." In terms of the current study, each case was made up of data collected from an individual aircraft accident. The occurrence of one aircraft accident had no influence over the occurrence of another aircraft accident. If the occurrence of one accident influenced the occurrence of another accident, both accidents would have been considered out of scope. An example of such occurrences would be a ground-based or mid-air collision. Certain factors could have existed that led to an aircraft deviating from its intended or assigned flight path and into the vicinity of a second aircraft. The second aircraft would not have suffered an accident without the deviation of the first aircraft. Therefore, the accidents of both aircraft would be considered dependent of one another and out of scope for the current study. In addition, all the accidents that were included in the final dataset were only counted once; no duplications were identified. Therefore, the data associated with each accident met the assumption of independence on the criterion variable.

Correct Specification of the Hypothesized Model. The assumption of correct specification of selected variables on the hypothesized model requires that predictor variables should only be selected if they are relevant in differentiating between group membership in the criterion variable. The selection of all predictor variables was supported by prior research discussed in Chapter 2. Prior research in

Chapter 2 was also used to support the grouping of predictor variables according to the levels of the SHELO model. Warner (2008) recommended that a null model should be developed for the data in the absence of the targeted groups of predictor variables. The fit of the null was tested using a chi-square analysis, and this was compared to the fit of the hypothesized model. The chi-square test of the hypothesized model was statistically significant, $\chi^2(29) = 199.88$, $p < .0001$, in terms of fit compared to the null model. Therefore, the assumption of correct specification of the hypothesized model was met. Data related to this assumption of logistic regression is discussed later in this chapter.

The following assumptions are not required for logistic regression but have been addressed in order to further increase the validity and reliability of each analysis.

1. Multicollinearity must not occur between the predictor variables. Multicollinearity, which is the presence of highly correlated predictor variables, can result in unstable regression coefficients associated with large standard errors (Cohen et al., 2003). The current study utilized one simultaneous regression analysis with all predictor variables present, and four smaller simultaneous analyses, each containing select variables from the four levels of the SHELO model. This divided the overall set of predictor variables into four groups, decreasing the effects of related predictors on the criterion variable. Lastly, the statistical software used for data analysis, JMP, contained a feature that would identify unstable predictor variables with large standard error.

None of the regressions performed for the current study yielded unstable predictor variables. However, initial results for the variables Accident Location and Operator Location were almost identical. In order to determine if these two variables were highly correlated, the dummy–coded variables were transformed into ordinal variables. This allowed for a correlation to be run using JMP, which produced a correlation coefficient of $R = 0.93$. Due to the strong correlation between Accident Location and Operator Location, one variable was removed from the analysis. It was determined that Accident Location would be removed from all analyses. This variable was one of two predictors categorized under the Environmental level of the SHELO model in order to retain Operator Location under Organizational Influences, which was the only predictor under this level. In addition, only one region under Accident Location was statistically significant in distinguishing between passenger and cargo operations while more than a single location were significant for Operator Location.

2. The assumption of linearity of the logit only pertains to continuous predictor variables. Due to all of the predictors within the current study being categorical in nature, this assumption was not required to be met.

Dataset Modifications

The complete set of predictor variables in the current study were nominal and required modification in order to be properly analyzed and interpreted. Dummy coding was selected as the data modification strategy which transforms all categories within a nominal variable into zeros or ones. This required one category within a nominal variable to be selected as the reference group, in which comparisons to all other categories within the same nominal variable would be made. For example, X_4 = aircraft generation had four categories: first, second, third, and fourth. The generation 1 category was selected as the reference group. Therefore, all of the data that identified a generation 1 aircraft within the dataset was removed and was instead represented as the absence of data identifying a generation 2, 3, or 4 aircraft. If an accident was categorized as involving a generation 2 aircraft, the data used in the analysis was a comparison of generation 2 to generation 1.

Primary Analyses

Simultaneous Analysis of Full Model. The first objective of the current study was to determine the relationship between the complete set of predictor variables and the group membership within the criterion variable. This analysis was conducted in a simultaneous fashion where all predictor variables entered the model at the same time. While the selection of predictor variables was guided by prior research, the regression of the criterion variable on all predictor variables simultaneously was in absence of the theoretical SHELO model. Subsequent analyses regressed the criterion variable on four sets of predictor variables organized according to the levels of the SHELO model. Warner (2008) recommended the development of a baseline or null model to be compared to the full model. This null model was generated by regressing group membership in absence of the predictor variables, with the overall goodness of fit of the null model compared to the full model. While multiple linear regression utilizes the sum of squared residuals to compare the null model to the full model, a logistic regression analysis uses the log likelihood (LL) function. The difference between the full model and the null model, analyzed using a chi-square statistic, should be large enough for the full model to be statistically significant.

The full model was statistically significant, $\chi^2(22) = 194.86$, $p < .01$. Choen et al. (2003) recommended the usage of the Pseudo-R^2 (R_L^2) when conducting a logistic regression analysis, which is comparable to the analog for R^2 in multiple regression. The simultaneous analysis for all predictor variables in the current study produced $R_L^2 = .26$. It must be noted that R_L^2 cannot be interpreted as the proportion of variance accounted for by regressing the criterion variable on the predictor variables. Instead, R_L^2 should be interpreted as the gain in prediction when predictor variables are added a full model compared to the absence of predictor variables in a null model. In the context of the current study, the full model provided a predictive gain of 26.43% over the null model ($R_{Lfull}^2 = .26$, $df = 22$), as outlined in Table 10.

Table 10

Significance of the Simultaneous (Full) Model for Passenger and Cargo Accident Factors

Model	***Log Likelihood***	***df***	χ^2
Null	378.09		
Full	280.66		
Difference	97.43	22	194.86**

Note. N = 594. R_L^2 = 0.26

Log Likelihood (LL) indicates the agreement between the probabilities of group membership generated by the logistic regression model and the actual group membership within the sample. Larger absolute LL values represent a worse model fit. $\chi^2 = -2(LL_{\text{null model}} - LL_{\text{full model}})$. The null model represents the baseline model without information about the predictor variables. °The full model represents the hypothesized model with the independent variables entered into the model simultaneously.

**p <.01

The null model, absent of all predictor variables, was also significant $\chi^2(0) = 375.78$, $p < .05$. The logit of the null model for an accident being classified for membership in the "Cargo" group was -0.69. In the context of the current model and in the absence of information provided by the predictor variables, the odds of an accident being classified as "cargo" can be calculated as $e^{-0.69} = 0.50$. A second way to interpret these odds, converted according to Warner (2008), is to use the mathematical expression $e^{0.50} / (1 + e^{0.50})$. This expression, applied to the null model, indicates that the probability of an accident that occurred between 2002 and 2019 being classified as cargo was 33%, while the probability of an accident being categorized as passenger was 67%. The full model yielded a statistically significant increase in the Chi-square statistic. Therefore, the full model was correctly specified and the relationships between each predictor variable and the criterion variable were able to be examined.

The full, simultaneous model is summarized in Table 21 in Appendix E. The full model logit (L_i) for group membership in the criterion variable is represented by the equation $L_i = -2.33 - 0.30X_1 - 0.34X_2 + 0.06X_3 - 0.59X_4 + 0.24X_5 + 0.09X_6 + 0.38X_7 + 0.75X_8 - 0.17X_9 + 0.04X_{10} - 0.84X_{11} - 0.82X_{12} - 1.40X_{13} + 0.12X_{14} + 0.57X_{15} - 0.16X_{16} - 0.90X_{17} - 0.19X_{18} - 0.14X_{19} - 0.26X_{20} + 0.41X_{21} - 0.00X_{22}$. Seven predictor variables were statistically significant in relation to the criterion variable when in the presence of other predictors: X_4 = Landing Phase of Flight (compared to the Cruise Phase), X_8 = Aircraft Manufacturers Located in the CIS (compared to Manufacturers Located in NA), $X_{11,\ 12,\ \&\ 13}$ = Generation 2, 3, and 4 respectively (in comparison to Generation 1 Aircraft), X_{15} = Time of Day, and X_{15} = Operators Based in the CIS (compared to Operators Based in Africa). The regression coefficient for each of the predictor variables specifies the change in the log odds of the criterion variable when controlling for other predictor variables. The regression coefficients can be expressed as odds if the exponent for each regression coefficient is calculated. In the context of the current study, $e^{Bi} < 1.00$ would signify odds decreasing for an accident being categorized as cargo. Likewise, if $e^{Bi} > 1.00$, then the odds would increase for an accident to be categorized as cargo. In the event that $e^{Bi} = 1.00$, then there is no change in the odds for an accident to be categorized as cargo relative to changes in a specific predictor variable. The 95% confidence interval for each significant regression coefficient is provided in Table 11. Confidence intervals provide insight into how accurate a parameter estimation is within the target population. A wide confidence interval infers low parameter accuracy for the target population, while a narrow confidence interval infers high accuracy. In the context of the current study, the widths of the confidence intervals for all significant predictors were categorize as follows: an odds ratio ranging from 0 to less than 10 was categorized as narrow, greater than 10 and but less than 20 would was categorized as moderate, and 20 or greater was categorized as wide.

Table 11

Summary of Odds Ratios for Statistically Significant Predictor Variables in Full Model

Predictor Variables	Odds Ratios	95% CI	*p*
Phase of Flight			
X_4 = Landing			
Passenger vs Cargo	3.25	[1.78, 5.94]	<0.01**
Aircraft Manufacturer			
X_8 = Man in CIS			
Cargo vs Passenger	4.46	[1.51, 13.14]	>0.01*
Aircraft Generation			
X_{11} = Generation 2			
Passenger vs Cargo	5.41	[2.03, 14.44]	<0.01**
X_{12} = Generation 3			
Passenger vs Cargo	5.13	[2.00, 13.16]	<0.01**
X_{13} = Generation 4			
Passenger vs Cargo	16.57	[6.85, 40.05]	<0.01**
Time of Day			
X_{15} = Day/Night			
Cargo vs Passenger	3.12	[2.00, 4.86]	<0.01**
Location of Operator			
X_{17} = CIS			
Cargo vs Passenger	6.03	[1.28, 28.33]	0.02*

Note. N = 594.

Significance tests and confidence intervals (CI) on odds ratios for the predictor variables are likelihood ratio (χ^2) based.

CI = Confidence Interval; *p* = probability; CIS = Commonwealth of Independent States.

**p* < .05. ***p* < .01.

X_4 = *Landing Phase of Flight.* The Landing Phase of Flight (compared to the Cruise Phase) had a statistically significant regression coefficient of B_4 = -0.59. This log odds can be expressed as an odd by calculating $e^{-0.59}$ = 0.55. In the context of the current study, the odds of an accident being categorized as cargo decreased significantly if this accident occurred during the Landing Phase of Flight (compared to the

Cruise Phase of Flight). More concretely, this result suggests that the odds of an air carrier accident being categorized as cargo decreased by 44.6% if it occurred during the Landing Phase (compared to the Cruise Phase) versus passenger accidents that occurred in the Landing Phase (compared to the Cruise Phase). The reciprocal, $e^{0.59} = 1.80$ can be interpreted as a significant increase in the odds of an accident being categorized as passenger if it occurred in the Landing Phase of Flight (compared to the Cruise Phase of Flight). Another interpretation of this coefficient would be an air carrier accident that occurred during the Landing Phase of Flight is 1.80 times more likely to be categorized as a passenger accident than a cargo accident when compared to the Cruise Phase of Flight, while holding all other predictor variables constant. The odds of an accident in the Landing Phase of Flight (compared to the Cruise Phase) being categorized as passenger (1.80) compared to the odds of an accident in the Landing Phase of Flight (compared to the Cruise Phase) being categorized as cargo (0.55) is interpreted as the odds ratio ($\frac{1.80}{0.55}$), or approximately 3.25. The 95% confidence interval listed in Table 11 indicates that 95% of the time, the odds ratio would vary between 1.78 and 5.94. This can also be interpreted as 95% of the time, an air carrier accident that occurred during the landing phase (compared to the cruise phase) would be between 1.78 and 5.94 times more likely to be a passenger accident than a cargo accident. The width of this interval suggests high accuracy for parameter estimation.

X_8 = Manufactured in CIS. Aircraft Manufactured in the CIS (compared to Aircraft Manufactured in NA) had a statistically significant regression coefficient of $B_8 = 0.75$. This log odds can be expressed as an odd by calculating $e^{0.75} = 2.12$. In the context of the current study, the odds of an accident being categorized as cargo increased significantly if this accident involved an Aircraft Manufactured in the CIS (compared to an Aircraft Manufactured in NA). Another interpretation of this coefficient would be an air carrier accident that involved a CIS-Manufactured Aircraft is 2.12 times more likely to be a cargo accident compared to a passenger accident (compared to NA-Manufactured Aircraft), while holding all other predictor variables constant. More concretely, this result suggests that the odds an air carrier accident being categorized as cargo increased by 112% if the aircraft involved in the accident was Manufactured in the CIS (compared to NA-Manufactured Aircraft) compared to passenger accidents with CIS-Manufactured Aircraft (compared to NA-Manufactured Aircraft). The reciprocal, $e^{-0.72} = 0.47$ can be interpreted as a significant decrease in the odds of an accident being categorized as cargo if it did not involve an Aircraft Manufactured in the CIS (compared to Aircraft Manufactured in NA). The odds of an accident

involving a CIS-Manufactured Aircraft (compared to a NA-Manufactured Aircraft) being categorized as cargo (2.12) compared to the odds of an accident involving a CIS-Manufactured Aircraft (compared to NA-Manufactured Aircraft) being categorized as passenger (0.47) is interpreted as the odds ratio ($\frac{2.12}{.47}$), or approximately 4.46. The 95% confidence interval listed in Table 11 indicates that 95% of the time, the odds ratio would vary between 1.51 and 13.14. This can also be interpreted as 95% of the time, an air carrier accident that involved a CIS-manufactured aircraft (compared to NA-manufactured aircraft) would be between 1.51 and 13.14 times more likely to be a cargo accident compared to a passenger accident. The width of this interval suggests moderate accuracy for parameter estimation.

X_{11} = *Generation 2.* Aircraft categorized as Generation 2 (compared to aircraft categorized as Generation 1) had a statistically significant regression coefficient of $B_{11} = -0.84$. This log odds can be expressed as an odd by calculating $e^{-0.84} = 0.43$. In the context of the current study, the odds of an accident being categorized as cargo decreased significantly if this accident involved a Generation 2 aircraft (compared to a Generation 1 aircraft). More concretely, this result suggests that the odds of an air carrier accident being categorized as cargo decreased by 56.9% if the aircraft involved in the accident was from Generation 2 (compared to Generation 1) compared to a passenger accident involving Generation 2 Aircraft (compared to a Generation 1 Aircraft). The reciprocal, $e^{0.84}$ = 2.32 can be interpreted as a significant increase in the odds of an accident being categorized as passenger if it involved a Generation 2 aircraft compared to Generation 1 aircraft. Another interpretation of this coefficient would be an air carrier accident that involved a Generation 2 aircraft is 2.32 times more likely to be a passenger accident compared to a cargo accident compared to Generation 1 Aircraft, while holding all other predictor variables constant. The odds of an accident involving a Generation 2 aircraft (compared to Generation 1 aircraft) being categorized as passenger (2.32) compared to the odds of an accident involving a Generation 2 aircraft (compared to Generation 1 aircraft) being categorized as cargo (0.43) is interpreted as the odds ratio ($\frac{2.32}{0.43}$), or approximately 5.41. The 95% confidence interval listed in Table 11 indicates that 95% of the time, the odds ratio would vary between 2.03 and 14.44. This can also be interpreted as 95% of the time, an air carrier accident that involved a Generation 2 Aircraft (compared to Generation 1 Aircraft) would be between 2.03 and 14.44 times more likely to be a passenger accident compared to a cargo accident. The width of this interval suggests moderate accuracy for parameter estimation.

X_{12} = *Generation 3.* Aircraft categorized as Generation 3 (compared to aircraft categorized as Generation 1) had a statistically significant regression coefficient of B_{12} = -0.82. This log odds can be expressed as an odd by calculating $e^{-0.82} = 0.44$. In the context of the current study, the odds of an accident being categorized as cargo decreased significantly if this accident involved a Generation 3 aircraft (compared to a Generation 1 aircraft). More concretely, this result suggests that the odds of a cargo accident occurring decreased by 56% if the aircraft involved in the accident was from Generation 3 (compared to Generation 1 Aircraft) compared to passenger accidents involving Generation 3 Aircraft (compared to Generation 1 Aircraft). The reciprocal, $e^{0.82} = 2.27$ can be interpreted as a significant increase in the odds of an accident being categorized as passenger if it involved a Generation 3 aircraft compared to Generation 1 aircraft. Another interpretation of this coefficient would be an air carrier accident that involved a Generation 3 aircraft is 2.27 times more likely to be a passenger accident compared to a cargo accident compared to Generation 1 aircraft, while holding all other predictor variables constant. The odds of an accident involving a Generation 3 Aircraft (compared to Generation 1 Aircraft) being categorized as passenger (2.27) compared to the odds of an accident involving a Generation 3 Aircraft (compared to Generation 1 Aircraft) being categorized as cargo (0.44) is interpreted as the odds ratio ($\frac{2.27}{0.44}$), or approximately 5.13. The 95% confidence interval listed in Table 11 indicates that 95% of the time, the odds ratio would vary between 2.00 and 13.16. This can also be interpreted as 95% of the time, an air carrier accident that involved a Generation 3 aircraft (compared to Generation 1 Aircraft) would be between 2.00 and 13.16 times more likely to be a passenger accident compared to a cargo accident. The width of this interval suggests moderate accuracy for parameter estimation.

X_{13} = *Generation 4.* Aircraft categorized as Generation 4 (compared to aircraft categorized as Generation 1) had a statistically significant regression coefficient of B_{13} = -1.40. This log odds can be expressed as an odd by calculating $e^{-1.40} = 0.25$. In the context of the current study, the odds of an accident being categorized as cargo decreased significantly if this accident involved a Generation 4 Aircraft (compared to a Generation 1 Aircraft). More concretely, this result suggests that the odds of a cargo accident occurring decreased by 75% if the aircraft involved in the accident was from Generation 4 (compared to Generation 1 Aircraft) compared to passenger accidents involving Generation 4 aircraft (compared to Generation 1 Aircraft). The reciprocal, $e^{1.40} = 4.06$ can be interpreted as a significant increase in the odds of an accident being categorized as passenger if it involved a Generation 4 aircraft compared to Generation 1 aircraft. Another interpretation of this coefficient would be an air carrier accident that involved a Generation 4 aircraft is 4.06 times more likely to be a passenger accident compared to a cargo accident compared to Generation 1 aircraft, while holding all other predictor variables constant. The odds of an accident involving a Generation 4 Aircraft (compared to Generation 1 Aircraft) being categorized as passenger (4.06) compared to the odds of an accident involving a Generation 3 Aircraft (compared to Generation 1 Aircraft) being categorized as cargo (0.25) is interpreted as the odds ratio ($\frac{4.06}{0.25}$), or approximately16.57. The 95% confidence interval listed in Table 11 indicates that 95% of the time, the odds ratio would vary between 6.85 and 40.05. This can also be interpreted as 95% of the time, an air carrier accident that involved a Generation 4 Aircraft (compared to Generation 1 Aircraft) would be between 6.85 and 40.05 times more likely to be a passenger accident compared to a cargo accident. The width of this interval suggests low accuracy for parameter estimation.

X_{15} = *Time of Day.* Air carrier accidents that occurred at Night (compared to accidents that occurred during the Day) had a statistically significant regression coefficient of $B_{15} = 0.57$. This log odds can be expressed as an odd by calculating $e^{0.57} = 1.77$. In the context of the current study, the odds of an accident being categorized as cargo increased significantly if this accident occurred at Night compared to an accident that occurred in the Day. More concretely, this result suggests that the odds of a cargo accident occurring increased by 77% if the accident occurred at Night (compared to an accident that occurred during the Day) compared to a passenger accident that occurred at Night (compared to an accident that occurred during the Day). The reciprocal, $e^{-0.57} = 0.57$ can be interpreted as a significant decrease in the odds of an accident being categorized as cargo if it occurred during the Day compared to an accident that occurred during the Night. The odds of an accident occurring at Night (compared to an accident that occurred during the Day) being categorized as cargo (1.77) compared to the odds of an accident occurring at Night (compared to an accident that occurred during the Day) being categorized as passenger (0.57) is interpreted as the odds ratio ($\frac{1.77}{0.57}$), or approximately 3.11. The 95% confidence interval listed in Table 11 indicates that 95% of the time, the odds ratio would vary between 2.00 and 4.86. This can also be interpreted as 95% of the time, an air carrier accident that occurred at night (compared to an accident that occurred during the day) would be between 2.00 and 4.86 times more likely to be a cargo accident compared to a passenger accident. The narrow width of this interval suggests high accuracy for parameter estimation.

X_{17} = *Operators Based in the CIS.* Accidents that involved CIS–Based Operators (compared to NA–Based Operators) had a statistically significant regression coefficient of $B_{17} = -0.91$. This log odds can be expressed as an odd by calculating $e^{-0.91} = 0.41$. In the context of the current study, the odds of an accident being categorized as cargo decreased significantly if this accident involved a CIS–Based Operator (compared to a NA–Based Operator). More concretely, this result suggests that the odds of an air carrier accident being categorized as cargo decreased by 59% if the Operator was Based in the CIS (compared to an Operator Based in NA) compared to a passenger accident involving a CIS–Based Operator (compared to a NA–Based Operator). The reciprocal, $e^{0.91} = 2.48$ can be interpreted as a significant increase in the odds of an accident being categorized as passenger if it involved a CIS–Based Operator (compared to NA–Based Operator). Another interpretation of this coefficient would be an air carrier accident that involved a CIS–Based Operator is 2.48 times more likely to be a passenger accident compared to a cargo accident compared to a NA–Based Operator, while holding all other predictor variables constant. The odds of an accident involving a CIS–Based Operator (compared to a NA–Based Operator) being categorized as passenger (2.48) compared to the odds of an accident involving a CIS–Based Operator (compared to a NA–Based Operator) being categorized as cargo (0.41) is interpreted as the odds ratio ($\frac{2.48}{0.41}$), or approximately 6.03. The 95% confidence interval listed in Table 11 indicates that 95% of the time, the odds ratio would vary between 1.28 and 28.33. This can also be interpreted as 95% of the time, an air carrier accident that involved a

CIS–Based Operator (compared to a NA–Based Operator) would be between 1.28 and 28.33 times more likely to be a passenger accident compared to a cargo accident. The width of this interval suggests moderate accuracy for parameter estimation.

Following the full analysis of the criterion variable regressed on all of the predictor variables, four subsequent simultaneous analyses were performed. Each of the four simultaneous analyses were made up of predictor variables categorized by the four relevant levels of the SHELO model: Software, Hardware, Environmental Factors, and Organizational Influences. The results of each of the four subsequent simultaneous analyses are presented in the same manner as the results from the prior analysis which used all predictor variables: the full model and regression equation, and the log odds, odds, odds ratios, and confidence intervals of the statistically significant predictor variables. The null model, absent of all predictor variables, can be found on Table 10, and was not reanalyzed the same criterion variable (*Y* = *Cargo or Passenger*) being used in all subsequent analyses. All four of the simultaneous regression analyses, which were run in accordance with the four levels of the SHELO model, were in compliance with all of the assumptions for logistic regression which were discussed earlier in this chapter.

Simultaneous Analysis with the Predictor Variables Relevant to the Software Level of the SHELO Model. The first level of the SHELO model was Software, and this was defined as a supporting system available to employees (Edwards, 1972). In the context of the current study, Software can include checklists, manuals, publications, and standard operating procedures. Four predictor variables used in the current study were categorized as Software: Phase of Flight, LOC, CFIT, and Weight Factor. As explained earlier in this chapter, certain predictor variables were divided into more than 2 groups, which required dummy coding for proper analysis and interpretation. The Phase of Flight variable was split into 5 groups, with the Climb Phase selected as the reference group. The LOC, CFIT, and Weight Factor variables were all dichotomous, with yes coded as "1" and no coded as "0.". Therefore, the predictor variables used in this simultaneous regression were as follows: X_1 = Takeoff, X_2 = Climb, X_3 = Approach, X_4 = Landing, X_5 = LOC, X_6 = CFIT, and X_7 = Weight Factor.

The full model was statistically significant, $\chi^2(7) = 47.22$, $p < .01$. The Pseudo-R^2 (R_L^2), recommended by Choen et al. (2003), was $R_L^2 = .06$. In the context of the current study, the full model provided a predictive gain of 6.24% over the null model ($R_{Lfull}^2 = .06$, $df = 7$).

The full, simultaneous model with predictor variables relevant to the software level of the SHELO model is summarized in Table 12. The full model logit (L_i) for group membership in the criterion variable is represented by the equation $L_i = -0.69 - 0.29X_1 - 0.13X_2 + 0.04X_3 - 0.63X_4 + 0.09X_5 + 0.01X_6 + 0.46X_7$. Two predictor variables were statistically significant in relation to the criterion variable when in the presence of other predictors: X_4 = Landing Phase of Flight (compared to the Cruise Phase) and X_7 = Weight Factor.

Table 12

Summary of Logistic Regression Estimates for the Null and Simultaneous (Full) Models for Predictor Variables Relevant to the Software Level of the SHELO Model

	B_i	*SE*	χ^2	*p*
Null Model				
Constant	-0.69	0.09	63.42	<0.001
Full Model				
Constant	-0.69	0.38	3.24	0.07
Phase of Flight				
X_1 = Takeoff	-0.29	0.16	3.12	0.08
X_2 = Climb	-0.13	0.20	0.40	0.53
X_3 = Approach	0.04	0.15	0.06	0.81
X_4 = Landing	-0.63	0.13	23.93	<.01**
X_5 = Loss of Control	0.09	0.12	0.65	0.42
X_6 = Controlled Flight into Terrain	0.01	0.16	0.00	0.96
X_7 = Weight Factor	0.46	0.20	5.49	0.02*

Note. N = 594. $R_L^2 = .06$, $df = 7$ for the full model.

B_i = Logit; *SE* = Standard Error; χ^2 = Chi Statistic; *p* = Probability.

$*p < .05$. $**p < .01$.

X_4 = *Landing Phase of Flight.* The Landing Phase of Flight (compared to the Cruise Phase) had a statistically significant regression coefficient of $B_4 = -0.63$. This log odds can be expressed as an odd by calculating $e^{-0.63} = 0.53$. In the context of the current study, the odds of an accident being categorized as cargo decreased significantly if this accident occurred during the Landing Phase of Flight compared to the Cruise Phase of Flight. More concretely, this result suggests that the odds of a cargo accident occurring decreased by 46.4% if it occurred during the Landing Phase (compared to the Cruise Phase) compared to passenger accidents that occurred in the Landing Phase (compared to the Cruise Phase). The reciprocal, $e^{0.63} = 1.87$ can be interpreted as a significant increase in the odds of an accident being categorized as passenger if it occurred in the Landing Phase of Flight compared to the Cruise Phase of Flight. Another interpretation of this coefficient would be an air carrier accident that occurred during the Landing Phase of Flight is 1.87 times more likely to be a passenger accident compared to a cargo accident when compared to the Cruise Phase of Flight, while holding all other predictor variables constant. The odds of an accident in the Landing Phase of Flight (compared to the Cruise Phase) being categorized as passenger (1.87) compared to the odds of an accident in the Landing Phase of Flight (compared to the Cruise Phase) being categorized as cargo (0.53) is interpreted as the odds ratio ($\frac{1.87}{0.53}$), or approximately 3.50. The 95% confidence interval listed in Table 13 indicates that 95% of the time, the odds ratio would vary between 2.12 and 5.79. This can also be interpreted as 95% of the time, an air carrier accident that occurred during the landing phase (compared to the cruise phase) would be between 2.12 and 5.79 times more likely to be a passenger accident compared to a cargo accident. The width of this interval suggests high accuracy for parameter estimation.

Table 13

Summary of Odds Ratios for Statistically Significant Predictor Variables Relevant to the Software Level of the SHELO Model

Predictor Variables	Odds Ratios	95% CI	*p*
Phase of Flight			
X_4 = Landing			
Passenger vs Cargo	3.51	[2.12, 5.79]	<0.01**
X_7 = Weight Factor			
Cargo vs Passenger	2.53	[1.16, 5.51]	0.02*

Note. N = 594.

CI = Confidence Interval.

*p < .05. **p < .01.

X_7 = Weight Factor. Air carrier accidents involved a Weight Factor, which was defined earlier in this chapter, had a statistically significant regression coefficient of $B_7 = 0.46$. This log odds can be expressed as an odd by calculating $e^{0.46} = 1.59$. In the context of the current study, the odds of an accident being categorized as cargo increased significantly if this accident was related to a Weight Factor (compared to an accident that was not related to a Weight Factor). More concretely, this result suggests that the odds of a cargo accident occurring increased by 59% if the accident was related to a Weight Factor (compared to a cargo accident that was not related to a Weight Factor) compared to a passenger accident that was related to a Weight Factor (compared to a passenger accident that was not related to a Weight Factor). The reciprocal, $e^{-0.46} = 0.62$ can be interpreted as a

significant decrease in the odds of an accident being categorized as cargo if it involved a weight factor compared to an accident that did not involve a weight factor. The odds of an accident that involved a Weight Factor being categorized as cargo (1.59) compared to the odds of an accident that involved a Weight Factor being categorized as passenger (0.63) is interpreted as the odds ratio ($\frac{1.59}{0.63}$), or approximately 2.53. The 95% confidence interval listed in Table 13 indicates that 95% of the time, the odds ratio would vary between 1.16 and 5.51. This can also be interpreted as 95% of the time, an air carrier accident involved a Weight Factor (compared to an accident that did not involve a Weight Factor) would be between 1.16 and 5.51 times more likely to be a cargo accident compared to a passenger accident. The width of this interval suggests high accuracy for parameter estimation.

Simultaneous Analysis with the Predictor Variables Relevant to the Hardware Level of the SHELO Model. The second level of the SHELO model was hardware, and this was defined as the physical attributes of a machine, equipment, or facilities used by employees. (Edwards, 1972). In the context of the current study, hardware can include attributes of an aircraft, including manufacturer and age. Three predictor variables used in the current study were categorized as hardware: Aircraft Manufacturer, Aircraft Generation, and Mechanical Failure. As explained earlier in this chapter, certain predictor variables were divided into more than 2 groups, which required dummy coding for proper analysis and interpretation. The Aircraft Manufacturer variable was split into 4 groups after the outlier analysis was performed, with NA selected as the reference group. The Aircraft Generation variable was split into 4, with the Generation 1 selected as the reference group. The Mechanical Failure variable was dichotomous, with yes coded as “1” and no coded as “0.”. Therefore, the predictor variables used in this simultaneous regression were as follows: X_8 = CIS, X_9 = European, X_{10} = LA, X_{11} = Generation 2, X_{12} = Generation 3, X_{13} = Generation 4, and X_{14} = Mechanical Failure.

The full model was statistically significant, $\chi^2(7) = 98.91$, $p < .01$. The Pseudo-R^2 (R_L^2), recommended by Choen et al. (2003), was $R_L^2 = .13$. In the context of the current study, the full model provided a predictive gain of 13.08% over the null model ($R_{Lfull}^2 = .13$, $df = 7$).

The full, simultaneous model with predictor variables relevant to the hardware level of the SHELO model is summarized in Table 14. The full model logit (L_{i}) for group membership in the criterion variable is represented by the equation $L_{\mathrm{i}} = -1.67 + 0.17X_8 - 0.31X_9 - 0.07X_{10} - 0.87X_{11} - 0.84X_{12} - 1.43X_{13} - 0.01X_{14}$. Four predictor variables were statistically significant in relation to the criterion variable when in the presence of other predictors: X_9 = manufacturer-Europe (compared to manufacturer-NA), X_{11} = generation 2 (compared to generation 1), X_{12} =

generation 3 (compared to generation 1), and X_{13} = generation 4 (compared to generation 1).

Table 14

Summary of Logistic Regression Estimates for the Null and Simultaneous (Full) Models for Predictor Variables Relevant to the Hardware Level of the SHELO Model

	B_i	*SE*	χ^2	*p*
Null Model				
Constant	-0.69	0.09	63.42	<.01**
Full Model				
Constant	-1.67	0.39	18.44	< .01**
Aircraft Manufacturer				
X_8 = CIS	0.17	0.21	0.68	0.41
X_9 = Europe	-0.31	0.12	7.36	.01**
X_{10} = Latin America	-0.07	0.23	0.10	0.76
X_{11} = Generation 2	-0.87	0.23	14.37	<0.01**
X_{12} = Generation 3	-0.84	0.22	14.73	<0.01**
X_{13} = Generation 4	-1.43	0.21	47.97	<.001**
X_{14} = Mechanical failure	-0.01	0.10	0.01	0.92

Note. N = 594. R_L^2 = .13, *df* = 7 for the full model.

B_i = Logit; *SE* = Standard Error; χ^2 = Chi Statistic; *p* = Probability.

**p* < .05. ***p* < .01.

X_9 = *European-Based Manufacturer.* Aircraft Manufactured in Europe (compared to Aircraft Manufactured in NA) had a statistically significant regression coefficient of B_9 = -0.31. This log odds can be expressed as an odd by calculating $e^{-0.31}$ = 0.73. In the context of the current study, the odds of an accident being categorized as cargo decreased significantly if this accident involved an Aircraft Manufactured in Europe (compared to Aircraft Manufactured in NA). More concretely, this result suggests that the odds an air carrier accident being categorized as cargo decreased by 26.9% if the aircraft involved in the accident was Manufactured in Europe (compared to NA-

Manufactured Aircraft) compared to passenger accidents with European-Manufactured Aircraft (compared to NA-Manufactured). The reciprocal, $e^{0.31} = 1.37$ can be interpreted as a significant increase in the odds of an accident being categorized as passenger if it did involve an Aircraft Manufactured in Europe (compared to Aircraft Manufactured in NA). The odds of an accident involving a European-Manufactured Aircraft (compared to a NA-Manufactured Aircraft) being categorized as passenger (1.37) compared to the odds of an accident involving a European-Manufactured Aircraft (compared to NA-Manufactured Aircraft) being categorized as passenger (0.73) is interpreted as the odds ratio ($\frac{1.37}{0.73}$), or approximately 1.87. The 95% confidence interval listed in Table 15 indicates that 95% of the time, the odds ratio would vary between 1.19 and 2.94. This can also be interpreted as 95% of the time, an air carrier accident that involved a European-Manufactured Aircraft (compared to NA-Manufactured Aircraft) would be between 1.19 and 2.94 times more likely to be a passenger accident compared to a cargo accident. The narrow width of this interval suggests high accuracy for parameter estimation.

Table 15

Summary of Odds Ratios for Statistically Significant Predictor Variables Relevant to the Hardware Level of the SHELO Model

Predictor Variables	**Odds Ratios**	**95% CI**	***p***
Aircraft Manufacturer			
X_9 = Europe			
Passenger vs Cargo	1.87	[1.19, 2.94]	0.01**
Aircraft Generation			
X_{11} = Generation 2			
Passenger vs Cargo	5.73	[2.32, 14.14]	<0.0**
X_{12} = Generation 3			
Passenger vs Cargo	5.40	[2.28, 12.79]	<0.01**
X_{13} = Generation 4			
Passenger vs Cargo	17.32	[7.73, 38.81]	<0.01**

Note. N = 594.

CI = Confidence Interval.

*p < .05. **p < .01.

X_{11} = *Generation 2.* Aircraft categorized as Generation 2 (compared to aircraft categorized as Generation 1) had a statistically significant regression coefficient of B_{11} = -0.87. This log odds can be expressed as an odd by calculating $e^{-0.87}$ = 0.42. In the context of the current study, the odds of an accident being categorized as cargo decreased significantly if this accident involved a Generation 2 Aircraft compared to a Generation 1 Aircraft. More concretely, this result suggests that the odds of an air carrier accident being categorized as cargo decreased by 58.2% if the aircraft involved in the accident was from Generation 2 (compared to Generation 1 Aircraft) compared to a passenger accident involving Generation 2 Aircraft (compared to Generation 1 Aircraft). The reciprocal, $e^{0.87}$ = 2.39 can be interpreted as a significant increase in the odds of an accident being categorized as passenger if it involved a Generation 2 Aircraft compared to Generation 1 Aircraft. Another interpretation of this coefficient would be an air carrier accident that involved a Generation 2 Aircraft is 2.39 times more likely to be a passenger accident compared to a cargo accident compared to Generation 1 Aircraft, while holding all other predictor variables constant. The odds of an accident involving a Generation 2 Aircraft (compared to Generation 1 Aircraft) being categorized as passenger (2.39) compared to the odds of an accident involving a Generation 2 Aircraft (compared to Generation 1 Aircraft) being categorized as cargo (0.42) is interpreted as the odds ratio ($\frac{2.39}{0.42}$), or approximately 5.73. The 95% confidence interval listed in Table 15 indicates that 95% of the time, the odds ratio would vary between 2.32 and 14.14. This can also be interpreted as 95% of the time, an air carrier accident that involved a Generation 2 Aircraft (compared to Generation 1 Aircraft) would be between 2.32 and 14.14 times more likely to be a passenger accident compared to a cargo accident. The width of this interval suggests moderate accuracy for parameter estimation.

X_{12} = *Generation 3.* Aircraft categorized as Generation 3 (compared to aircraft categorized as Generation 1) had a statistically significant regression coefficient of B_{12} = -0.84. This log odds can be expressed as an odd by calculating $e^{-0.84} = 0.43$. In the context of the current study, the odds of an accident being categorized as cargo decreased significantly if this accident involved a Generation 3 Aircraft compared to a Generation 1 Aircraft. More concretely, this result suggests that the odds of a cargo accident occurring decreased by 57% if the aircraft involved in the accident was from Generation 3 (compared to Generation 1 Aircraft) compared to passenger accidents involving Generation 3 Aircraft (compared to Generation 1 Aircraft). The reciprocal, $e^{0.84} = 2.33$ can be interpreted as a significant increase in the odds of an accident being categorized as passenger if it involved a Generation 3 Aircraft compared to Generation 1 Aircraft. Another interpretation of this coefficient would be an air carrier accident that involved a Generation 3 aircraft is 2.33 times more likely to be a passenger accident compared to a cargo accident compared to Generation 1 Aircraft, while holding all other predictor variables constant. The odds of an accident involving a Generation 3 Aircraft (compared to Generation 1 aircraft) being categorized as passenger (2.33) compared to the odds of an accident involving a Generation 3 Aircraft (compared to Generation 1 Aircraft) being categorized as passenger (0.43) is interpreted as the odds ratio ($\frac{2.33}{0.43}$), or approximately 5.40. Due to the odds of an air carrier accident involving a Generation 3 Aircraft (compared to a Generation 1 Aircraft) are higher for passenger accidents in comparison to cargo accidents, it makes sense to interpret the confidence interval as passenger and cargo. The 95% confidence interval listed in Table 15 indicates that 95% of the time, the odds ratio would vary between 2.28 and 12.79. This can also be interpreted as 95% of the time, an air carrier accident that involved a Generation 3 Aircraft (compared to Generation 1 Aircraft) would be between 2.28 and 12.79 times more likely to be a passenger accident compared to a cargo accident. The width of this interval suggests moderate accuracy for parameter estimation.

X_{13} = *Generation 4.* Aircraft categorized as Generation 4 (compared to aircraft categorized as Generation 1) had a statistically significant regression coefficient of $B_{13} = -1.43$. This log odds can be expressed as an odd by calculating $e^{-1.43} = 0.24$. In the context of the current study, the odds of an accident being categorized as cargo decreased significantly if this accident involved a Generation 4 Aircraft compared to a Generation 1 Aircraft. More concretely, this result suggests that the odds of a cargo accident occurring decreased by 76% if the aircraft involved in the accident was from Generation 4 (compared to Generation 1 Aircraft) compared to passenger accidents involving Generation 4 Aircraft (compared to Generation 1 Aircraft). The reciprocal, $e^{1.43} = 4.16$ can be interpreted as a significant increase in the odds of an accident being categorized as passenger if it involved a

Generation 4 Aircraft compared to Generation 1 Aircraft. Another interpretation of this coefficient would be an air carrier accident that involved a Generation 4 Aircraft is 4.16 times more likely to be a passenger accident compared to a cargo accident compared to Generation 1 Aircraft, while holding all other predictor variables constant. The odds of an accident involving a Generation 4 Aircraft (compared to Generation 1 Aircraft) being categorized as passenger (4.16) compared to the odds of an accident involving a Generation 3 Aircraft (compared to Generation 1 Aircraft) being categorized as cargo (0.24) is interpreted as the odds ratio ($\frac{4.16}{0.24}$), or approximately 17.32. The 95% confidence interval listed in Table 15 indicates that 95% of the time, the odds ratio would vary between 7.73 and 38.81. This can also be interpreted as 95% of the time, an air carrier accident that involved a Generation 4 Aircraft (compared to Generation 1 Aircraft) would be between 7.73 and 38.81 times more likely to be a passenger accident compared to a cargo accident. The width of this interval suggests low accuracy for parameter estimation.

Simultaneous Analysis with the Predictor Variables Relevant to the Environmental Level of the SHELO Model. The third level of the SHELO model was the Environment, and this was defined as the internal and external factors in relation to the operation of an aircraft. (Edwards, 1972). After the removal of a variable due to multicollinearity, a single predictor variable was categorized as Environment: Time of Day. The time-of-day variable was dichotomous, with night coded as “1” and day coded as “0.”. Therefore, the predictor variable used in this simultaneous regression was as follows: X_{15} = time of day.

The full model was statistically significant, $\chi^2(1) = 21.82$, $p < .01$. The Pseudo-R^2 (R_L^2), recommended by Choen et al. (2003), was $R_L^2 = .03$. In the context of the current study, the full model provided a predictive gain of 3% over the null model ($R_{Lfull}^2 = .03$, $df = 1$).

The full, simultaneous model with the single predictor variable relevant to the Environmental Level of the SHELO model is summarized in Table 16. The full model logit (L_i) for group membership in the criterion variable is represented by the equation $L_i = -0.58 + 0.42X_{15}$. X_{15} = Time of Day was statistically significant in relation to the criterion variable when in the presence of other predictors.

Table 16

Summary of Logistic Regression Estimates for the Null and Simultaneous (Full) Models for Predictor Variables Relevant to the Environmental Level of the SHELO Model

	B_i	*SE*	χ^2	*p*
Null Model				
Constant	-0.69	0.09	63.42	<.01**
Full Model				
Constant	-0.58	0.09	41.16	<.01**
X_{15} = Time of Day	0.42	0.09	21.77	<.01**

Note. N = 594. $R_L^2 = .03$, $df = 1$ for the full model.

B_i = Logit; *SE* = Standard Error; χ^2 = Chi Statistic; *p* = Probability.

*$p < .05$. **$p < .01$.

X_{15} = *Time of day.* Air carrier accidents that occurred at Night (compared to accidents that occurred during the Day) had a statistically significant regression coefficient of $B_{15} = 0.42$. This log odds can be expressed as an odd by calculating $e^{0.42} = 1.52$. In the context of the current study, the odds of an accident being categorized as cargo increased significantly if this accident occurred at Night compared to an accident that occurred in the Day. More concretely, this result suggests that the odds of a cargo accident occurring increased by 52.8% if the accident occurred at Night (compared to an accident that occurred during the Day) compared to a passenger accident that occurred at Night (compared to an accident that occurred during the Day). The reciprocal, $e^{-0.42} = 0.65$ can be interpreted as a significant decrease in the odds of an accident being categorized as cargo if it occurred during the Day compared to an accident that occurred during the Night. The odds of an accident occurring at Night (compared to an accident that occurred during the Day) being categorized as cargo (1.53) compared to the odds of an accident occurring at Night (compared to an accident that occurred during the Day) being categorized as passenger (0.65) is interpreted as the odds ratio ($\frac{1.53}{0.65}$), or approximately 2.34. The 95% confidence interval listed in Table 17 indicates that 95% of the time, the odds ratio would vary between 1.63 and 3.33. This can also be interpreted as 95% of the time, an air carrier accident that occurred at Night (compared to an accident that occurred during the Day) would be between 1.61 and 3.39 times more likely to be a cargo accident compared to a passenger accident. The width of this interval suggests high accuracy for parameter estimation.

Table 16

Summary of Odds Ratios for Statistically Significant Predictor Variables Relevant to the Environmental Level of the SHELO Model

Predictor Variables	Odds Ratios	95% CI	*p*
X_{15} = Day/night			
Cargo vs Passenger	2.33	[1.63, 3.33]	<0.01**

Note. N = 594.

CI = Confidence Interval.

*p < .05. **p < .01.

Simultaneous Analysis with the Predictor Variables Relevant to the Organizational Influences Level of the SHELO Model. The fourth level of the SHELO model was Organizational Influences, and this was defined as factors that exist within the structure or operations of a company. (Chang & Wang, 2009). In the context of the current study, Organizational Influences can include regulations that govern the operation of an air carrier and the socioeconomic status of the country in which an air carrier is based. One predictor variable that was used in the current study was categorized as Organizational Influences: Location of an Operator. As explained earlier in this chapter, certain predictor variables were divided into more than 2 groups, which required dummy coding for proper analysis and interpretation. The Location of the Operator variable was split into 8 groups, with Africa selected as the reference group. Therefore, the predictor variables used in this simultaneous regression were as follows: X_{16} = Asia, X_{17} = CIS, X_{18} = Europe, X_{19} = LA, X_{20} = ME, X_{21} = NA, and X_{22} = Oceania.

The full model was statistically significant, $\chi^2(7) = 56.20$, $p < .01$. The Pseudo-R^2 (R_L^2), recommended by Choen et al. (2003), was $R_L^2 = .07$. In the context of the current study, the full model provided a predictive gain of 7% over the null model ($R_{Lfull}^2 = .07$, $df = 7$).

The full, simultaneous model with predictor variables relevant to the Organizational Influences level of the SHELO model is summarized in Table 18. The full model logit (L_i) for group membership in the criterion variable is represented by the equation $L_i = -1.66 – 0.38X_{16} – 0.30X_{17} – 0.44X_{18} – 0.04X_{19} – 0.19X_{20} + 0.39X_{21} – 0.02X_{22}$. Two predictor variables were statistically significant in relation to the criterion variable when in the presence of other predictors: X_{18} = Europe (compared to Africa) and X_{21} = NA (compared to Africa).

Table 17

Summary of Logistic Regression Estimates for the Null and Simultaneous (Full) Models for Predictor Variables Relevant to the Organizational Influences Level of the SHELO Model

	B_i	*SE*	χ^2	*p*
Null Model				
Constant	-0.69	0.09	63.42	<.001
Full Model				
Constant	-1.66	0.94	3.14	0.08
Operator Location				
X_{23} = Asia	-0.38	0.21	3.24	0.07
X_{24} = CIS	-0.30	0.30	1.03	0.31
X_{25} = Europe	-0.44	0.21	4.29	0.04*
X_{26} = Latin America	-0.04	0.21	0.03	0.86
X_{27} = Middle East	-0.19	0.26	0.50	0.48
X_{28} = North America	0.39	0.18	4.94	0.03*
X_{29} = Oceania	-0.02	0.28	0.00	0.95

Note. N = 594. R_L^2 = .07, *df* = 7 for the full model.

B_i = Logit; *SE* = Standard Error; χ^2 = Chi Statistic; *p* = Probability.

CIS = Commonwealth of Independent States

**p* < .05. ***p* < .01.

X_{18} = *Operators Located in Europe.* Air carrier operators that are Located in the Europe (compared to Operators Located in the Africa) had a statistically significant regression coefficient of B_{18} = -0.44. This log odds can be expressed as an odd by calculating $e^{-0.44}$ = 0.64. In the context of the current study, the odds of an accident being categorized as cargo decreased significantly if this accident involved an Operator that was Based in Europe (compared to an Operator Based in Africa). More concretely, this result suggests that the odds an air carrier accident being categorized as cargo decreased by 44% if the operator involved in the accident was Based in Europe (compared to Africa-Based Operators) compared to passenger accidents with European-Based Operators (compared to NA-Based Operators). The reciprocal, $e^{0.44} = 1.55$ can be interpreted as a significant increase in the odds of an accident being categorized as passenger if it did involve an Operator Based in Europe (compared to an Operator Based in Africa). The odds of an accident involving a European-Based Operator (compared to an African-Based Operator) being categorized as cargo (0.64) compared to the odds of an accident involving a European-based operator (compared to an African-based operator) being categorized as passenger (1.55) is interpreted as the odds ratio ($\frac{1.55}{0.64}$), or approximately 2.41. The 95% confidence interval listed in Table 19 indicates that 95% of the time, the odds ratio would vary between 1.10 and 4.39. This can also be interpreted as 95% of the time, an air carrier accident that involved a European-Based Operator (compared to an African-based operator) would be between 1.10 and 4.39 times more likely to be a passenger accident compared to a cargo accident. The width of this interval suggests high accuracy for parameter estimation.

Table 19

Summary of Odds Ratios for Statistically Significant Predictor Variables Relevant to the Organizational Influences Level of the SHELO Model

Predictor Variables	Odds Ratios	95% CI	*p*
Operator Location			
X_{18} = Europe			
Passenger vs Cargo	2.41	[1.05, 5.56]	<0.05*
X_{21} = North America			
Cargo vs Passenger	2.19	[1.10, 4.39]	<0.05*

Note. N = 594.

CI = Confidence Interval.

*p < .05. **p < .01.

X_{21} = *Operators Located in NA.* Air carrier operators that are located in the NA region (compared to operators located in the Africa region), had a statistically significant regression coefficient of B_{21} = 0.39. This log odds can be expressed as an odd by calculating $e^{0.39}$ = 1.48. In the context of the current study, the odds of an accident being categorized as cargo increased significantly if this accident involved an air carrier Based in NA (compared to an air carrier Based in Africa). More concretely, this result suggests that the odds of a cargo accident occurring increased by 48% if the accident involved an air carrier Based in NA (compared to an air carrier Based in Africa) compared to a passenger accident that involved an air carrier Based in NA (compared to an air carrier Based in Africa). The reciprocal, $e^{-0.39}$ = 0.68 can be interpreted as a significant decrease in the odds of an accident being categorized as passenger if it involved an air carrier Based in NA (compared to an air carrier Based in Africa). The odds of an accident involving an Operator Based in NA (compared to an Operator Based in Africa) being categorized as cargo (1.48) compared to the odds of an accident involving an operator based in NA (compared to an air carrier based in Africa) being categorized as passenger (0.68) is interpreted as the odds ratio ($\frac{1.48}{0.68}$), or approximately 2.18. The 95% confidence interval listed in Table 19 indicates that 95% of the time, the odds ratio would vary between 1.10 and 4.39. This can also be interpreted as 95% of the time, an air carrier accident involving an Operator Based in NA (compared to an Operator Based in Africa) would be between 1.10 and 4.39 times more likely to be a cargo accident compared to a passenger accident. The narrow width of this interval suggests high accuracy for parameter estimation.

Results of Hypotheses Testing

The research questions and corresponding research hypotheses were listed in Chapter 1 of the current study. Each of the null hypotheses have been restated below and tested for the decision to reject or fail to reject the hypothesis using the data discussed earlier in this chapter. It should be restated to the reader that one of the groups within the variable *X* = Aircraft Manufactured in Asia, was removed during the outlier screening and was not included in the primary analysis.

Null Hypothesis 1

When examined from a simultaneous perspective, the variable set related to the Software level of the SHELO model will not have a statistically significant influence on group membership in either passenger or cargo air carrier accidents. The simultaneous model for predictor variables categorized as the Software level of the SHELO model was significant, χ^2 (7) = 47.22, p < .01. Given the significance of the overall model, the parameters within the model were able to be examined for statistical significance. Two variables were statistically significant: X_4 = Landing (-0.63, p <.0001) and X_7 = Weight Factor (0.46, p = 0.02). The corresponding odds ratios for the Landing Phase of Flight (OR = 3.51), and Weight Factor (OR = 2.53) differed significantly from 1.00, null Hypothesis 1 was rejected.

Null Hypothesis 2

When examined from a simultaneous perspective, the variable set related to the Hardware level of the SHELO model will not have a statistically significant influence on group membership in either passenger or cargo air carrier accidents. The simultaneous model for predictor variables categorized as the Hardware level of the SHELO model was significant, χ^2 (7) = 98.91, p < .01. Given the significance of the overall model, the parameters within the model were able to be examined for statistical significance. Four variables were statistically significant: X_9 = Aircraft Manufactured in Europe (-0.31, p = .01), X_{11} = Generation 2 (-0.87, p = <.01), X_{12} = Generation 3 (-0.84, p = <.01) and X_{13} = Generation 4 (-1.43, $p < .01$). The corresponding odds ratios for Aircraft Manufactured in Europe (OR = 1.87), Generation 2 (OR = 5.73), Generation 3 (OR = 5.40) and Generation 4 (OR = 17.32) differed significantly from 1.00, null Hypothesis 2 was rejected.

Null Hypothesis 3

When examined from a simultaneous perspective, the variable set related to the Environmental level of the SHELO model will not have a statistically significant influence on group membership in either passenger or cargo air carrier accidents. The simultaneous model for predictor variables categorized as the Environmental level of the SHELO model was significant, χ^2 (1) = 21.82, $p < .01$. Given the significance of the overall model, the parameters within the model were able to be examined for statistical significance. One variable was statistically significant: X_{15} = Time of Day (0.42, $p < .0001$). The corresponding odds ratio found in for the Time of Day (OR = 2.33) differed significantly from 1.00, null Hypothesis 3 was rejected.

Null Hypothesis 4

When examined from a simultaneous perspective, the variable set related to the Organizational Influences level of the SHELO model will not have a statistically significant influence on group membership in either passenger or cargo air carrier accidents. The simultaneous model for predictor variables categorized as the organizational influences level of the SHELO model was significant, χ^2 (7) = 56.20, $p < .01$. Given the significance of the overall model, the parameters within the model were able to be examined for statistical significance. Two variables were statistically significant: X_{18} = Operators Located in Europe (-0.44, $p = .04$) and X_{21} = Operators Located in NA (0.39, $p = .03$). The corresponding odds ratios for the Operators Based in Europe (OR = 2.41) and Operators Based in NA (OR = 2.19) differed significantly from 1.00, null Hypothesis 4 was rejected.

Chapter 5

Conclusions, Implications, and Recommendations

Summary of Study

The purpose of this study was to identify factors that could distinguish between two types of air carrier accidents: passenger and cargo. Several factors were identified through previous studies and related literature and were categorized according to levels of the SHELO model (Edwards, 1972; Chang & Wang, 2009) apart from the Liveware level. The following factors were categorized in the Software level of the SHELO model: Phase of Flight, LOC, CFIT, and Weight Factor. The following factors were categorized in the Hardware level of the SHELO model: Aircraft Manufacturer, Aircraft Generation, and Mechanical Failure. The following factor was categorized in the Environmental level of the SHELO model: Time of Day. Lastly, the following factor was categorized in the Organizational Influences level of the SHELO model: Operator Location. After all factors were identified and categorized, they were treated as predictor variables and used to conduct several logistic regression analyses. Each analysis used the same dichotomous group membership criterion variable: Passenger or Cargo.

The study utilized a causal-comparative design as pre-existing air carrier accident data was used to identify factors that determined group membership between Passenger and Cargo. Specifically, a retroactive causal-comparative design was used as the group membership of Passenger or Cargo was represented in the single criterion variable used in all analyses. This particular design was appropriate as the membership of Passenger or Cargo for each air carrier accident had already occurred.

The target population for this study was every commercial passenger and cargo air carrier accident globally, as the dataset used for all analyses contained international air carrier accident data. According to IATA, over 1,100 air carriers exist globally. With respect to the ratio of passenger to cargo air carrier operations, the ATCA determined that approximately 8% of air carrier operations in the United States were cargo and 92% were passenger. The accessible population for this study consisted of any air carrier accident whose investigation led to a published final accident report that was made publicly available. All archival data collected for this study was obtained through the ASN from the years 2002 through 2019. In total, 3,806 aircraft accidents occurred globally within this time frame, but only 594 accidents were considered in-scope air carrier accidents with published final accident reports. The final sample size of 594 remained consistent throughout preliminary and primary data analyses, as described in Chapter 4.

Summary of Findings

Before the primary analysis began, a preliminary analysis was conducted to produce a "clean" dataset and identify any potential outliers. During the preliminary analysis, no instances of missing data were identified and all of the assumptions for logistic regression were met. Four cases were determined to be outliers and were removed from the final dataset.

Before the findings are summarized, it is important to understand the method of dummy coding that was used during data organization and analysis. All of the predictor variables in the current study were categorical. Some of these variables were dichotomous, such as Time of Day (Day or Night) or Weight Factor (yes or no). This allowed for a direct comparison of one group to another by coding data with a 0 or a 1. Time of day followed this coding scheme (day = 0, night = 1). If an accident occurred at Night, the dummy coding allowed for the influence this predictor had on the criterion variable to be interpreted as a comparison to the same accident if it had occurred during the Day. However, several of the predictor variables had more than two groups, such as Phase of Flight (Takeoff, Climb, Cruise, Approach, and Landing). Therefore, one of these groups had to be selected as the reference group which would provide a direct comparison to all other groups within this single variable. The reference group that was selected and the rationale behind the selection for each variable was described in Chapter 3.

Certain levels of the SHELO model, such as Environment or Organizational Influences, required specific data that would have been difficult to extract from the large number of aircraft accident reports that made up the current study's sample. Instead, more general accident factors were selected which on their own, would have been difficult to generalize to the target population. For example, Time of Day is an accident factor that distinguishes between daytime and nighttime. If this variable can distinguish between passenger and cargo air carrier accidents with a degree of statistical significance, it would not be possible to identify the specific causal factor between the two operators based on this alone. Flying at nighttime introduces risks such as low–light conditions and the potential for flight crew fatigue, but additional data would be required before inferences like that could be made. Location of the Operator is a second variable that would require more specific data before inferences could be made. The eight global regions used within this variable provided some sort of window into the differences between passenger and cargo accidents between these regions, but generalizability to the target population was very limited.

The primary analysis was conducted, which was made up of five simultaneous logistic regression analyses. The first analysis regressed the criterion variable on all predictor variables. This analysis was statistically significant and allowed for closer inspection of the significant predictor variables: the Landing Phase of Flight (compared to the Cruise Phase of Flight), Aircraft Manufactured in the CIS (compared to Aircraft Manufactured in NA), Generation 2 Aircraft (compared to Generation 1 Aircraft), Generation 3 Aircraft (compared to Generation 1 Aircraft), Generation 4 Aircraft (compared to Generation 1 Aircraft), Time of Day, and Operators Based in the CIS (compared to Operators Based in Africa).

The results indicated:

- Accidents that occurred in the Landing Phase of Flight (compared to the Cruise Phase of Flight) were 1.83 times more likely to be categorized as a passenger accident than a cargo accident.
- Accidents that involved Aircraft Manufactured in the CIS (compared to Aircraft Manufactured in NA) were 2.05 times more likely to be a cargo accident than a passenger accident.
- Accidents that involved a Generation 2 aircraft (compared to a Generation 1 aircraft) were 2.32 times more likely to be a passenger accident than a cargo accident.
- Accidents that involved a Generation 3 aircraft (compared to a Generation 1 aircraft) were 2.26 times more likely to be a passenger accident than a cargo accident.
- Accidents that involved a Generation 4 aircraft (compared to a Generation 1 aircraft) were 4.06 times more likely to be a passenger accident than a cargo accident.
- Accidents that occurred at Night were 1.79 times more likely to be a cargo accident than a passenger accident.
- Accidents that involved Operators Based in the CIS (compared to Operators Based in Africa) were 2.46 times more likely to be a passenger accident than a cargo accident.

Next, the first of four smaller simultaneous analyses specific to the levels of the SHELO model were performed. The first analysis regressed the same group membership criterion variable on the predictor variables that were categorized as Software. The full model was statistically significant, which allowed for closer inspection of the predictor variables. Two factors were statistically significant: the Landing phase of Flight (compared to the Cruise phase of Flight), and accidents that involved a Weight Factor. The results indicated: (a) accidents that occurred in the Landing Phase of Flight (compared to the Cruise Phase of Flight) were 1.87 times more likely to be categorized as a passenger accident than a cargo accident and (b) accidents that involved a Weight Factor (compared to accidents that did not involve a Weight Factor) were 1.59 times more likely to be a cargo accident than a passenger accident.

The second simultaneous analysis regressed the criterion variable on all predictor variables categorized under the Hardware level of the SHELO model. The full model was statistically significant, which allowed for closer inspection of the predictor variables. Four factors were statistically significant: Aircraft Manufactured in Europe (compared to Aircraft manufactured in NA), Generation 2 Aircraft (compared to Generation 1 Aircraft), Generation 3 Aircraft (compared to Generation 1 Aircraft), and Generation 4 Aircraft (compared to Generation 1 Aircraft). The results indicated: (a) accidents that involved Aircraft Manufactured in Europe (compared to Aircraft that were Manufactured in NA) were 1.37 times more likely to be a passenger accident than a cargo accident, (b) accidents that involved a Generation 2 Aircraft (compared to a Generation 1 Aircraft) were 2.39 times more likely to be a passenger accident than a cargo accident, (c) accidents that involved a Generation 3 Aircraft (compared to a Generation 1 Aircraft) were 2.33 times more likely to be a passenger accident than a cargo accident, and (d) accidents involved a Generation 4 Aircraft (compared to a Generation 1 Aircraft) were 4.16 times more likely to be a passenger accident than a cargo accident.

The third simultaneous analysis regressed the criterion variable on the single predictor variable categorized under the Environment level of the SHELO model. The full model was statistically significant, which allowed for closer inspection of the predictor variable. The single factor under this level was statistically significant: Time of Day. The results indicated that accidents that occurred at Night (compared to accidents that occurred during the Day) were 1.53 times more likely to be a cargo accident than a passenger accident.

The fourth simultaneous analysis regressed the criterion variable on all predictor on all predictor variables categorized under the organizational influences level of the SHELO model. The full model was statistically significant, which allowed for closer inspection of the predictor variables. Two factors were statistically significant: accidents involving an Operators Based in Europe (compared to an Operator Based in Africa) and accidents involving an Operator Based in NA (compared to an Operator Based in Africa) and. The results indicated: (a) accidents that involved an Operator based in Europe (compared to an Operator based in Africa) were 1.55 times more likely to be a passenger accident than a cargo accident and (b) accidents that involved an Operator Based in NA (compared to an Operator Based in Africa) were 1.48 times more likely to be a cargo accident than a passenger accident.

Table 20 summarizes the current study's four research hypotheses with the decision to reject or fail to reject each null hypothesis. As previously discussed, all four simultaneous analyses were statistically significant, resulting in the rection of all four null hypotheses.

Table 20

Summary of the Results of Hypothesis Testing

Research Hypothesis	**Null Hypothesis**	**Decision Regarding Null Hypothesis**
H_1: When examined from a simultaneous perspective, the variable set related to the software factor of the SHELO model is predicted to have a statistically significant influence on group membership in either passenger or cargo air carrier accidents.	$^{\Delta}\chi^2 = 0$	Rejected
H_2: When examined from a simultaneous perspective, the variable set related to the hardware factor of the SHELO model is predicted to have a statistically significant influence on group membership in either passenger or cargo air carrier accidents.	$^{\Delta}\chi^2 = 0$	Rejected
H_3: When examined from a simultaneous perspective, the variable set related to the environment factor of the SHELO model is predicted to have a statistically significant influence on group membership in either passenger or cargo air carrier accidents.	$^{\Delta}\chi^2 = 0$	Rejected
H_4: When examined from a simultaneous perspective, the variable set related to the organizational influences factor of the SHELO model is predicted to have a statistically significant influence on group membership in either passenger or cargo air carrier accidents.	$^{\Delta}\chi^2 = 0$	Rejected

Conclusions and Inferences

The following section provides inferences based on the outcome of the statistical analyses that regressed the group membership criterion variable on sets of predictor variables according to the levels of the SHELO model to distinguish between passenger and cargo air carrier accidents. The four original research questions are provided, as well as plausible explanations for the outcome of each analysis.

Research Questions

Research Question 1: To what extent does the variable set related to the software level of the SHELO model distinguish between passenger and cargo air carrier accidents?

The results of the simultaneous logistic regression relative to Software revealed that two predictor variables: X_4 = Landing Phase of Flight (compared to the Cruise Phase of Flight) and X_7 = Weight Factor, were significant in distinguishing between passenger and cargo air carrier accidents.

X_4 = Landing Phase of Flight. Within the current study sample, 57% of passenger air carrier accidents occurred during the landing compared to 30% of cargo air carrier accidents. The landing phase of flight has historically had the highest frequency of accidents for all types of commercial operations (Airbus, 2022), but this does not explain how this factor can distinguish between passenger and cargo accidents. The results become more meaningful when the landing phase of flight is analyzed specifically for accidents that were categorized as LOC. Results from Lacagnina (2006) concluded that, of the landing-phase accidents attributed to LOC, there is a higher frequency of accidents for passenger air carriers compared to cargo air carriers. Within the current study sample, 70% of passenger air carrier accidents that occurred during landing were categorized as LOC, compared to only 42% for cargo accidents. Lacagnina did not provide a plausible reason for the higher frequency of LOC accidents during landing for passenger air carriers compared to cargo carriers in his study. This predictor will require additional data from accident factors related to LOC during landing in order to infer why there is a significant difference in accidents during landing for passenger and cargo air carriers.

X_7 = Weight Factor. Within the current study sample, 9% of cargo air carrier accidents involved a Weight Factor, compared to only 3% of passenger air carrier accidents. Cargo air carriers suffer a higher frequency of weight issues as a factor from shifting cargo or improper loading procedures compared to passenger air carriers (Roelen et al., 2000; Lacagnina, 2006). Within the current dataset, 33% of cargo accidents that occurred on takeoff involved a weight factor, compared to only 9% for passenger accidents.

If an aircraft were to takeoff overweight or out of balance, this would likely result in a LOC. Data from the current dataset supports the relationship between these two factors: out of 31 accidents that were categorized as involving a Weight Factor, 74% ended in a LOC. However, an accident being categorized as LOC was not a significant variable in distinguishing between passenger and cargo air carrier accidents and neither was the Takeoff Phase of Flight (compared to the Cruise Phase). This was likely due to the accidents within the current dataset being categorized as LOC regardless of the phase of flight in which the accident took place. Future studies can separate LOC into a LOC inflight (LOC-I) and LOC on the ground (LOC-G). Separating these two types of accidents will allow researchers to more closely investigate the relationships between Weight Factor, Phase of Flight and various types of LOC.

Research Question 2: To what extent does the variable set related to the hardware level of the SHELO model distinguish between passenger and cargo air carrier accidents?

The results of the simultaneous logistic regression relative to hardware revealed that four predictor variables were significant in distinguishing between passenger and cargo air carrier accidents: X_9 = Aircraft Manufactured in Europe (compared to Aircraft Manufactured in NA), X_{11} = Generation 2 (compared to Generation 1), X_{12} = Generation 3 (compared to Generation 1), and X_{13} = Generation 4 (compared to Generation 1). See Table 15 for details. The variable, X_8 = aircraft Manufactured in the CIS (compared to aircraft manufactured in NA) was only significant in the simultaneous analysis that regressed the criterion variable on all predictor variables. This variable was not significant in the smaller simultaneous analysis that only regressed the criterion variable on hardware-related predictors. This indicates a mediating effect with another variable, which is discussed later within this chapter.

X_9 = Aircraft Manufactured in Europe. Within the current study sample, 33% of aircraft involved in passenger accidents were manufactured in Europe, compared to only 19% of aircraft involved in cargo accidents. A plausible explanation of this difference is that passenger air carriers operate more European-manufactured aircraft compared to cargo air carriers.

Airbus (2018) claimed that of the aircraft that made up Generation 4, 78% of them were manufactured by Airbus. Even though Airbus is the world's largest air carrier manufacture, Baily (2021) stated that Airbus had not sold an aircraft to a cargo air carrier in the previous 6 years, and this is in contrast to Boeing, the world's largest air carrier manufacturer, who has delivered more than 730 aircraft to cargo air carriers, with more orders yet to be filled. Baily gave several reasons as to why cargo operators prefer Boeing aircraft over Airbus, including wider fuselages that allow for greater cargo capacity and a more developed conversion program to modify existing passenger aircraft into freighters.

***X_8* = Aircraft Manufactured in the CIS.** In the large simultaneous analysis that regressed the criterion variable against predictor variables from all four levels of the SHELO model, aircraft involved in air carrier accidents that were Manufactured in the CIS became a significant predictor. Aircraft manufactured in the CIS were more likely to be involved in a cargo accident compared to a passenger accident due to their common use by cargo air carriers. This is supported by Kharoufah et al. (2018) who stated that the observed accident frequencies for three manufacturers based in the CIS (Tupolev, Antonov, and Ilyushin) were much higher than what was expected based on the small amount of these aircraft that exist within the air carrier industry. These three manufacturers have relatively poor safety records due to the collapse of the Soviet Union in the early 1990s causing the aviation industry to collapse under hyperinflation. This severely limited the number of CIS-manufactured aircraft in operation, thus making the ability to maintain these aircraft difficult (Loffe, 2011). Kharoufah et al. went on to state that CIS-Manufactured Aircraft are most commonly used by cargo air carriers, providing evidence as to why CIS-Manufactured Aircraft was significant in distinguishing between passenger than cargo accidents. An explanation of why this factor was significant in the presence of all other predictor variables, but not in the regression for hardware-related factors is explained in the implications section of this chapter.

$X_{11, 12, \& 13}$ = Aircraft Generation. Results indicated that aircraft from Generations 2, 3, and 4 that were involved in air carrier accidents (compared to aircraft from Generation 1) were more likely to be categorized as a passenger accident than a cargo accident respectively. Both Roelen et al. (2000) and Airbus (2022) stated that technological advancements in newer-generation aircraft have reduced air carrier accident rates over the past several decades. Roelen et al. explained that the higher frequency of cargo accidents involving Generation 1 aircraft could be causal to the higher overall accident rate for cargo operations. Therefore, it is not inferred that Generation 1 aircraft suffer more accidents than newer generation aircraft to a significant degree. Instead, it is inferred that cargo air carriers operate a higher percentage of Generation 1 aircraft compared to passenger air carriers, which makes all aircraft generations significant distinguishers between these two types of operations. This is supported by accident data within the current study sample: 20% of the cargo accidents involved a Generation 1 aircraft compared to less than 1% of passenger accidents.

Cummins (2020) provides an explanation for why passenger air carriers choose to purchase newer-generation aircraft compared to cargo air carriers. Passenger air carriers often operate shorter-haul flights within the same domestic region, increasing the total number of flights per aircraft and increasing the frequency of takeoffs and landings. These two phases of flight cause the most wear and tear on an aircraft, compounded with flying a greater number of operations per aircraft means that passenger aircraft will require more maintenance compared to cargo aircraft. It would be more beneficial to utilize newer generation aircraft with a greater availability of spare parts compared to older generation aircraft that may have been out of production for several decades. In addition, the customer perception of passenger air carriers is important to consider. Cummins also stated that an airline passenger will be concerned with the age of the aircraft they are flying on, which influences passenger air carriers to purchase newer aircraft and decrease the average fleet age of their aircraft.

Research Question 3: To what extent does the variable set related to the Environment level of the SHELO model distinguish between passenger and cargo air carrier accidents? The results of the simultaneous logistic regression relative to Environmental factors revealed that a single predictor variable, X_{15} = Time of Day, was significant in distinguishing between passenger and cargo air carrier accidents. See Table 17 for details.

X_{15} = Time of Day. Results indicated that air carrier accidents that occurred at Night (compared to air carrier accidents that occurred during the Day) were more likely to be categorized as a cargo accident than a passenger accident. Within the current study sample, 28% of passenger air carrier accidents occurred at night while 47% of cargo air carrier accidents occurred at night. One plausible explanation is that there is a higher percentage of cargo operations that take place at night compared to passenger operations. Lacagnina (2006) stated that more than 50% of cargo operations take place at night, while approximately 20% of passenger operations take place at night. Operating at night means flying in conditions of lower light, which can increase the likelihood of CFIT. An accident categorized as CFIT was a variable in the current study, but it was not significant in distinguishing between passenger and cargo accidents. A high percentage of nighttime operations also increases pilot fatigue, caused by flying outside of the natural sleep cycle. A lack of sleep by flight crew members can result in many hazards to the safety of the flight, including a loss of situational awareness or a failure to follow SOPs and checklists (Gander et al., 1996; Lacagnina, 2006). The reader should be cautioned that the Time of Day variable only captures the time in which an accident took place. While inferences related to phenomena that occur more frequently at night compared to the day can be made, recommendations cannot be made to the target population without additional data on more specific accident factors.

Research Question 4: To what extent does the variable set related to the organizational influences level of the SHELO model distinguish between passenger and cargo air carrier accidents? Only two predictor variables were statistically significant: X_{25} = Air carriers that are based in Europe (compared to air carriers based in Africa), and X_{28} = Air carriers that are based in NA (compared to air carriers based in Africa). See Tables 19 and 20.

***X_{18}* = Operators Based in Europe.** Within the current study sample, 21% of passenger accidents involved air carriers based in Europe. In comparison, only 8% of cargo accidents involved air carriers based in Europe. IATA (2021) provided traffic data on the 10 largest cargo operators in the world, and only a single operator was from Europe: Cargolux, based in Luxembourg, accounted for 7% of global cargo traffic in 2021. The disproportionally high number of European-based passenger operators compared to European-based cargo operators makes this variable significant in distinguishing between these two types of accidents, with accidents involving a European-based air carrier being statistically more likely to be categorized as passenger. While this variable was statistically significant in distinguishing between passenger and cargo accidents, there is little practical significant. The large percentage of passenger accidents compared to the low number of cargo accidents within Europe can be explained by the difference in percentage of annual passenger and cargo operations.

Europe accounted for 23.7% of the global air carrier traffic in 2021 (IATA, 2021). Passenger flights that both departed and arrived within Europe accounted for 21.1% of global passenger traffic in 2021. In comparison, only 2.3% of global cargo traffic departed and arrived within the European region. This extreme difference in the percentage of global passenger and cargo operations that took place within Europe in 2021 in addition to a lack of major cargo operators being based in Europe explains the difference in accident frequency counts.

***X_{21}* = Operators Based in NA.** Within the current study sample, 26% of passenger air carrier accidents involved Operators Based in NA and 55% of cargo accidents involved Operators Based in NA. Passenger air carrier operations arriving and departing NA accounted for 25% of global passenger traffic in 2021 (IATA, 2021). In comparison, cargo air carrier operations arriving and departing NA accounted for more than 45% of global cargo traffic in 2021. The operations of the two largest cargo air carriers, Federal Express and UPS, both of which are operators based in NA, far outweighs the operations from cargo air carriers based in other regions. These two operators alone made up 34% of the global cargo air carrier traffic in 2021. However, this does not infer that NA-based operators have higher accident rates compared to other air carriers due to poorer safety records. Instead, the higher accident rate of cargo compared to passenger air carriers and the majority of cargo air carrier operations being based in NA make this a statistically significant distinguisher between the two types of accidents. However, this does not provide practical significance for distinguishing between passenger and cargo air carrier accidents.

Implications

The following section discusses implications of the results in terms of its relation to the theoretical grounding in the SHELO model, past studies, and practice within the air carrier industry. The inferences discussed in the previous section will be supported by related literature in order to provide a more thorough explanation of the results of the current study and how they can differentiate between passenger than cargo air carrier accidents.

Implications Relative to the SHELO Model.

The SHEL model was originally proposed by Edwards (1972) and contained four levels: Software, Hardware, Environmental Factors, and Liveware. This model has been frequently used in the aviation safety to organize factors from aircraft accidents and analyze them according to the four individual levels. The current study was grounded in the more the more recent SHELO model, proposed by Chang and Wang (2009), who added a fifth level to the model: Organizational Influences. In addition, the Liveware model was considered out of scope for the current study as the purpose was limited to analyzing predictor variables in the absence of factors related to human beings. The results of the current study support using the various levels of the SHELO model for identifying factors that can distinguish between two types of air carrier accidents: passenger and cargo.

In the context of the current study, it was hypothesized that loading cargo and ensuring proper weight and balance of a freighter aircraft required different SOPs and checklists compared to those used for loading passengers. Failure to follow these SOPs or checklists could lead to an increase in LOC accidents as an aircraft changes configuration between phases of flight. The factors in the current study that were categorized under the Software level of the SHELO model accounted for a predictive gain of approximately 6% over the null model. A researcher will be 6% more likely in successfully distinguishing between two types of accidents when utilizing factors categorized in this study as Software compared to an analysis absent of these predictors.

The factors in the current study that were categorized under the Hardware level of the SHELO model accounted for a significant predictive gain of approximately 13% over the null model. This level of the SHELO model accounted for more than twice the predictive gain compared to the Software level of the SHELO model. Therefore, factors categorized as Hardware are of particular interest to a researcher trying to distinguish between passenger and cargo air carrier accidents. This implies that the significant differences between the two types of accidents are closely related to the properties of the aircraft involved, such as Manufacturer and Aircraft Generation.

The Environmental and Organization Influences levels of the SHELO both accounted for predictive gains of approximately 3% compared to the null model. The inclusion of the variables categorized under these two levels was significant and should be considered for future research that requires identifying factors to distinguish between two types of aircraft accidents. However, the practical significance of these two levels is not as straight-forward in the context of aviation research. The variable, Time of Day, was significant in distinguishing between passenger and cargo air carrier operations as hypothesized. The statistical significance of the Time of Day variable warrants future research into more specific accident factors that distinguish between daytime operations and nighttime operations. On its own, the Time of Day variable does not provide practical significance in distinguishing between passenger and cargo accidents. While past research, such as Gander et al. (1996) identifies flight crew fatigue as a greater threat to cargo air carrier safety compared to passenger air carrier safety, additional data beyond the scope of the current study is required to support those claims. The Operator Location variable is similar in which statistical significance does not translate to practical significance. As previously discussed, the disproportionally high volume of cargo traffic in NA and the disproportionally high volume of passenger traffic in Europe are enough to make this variable significant in distinguishing between passenger and cargo accidents.

Overall, the SHELO model should be used in the context of aviation research when analyzing factors. The variables identified within the current study accounted for a predictive gain of 26% over the null model when analyzed simultaneously, or when not organized into the various SHELO levels. When organized into the various levels of the SHELO model, a predictive gain of 32% over the null model is accumulated. This 32%, compared to the 26% predictive gain when analyzed simultaneously, means that there is only a 6% overlap between the four levels of the SHELO model within the current study. This supports the inclusion of each of these four SHELO levels in future research instead of only analyzing accident factors in a simultaneous manner.

Lastly, certain predictor variables become significant while absent of other predictor variables. For example, the variable Weight Factor was only significant when analyzed in the presence of other Software variables. Possible interactions with variables from the Hardware and Organizational Influences levels caused Weight Factor to lose its significance and was, absent from further analysis. In comparison, some predictor variables become significant while in the presence of other predictors. CIS-Manufactured Aircraft and Operators Based in the CIS were categorized as Hardware and Organizational Influences respectively. Neither variable was statistically significant in their respective levels. However, when analyzed simultaneously and within the presence of all other predictors, their negative mediating effect caused each variable to become significant.

Implications Relative to Prior Research

The following section recalls prior research, discussed in Chapter 2 of the current study, and relates the findings of those studies to the results and inferences discussed in the previous section. Related literature has been organized based upon the four levels of the SHELO model: Software, Hardware, Environment, and Organizational Influences. The statistically significant predictor variables from each of the four simultaneous logistic regressions, one for each level of the SHELO model, are discussed in terms of their relation to prior research.

Software. The Landing Phase of Flight was a factor that significantly distinguished between passenger and cargo air carrier accidents. This is not in line with Roelen et al. (2000) who found no significant influence of Phase of Flight on distinguishing between passenger and cargo accidents. However, Lacagnina (2006) did find a significant difference between the Phases of Flight, but only when analyzing LOC accidents. Lacagnina found that cargo accidents suffered a higher frequency of LOC accidents on takeoff while passenger accidents suffered a higher frequency of LOC accidents during landing. Accidents categorized as LOC was a predictor variable within the current study but was found to not significantly distinguish between passenger and cargo accidents. This was due to the frequency of LOC accidents per operator being almost equal: 67% of passenger air carrier accidents were categorized as LOC compared to 61% for cargo air carrier accidents. However, analyzing LOC per phase of flight as recommended by Lacagnina yields more practical results. LOC accidents in cargo air carrier accidents on takeoff is hypothesized to be due to Weight Factors, which is discussed in the next section.

Weight Factor was significant in distinguishing between passenger and cargo accidents. This was supported by Roelen et al. (2000) who found that cargo air carriers suffer a higher frequency of accidents categorized as being “cargo related,” which included all instances of shifting cargo or aircraft that have been improperly loaded. Lacagnina (2006) supports these findings by relating an overweight or unbalanced aircraft to a LOC accident. Lacagnina connected Weight Factor to cargo air carrier accidents by explaining how an overweight or improperly loaded aircraft will suffer a LOC during the earliest Phase of Flight: Takeoff. The relationship between LOC, Weight Factor, and Takeoff and the ability for weight factor to distinguish between passenger and cargo accidents are all supported by the current study.

Hardware. Aircraft Manufactured in the CIS and Europe were significant factors in distinguishing between passenger and cargo air carrier accidents. It was more likely for an air carrier accident that involved an aircraft Manufactured in Europe to be a passenger accident compared to a cargo accident. This is supported by Kharoufah et al. (2018) who analyzed the accident frequencies of Europe's largest air carrier manufacturer, Airbus, while controlling for the considerable number of these aircraft currently in use. Kharoufah et al. concluded that Airbus produces reliable aircraft with few hardware-related issues, based on the high volume of Airbus aircraft in use compared to a lower-than-expected accident frequency. In addition, Airbus aircraft are used predominantly by passenger air carriers, thus supporting the finding from the current study that it is more likely for a passenger accident to involve a European-Manufactured Aircraft compared to a cargo accident. In contrast, Kharoufah et al. observed a higher-than-expected accident frequency for aircraft Manufactured in the CIS compared to the very low number of these aircraft currently in use. Kharoufah et al. concluded that CIS-Manufactured Aircraft suffer more maintenance-related issues, increasing the accident frequency. This is supported by data from the current study as it is more likely for an accident involving a CIS-manufactured aircraft to be cargo compared to passenger.

Aircraft Generation was the final significant factor related to hardware that distinguished between passenger and cargo air carrier accidents. This is supported by Roelen et al. (2000) who found that cargo air carriers operate a higher number of

Generation 1 aircraft (compared to newer generation aircraft operated predominantly by passenger air carriers) based on the low acquisition cost and on the reduced wear and tear from less-frequent takeoffs and landings of Generation 1 aircraft. As previously discussed, passenger air carriers operate a much higher number of newer-generation aircraft, thus supporting the finding that it is more likely for accidents involving newer-generation aircraft to be passenger compared to cargo. The current study also expanded upon related literature by including Generation 4 aircraft into the analysis, which were not being manufactured at the time of Roelen et al.'s study. Information on Generation 4 was provided by Airbus (2018) who also supported the implication that more of their newer generation aircraft are used predominantly by passenger air carriers, thus being able to distinguish between passenger and cargo operators.

Environment. Time of Day was statistically significant in distinguishing between passenger and cargo air carrier accidents, with accidents that occurred at night being more likely to be cargo compared to passenger. This was supported by Roelen et al. (2000) and Lacagnina (2006) who both stated that more than half of cargo operations take place at night, compared to only 20% of passenger operations. However, data from the current study was only able to support the higher frequency of cargo accidents that occurred at nighttime and did not offer data as to the cause of these nighttime accidents. Taking additional data from the current dataset into consideration reveals that the expected frequency of nighttime passenger accidents was higher than the expected frequency for cargo accidents.

Out of 594 total accidents, about 33% were cargo. Lacagnina (2006) stated that roughly 50% of cargo operations take place at night. Multiplying these values together gives us an expected accident frequency of 98 for the date range of 2002 through 2019. However, the actual accident frequency was 93. Passenger accidents made up roughly 67% of the total number of accidents in the dataset, 20% of which typically take place at night according to Lacagnina. This gives us an expected accident rate of 80, while the actual accident rate was 109 within the context of the current study. Additional data from each accident that occurred at nighttime will be required if inferences are to be made about causal factors between passenger and cargo air carrier accidents that only occur at night.

Implications Relative to Practice

The statistically significant results of the current study do have practical implications within the air carrier industry. The first significant Software related factor was the Landing Phase of Flight. Results from the current study and past literature do not provide a plausible explanation as to why it is more likely for a passenger air carrier to suffer an accident on landing compared to cargo air carriers. Accidents categorized as LOC continue to be the frequent compared to other types of accidents (IATA, 2021). The FAA has provided guidance to Part 121 operators as to the prevention and recovery from aircraft upsets that could lead to a LOC in the form of Advisory Circular (AC) 120-111 (FAA, 2015). Both passenger and cargo air carriers operating within the United States must include upset recovery within the training they provide to their pilots, but the guidance material provided by the FAA is only one means of compliance and for advisory purposes only. Additional accident data that can separate LOC-I and LOC-G as well as identify additional factors that can lead to a LOC during various phases of flight will provide more practical significance to this variable.

The current study concluded that Weight Factor is another Software variable that can distinguish between passenger and cargo air carrier accidents. The FAA is aware that improper aircraft loading is an issue that affects cargo air carriers more than passenger air carriers due to the nature of their payload. The FAA released AC 120-85B (FAA, 2022) on the topic of load planning, restraint methods, and guidance on weight and balance control programs and procedures for cargo air carriers. The scope of the current study was to identify factors that could distinguish between passenger and cargo air carrier accidents. Future research on other accident details related to Weight Factor could take guidance material, such as AC 120-85B into consideration in order to determine if the FAA has effectively targeted factors unique to cargo air carrier operations.

The final predictor variable with strong implications for the cargo air carrier industry is Time of Day, taking into consideration that the half of cargo operations take place at night. The scope of the current study did not analyze more specific data than the Time of Day in which an accident took place. However, organizations such as ALPA have target operational differences between various types of air carriers and have identified problems that they believe decrease the safety of cargo air carriers. In 2014, the air carrier industry saw major regulatory change to the flight crew rest requirements with the introduction of FAR Part 117: Flight and Duty Limitations and Rest Requirements, which outlined strict standards for how long flight crew members could fly between periods of rest. However, as of 2019, the participation in Part 117 for cargo air carriers has remained optional. ALPA has provided supporting documentation to aid cargo air carriers and individual flight crew members in complying with Part 117 requirements if they wish to do so (ALPA, 2019). While inferences related to flight crew fatigue cannot be made using the limited data from the current study, the efforts of ALPA and their focus on crew fatigue warrants future research into this area. More specific data on the condition of the flight crew can be categorized under the Liveware level of the SHELO model and can follow the same data collection and analysis methodology used within the current study.

Generalizability, Limitations, and Delimitations.

Generalizability

The target populations for the current study were all air carrier accidents, passenger, and cargo, which occur on the global scale. The dataset used in the current study was representative of the target population in terms of its demographics and inclusivity. The source of the data for the current study, the online database managed by the ASN, contained every air carrier accident that occurred for the target years of 2002 through 2019. Effectively, this allowed for all relevant air carrier accidents to be included in the analyses used in the current study in place of a sampling strategy that was used in prior, related studies. This produced a large dataset (N = 594). However, the requirement for accidents listed in the ASN database to have a published final accident report for inclusion in the current study eliminated a number of air carrier accidents from these analyses. This could have had a negative effect on the population generalizability of the current study, but the severity of this effect is considered fairly minor due to the large number of air carrier accidents used in the final dataset. It must also be mentioned that other aviation accidents found on the ASN database that are not considered air carrier operations were not in-scope for this study. Examples of these types of operations would be on-demand charters, training flights, or military operations. It is therefore concluded that aircraft accidents that are related to operations other than passenger or cargo air carrier make up a different target population and do not have an effect on the population generalizability for the current study.

The nature of the archival dataset used for the current study yields strong ecological generalizability. The data obtained from the ASN relative to each individual air carrier accident is objective and is related to an event that has already occurred. Future studies, whether they are replication studies that utilize the same factors or follow-up studies that investigate additional possible factors, would still obtain data from the final accident reports as used in the current study. However, the nature of the current study is time-based, and many of the factors related to air carrier accidents can change in the next several decades. Although the current study focused on the timeframe of 2002 through 2019, future studies may investigate air carrier accidents that took place at an earlier or later date. Although data from past or future air carrier accidents will still be published in final accident reports, identical to those used in the current study, the relationship between the targeted factors and the dichotomous group membership variable may change over time.

Limitations

Any condition of the archival dataset used in the current study or the data collection process that is beyond the control of the researcher is considered a limitation to the generalizability of the study's results and conclusions. The following limitations must be considered when making inferences or recommendations based off of the results of the current study.

1. **Data Collection Method.** The dataset of air carrier accidents that was be used within the proposed study is comprised of historical data. The data within this dataset were objective details about the conditions of the aircraft or flight before the accident occurred. However, any mistakes or inconsistencies in data collection on behalf of the entities which investigated each accident exist within the historical dataset.
2. **Missing Data.** Almost all air carrier accidents, both domestic and international, are investigated by a government entity depending on the country in which the accident occurred and the country in which the air carrier is based. Aircraft manufactures and the air carriers themselves are frequently involved in the accident investigation. Final accident reports are often made available due to the public awareness of an air carrier accident. However, it is possible that data on a small number of air passenger or air

cargo accidents may have been missing from the historical dataset. This could be due to a mistake in data collection by the original owner of the dataset or inconsistencies in the procedures for thoroughly investigating an air carrier accident and reporting the findings.

Delimitations

Any condition of the selection of the archival dataset or the data collection method used in the current study that is implemented by the researcher to improve feasibility is considered a delimitation to the generalizability of the study's results and conclusions. The following delimitations must be considered when making inferences or recommendations based off of the results of the current study.

1. **Selection of ASN Database.** The ASN online database of air carrier accidents was the only source of archival accident data. The content, validity, and reliability of the ASN was described in detail in Chapter 3 of this manuscript. This excluded any other source of air carrier accident data, which limits the accessible population of air carrier accidents. A passenger or cargo air carrier accident that was listed on the ASN database but did not contain a final accident report was excluded from the dataset constructed for the proposed study.
2. **Timeframe of Air Carrier Accidents within the Dataset.** The years 2020 and 2021 were excluded from the dataset that was used in the proposed study. Any air carrier accident that has occurred post-2019 was excluded for two reasons. The first reason was the unlikelihood that a final accident

report was published within the same year or one year after the occurrence of an air carrier accident. Aircraft accident investigations and the publication of a final accident report can take several years to complete. Although preliminary reports may have been available, these reports may have contained speculation as to the causes of the accident. Only final accident reports were used in the current study in order to ensure the validity and reliability of the data. The years 2020 and 2021 were also excluded from the proposed study due to the unprecedented events of the COVID–19 global pandemic. This historical event caused a downturn in global air passenger traffic. Some passenger air carriers have converted select aircraft within their fleet into temporary cargo aircraft in order to generate as much revenue as possible given the restrictions on passenger travel (Quayle & Checksfield, 2020). As a result, accidents involving these aircraft would have been difficult to classify as air passenger or cargo air carrier operations. In addition, the global decrease in air carrier operation frequency would have affected the time-sensitive data used in this study.

3. **Selection of Factors.** Only select data from each air carrier accident within ASN database were selected as factors for the current study. Certain data within the database was excluded from the primary analysis due to several reasons, including difficulty in classifying the data as a casual factor according to the SHELO model, or a lack of supporting evidence as to how

certain factors could have been used to differentiate between passenger than cargo air carrier accidents.

4. **Exclusion of Air Carrier Incidents.** The ASN dataset that was used for the current study contained reports on air carrier incidents as well as accidents. However, incident reports were intentionally excluded from the current study and deemed out of scope. This was due to the requirements for reporting aircraft incidents to investigatory entities being differing from those used for reporting aircraft accidents. Aircraft incidents do not involve the loss of human life, substantial property, or aircraft damage, or induce a hefty financial burden on an air carrier. Therefore, many air carrier incidents occur without a subsequent investigation, making the availability of data on all air carrier incidents scarce.

5. **Removal of Liveware Level from SHELO Model.** As discussed earlier within this study, the liveware level representative of the actions of the flight crew, was deemed out of scope for the current study. The purpose of this study was to examine all related factors for air carrier accidents to distinguish between passenger than cargo that were not directly related to the actions of the flight crew. The removal of the liveware component was decided upon by the researcher due to the objective and limited data within the dataset that would not have been significant enough to examine a possible relationship between the flight crew and the accidents.

6. **Removal of Air Carrier Data based upon Type of Accident.** The following types of accidents were unsupported from previous studies or related literature on distinguishing between passenger and cargo air carrier accidents: ground operations (aircraft was standing or taxing), acts of terrorism (sabotage, hijacking, aircraft shoot-down, or attempted takeovers), mid-air collision, pilot error, fuel exhaustion, wildlife strike, fuel contamination, aircraft missing, runway incursions,
7. **Exclusion of Narrative Data from the Dataset.** All the accidents within the dataset contain a brief summary of events that led up to the accident. These summaries are in narrative form. Analyzing these narratives would require coding and a standardized process for transforming the narrative data into quantitative data. Given the availability of objective data that is already in quantitative form, all narratives have been excluded from the analysis. Full narratives for every aircraft accident are available through sources such as the online NTSB database. However, analyzing these detailed narratives would be a qualitative approach that was not part of the methodology for current study.

Recommendations for Research and Practice

Recommendations for Future Research Relative to Study Limitations

1. **Data Collection Method.** The current study analyzed data that was available at the time, ranging from 2002 through 2019. Related literature that was closest in scope to the current study was Roelen et al. (2000), who

analyzed accident data up until the year 2000. Therefore, it is recommended that future research analyze air carrier accident data for future decades when this data becomes publicly available.

2. **Missing Data.** Any air carrier accident listed on the ASN database that did not have a published final accident report was not included in the current study sample. An extra effort to locate missing final accident reports outside of the ASN database was not attempted. It is recommended that future research attempt to locate any missing accident reports for cases that would otherwise be considered in scope for the current study.

Recommendations for Future Research Relative to Study Delimitations

1. **Selection of ASN Database.** The ASN online database was considered exhaustive in terms of containing all air carrier accident reports from 2002 through 2019. However, the ASN is a repository of aircraft accident reports that were collected and summarized from their original sources, predominantly the aircraft accident investigative bureaus for each nation. It is recommended that future research attempt to acquire accident reports from their original sources to ensure that reports were not omitted by the creators of the ASN database.

2. **Timeframe of Air Carrier Accidents within the Dataset.** It has already been recommended that future research utilize additional accident data that will be made available within the next several years. However, it is recommended that special consideration should be taken for the years 2020

and 2021 based on the impact of the COVID-19 pandemic on the frequency of passenger and cargo air carrier operations and the effects on accident rates.

3. **Selection of Factors.** Accident data from each case within the ASN database was selected based on the predictor variables used within the current study. Future studies should consider additional details in final accident reports that can be treated as different factors, such as the type of aircraft, interactions with air traffic control (ATC), hazardous weather conditions, and any liveware related factors. The variables used in the current study were not verified as being causal to the outcome of each accident. Future research can limit its scope to analyzing accident details that have been identified within each accident report as being causal factors. This will provide greater generalizability if the purpose of the research is to analyze factors that caused an accident, compared to factors that simply existed at the time of the accident but were otherwise unrelated.
4. **Exclusion of Air Carrier Incidents.** The current study analyzed only accident that were categorized as scheduled passenger or cargo air carrier operations. Future research should consider additional types of operations, such as on-demand/charter, private flights, training flights, maintenance/test flights, and more specific types of operations, such as aerial firefighting and air ambulance.

5. **Removal of Liveware Level from SHELO Model.** Additional factors that can be found within each accident report can be categorized under the final level of the SHELO model: liveware. Future researchers are cautioned that data within final accident reports related to liveware factors can be subjective in nature. Details about a flight crew member's mindset or mental condition before and during the flight come from sources such as ATC transcripts, cockpit voice recordings, and interviews with other flight crew members, passengers, or family members. In addition, the proper categorization of liveware-related factors can be subjective and relies on the researcher's expertise in air carrier operations and aviation human factors. It is recommended that if a researcher lacks expertise in either of these two areas that a subject matter expert (SME) be consulted for assistance in categorizing liveware-related factors.
6. **Removal of Air Carrier Data based upon Type of Accident.** The following types of accidents were considered out of scope for the current study, but should be analyzed using factors according to the SHELO model: ground operations (aircraft was standing or taxing), acts of terrorism (sabotage, hijacking, aircraft shoot-down, or attempted takeovers), mid-air collision, pilot error, fuel exhaustion, wildlife strike, fuel contamination, aircraft missing, runway incursions,
7. **Exclusion of Narrative Data from the Dataset.** It is recommended that future researchers utilize the narrative in each of the final accident reports,

especially if future research involves analysis of liveware-related factors. While the ASN database is reliable in terms of summarizing objective accident details, such as time of day or aircraft manufacturer, data that can be subjective in nature is best understood when read in narrative form to ensure that the researcher fully understands what the author of the accident report has inferred about the condition of the flight crew members before and during the accident.

8. **Inclusion of Accident Rate and Annual Operations.** It is recommended that future research include the accident rate and annual operations of passenger and cargo air carriers in differentiating the factors in the SHELO model. Data on annual operations is available from organizations, such as IATA, and can be specified by region. However, accident rate of passenger and cargo air carriers per region is not currently available, as verified by IATA (2021). Past research, such as Roelen et al. (2000) created their own accident rate variable using related data from aircraft manufacturers. If a custom accident rate variable is created, its validity and reliability must be calculated before it can be used in an analysis alongside other variables known to be both valid and reliable. The inclusion of data on accident rate and annual air carrier traffic will help control the influence these variables have on other predictors, such as Time of Day and Location of an Operator. Both of these variables, while statistically significant in the current study, provided little practical significance due to the variation in passenger vs.

cargo operations during day or night and based on global region. IATA has data readily available for the number of annual passenger and cargo air carrier operations per global region. This continuous variable can be included in a future analysis to control for the difference in annual operations between passenger and cargo air carriers. In addition to annual operations, IATA provides annual frequency counts of passenger and cargo air carrier accidents per global region. However, the accident rate per carrier per global region is not readily available. A new, continuous variable would have to be calculated to control for the effects of actual accident rate per year on other variables, such as Location of Operator and Time of Day.

Recommendations for Future Research Relative to Implications

The following section outlines potential future research that can be conducted based off of the implications related to theory and related literature discussed earlier within this chapter. It is recommended that future researchers utilize the SHELO model to categorize accident factors related to software, hardware, the environment, and organizational influences. The statistical significance of each one of the levels would allow a researcher to determine if the set of variables categorized under a specific level can significantly distinguish between distinct types of aircraft accidents. If a specific level of the SHELO model is found to be statistically significant, this would allow a researcher to analyze each predictor variable categorized under that set for statistical and practical significance for its effect on the criterion variable. However, future researchers should run a larger analysis that regresses the criterion variable on all predictor variables simultaneously, in the absence of the separate levels of the SHELO model. As discussed previously in this chapter, certain factors gain or lose statistical significance when in the presence or when in the absence of other predictor variables. The interactions between these variables are important to understanding how these factors exist in real life and their influence on aircraft accidents. Future researchers should also be cautioned that categorizing factors under the liveware level of the SHELO model may require the use of subjective data. As mentioned in the delimitations section above, SMEs should be consulted to ensure validity and reliability in interpreting subjective data from accident reports and how this data is categorized within the liveware level.

Possible interactions between variables within the current dataset can be further explored in future research. It was concluded that cargo air carriers are distinguished based on LOC accidents that occur on takeoff due to weight-related factors. This is supported by data from the current dataset: 78% of cargo accidents that occurred during takeoff were categorized as LOC, compared to 62% of passenger accidents. In contrast, passenger air carrier carriers are distinguished based on LOC accidents that occur during landing. The cause of the higher number of passenger LOC accidents on landing is unsupported based on the findings from the current study and should be analyzed using additional accident data from available accident reports. Additional factors should include the weather at the time of landing, aircraft configuration, communications with ATC, and the conditions of the flight crew members in the events leading up to the landing phase of flight.

Several variables within the current study were statistically significant, but offer little practical significance based on their non-specific nature of acting as proxy variables to more specific factors. The first variable that should be more closely analyzed is the location in which an accident takes place, which was categorized as an environmental factor. This variable inferred differences in the terrain and airport infrastructure between various global regions. More specific data on terrain and airport infrastructure is available per the location listed in each final accident report and would allow a researcher to more closely analyze the relationship between accident location and the type of accident that occurred. In addition, more specific regions can be used for future research. For example, Europe was one of the global regions used in the current study. Europe is a diverse continent made up of many countries that are diverse in terms of their terrain features and airport infrastructure.

A second proxy variable that should be more closely analyzed is the location of the operator, which inferred socioeconomic details about each region the aviation regulations that govern operators within these regions. Future research can analyze specific socioeconomic data as well as perform a content analysis of the regulations and recommend practices for commercial air carrier operators within each region, and how these factors affect the type of accident that has taken place. By analyzing more specific factors compared to the high-level proxy variables used within the current study, future research may also be able to factor out many of the interactions that were observed between these variables. For example, it was found that aircraft manufactured in Europe, accidents that took place within Europe, and air carrier operators base in Europe were all statistically significant predictors in distinguishing passenger air carrier accidents from cargo accidents. However, it was concluded that the considerable number of European-based passenger operators that conduct most of their operations within the same region and purchase newer-generation European aircraft explained the significance of these variables. While the interpretation of these variables was accurate in their ability to significantly distinguish between passenger and cargo air carrier accidents, these findings offer little practical significance to the air carrier industry.

Recommendations for Practice Relative to Implications

The first recommendation for cargo air carriers is to be aware of the changes in software related to the proper loading of their cargo aircraft. Software, such as manuals, SOPs, and ACs can help operators avoid loading their aircraft beyond maximum weight, the location of the center of gravity from being out of bounds, or the cargo inside of the aircraft shifting during flight. While Software related to Weight Factor is already widely used within the cargo air carrier industry, changes to this Software without the knowledge of the cargo operators can lead to an increase in the frequency of weight–related accidents.

The second recommendation for cargo air carriers consider the impact of Hardware factors on their operations. Cargo air carriers will continue to purchase older aircraft retired from passenger air carriers and convert them to cargo aircraft. Although older-generation aircraft may be missing some of the technology found in newer-generation aircraft, such as cockpit automation and digital flight-deck displays, these types of technologies can often be installed in older aircraft. This practice of upgrading older aircraft will help cargo air carriers benefit from the same type of advancements as newer–generation aircraft that were defined by Airbus (2019).

Lastly, all cargo air carriers should consider the inclusion of flight crew rest requirements within their operations. Supporting documentation from the FAA and ALPA can be used to help voluntarily implement crew rest requirements and SOPs without the need for regulatory change.

References

Abowitz, D. A., & Toole, T. M. (2010). Mixed Method Research: Fundamental Issues of Design, Validity, and Reliability in Construction Research. Journal of Construction Engineering & Management, 136(1), 108–116. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000026

African Development Bank Group, A poor safety record—largely attributable to low standards and lax supervision—is the greatest challenge facing the air transport industry in Africa today. http://www.infrastructureafrica.org/keymsg/sector/poor-safety, 2011.

Airbus. (2019). *A Statistical Analysis of Commercial Aviation Accidents 1958-2018* (Issue 3., Rep.). Blagnac Cedex, France.

Airbus. (2022). *A Statistical Analysis of Commercial Aviation Accidents 1958-2021* (Issue 56., Rep.). Blagnac Cedex, France.

Air Line Pilots Association. (n.d.). Well Rested Pilots = Safe Skies. Retrieved from http://www.alpa.org/advocacy/cta/safe-skies

Air Line Pilots Association. (2019). Guide to Part 117 Flight-Time Limitations and Rest Requirements, (Edition 5A).

American Institute of Chemical Engineers. (2020). CCPS Process Safety Glossary. Retrieved from https://www.aiche.org/ccps/resources/glossary/processafety

Ary, D., Jacobs, L., & Sorenson, C. (2010). Introduction to research in education (8th ed.). Belmont, CA. Wadsworth.

Aviation Safety Network. (2016). Retrieved from https://aviation-safety.net/

Baily, J. (n.d.). *Why Is Airbus Lagging Behind Boeing In The Freighter Market?* Simple Flying. Retrieved March 9, 2021, from https://simpleflying.com/airbus-vs-boeing-freighters/

Boeing. (2017). *Current Market Outlook 2017-2036* (56th ed., Rep.). Seattle, WA.

Chang, Y., & Wang, Y. (2009). Significant Human Risk Factors in Aircraft Maintenance Technicians. *Safety Science, 48*, 54-62. doi:10.1016/j.ssci.2009.05.004

Civil Aviation Authority, & Safety Regulation Group, CAP 1036Global Fatal Accident Review (2013).

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). Applied multiple regression/correlation analysis for the behavioral sciences (3rd ed.). Hillsdale, NJ: Lawrence Erblaum Associates.

Cummins, N. (n.d.). *Why Do Cargo Operators Fly Older Planes?* Simple Flying. Retrieved June 2, 2020, from https://simpleflying.com/cargo-operators-older-planes/

Edwards, E. (1972, November). Man and Machine: Systems for Safety. *British Air Line Pilots Association 1972 Technical Symposium*, 21-45.

Enomoto, C. E., Geisler, K. R. (2017). Culture and Plane Crashes: A Cross Country Test of The Gladwell Hypothesis. Economics and Sociology, 10(3), 281-293. doi:10.14254/2071-789X.2017/10-3/20

Egypt, Egyptian Civil Aviation Authority. (2000). *Report of Investigation of Accident EgyptAir Flight 990*.

Flight Global. (2020). Retrieved from https://www.flightglobal.com/

Flight Safety Foundation. (2020). Retrieved from https://flightsafety.org/

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods, 41*, 1149-1160.

Gander, P. H., Gregory, K. B., Connell, L. J., Miller, D. L., Graeber, R. C., & Rosekind, M. R. (1996). Crew Factors in Flight Operations VII: Psychophysiological Responses to Overnight Cargo Operations. *NASA Technical Memorandum 110380*.

Hawkins, F. (1993). *Human Factors in Flight* (2nd ed.). Aldershot, U.K.: Ashgate Publishing Company.

International Civil Aviation Organization, 1998. Human Factors Training Manual, first ed. International Civil Aviation Organization, Doc. 9683-AN/950.

International Civil Aviation Organization. (2004). *Annex 12 - Search and Rescue*

(8th ed., Publication).

International Civil Aviation Organization. (2020). *Annex 13 - Aircraft Accident and Incident Investigation* (12th ed., Publication).

Hofstede, G. (2001). Culture’s consequences: Comparing values, behaviors, institutions, and organizations across nations (2nd ed.). Thousand Oaks, CA: Sage Publications. International Air Transport Association, 2006. Safety Report. International Air Transport Association. Geneva, Switzerland/Montreal, Canada.

International Air Transport Association. (2020). *Safety Report 2019* (56th ed., Publication).

International Air Transport Association. (2021). *World Air Transport Statistics 2021*. Montreal.

Kharoufah, H., Murray, J., Baxter, G., & Wild, G. (2018). A Review of Human FactorsCausations in Commercial Air Transport Accidents and Incidents: From to 2000–2016. *Progress in Aerospace Sciences, 99,* 1-13. Retrieved from https://doi.org/10.1016/j.paerosci.2018.03.002

Lacagnina, M. (2006). Balancing. *Aviation Safety World*. Retrieved from www.flightsafety.org

Lee, S., & Kim, J. (2018). Factors Contributing to the Risk of Airline Pilot Fatigue. *Journal of Air Transport Management, 67*, 197-207. Retrieved from https://doi.org/10.1016/j.jairtraman.2017.12.009

Leleu, C., & Marsh, D. (2009). Dependent on the Dark: Cargo and other Night Flights in European Airspace. *EUROCONTROL Trends in Air Traffic, 5*.

Levin, A., Surane, J., & Black, T. (2013, August 15). UPS Jet Crash in Alabama Is

Latest Fatal Cargo Accident [Editorial]. *Bloombrerg*. Retrieved from https://www.bloomberg.com/news/articles/2013-08-15/ups-jet-crash-inalabama-is-latest-fatal-cargo-accident

Loffe, J. (2011, November 2). *Fly the Deadly Skies*. Forbes. Retrieved from https://www.forbes.com/forbes/2011/1121/feature-deadly-skies-russia-soviet-julia-ioffe.html?sh=1546bdbf6f43

MacKinnon D. P., & Dwyer, J. H. (1993). Estimating mediated effects in prevention studies. Evaluation Review, 17(2), 144-158.

MacLean, L., Richman, V., & Richman, A. (2003). The Predictability of Aircraft Failures with Age. In *SAE Advances in Aviation Safety Conference 2003 Aerospace Congress and Exhibition*. Warrendale, PA: SAE International.

McDonald, N., Corrigan, S., Daly, C., Cromie, S., 2000. Safety management (1–3), 151–176.

Metso, L., Marttonen, S., Thenent, N., & Newnes, L. (2015). Adapting the SHEL Model in Investigating Industrial Maintenance. *Journal of Quality in Maintenance Engineering*, *22*(1), 62-80. doi:10.1108/JQME-12-2014-0059

National Transportation Safety Board. (n.d.). The Investigative Team. Retrieved from https://www.ntsb.gov/investigations/process/Pages/default.aspx

Pandey, A. (2020, February 1). *Airbus topples Boeing as biggest plane maker*. DW.

Peduzzi, P., Concato, J., Kemper, E., Holford, T. R., & Feinstein, A. R. (1996). A simulation study of the number of events per variable in logistic regression analysis. Journal of Clinical Epidemiology, 49(12), 1373-1379.

Quayle, R., & Checksfield, A. (2020, May 26). *Temporary aircraft cargo conversion – what legal and regulatory issues should airlines and lessors be considering?* BCLP Law. Retrieved from https://www.bclplaw.com/en-US/insights/temporary-aircraft-cargo-conversion-what-legal-and-regulatory-issues-should-airlines-and-lessors-be-considering.html

Roelen, A., Pikaar, A., & Ovaa, W. (2000). An Analysis of the Safety Performance of Air Cargo Operators. *National Aerospace Laboratory NLR,* nlr-tp-2000210.

Schenker, J. D., & Rumrill, J. P. D. (2004). Causal-comparative research designs. Journal of Vocational Rehabilitation, 21(3), 117–121.

Tabachnick, B., G., & Fidel, L., S. (2013). Using multivariate statistics (6th ed.). Pearson

Education Inc. Upper Saddle River, NJ. Tarnowski, E., & Speyer, J. (1997). Integrating Human Factors and Automation with Progress in Aircraft Design and Flight Management. *Proceedings of the IASC-97 International Aviation Safety Conference*.

Time and Date AS. (2022). *Sunrise, Sunset, and Daylength*. Time and Date. Retrieved from https://www.timeanddate.com

Title 14, Code of Federal Regulations § 1 - Definitions and Abbreviations (Federal Aviation Administration 2020).

Title 14, Code of Federal Regulations § 61 – Certification: Pilots, Flight

Instructors, and Ground Instructors: Flightcrew Members (Federal Aviation Administration 2020).

Title 14, Code of Federal Regulations § 117 - Flight and Duty Limitations and Rest Requirements: Flightcrew Members (Federal Aviation Administration 2020).

United Kingdom, Civil Aviation Authority. (2013). *Global Fatal Accident Review 2002 to 2011* (CAP 1036). Norwich, NR3 1GN: The Stationary Office.

United States of America, Federal Aviation Administration, FAASTeam. (n.d.). *Loss of Control - Inflight.*

United States of America, Federal Aviation Administration. (2003). *General Aviation Controlled Flight into Terrain Awareness* (61-134).

United States of America, Federal Aviation Administration. (2015). *Air Cargo Operations* (120-85A).

United States of America, Federal Aviation Administration. (2022). *Air Cargo Operations* (120-85B).

United States of America, Federal Aviation Administration. (2019). *Stall Prevention and Recovery Training* (120-109A).

United States of America, Federal Aviation Administration. (2015). *Upset Prevention and Recovery Training* (120-111).

United States of America, National Transportation Safety Board, Office of Research and Engineering; Office of Aviation Safety. (2000). *Flight Data Recorder Handbook for Aviation Accident Investigations*. Washington, D.C.

United States of America, National Transportation Safety Board. (2001). *Runway Overrun During Landing American Airlines Flight 1420* (NTSB/AAR-01/02). Washington, D.C. United States of America, National

Transportation Safety Board, Office of Research and Engineering; Office of Aviation Safety. (2011). *Cockpit Voice Recorder Handbook for Aviation Accident Investigations*. Washington, D.C.

United States of America, National Transportation Safety Board. (2010). *U. S. Air Carrier Operations Calendar Year 2006* (NTSB/ARC-10/01). Washington, D.C.

United States of America, National Transportation Safety Board. (2014). *Crash During a Nighttime Nonprecision Instrument Approach to Landing UPS Flight 1354* (NTSB/AAR-14/02). Washington, D.C.

United States of America, U.S. Department of Transportation, Research and Innovative Technology Administration. (2005). *Airline Travel Since 9/11* (13th ed.). Washington, D.C.: Bureau of Transportation Statistics.

Warner, R. M. (2008). Applied statistics: From bivariate through multivariate techniques. Sage Publications Inc. Thousand Oaks, CA. from https://www.dw.com/en/airbus-topples-boeing-as-biggest-plane-maker/a-49536539

Appendix A

List of Countries per Global Region

Global Region	Country
Africa	Algeria
	Benin
	Cameroon
	Comoros
	Cote d'Ivoire
	Democratic Republic of the Congo
	Ethiopia
	Ghana
	Kenya
	Libya
	Mali
	Morocco
	Nigeria
	Senegal
	South Africa
	South Sudan
	Tanzania
	Tunisia

Global Region	Country
Asia	Bangladesh
	East Timor
	French Polynesia
	India
	Indonesia
	Japan
	Laos
	Malaysia
	Myanmar
	Nepal
	Philippines
	Singapore
	South Korea
	Taiwan
	Taiwan
	Thailand

Global Region	Country
CIS	Kazakhstan
	Kyrgyzstan
	Russia
	Tajikistan
	Ukraine

Global Region	Country
Europe	Austria
	Belgium
	Denmark
	Estonia
	Finland
	France
	Germany
	Greece
	Greenland
	Ireland
	Italy
	Lithuania
	Luxembourg
	Netherlands
	Norway
	Poland
	Portugal
	Romania
	Saudia Arabia
	Slovakia
	Spain
	Sweden
	Switzerland
	United Kingdom

Global Region	Country
Latin America	Argentina
	Bolivia
	Brazil
	Carribean
	Chile
	Columbia
	Cuba
	Ecuador
	Falkland Islands

Global Region	Country
Latin America	Guadeloupe
	Guyana
	Haiti
	Honduras
	Mexico
	Montserrat
	Peru
	Turks and Caicos
	Uruguay
	Venezuela
Global Region	**Country**
Middle East	Afghanistan
	Egypt
	Iran
	Lebanon
	Pakistan
	Somalia
	Sudan
	United Arab Emirates
Global Region	**Country**
North America	Bahamas
	Canada
	Colombia
	Guam
	Haiti
	Jamaica
	United States
Global Region	**Country**
Oceania	Australia
	Micronesia
	New Zealand
	Papua New Guinea
	Vanuatu

Appendix B

Format and Information Summarized within ASN Database

Figure 3.

Example of Accident Summary on ASN Database

Status:	Final
Date:	**Monday 1 June 2009**
Time:	00:14
Type:	Airbus A330-203
Operator:	Air France
Registration:	F-GZCP
MSN:	660
First flight:	2005-02-25 (4 years 3 months)
Total airframe hrs:	18870
Cycles:	2644
Engines:	2 General Electric CF6-80E1A3
Crew:	Fatalities: 12 / Occupants: 12
Passengers:	Fatalities: 216 / Occupants: 216
Total:	Fatalities: 228 / Occupants: 228
Aircraft damage:	Destroyed
Aircraft fate:	Written off (damaged beyond repair)
Location:	c 160km NNW off São Pedro and São Paulo Archipelago (Atlantic Ocean)
Phase:	En route (ENR)
Nature:	International Scheduled Passenger
Departure airport:	Rio de Janeiro-Galeão International Airport, RJ (GIG/SBGL), Brazil
Destination airport:	Paris-Charles de Gaulle Airport (CDG/LFPG), France
Flightnumber:	AF447

Note. Accident factors summarized within Figure 3. Include Time of Day, Aircraft Generation, Aircraft Manufacturer, Location of Operator, Passenger or Cargo, Accident Location, and Phase of Flight.

Figure 4.

Example of Accident Classification and Final Accident Report on ASN Database

Accident investigation:

Investigating agency:	BEA
Status:	Investigation completed
Duration:	3 years and 1 months
Accident number:	f-cp090601en
Download report:	Final report

Classification:

Loss of control

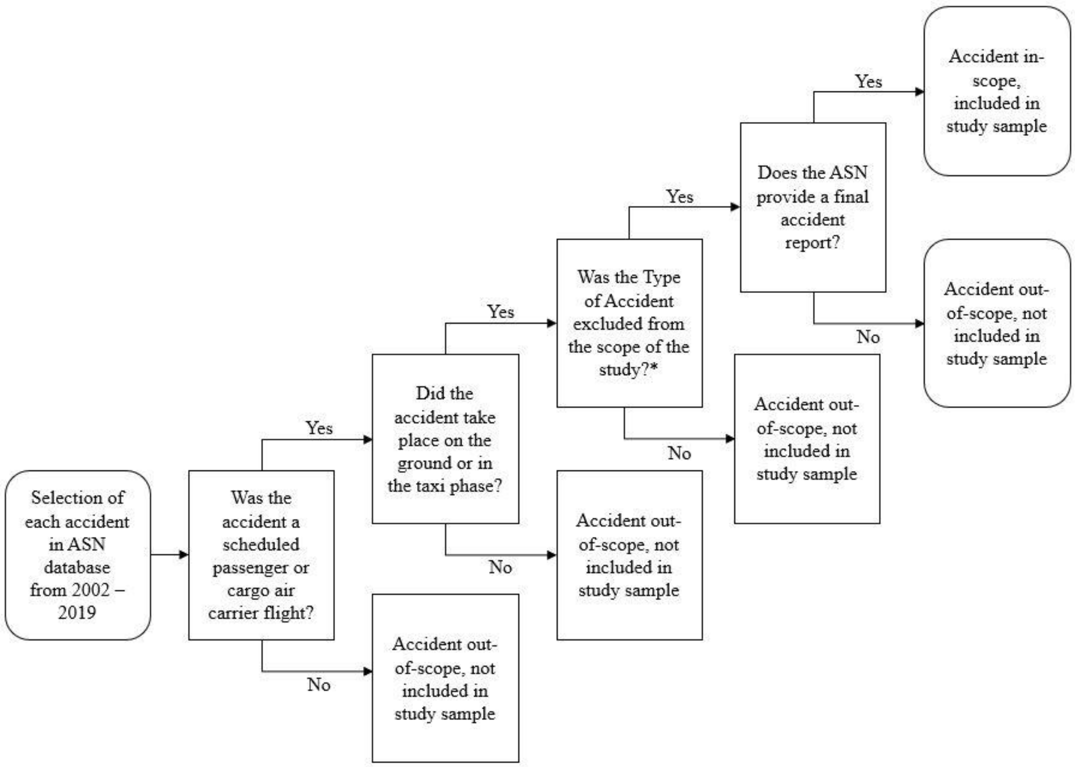
Note. The inclusion of a final accident report confirms that this accident will be in–scope. Accident factors summarized under Classification include CFIT, LOC, Mechanical Failure, and Weight Factor.

Appendix C

Data Collection Process Part 1

Figure 5.

Process for Determining if an Accident Was In–Scope or Out–of–Scope for Inclusion in Study Sample



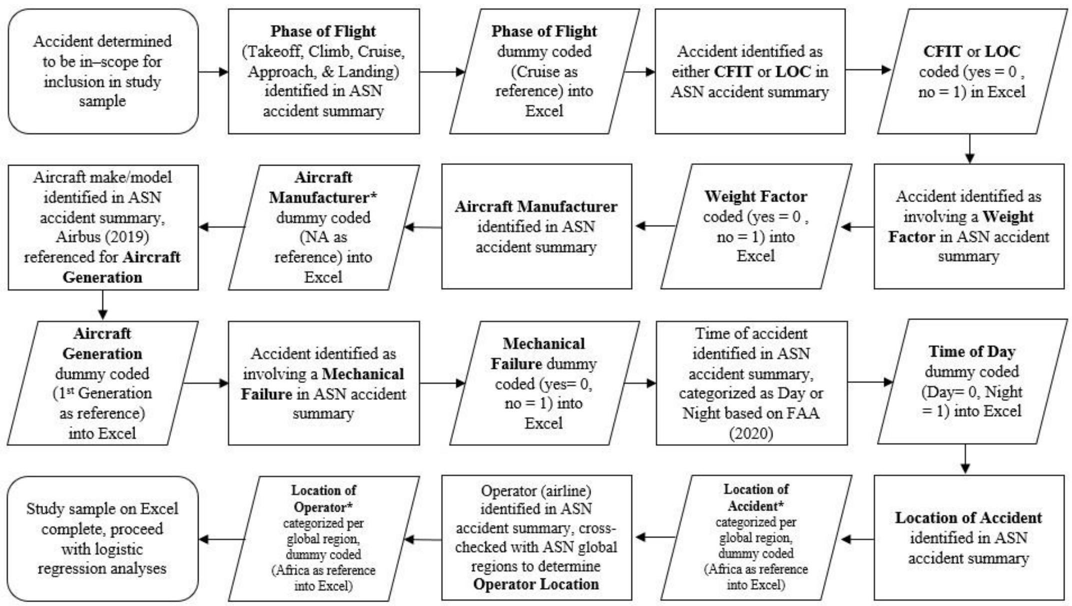
**Note.* The following types of accidents were considered out–of–scope for inclusion in the study sample: ground operations or collisions (aircraft was standing or taxing), acts of terrorism (sabotage, hijacking, aircraft shoot-down, or attempted takeovers), mid-air collision, pilot error, fuel exhaustion, wildlife strike, fuel contamination, aircraft missing, and runway incursions.

Appendix D

Data Collection Process Part 2

Figure 6.

Process for Extracting Data from ASN Database and Populating Study Sample Using Dummy Coding



Note. Names of predictor variables are bolded.

*Global regions for Aircraft Manufacturer include Asia, Commonwealth of Independent States, Europe, Latin America, and North America. Global regions for Location of Accident and Location of Operator include Africa, Asia, Commonwealth of Independent States, Europe, Latin America, Middle East, North America, and Oceania.

Appendix E

Results of Logistic Regression with All Predictor Variables Present

Table 21

Summary of Logistic Regression Estimates for the Null and Simultaneous (Full) Models

	B_i	*SE*	χ^2	*p*
Null Model				
Constant	-0.69	0.09	63.42	<0.001
Full Model				
Constant	-2.33	1.25	3.50	0.06
Phase of Flight				
X_1 = Takeoff	-0.30	0.19	2.48	0.12
X_2 = Climb	-0.34	0.24	2.07	0.15
X_3 = Approach	0.06	0.18	0.12	0.73
X_4 = Landing	-0.59	0.15	14.72	<0.01**
X_5 = Loss of Control	0.24	021	1.39	0.24
X_6 = Controlled Flight into Terrain	0.09	0.26	0.13	0.72
X_7 = Weight Factor	0.38	0.23	2.72	0.10
Aircraft Manufacturer				
X_8 = Commonwealth of Independent States	0.75	0.28	7.34	0.01*
X_9 = Europe	-0.17	0.13	1.68	0.20
X_{10} = Latin America	0.04	0.26	0.02	0.88
Aircraft Generation				
X_{11} = Generation 2	-0.84	0.25	11.38	<0.01**
X_{12} = Generation 3	-0.82	0.24	11.61	<0.01**
X_{13} = Generation 4	-1.40	0.23	38.86	<0.001**
X_{14} = Mechanical Failure	0.12	0.18	0.47	0.49
X_{15} = Time of Day	0.57	0.11	25.22	<0.01**
Operator Location				
X_{16} = Asia	-0.16	0.24	0.44	0.51
X_{17} = Commonwealth of Independent States	-0.90	0.40	5.18	0.02*
X_{18} = Europe	-0.19	0.24	0.59	0.44
X_{19} = Latin America	-0.14	0.25	0.31	0.58
X_{20} = Middle East	-0.26	0.31	0.72	0.40
X_{21} = North America	0.41	0.21	3.81	>0.05
X_{22} = Oceania	<0.00	0.34	0.00	0.99

Note. N = 594. R_L^2 = .26, *df* = 22 for the full model.

In the null model, B_0 = -0.69, and this can be transformed into the odds ratio, $e^{-0.693}$ = 0.5. This indicates that approximately 1/3 of the air carrier accidents were classified as cargo.

The full model is representative of the hypothesized model, which predicts the odds for an accident being classified as cargo with all predictor variables entered into the model simultaneously. The predicted odds differed from the null model, and this difference was statistically significant.

B_i = Logit; *SE* = Standard Error; χ^2 = Chi Statistic; *p* = Probability.

**p* < .05. ***p* < .01.