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Relationship Between Airline Category, Geographical Region, and Safety Performance

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<u>Walden University</u>

College of Management and Technology

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Peter Simpson

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Walden University
2018

Abstract

Relationship Between Airline Category, Geographical Region, and Safety Performance

by

Peter A. Simpson

MA, Australian Catholic University, 2012

MBA, University of Southern Queensland, 2005

MSc, Loughborough University, 1999

BSc(Hon), University of Newcastle, 1995

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Business Administration

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September 2018

Abstract

Passengers rank safety as a key factor in airline choice. Thus, safety performance impacts an airline's ability to attract customers. The purpose of this correlational study was to examine the relationship and difference between airline category low-cost carriers (LCCs) and full-service carriers (FSCs), geographical region, and safety performance measured by accident rates. The target population comprised all airlines in all countries that had an accident during the 14-year period 2004 to 2017. Data consisted of archival data of all global airline accidents and airline departure frequencies for the 14-year period. The theory of organizational accidents in complex sociotechnical systems explains the relationship between LCC and FSC safety performance, as well as between global geographical regions. The Swiss cheese model of organizational accidents theoretical framework remains a relevant model to examine airline accidents and improve airline safety. Data analysis consisted of the *t* test, ANOVA, correlation, and regression analysis. LCCs were found to be as safe as FSCs on a global level, and safer than FSCs in some regions. There were regional differences in safety, with North America being safer than Africa. The implications for positive social change include the potential for airline leaders to improve the safety image of their airline and provide passengers a better understanding of airline safety. Providing passengers with information on airline safety performance allows passengers to make informed choices on using different categories of airlines in different geographical regions. The research may result in new travel opportunities for travelers that were previously unrealized due to safety concerns, particularly around the increased use of LCCs.

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Table of Contents

List of Tables

List of Figures

Section 1: Foundation of the Study

Safety is one of the most important elements of the global aviation industry (Kalemba & Campa-Planas, 2017; Kim & Park, 2017), and aviation is the safest form of transport (Balcerzak, 2017). Improved safety and security standards have been the industry's key objectives for many reasons. Airlines accidents have immediate, negative, and extended global media coverage (Balcerzak, 2017). Airline accidents are very costly and have a financial impact on the airline (Walker, Walker, Thiengtham, & Pukthuanthong, 2014). Passengers rank safety as a key factor in airline choice (Kim & Park, 2017; Lu, 2017; Min & Min, 2015), and accidents have a negative impact on an airline's reputation (Molin, Blange, Cats, & Chorus, 2017). Thus, safety performance impacts an airline's ability to attract customers (Sandada & Matibiri, 2016). Despite the fundamental importance of safety to airlines, there is a lack of understanding about the safety performance of low-cost carriers (LCCs) and full-service carriers (FSCs) and how that may differ around the world. The purpose of this quantitative correlation study was to examine the relationship between airline category, geographical region, and safety performance.

Background of the Problem

Passengers are important stakeholders in the airline business. Airline safety is one of the most important factors that passengers consider when selecting an airline for travel (Desai, Siddique, & Yaseen, 2014; Jeeradista, Thawesaengskulthaib, & Sangsuwanc, 2016; Milioti, Karlaftis, & Akkogiounoglou, 2015). Thus, a poor safety image impacts an airline's ability to attract customers (Sandada & Matibiri, 2016). Passengers have a poor understanding of airline safety performance, incorrectly judging airline safety performance and making safety judgments based on an airline's image (Hagmann, Semeijn, & Vellenga, 2015; Jeeradista et al., 2016; Milioti et al., 2015; Molin et al., 2017). The image of LCCs is not as good as the image of FSCs (Molin et al., 2017). The public perceives LLCs as being less safe than FSCs, despite the lack of evidence to support that perception (Chang & Hung, 2013; Hagmann et al., 2015; Mikulic & Prebezac, 2011; Molin et al., 2017; Wahyuni & Fernando, 2016). The lack of understanding of airline safety and incorrect judgment of LCC safety may impact passenger choice of using LCCs (Lu, 20017), which may have a business impact on LCCs (Moon, 2017).

Aviation authorities do not regulate or control airline service, product quality, or airfares, but safety is highly controlled and regulated by global and national regulators (Yadav & Nikraz, 2014). All airlines within a country must meet the same minimum regulatory standards of safety and security required by that country's regulator. Therefore, service quality, product, and pricing can differ significantly between airlines within a country, but safety standards meet the same minimum requirements. The problem facing LCCs is the negative perception of LCC safety performance as it impacts passenger airline choice, which may ultimately constrain LCC business. Research can provide a better understanding of the safety performance of LCCs and FSCs and the way in which this may vary across countries or regions. Fleischer, Tchetchik, and Toledo (2015) noted that when objective safety information is available, passengers will discount their subjective opinions and perceptions and incorporate that objective information into their decision making. I have presented the background to the problem, and the focus will now shift to the problem statement**.**

Problem Statement

Poor safety performance in the airline industry impacts airline economic performance (Walker et al., 2014). Airline accidents can result in direct costs of over US$500 million per accident (Walker et al., 2014). The general business problem was that airline safety performance impacts airline reputation and sustainability. The specific business problem was that some airline managers do not understand the relationship between airline category, geographical region, and safety performance.

Purpose Statement

The purpose of this quantitative correlation study was to examine the relationship between airline category, geographical region, and safety performance. The independent variables were the category of an airline classified as an LCC or FSC and the geographic region classified as the global region in which the airline is based. The dependent variable was the safety performance measured by aircraft accidents. The target population comprised archival data records of global passenger airlines. The implications for positive social change include the potential for airline leaders to improve the safety image of their airline and provide passengers a better understanding of airline safety. Providing passengers with information on airline safety performance is beneficial for nervous flyers (Graham & Metz, 2017) and may allow passengers to make more informed choices on using different categories of airlines in different geographical regions. The research may result in new travel opportunities for travelers that were previously unrealized due to safety concerns.

Nature of the Study

I chose a quantitative methodology for this study. Airline accident rates are the most common measure of safety performance (Neves, 2015; Oster, Strong, & Zorn, 2013), and the use of accident numbers and rates lends itself to quantitative analysis. Quantitative researchers identify changes in numerical characteristics of the population being studied and examine statistical relationships between the variables (Paul & Garg, 2014), which was the purpose of this study. Qualitative methods are appropriate when the intent is to explore a business process or how people make sense and meaning of their experiences (McCusker & Gunaydin, 2015). A mixed methods study contains the attributes of both quantitative and qualitative methods (Guetterman, Fetters, & Creswell, 2015). Because the intent of my study was quantitative, the qualitative and mixed-method approaches were not appropriate.

Correlation is the statistical measure of how closely and in what direction two variables are related (Emerson, 2015). Differences in independent group means are measured with the *t* test and ANOVA (Sullivan, Weinberg, & Keaney, 2016). The correlation design, *t* tests, and ANOVAs were appropriate for this study because a key objective was to explore differences between and predict the relationship between the nominal independent variables of airline category categorized as LCC or FSC and airline geographical location, and a ratio dependent variable of airline safety performance measured by accident rate. Other designs, such as experimental and quasi-experimental designs are appropriate for assessing cause and effect (Froman & Owen, 2014). The objective of this study was to examine the relationship between variables, not to assess cause and effect. Thus, the experimental and quasi-experimental designs were not appropriate.

Quantitative Research Question and Hypotheses

RQ: What is the relationship between airline category, geographical region, and safety performance?

H_0: There is no statistically significant relationship between airline category, geographical region, and safety performance.

H_1: There is a statistically significant relationship between airline category, geographical region, and safety performance.

Theoretical Framework

Reason’s (1995, 1997, 1998) systems approach to organizational accidents, visualized as the Swiss cheese model, is the most widely-used theory of accident causation throughout various industries, including aviation (Underwood & Waterson, 2014). Reason’s theory is that active failures are unsafe acts (errors and violations) by front-end operators. In contrast, latent failures are weaknesses or gaps in system safety defenses created by distant stakeholders, such as designers, builders, regulators, or top-level managers. High technology systems have multiple defenses in layers. The layers of defense in the system are like pieces of Swiss cheese as they have weaknesses or holes. The holes are dynamic, changing in size and location. Holes in a single slice or defense does not normally cause a bad outcome, but when all the holes momentarily align is when a failure has a clear path through the system, resulting in a catastrophic accident (Reason, 1995, 1997, 1998)

The aviation safety regulator and its regulations are an organizational factor and defense in the Swiss cheese model. All airlines within a country must meet the same minimum regulatory standards of safety and security set by the national regulator (Yadav & Nikraz, 2014). Thus, within a country, both LCCs and FSCs should have similar levels of safety performance. National aviation regulators have varying levels of sophistication to implement, assure, and enforce safety regulations and programs, resulting in different safety performance between countries and regions (Faure, 2014; Oster et al., 2013).

Operational Definitions

Accident: An event where all the following criteria are satisfied (International Air Transport Association [IATA], 2017):

- Persons have boarded the aircraft with the intention of flight (flight crew or passengers).
- The intention of the flight is limited to normal commercial aviation activities, specifically scheduled/charter passenger or cargo service. Executive jet operations, training, maintenance/test flights are all excluded.
- The aircraft is turbine powered and has a certificated maximum take-off weight of at least 5,700KG.
- The aircraft has sustained major structural damage which adversely affects the structural strength, performance or flight characteristics of the aircraft, and would normally require major repair or replacement of the affected

component, exceeding US$1million or 10% of the aircraft's hull reserve value, whichever is lower, or the aircraft has been declared a hull loss.

Full-service carrier (FSC): A traditional national or major carrier that operates on a relatively extensive route network (thus, also referred to as a network carrier) and provides a full range of in-flight services, ground services, and frequent flyer programs (International Civil Aviation Organization [ICAO], 2004)

Low-cost carrier (LCC): A carrier that focuses on providing low-cost air transport services to customers with simple or limited in-flight services (ICAO, 2004). I categorized airlines as LCC based on ICAO's (2017) list of LCCs.

Assumptions, Limitations, and Delimitations

Assumptions

Assumptions are elements of the research study taken for granted or accepted as true without concrete proof (Kirkwood & Price, 2013). The first assumption in this study was that accidents are a valid and reliable measure of airline safety performance. Accidents are commonly used to measure aviation safety performance (Boyd, 2016, 2015; Knecht, 2013; Elvik & Elvebakk, 2016). The second assumption was that the OAG Aviation Worldwide Ltd. (OAG) accurately and consistently recorded flight frequency for all global regions. The final assumption is that IATA captured all airline accidents each year that met their definition of an accident. To ensure that IATA captured all airline accidents, IATA and ICAO have produced a harmonized accident list since 2011 (ICAO, 2013b).

Limitations

Limitations are potential weaknesses or problems with the study that cannot be controlled by the researcher. Stating the limitations allows other researchers to replicate or expand on the study (Simon, 2011). The main limitation of the study was the use of archived data and records from the IATA, ICAO, and OAG. Any inaccuracy in the data reported by these organizations could negatively affect the accuracy of the study. My accident data set was limited to the period from 2004 to 2017. I measured safety performance by accidents, which are retrospective and limited in number. A lack of flight sector data for all airlines in the accident database does not permit the calculation of accident rates for individual airlines.

Delimitations

Delimitations set the scope or boundary of the study, stating what constructs and factors the researcher leaves out of the study (Simon, 2011). I only used airline accidents reported by IATA in their Annual Safety Report in the study to ensure geographical and historical consistency. The accident data is limited to the 14-year period 2004 to 2017.

Significance of the Study

Contribution to Business Practice

Passengers rank airline safety as one of the most important factors in airline choice selection (Desai et al., 2014; Jeeradista et al., 2016; Jiang, 2013; Min & Min, 2015). Thus, safety performance impacts an airline’s ability to attract customers (Sandada & Matibiri, 2016). The research may be of value to airline leaders as the findings from the study will determine if there is a significant relationship between airline category

(LCC or FSC), geographical region, and safety performance. Establishing a relationship between the variables may allow predictions of safety performance. Passengers are often willing to pay more to fly with airlines they perceive as safe (Molin et al., 2017), and passengers are more loyal to safe airlines, avoiding unsafe airlines, particularly in regions with historically poor airline safety performance (Sandada & Matibiri, 2016).

Passengers have previously chosen to fly FSCs over LCCs due to the better safety image of FSCs (Lu, 2017). Information related to airline safety performance might be used by airline managers to shape airline image and influence passenger airline choice, which may impact business performance. Fleischer et al. (2015) noted that when objective safety information is available, passengers will discount their subjective opinions and perceptions and incorporate that objective information into their decision making on airline choice, and that includes paying a premium to travel on airlines with high safety performance. In summary, there is a potential business benefit through increased knowledge of airline safety performance.

Implications for Social Change

The implications for positive social change include the potential to provide passengers a better understanding of airline safety performance, presenting greater opportunities for passengers to make informed choices about airline selection. Improving travelers' awareness of safety is important, as safety is one of the most important considerations in airline choice. Information that can reduce the safety concerns of nervous flyers is of benefit to those travelers (Graham & Metz, 2017). The inclination to avoid an airline perceived as having poor safety performance is stronger in individuals with a high fear of flying. Fleischer et al. (2015) noted that up to 30% of the adult population has a fear of flying and providing airline safety information to that population allows a more rational airline choice. Removing any barriers to air travel, especially those around safety, may result in new travel opportunities for travelers that were previously unrealized due to their safety concerns.

A Review of the Professional and Academic Literature

The purpose of this quantitative correlation study was to examine the relationship between airline category, geographical region, and safety performance. The independent variables were the category of an airline classified as an LCC or FSC, and the geographic region classified as the global region of base operations of the airline. The dependent variable was the safety performance measured by aircraft accidents. Reason’s Swiss cheese model (Reason, 1997) was the theoretical framework for the study.

I searched EBSCO host (all databases), ProQuest, Thoreau multidatabase, and Google Scholar for relevant articles in the topic areas of *transport safety and regulation, airline safety, regional safety, low-cost carriers, system and organizational safety,* and *the Swiss cheese model.* I obtained professional literature, databases, and material from aviation regulatory bodies (ICAO, US FAA, UK, CAA, and IATA). The review of the literature included 126 references. Eighty-eight percent of the references were within five years of expected completion of the study, and 85% were peer-reviewed.

The Swiss Cheese Model

Organizational accident theory. The organizational approach, also called the systems approach, is the dominant paradigm in operational safety and accident analysis of complex and dynamic sociotechnical systems (Underwood & Waterson, 2013). Accidents in complex sociotechnical systems are the result of unexpected, dynamic, uncontrolled, and often complex relationships and interactions between the system's components. In complex sociotechnical systems, such as aviation, nuclear, and petrochemical industries, the frequency of accidents is low, but the consequence is catastrophic (Li, Zhang, & Liang, 2017). Underwood and Waterson (2013) advocated studying systems as whole entities rather than considering the components in isolation due to the involvement and interaction of the system's components. Indeed, the system life cycle phases of design, development, construction, operation, and maintenance and modification are all phases when latent weakness may be introduced (Stoop, de Kroes, & Hale, 2017). This situation highlights the interactions and tight coupling between all elements and even phases of complex sociotechnical systems. The Swiss cheese model is the central model of the systems approach to accidents in sociotechnical systems (Le Coze, 2013).

Swiss cheese model. Reason's (1995, 1997, 1998, 2000b) systems approach to organizational accidents, visualized as the Swiss cheese model, is the most widely-used theory of accident causation throughout various industries (Underwood & Waterson, 2014). Larouzee and Guarnieri (2015) described the Swiss cheese model as having established itself as the reference model in the causation, investigation, and understanding, and prevention of organization accidents. In many industries, the Swiss cheese model has been the vector of a new paradigm of safety science, namely the organizational accident (Le Coze, 2013). Indeed, the Swiss cheese model has become the global model of aviation accident causation and prevention used by the ICAO. Google scholar has over 25,000 citations of Reason's Swiss cheese model (Larouzee & Guarnieri, 2015). These statements provide insight into the importance of Reason's theory of organizational accidents and the Swiss cheese model to the safety field. The Swiss cheese model has been applied to multiple industries including aviation (Gerstle, 2018), medical and healthcare (Collins, Newhouse, Porter, & Talsma, 2014; Gerstle, 2018; Stein & Heiss, 2015), nursing (Correia, Martins, & Forte, 2017; de Lima Gomes et al., 2016), mining (Bonsu, Franzidis, Isafiade, van Dyk, & Petersen, 2017), nuclear (Reason, 1995), chemical processing (Soignier, Summers, & Williams, 2014), oil and gas (Chen et al., 2017), and rail (Matsika, Ricci, Mortimer, Georgiev, & O'Neill, 2013; Underwood & Waterson, 2014).

Humans cannot eliminate error; human error is inevitable (Reason, 1995). Thus, systems must be error-tolerant to prevent errors leading to accidents. In these situations, human error is a consequence rather than a cause, and blaming operators for errors and subsequent accidents does not improve safety. The traditional model of safety and accident causation that focused on active failures (human errors and mistakes) and single causes is inadequate (Aini & Fakhru'l-Razi, 2013; Xia, Liu, Wang, Zhu, & Zou, 2018). The person-centered approach does not address contextual or task-related factors, nor any supervisory, managerial, or organizational factors. The person-centered approach does not improve on poor design or procedures, nor does it strengthen defenses or address all hazards and risks. Aini and Fakhru'l-Razi (2013) suggested the medical industry's continual adherence to the person-centered approach to safety continues to hinder safety progress and result in no significant reduction in patient deaths from medical errors.

Reason (1995) explored broader conditions that led to, exacerbated, or did not prevent human error from resulting in disaster. The fundamental principle of Reason's theory of organizational accidents is that organizational accidents are the catastrophic events that occur in complex sociotechnical systems involving many different people at different levels (Reason, 1997). The systems approach to organizational accidents explores the multiple latent and systemic factors that interact to contribute to accidents.

In the Swiss cheese model, active failures (errors, mistakes, and violations) are unsafe acts by front-end operators. In contrast, latent failures are weaknesses or gaps in system safety defenses created by distant stakeholders, such as designers, builders, regulators, or top-level managers. Complex sociotechnical systems have multiple defenses in layers or barriers. The layers of defense in the system have holes and weaknesses, like pieces of Swiss cheese. The holes are dynamic and change in size and location. Holes or weakness in a single slice or defense do not normally result in a catastrophic outcome, but when all the holes momentarily align, any failure has a clear path through the system, with the potential to result in a catastrophic accident (Reason, 1995, 1997, 1998, 2000b). Thus, in a complex system, accidents only occur when all the defenses fail, reinforcing the convergence of events and conditions (Chen et al., 2017). Figure 1 depicts Reason's (1997) model of organizational accidents.

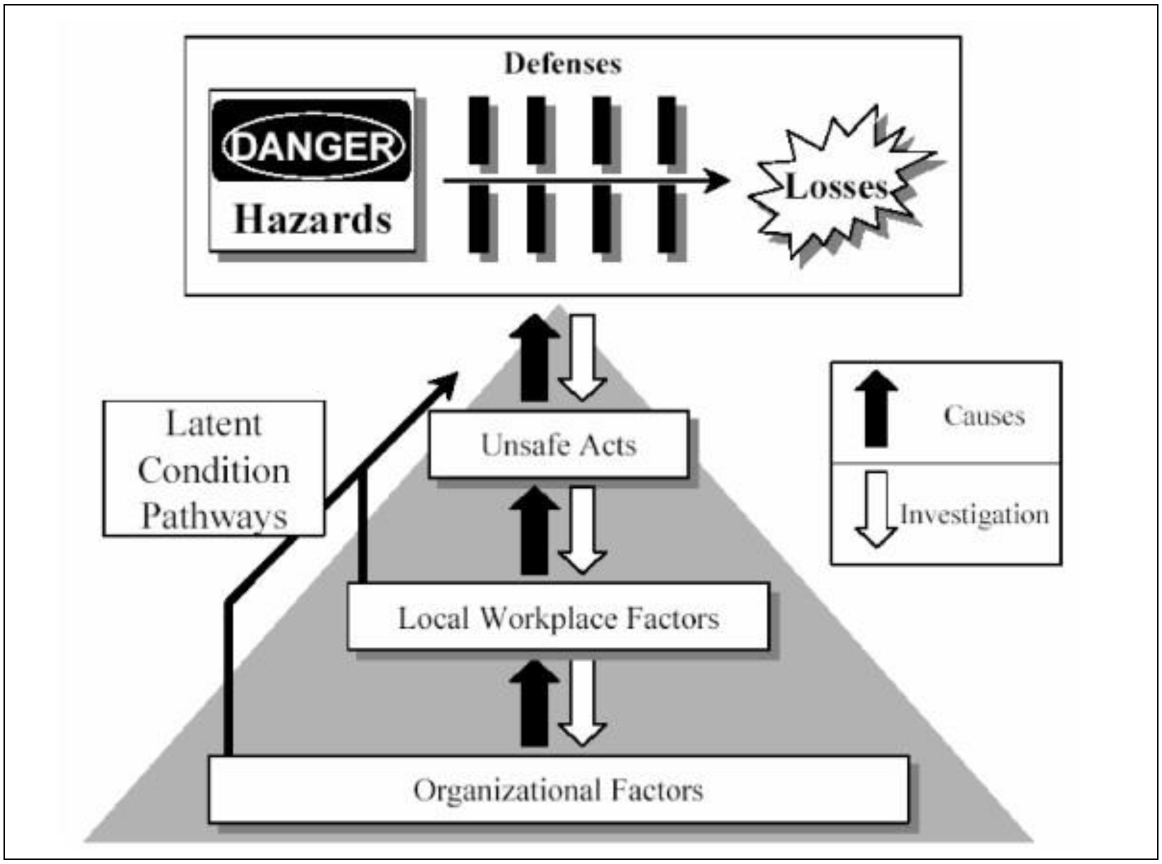

Figure 1. Model of organizational accidents (Reason, 1997).

The development of the Swiss cheese model. The Swiss cheese model had its origins in 1987 when Reason was writing his seminal book, *Human Error* (Reason, 1990a), in which Reason explored the nature, variety, and cognitive sources of human error. Through accident analysis, Reason (1990a) distinguished between active errors and latent errors. The performance of operators at the sharp end (active errors, mistakes, and violations) is influenced by local workplace conditions and upstream organizational factors (latent errors). Reason compared the latent errors to resident pathogens in the body, lying dormant until they combined with other factors to breach system defenses and result in an accident. Perrow's (1984) normal accident theory had previously described the concept of organizational issues influencing operator action, and the normal accident theory also contained the concept of defenses-in-depth creating system opacity, complexity, and interdependencies. The concept of accident pathogens is still in contemporary accident theory. For example, Gnoni and Saleh (2017) noted that accident pathogens are adverse latent or preexisting conditions, passive or with no impact on the system until triggered by other adverse events.

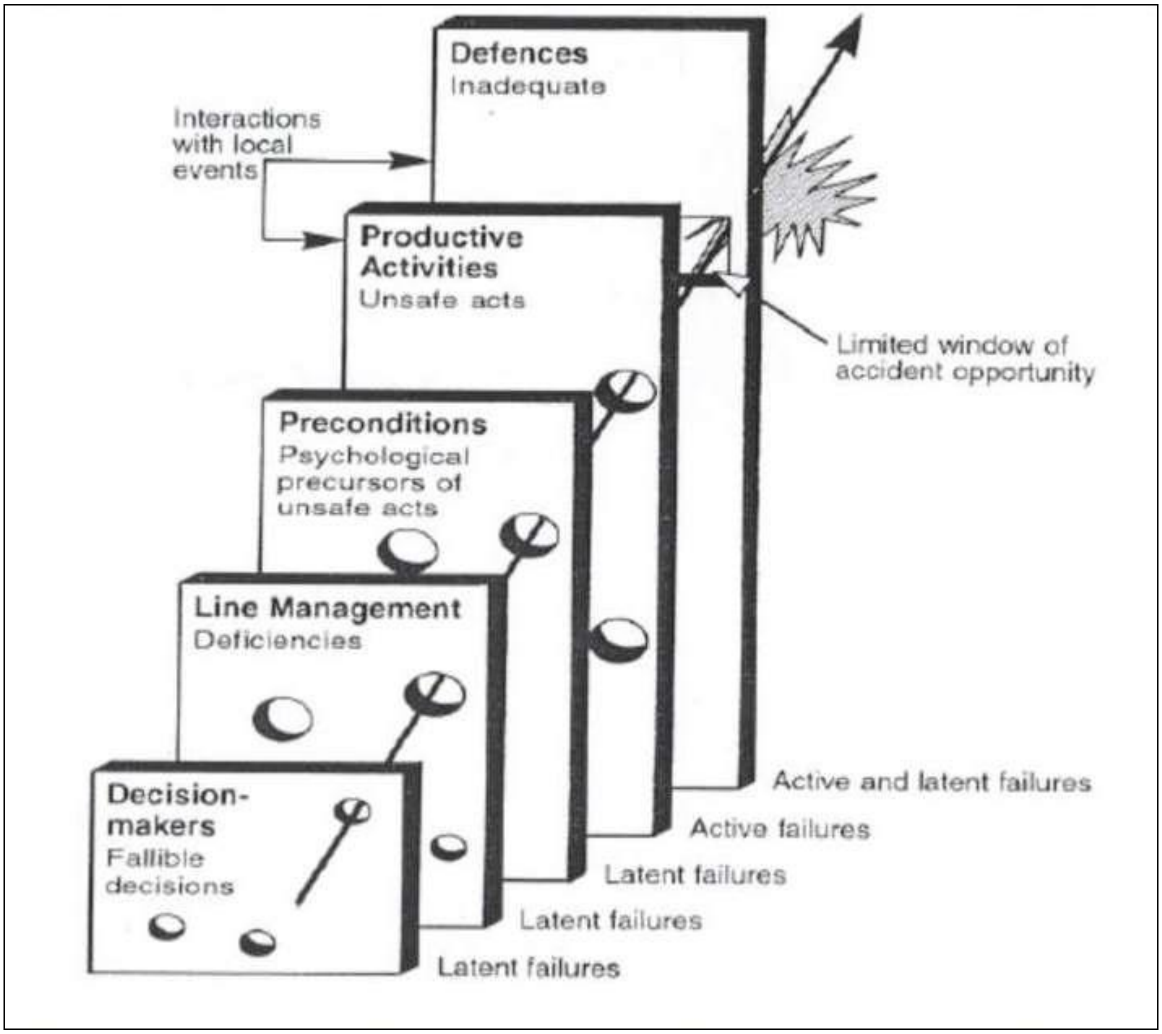

Figure 2. An early edition of James Reason’s model.

Reason's original model, shown in Figure 2, was simple and focused on human error, consisting of psychological precursors and unsafe acts that both had weakness and holes, as well as multiple defenses-in-depth which had holes to allow the trajectory of accident opportunity to breach the defenses (Reason, 1990a). Shortly after, Reason reengineered and refocused the model towards a more organizational approach, with five planes consisting of elements that make up complex sociotechnical systems: top-level decision makers, line managers, preconditions, production activities, and defenses (Reason, 1990b). Reason later expanded these elements and renamed them organizational elements (management decisions, procedures, and culture), task/environment (conditions that produce errors and violations), and operator/individual (persons who make errors and violations), as shown in Figure 3.

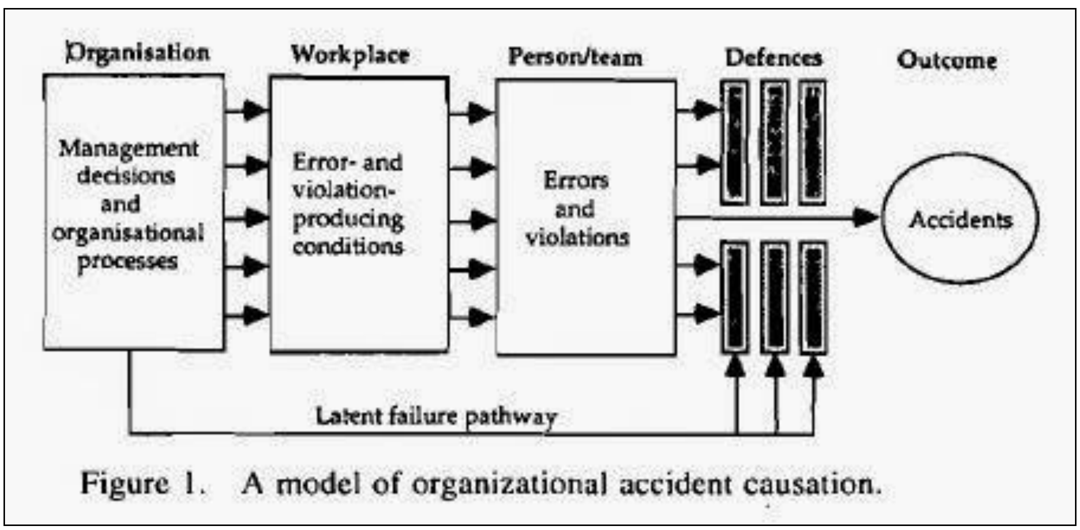

Figure 3. Reason model in the mid-1990s (Reason, 1995).

In the mid-1990s latent errors were renamed latent failures, which later became latent conditions (Reason, 1997), acknowledging the fact that effective decisions at one point in time may have unintended negative outcomes at another time and place in the system (Larouzee & Guarnieri, 2015). The decisions may not have been wrong at the time they were made, and accident investigators should not consider the decisions as errors or failures. The Swiss cheese model appeared in the late-1990s with the transformation of the defensive barriers and elements in the system from simple layers with weaknesses and holes to slices of Swiss cheese (see Figure 4; Reason, 1998). The model then moved from the academic world into the mainstream, practitioner environment of accident investigation and operational safety management. Reason (1995) applied the model to case studies of the Dryden air crash and a nuclear accident, demonstrating its validity and use across various industries.

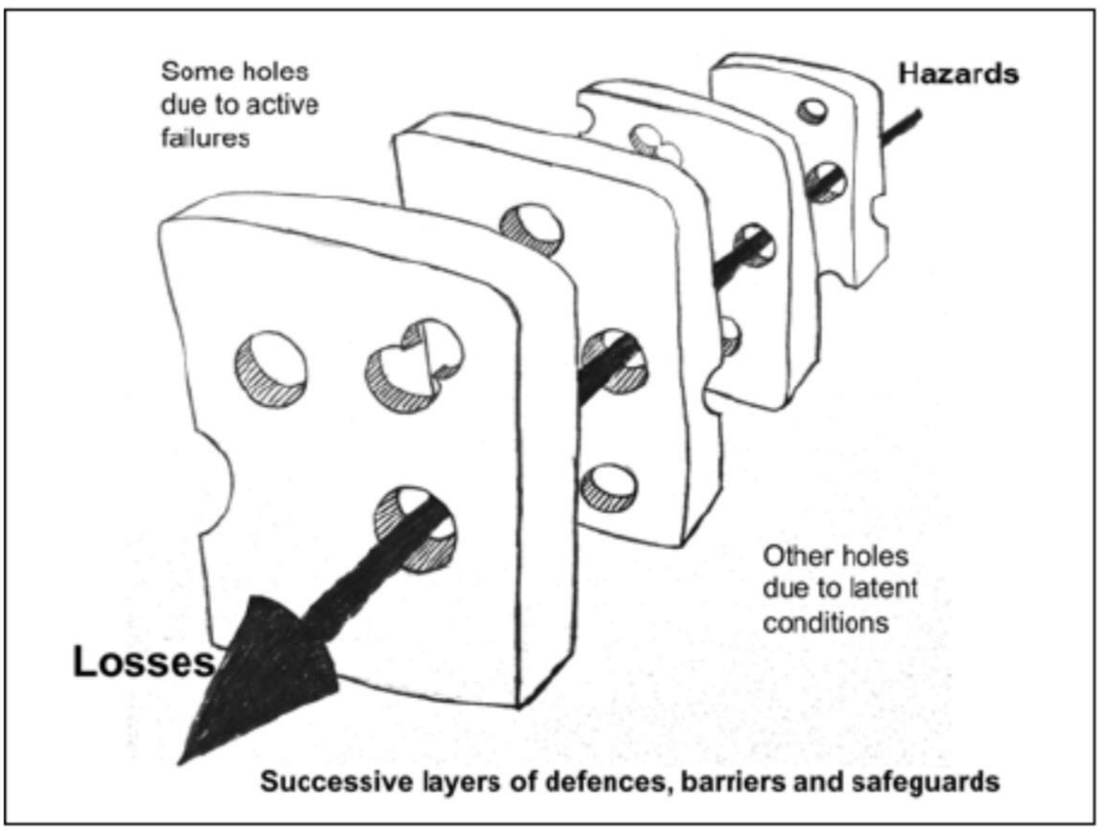

Figure 4. The current version of Swiss cheese model (Li & Thimbleby, 2016)

Larouzee and Guarnieri (2015) cataloged the history and development of Reason's Swiss cheese model from its first publication in 1990 to its current form published in 2000. In doing so, Larouzee and Guarnieri inadvertently highlighted a weakness of the model, that Reason has not updated the Swiss cheese model since 2000. Thus, the model has become stagnant.

The Swiss cheese model in detail. The components of Reason's model are organizational elements, workplace or environmental elements, and person/team elements. The components have weaknesses, vulnerabilities, and failures represented by holes. All systems have defenses which are either effective, failed or ineffective, or absent. Failure pathways are active failures or latent conditions. The following sections described these components in more detail.

Active failures**.** Reason (2000b) noted that active failures are unsafe acts, categorized as errors, mistakes, lapses, and violations. Front-end operators or those in direct contact with the system, introduce active failures. Active failures create weaknesses in the defenses or protective layers. Active failures usually have a direct and short-lived impact on the integrity of the system defenses (Reason, 2000b). While many legal approaches to accidents seek an individual to blame for the proximal unsafe acts, Reason (2000b) noted that almost all such acts have a causal history that extends back in time or up through the levels of the system.

Latent Conditions**.** Latent conditions are present in the system before the operator interacts with it. Latent conditions are gaps, weaknesses, or absence in or of defenses unwittingly created by distant stakeholders, such as designers, builders, regulators, or top-level managers. Latent conditions can lay dormant for many years before interacting with active failures and local conditions to create the opportunity for an accident. For example, the design flaws of the Concorde fuel tank lay dormant for 40 years until exposed in the 2000 Air France crash of the Concorde (Moyer, 2014). Latent conditions are removed in proximity to an accident. For example, both Aini and Fakhru'l-Razi (2013) and Waring (2015) highlighted the importance of regulators in organizational accidents, despite regulators being removed in both time and space from the accident.

Reason reinforced that latent conditions are present in every complex system, as no system is perfect. The positive aspect of latent conditions is the potential to identify and resolve the issues before they cause harm. Reason (2000b) provided an analogy of active and latent failures: active failures are like mosquitos which can be swatted one-by-one, but they keep coming. The best remedy is to create more effective defenses and to drain the swamps in which the mosquitos breed. In this case, the swamps are the latent conditions.

Defenses. Defenses, barriers, or safeguards protect people and assets from local hazards. Local hazards can include human error and violations. High technology systems often have multiple defenses in layers, known as defenses-in-depth, which Gnoni and Saleh (2017) noted as a fundamental safety principle. The layers of defense should be diverse. Some system defenses are engineered (e.g., alarms, physical barriers, and automatic shutdowns), some defenses rely on people (e.g., pilots, ATC, surgeons, and control room operators), other defenses rely on procedures and administrative controls (e.g., checklists, rules, and procedures), and some rely on organizational structures (e.g., regulators, and oversight). The multiple defenses in the Swiss cheese model that gives the model its name. The layers of defense have weaknesses or holes like pieces of Swiss cheese. The holes are dynamic, opening and closing, growing, and shrinking, and shifting location. Having holes in a single slice or defense does not normally cause a bad outcome but, an error trajectory has a clear path through the system when all the holes momentarily align, resulting in a catastrophic accident. The holes due to active failures are likely to be dynamic and short-lived, while the holes arising from latent conditions are less dynamic and long-term, lying dormant for many years (Reason, 1998).

One of the defensive layers in the aviation system is the regulatory layer. In a study of sociotechnical disasters, Aini and Fakhru’l-Razi (2013) found that organizational and regulatory failures were the main contributing factors to the disasters. Such regulatory failures may be due to inadequate or outdated laws and regulations, poor regulatory reinforcement, and inadequate or incompetent personnel, all of which fail to effectively govern and monitor safety (Aini & Fakhru’l-Razi, 2013). Regulatory systems are country-specific, and regulators have varying degrees of competence, resource, and effectiveness. Thus, the strength of the regulatory defense varies between countries. All the airlines within a country are subject to the same strength (or weakness) of regulatory defenses. The varying strength of the regulatory layer forms the basis for the assertion that airlines within a country will all have similar levels of safety, but safety will differ between countries or regions.

Comparing the Swiss cheese model to other models. Researchers have compared and tested the Swiss cheese model with and against other models of organizational safety (Le Coze, 2013; Underwood & Waterson, 2013). A model can never fully capture complex operational reality and models will always remain limited and inadequate. No model is without limitations, and the limitations also relate to the application context, and the background and knowledge of the user (Le Coze, 2013).

Le Coze (2013) produced a comprehensive analysis of the Swiss cheese model and two of its contemporary models of system safety, Rasmussen's migration model and Weick's collective mindfulness model. Le Coze based his analysis of the three models on eight attributes of the models, and general commentary on the strengths and weaknesses of the models. A weakness identified in the Swiss cheese model was the lack of detail and explanation about the nature of the holes, precisely what the holes represent and how they occur. The Swiss cheese model was more popular with practitioners, while Rasmussen's and Weick's models were more aligned with academia and rarely used by accident investigators (Le Coze, 2013).

Underwood and Waterson (2014) applied three models of organizational safety (Swiss cheese model, AcciMap, and STAMP) to the Grayrigg train derailment. The application all three models to one common accident allowed for the identification and comparison of the strength and weakness of each model. The Australian Transport Safety Bureau (ATSB) used the Swiss cheese model for accident investigation and reporting, while research and academic applications of accident analysis often use the AcciMap and STAMP models (Underwood & Waterson, 2014).

Underwood and Waterson (2013) noted that the Swiss cheese model is the most popular and widely used systems approach model. Although, various authors (e.g., Le

Coze, 2013; Li & Thimbleby, 2014; Wiegmann & Shappell, 2001), have criticized the Swiss cheese model for its sequential nature and oversimplification of accident causation. There has also been criticism over the Swiss cheese model's lack of description of how the holes line up, and the idea that some investigators take an overly-prescriptive application of the model. Underwood and Waterson balanced those criticisms by noting Reason's commentary on the use of the Swiss cheese model, which negates many of these criticisms, including statements that the linear serialization is simply a static representation, whereas Reason's theory of organizational accidents is neither linear nor static. The criticisms of the Swiss cheese model appear to arise from an overly-simplistic and inadequate understanding of the model and the detailed theory underpinning it, rather than a faulty model. Like Le Coze (2013), Underwood and Waterson (2014) concluded that the Swiss cheese model was better suited to investigation practitioners, whereas the AcciMap and STAMP models may be better suited to academic research scenarios. Underwood and Waterson also concluded that despite the criticisms, the Swiss cheese model remains a viable and important model for understanding complex organizational accidents.

Adaptations of the Swiss cheese model. There have been numerous adaptations and extensions of Reason's theory of organizational accidents. Arguably, the most successful adaptation has been Shappell and Weigmann's human factors analysis classification system (HFACS) (Cohen, Wiegmann, & Shappell, 2015; Ergai et al., 2016; Wiegmann & Shappell, 2001). HFACS has become a standard tool for examining and understanding the contribution of human factors to accidents across a range of industries.

Shappell and Wiegmann operationalized the concepts of the Swiss cheese model to develop a framework for classifying and analyzing the human factors associated with accidents. HFACS uses the same levels presented by Reason in his model; organizational influences, unsafe supervision, preconditions for unsafe acts, and unsafe acts (see Figure 5), which describe the holes of the Swiss cheese model at four levels (Fu, Cao, Zhou, & Xiang, 2017). Within each level of HFACS, causal categories identify the active and latent failures. Thus, the HFACS model continues the theory of preventing organizational accidents by identifying organizational and systemic weakness rather than focusing on and blaming the individual operators (Theophilus et al., 2017).

Wiegmann and Shappell (2001) criticized the Swiss cheese model as being insufficiently specific regarding the nature of the holes in the cheese and their inter-relationships, a criticism made by others as well (Le Coze, 2013). Thus, the HFACS defined what the holes are, with a focus on human factors. For example, supervisory factors are broken into subcategories of inadequate supervision, planned inappropriate operations, failure to correct known problems, and supervisory violation (Cohen et al., 2015). The HFACS has been applied to various domains, including aviation (Daramola, 2014), marine and shipping (Akyuz, 2017; Akyuz, Celik, & Cebi, 2016; Chen et al., 2013; Soner, Asan, & Celik, 2015), construction (Xia et al., 2018), rail (Zhan, Zheng, & Zhao, 2017), oil and gas (Theophilus et al., 2017), mining (Fu et al., 2017), and healthcare (Cohen, Wiegmann, Reeves, Boquet, & Shappell, 2016; Diller et al., 2014).

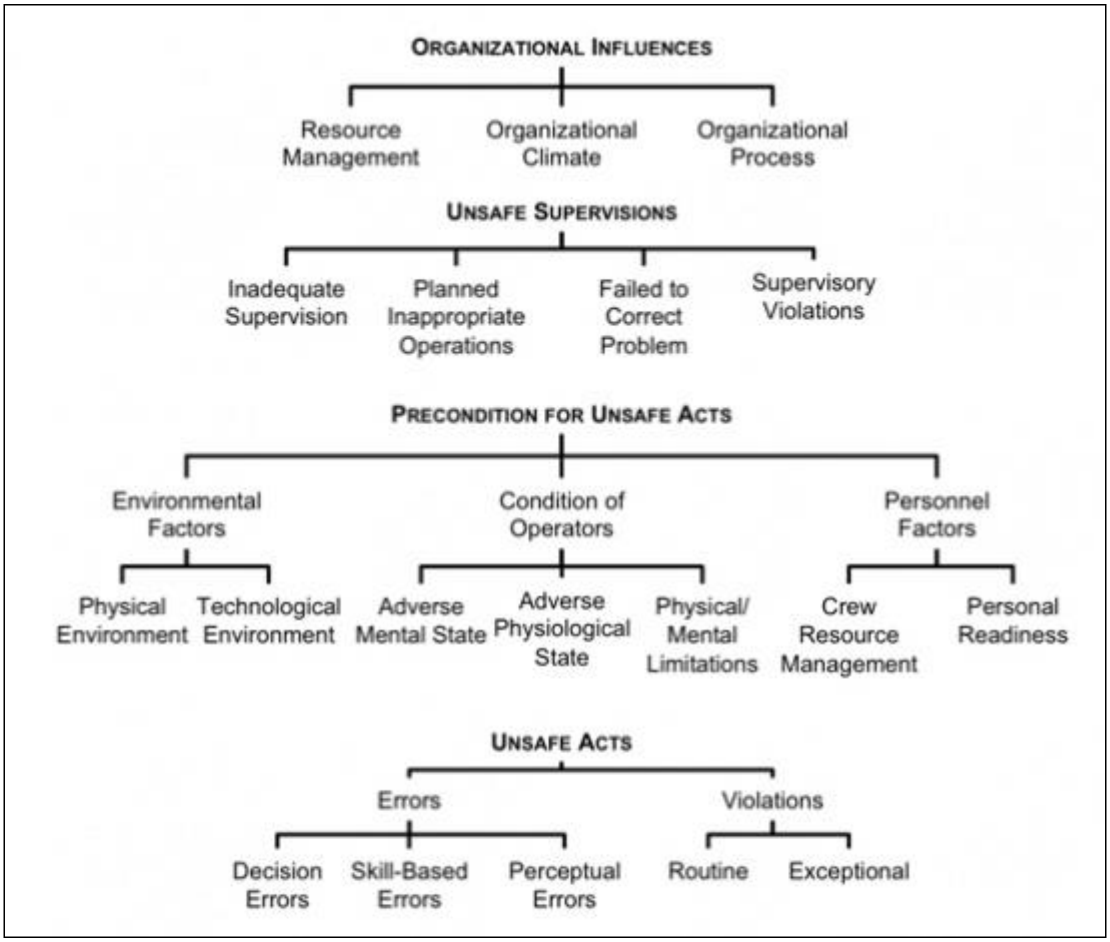

Figure 5. Human factors analysis classification system (Shappell & Wiegmann, 2000).

Developments and Updates of the Swiss cheese model. Some of the criticism of the Swiss cheese model may be due to its inappropriate use. For example, Collins et al. (2014) used the Swiss cheese model to examine the effectiveness of medical checklists to reduce active errors. Active errors are just one part of the Swiss cheese model, and the study reinforced that errors are the final active failure. However, the Swiss cheese model emphasizes the latent organizational issues impacting the active failures, highlighting the inappropriate use of the model in a narrow setting, rather than an organizational or system setting.

A criticism of the Swiss cheese model is that it has remained relatively static since its development in the 1990s. Le Coze (2013) questioned whether models such as Swiss cheese model have expired or are still valid. One argument is that safety-critical industries should consider and implement more insights from existing models rather than develop new models (Le Coze, 2013). While there have been advances in technology and automation, humans have not changed, nor have their interactions with technology. Organizations and regulators have not changed, nor have safety cultures, or our general understanding of organizational accidents. Le Coze also argued that no model is ever entirely satisfactory, as models cannot fully capture complex realities and all experienced phenomena. Models will always have limitations, and those limitations extend to the background, skills, and knowledge of the user, as well as the context in which the model is being used (Le Coze, 2013). Indeed, the Swiss cheese model is a relatively simple and intuitive model on the surface, but the complex theories of organizational accidents, human factors, and human error underpin the model.

While Reason has not updated the Swiss cheese model since 2000, other authors have developed and updated the Swiss cheese model. Li and Thimbleby (2014) developed the hot cheese model after criticizing the Swiss cheese model for being overly simplistic and static, not realistically portraying the dynamic situations and interactions between the layers, and not categorizing unsafe acts as errors, violations, or reckless behaviors. However, Li and Thimbleby's hot cheese model is complex and unintuitive, with eight different 'types' of cheese layers, requiring a reference key to understand what the eight types of cheese mean. The hot cheese model does not categorize operators' unsafe acts, despite Li and Thimbleby's criticism of that weakness in the Swiss cheese model. The authors have a fondue pot at the bottom of the model to catch drips of melted cheese which represent corporate knowledge and lessons learned, taking the cheese metaphor to an absurd level. Li and Thimbleby's statement that the Swiss cheese model is too simple and static, suggesting that they do not understand the theoretical foundations of the Swiss cheese model. Indeed, Reason had dedicated several books to explain the theory of organizational accidents (Reason, 1990a, 1997) and has stated that the elements of the Swiss cheese model, including the holes, are dynamic and changing (Reason, 1997). The success of the Swiss cheese model, particularly amongst practitioners has been its portrayal of a complex theory in an intuitive model (Underwood & Waterson, 2013). Furthermore, Reason's (1997) theory of organizational safety and human error contains a culpability decision tree that categorizes unsafe acts as errors, mistakes, violations, or reckless behaviors, further highlighting gaps in Li and Thimbleby's knowledge and understanding of the Swiss cheese model and its theoretical underpinnings. The hot cheese model has not successfully superseded the Swiss cheese model, nor have other authors have referenced it.

Hudson (2014) reviewed two methods for reducing the risks of accidents. Hudson first applied a legal model to identify the single cause of an accident and then applied the Swiss cheese model to look for more systematic, complex, latent causes. Hudson stated that 80% of accidents are preventable by using the legal model approach, and then a further 80% of remaining accidents reduced with the Swiss cheese model, leaving just 4% of accidents unpreventable by the two approaches. However, Hudson provided no evidence or data for his suggestion of an 80% reduction in accidents. The first model applied by Hudson was a purely legal model, and the problem with legal models is that what is legal is not necessarily safe, and what is illegal is not always unsafe. Legal models must find and allocate liability and blame, usually implicating the operators. Organizational accident theory and the Swiss cheese model operate on the concept that single active failures do not result in catastrophic accidents in complex sociotechnical systems. Thus, laying blame on a single person for a complex sociotechnical accident is inappropriate and unhelpful. Therefore, the concepts and models used by Hudson conflict and are incompatible with each other.

Meshkati and Placencia developed the double-shielded, fortified Swiss cheese model (Meshkati, 2014). The model added the safety regulator as a top-down influence on safety performance, and an organization’s safety culture as a bottom-up influence on safety performance. The model depicted strong and independent regulatory oversight, and rigorous and proactive safety inspection, enforcement, and verification by the regulator to influence and impact system safety from the top-down (Meshkati, 2014). However, Reason (1995, 1998) described and depicted both the safety regulator and safety culture as part of the Swiss cheese model in the organization section. Thus, it is unclear what additional value Meshkati’s double-shielded, fortified Swiss cheese model brings.

Low-Cost Carriers

The definition of an LCC. LCCs are also known as no-frills, low-fare, discount, or budget airlines. However, LCC is the name officially used by the IATA (2006), the ICAO (2004, 2017), and the U.S. Department of Transport (U.S. DOT) (1996). LCC is also the term commonly used in the academic literature (Bowen Jr, 2016; Buaphiban & Truong, 2017; Fageda, Suau-Sanchez, & Mason, 2016; Kwoka, Hearle, & Alepin, 2016; Lordon, 2014; Yu, Chang, & Chen, 2016). The UK Civil Aviation Authority (CAA) used the term no-frills carrier instead of LCC to avoid confusion with charter airlines which have also considered themselves to be low-cost (CAA, 2006). The UK CAA stated that it is the comparative lack of frills on-board, coupled with low airfares, which are defining characteristics of a no-frills airline for the public and media.

The ICAO is inconsistent with its definitions of LCCs. In the Manual on the Regulation of International Air Transport, the ICAO (2004) defined an LCC as a carrier that has a relatively low-cost structure in comparison with other comparable carriers and offers' low fares. In the same Manual, the ICAO defined a no-frills carrier as a carrier that focuses on providing low-cost air transport services to customers with simple or limited in-flight services. The ICAO also defined an FSC as a carrier, typically a traditional national or major carrier that operates on a relatively extensive route network (thus, also referred to as a network carrier) and provides a full range of in-flight services, ground services, and frequent flyer programs. Despite the ICAO's definitions, ICAO does not refer to the term low-frills carrier in other documents, press releases, or events. Instead, the ICAO use the term LCC in the way they define no-frills carriers (ICAO, 2017). The ICAO published and updated a list of 265 LCCs, including those no longer operating (ICAO, 2017). In this research study, I used the ICAO (2017) list of LCCs to categorize airlines as LCCs.

Academic literature that examines airlines as LCCs and FSCs aligns with the ICAO list (e.g., Bowen Jnr, 2016; Fageda et al., 2016; Hanaoka, Takebayashi, Ishikura, & Sarawati, 2014; Klein, Albers, Allroggen, & Malina, 2015; Kwoka et al., 2016; Lordon, 2014; Yu et al., 2016). The UK CAA (2006) produced a list of LCCs operating within and into Europe, which aligns with the ICAO's LCC list.

The characteristics of an LCC. There is no universally agreed definition or standard business model of an LCC (CAA, 2006; Fageda et al., 2016; IATA, 2006). The U.S. DOT (1996) categorized LCCs by unit costs (cost per available seat kilometers [ASK]) and airfare pricing practices. Although, the U.S. DOT contradicted their definition by categorizing some carriers as LCCs, such as Vanguard and Western Pacific, despite having higher unit costs than some legacy or network carriers (U.S. DOT, 1996). The UK CAA (2006) stated that judging whether an airline has high or low costs is more complicated than assessing its onboard services and the judgment is less relevant. Some FSCs have low operating costs, and some LCCs have high operating costs (Kwoka et al., 2016). Thus, operating cost is a poor differentiator between an LCC and an FSC. ICAO supported the UK CAA's statements by noting that FSCs are shifting their focus to cost reduction for a sustainable business model.

Despite the lack of agreed definition of an LCC, there is a general understanding in the industry, regulatory bodies, the media, and the public of what LCCs are, based on their operating model and consumer offering (CAA, 2006). IATA (2006) stated typical features and characteristics of LCCs, listed in Table 1. The academic literature supports the IATA list of LCC characteristics and features (Buaphiban & Truong, 2017; Fageda et al., 2016; Kwoka et al., 2016).

Table 1

Typical Features and Characteristics of LCCs

Point-to-point operations.
Serving short-haul routes, often to/from regional or secondary airports.
A strong focus on price-sensitive traffic, mostly leisure passengers.
One service class, with no customer loyalty programs.
Limited passenger services, with additional charges for some services such as food, beverages, baggage, seat selection, and amenities.
Low average fares, with a strong focus on price competition.
Airfare pricing related to aircraft load factors and length of time before departure.
A high proportion of bookings made through the Internet.
High aircraft utilization rates, with short turnaround times between flight.
A fleet consisting of just one or two types of aircraft.
Private-sector companies.
Simple management and overhead structure with a lean decision-making process.

Note. From IATA (2006).

LCC and FSC convergence. The distinction between LCC and FSC is becoming blurred. LCCs are now offering services such as networking and alliance partners (e.g., JetBlue, Air Berlin), long-haul flights (e.g., AirAsia X, Jetstar, Norwegian, Scoot), business class (e.g., airBaltic, Jetstar, Scoot), frequent flyer programs (Scoot), and complimentary food and drinks. In contrast to the classic LCC operational model, European and US LCCs are expanding operations into primary airports (Dobruszkes, Givoni, & Vowles, 2017; Ferrer-Rosell & Coenders, 2017) and Asian LCCs have concentrated their expansion and growth flying between primary airports and cities (Bowen Jr, 2016). Ferrer-Rosell and Coenders (2017) called this a convergence of LCC and FSC, noting a blurring of the LCC and FSC business models.

The convergence of LCC and FSC has prompted some researchers (e.g., Bachwich & Wittman, 2017) to describe an emerging market of ultra-low-cost carriers (ULCC). However, the U.S. airlines listed as ULCCs by Bachwich and Wittman (2017) (Allegiant, Frontier, and Spirit) all featured in ICAO's (2017) list of recognized LCCs, and the features of the ULCCs are vey closely aligned to the traditional LCC operational model of Ryanair or Whizz. The ULCC branding is perhaps unique to the U.S. market, where LCCs such as Southwest and JetBlue charge airfares and offer services much closer to U.S. FSC pricing than do the European and Asian LCCs. Hence, ULCC is a U.S-centric term that IATA or ICAO do not use.

Perception of Low-Cost Carrier Safety

Airline safety is one of the most important factors that passengers consider when selecting an airline for travel (Jeeradista et al., 2016; Jiang, 2013; Milioti et al., 2015; Min & Min, 2015). Despite the importance that passengers place on airline safety, passengers have a poor understanding of actual airline performance. Passengers often perceive LCCs as less safe than FSCs, despite the lack of evidence to support that perception (Chang & Hung, 2013; Hagmann et al., 2015; Lu, 2017; Min & Min, 2015;

Wahyuni & Fernando, 2016). Passenger's perception of airline safety is often incorrect and based on an airline's image and service quality (Hagmann et al., 2015; Jeeradista et al., 2016; Milioti et al., 2015; Min & Min, 2015; Molin et al., 2017). The image of LLCs is not as good as that of FSCs, resulting in an incorrect passenger assumption that LLCs are less safe than FSCs (Chang & Hung, 2013; Fleischer et al., 2015; Milioti et al., 2015; Wahyuni & Fernando, 2016). Fleischer et al. (2015) remind us that information on flight safety is not easily obtainable by passengers, and in the absence of objective safety information, passengers will revert to their own subjective opinions and perceptions driven by airline image and the media. Tourists without flying experience and infrequent travelers have shown the greatest lack of understanding of airline safety, as found by Galambos, Deri, Dragin, Galambos, and Markovic (2014).

Passengers are aware that the LCC operating model is to save money and reduce costs on all commercial aspects of a flight, and many passengers project this cost saving and reduction into safety aspects (Chang & Hung, 2013; Molin et al., 2017). As reported by Gao and Koo (2014), a common comment made by the public about LCCs, or even FSCs with lower fares, is that 'you get what you pay for.' Travelers assume that airlines charging airfares lower than the expected cost of production must be offering a poor quality or shoddy product (Savage, 2012). Thus, travelers attribute low airfares with low safety. Hagmann et al. (2015) found similar results when they compared the environmental image of airlines. Passengers rated prestigious airlines with good service reputations as significantly greener than LCCs, despite the opposite being true. The LCC desire to save on operating costs such as fuel and having newer fleets resulted in better environmental scores (Hagmann et al., 2015).

Indeed, even governments had acted on the misperception and misunderstanding of airline safety performance, as seen when the Indonesian Minister of Transport threatened to terminate all Indonesian LCCs and incorrectly stated that LCCs have a poor safety record compared to FSCs. The Minister stated that low prices must equate to low safety standards and cost-cutting on safety (Wahyuni & Fernando, 2016); an argument commonly stated by the media and public (Gao & Koo, 2014). The Indonesian government then put strict controls on LCCs but did not apply the same controls to FSCs. However, Wahyuni & Fernando (2016) reported that when the Indonesian safety regulator (the Director General of Civil Aviation) conducted a review of all 43 Indonesian airlines, 26 of the 43, or more than 60% of airlines did not meet all safety requirements. The Indonesian study found LCCs that met all the safety requirements and FSCs who did not, highlighting that the negative safety perception of LCCs is incorrect and not reflected in objective data.

Operational characteristics of LCCs, such as fast turnarounds and efficient maintenance are perceived as negatively impacting safety and showcasing the tension between safety and profit (Broderick, Emmel, Gierczak, & Gonzalez, 2017). Broderick et al. (2017) found no evidence that mechanics and engineers were under any greater pressure to cut corners or bypass procedures at one airline over another, or that more efficient maintenance programs impacted safety performance, nor any evidence that fast turnarounds had any impact on safety. Indeed, not all so-called ‘safety activities’ have a positive effect on safety or reduce risk, and thus have no safety value (Rae & Alexander, 2017). Safety activities that provide no additional safety assurance or value can result in a false assurance that safety goals are being achieved, which Rae and Alexander (2017) referred to as probative blindness. Probative blindness may be associated with some additional safety activities of FSCs; doing additional safety activities which do not improve safety or reduce risk.

Passengers have rated flight safety as the most important factor when choosing to fly on FSCs, whereas passengers have rated airfare as the most important reason for choosing an LCC (Kim & Park, 2017; Lu, 2017; Milioti et al., 2015). Although, Jiang's (2013) study of long-haul LCCs found that passengers rated safety as more important than cost. Passengers choose to fly FSCs as they are considered safer, and passengers are willing to pay a premium for what they perceive as high levels of safety (Fleischer et al., 2015; Koo, Caponecchia, & Williamson, 2015; Lu, 2017; Molin et al., 2017). Even though the perception and public's fear that some operating characteristics of LCCs may impact safety, Broderick et al. (2017) found no evidence to support such conclusions. Fleischer et al. (2015) found that passengers only distinguished between high safety airlines and airlines considered medium or low safety, which passengers grouped together. Thus, unless passengers consider LCC safety performance equal to FSC safety, they may incorrectly consider LCCs in the same category as airlines with poor safety performance.

Regulating Airline Safety

The aviation safety regulator and its regulations are an organizational factor and defense in the Swiss cheese model and are part of the top-down influence on safety in Meshkati's (2014) fortified Swiss cheese model. Indeed, the fortified Swiss cheese model depicts strong and independent regulatory oversight, and rigorous and proactive safety inspection, enforcement, and verification by the regulator to influence and impact system safety from the top-down (Meshkati, 2014). Regulatory oversight is also the basis for Shavell's (1984) theory of controlling safety risk through regulation, which Faure (2014) updated and expanded.

All airlines within a country must meet the same minimum regulatory standards of safety and security required by the national regulator (Yadav & Nikraz, 2014). Thus, within a country, both LCCs and FSCs should have similar levels of safety performance (Savage, 2012). National aviation regulators have varying levels of sophistication and resources to develop, implement, assure, and enforce safety regulations and programs, resulting in different safety performance between countries and regions (Faure, 2014; Oster et al., 2013; Savage, 2012). To compare aviation with another complex socio-technical system, the oil and gas industry, Theophilus et al. (2017) stated that the lack of strong international and national oil and gas regulations and regulatory oversight have resulted in a progressive reduction of safety barriers and layers. Waring (2015) noted that questionable motivations and ineffectiveness of safety regulators in some industries and countries had a detrimental effect on safety. Thus, regulators play a fundamental role in the strength of organizational safety.

The ICAO is a specialized agency of the United Nations with 191 of the 192-member states (countries) of the United Nations. The ICAO codifies the principles and techniques of international air navigation and fosters the planning and development of international air transport to ensure safe and orderly aviation operations. Yadav and Nikraz (2014) emphasized that the primary purpose of the ICAO's aviation regulations and global standards is to ensure flight safety. Annex 19 to the Convention on International Civil Aviation (ICAO, 2013a) is the ICAO document containing the international standards and recommended practices (ISARPS) for the management of aviation safety. Annex 19 is dedicated to the management of aviation safety and has several safety benefits including ensuring that safety risks are proactively identified, re-enforcing the role of the State in managing safety at the country level, and reinforcing the concept of overall safety performance in all air transport domains.

The global aviation system is complex with many interrelated activities required to assure the safe operation of aircraft. The ICAO developed the ISARPs in Annex 19 to assist countries in managing aviation safety risk (ICAO, 2013a). The ICAO bases its safety strategy on each country's implementation of a State Safety Program (SSP) that systematically addresses safety risks at a country level. The SSP is an integrated set of regulations and activities aimed at improving safety. ICAO requires that each country establishes an SSP for the management of safety, to achieve an acceptable level of safety performance in air transportation (ICAO, 2013a). The objective of the SSP is to achieve an acceptable level of safety of aviation services and products delivered by aviation service providers; airlines, air traffic control, airport operators, training, and engineering and maintenance organizations.

The ICAO launched the Universal Safety Oversight Audit Program (USOAP) in response to widespread concerns about the adequacy of aviation safety oversight around the world (ICAO, 2016b). USOAP activities consist of regular audits of ICAO Member States' safety oversight systems. USOAP audits focus on a State's capability in providing safety oversight by assessing whether the State has effectively and consistently implemented the critical elements of a safety oversight system, which enable the State to implement safety-related ISARPS and associated procedures and guidance material (ICAO, 2016b)

With 191-member states, ICAO’s USOAP audits require extensive resources, and as of December 2016, ICAO had still not conducted a USOAP audit of all member states (ICAO, n.d.). ICAO conducted around 30 USOAP audits per year (ICAO, 2016b). Thus, as Shavell (1984) and Faure (2014) noted, a limitation of controlling safety risk through regulation is the resource and effort required to ensure oversight. The weakness of regulation being dependent on enforcement is a potential reason for the poor aviation safety record of some countries and regions, particularly in developing regions with economic, political, resource, and competency constraints.

Faure (2014) extended Shavell’s (1984) theory of controlling safety risk through regulation by adding insurance to the model. Faure suggested that three risk controls of regulations, liability, and insurance manage safety and accidents, and described the limitations of the three risk controls. A lack of information to private and legal parties, the latency or long-tail effect of some risks, problems of proof and causality, and insolvency, all limit liability rules (Faure, 2014). Liability rules are ad-hoc and case-specific; thus, they do little to improve risk across the industry. The static or slow-moving nature of regulations, their requirement for strict enforcement, their openness to influence by lobbying and private interests, and their failure to control unknown risks are limits to regulations (Faure, 2014). Faure stated that insurance could overcome the limitations of liability and regulation.

Faure's (2014) theory applies to the aviation industry where insurance is a common risk control due to the large costs associated with an airline accident. The weakness of regulation being dependent on enforcement is a potential reason for the poor aviation safety record of some countries and regions, particularly in the developing world which has economic, political, resource, and competency constraints. Aviation regulations, particularly in the security area, are prone to lobby groups and reactive, unthinking reactions

A limitation of both Faure's (2014) and Shavell's (1984) theory is that both theories are based solely on economic and legal theory, not the practicalities and complexities of business. For example, Faure described insurance as creating a moral hazard because the risk of economic loss from a safety accident is covered by a third party. However, few managers in high-risk industries such as aviation would compromise safety knowing that insurance would cover economic losses. There are reputation and business sustainability issues to consider that relegate the moral hazard argument to the pages of irrelevant academic theory. A further weakness of Faure's model is that it does not account for the primary reason for global aviation regulation, and that is to ensure safe and efficient international operations. The purpose of the ICAO is to ensure safe international airline operations through global standards and rules. Faure's theory does not account for the control of safety risk in that international aviation situation.

Measuring Airline Safety

Defining safety. Li, Yin, and Fan (2014) noted that it is not possible to directly observe safety. Safety is defined as the absence of hazards, danger, risk, or injury (Boholm, 2017; Selcuk, 2015), or the avoidance of failure (Kaspers et al., 2016), which better describes the properties of 'unsafety' than safety (Reason, 2000a). Reason (2000a) described the safety paradox that regulators and passengers define and measure safety more by its absence rather than its presence. Regulators and passengers commonly measure and view safety by failures such as accidents. Failures and accidents better measure 'unsafety' and the occasional absence of safety. Safety is about reducing the possibility of accidents, incidents, and harm (Kalemba & Campa-Planas, 2017). Aviation, or indeed any sociotechnical system can never be free from danger or risk. Hence, safety is more practically defined as a level of minimal or acceptable risk.

The ICAO (2013a) defined safety as the state in which the possibility of harm or damage is reduced to, and maintained at, an acceptable level through a continuing process of identifying safety hazards and managing safety risk. Simply put, safety is about managing risk to an acceptable level (Kaspers et al., 2016), as the total elimination of all accidents or serious incidents is unachievable due to the sociotechnical nature of the complex aviation system (Reason, 2000a). Risk is not an observable item or outcome either, as Boholm (2017) reminded us that risk within the operational field is the numerical product of the probability (or likelihood) and magnitude (or consequence) of an unwanted outcome. Thus, safety is both a construct and a concept.

If safety is managing risk, the outcomes or consequences require definition, as does the likelihood or probability of the outcome or consequence. Using the ICAO's (2013a) definition of harm to persons or damage to property, the most common outcome or consequence to base safety risk on is an airline accident. While safety may be a construct and concept that is not directly observable, the outcomes of safety are quantifiable; the absence or presence of accidents.

Accidents, incidents, and near-miss. The most commonly used and thoroughly studied measure of safety performance in all transport activities including aviation is accidents. Both the ICAO and the IATA use accident data as the fundamental measure of airline safety performance and airline accident data is the primary metric used to examine aviation safety in the IATA and ICAO annual safety reports (IATA, 2017; ICAO, 2016a).

In alignment with the ICAO's (2013a) definition of safety, Neves (2015) described the concept of an acceptable level of safety performance derived from various safety performance indicators. The study was concerned with air traffic control (ATC) safety, but it is equally applicable to airline safety. Neves' (2015) safety performance indicators included runway incursions, surface occurrences, and aeronautical accidents and incidents. ATC agencies commonly report the safety indicators noted by Neves, and the indicators are often publicly available. While Neves (2015) used a variety of safety indicators to measure safety performance, the indicators were all reactive, outcome-based safety measures, consisting of various accident and incident types.

Safety reporting is a measure of airline safety performance. Gnoni and Saleh (2017) described the advantages that proactive, near-miss safety reporting can bring, noting that proactive learning from near-miss events is less costly than reactive learning from accidents. Although, there is a gap between the theory that airlines will learn from minor and near-miss events and the reality of airlines rarely making safety improvements based on near-miss events (Madsen, Dillon, & Tinsley, 2016). While the safety value of low-risk, minor, and near-miss events is not disputed and is supported by many authors (e.g., Gnoni & Saleh, 2017; Madsen et al., 2016), these minor events are not common measures of safety performance between airlines, countries, and regions.

Aircrew always report high-risk events such as accident and serious incidents as they are difficult to cover-up and cmust be reported by law. Low-risk events, such as near-misses, hazards, and minor incidents are under-reported and not reported consistently (Gilbey, Tani, & Tsui, 2016; Gnoni & Saleh, 2017; Oster et al., 2013; Savage, 2012). Airlines from different countries do not consistently report low risk and near-miss events, and reporting is subject to many pressures and variations, including such basic issues as a lack of consistent definitions (Savage, 2012). Even in countries with highly regulated, sophisticated aviation sectors, such as Australia and New Zealand, there is inconsistent and under-reporting (Gilbey et al., 2016), and the problem is even greater in developing regions (Oster et al., 2013). Both Koo et al. (2015) and Oster et al. (2013) noted that it is currently not possible to obtain accurate or consistent global reporting on airline safety incidents due to the inconsistency in the data between airlines on minor safety events and the data is not publicly available (Savage, 2012). Measuring safety via low-risk events is better suited to within-airline analysis and trending, rather than as a valid and reliable universal measure of airline safety.

A further challenge of using near-miss, low-risk, and minor safety events is the inconsistency of definitions between countries and within countries over time (Kaspers et al., 2016). For example, Zavila, Chmelik, and Dopaterova (2016) examined 67 years of military aviation accidents in Czechoslovakia/Czech Republic and found the definitions of even basic safety changed several times over the period. Indeed, there are so many confounding factors to make a valid and reliable conclusion on safety, that low-risk events and near-misses cannot be credibly used as a negative or positive indicator of safety (Gnoni & Saleh, 2017). Indeed, Kaspers et al. (2017) and Kaspers et al. (2016) found no relationship between safety performance and various proactive safety measures such as elements and processes of airline safety management systems. Kaspers et al. (2016) suggested there is little relationship between safety processes and outcomes because such links are based on a simplistic, linear accident model held together by plausible reasoning, rather than using a complex, sociotechnical systems approach, such as Reason’s Swiss cheese model.

Measuring safety performance through accidents. The most common measures of safety performance in transport studies are accidents and fatalities, as this is data that is commonly available and relatively accurate compared to other minor safety outcomes. Various authors have used accidents and fatal accidents to measure transportation safety outcomes (see Table 2), indicating that accident-based metrics are used universally as the fundamental measure of safety outcome and performance. Accidents and accidents rates have been used to study aviation safety performance in military aviation (Zavila et al., 2016).), airlines (Elvik & Elvebakk, 2016), general aviation (Boyd, 2016, 2015; Knecht, 2013), air traffic control (Di Gravio, Mancini, Patriarca, & Costantino, 2015), airports, and civil aviation units (Chen & Li, 2016). Recent aviation research studies have compared airline safety to airline efficiency (Cui & Li, 2015), airline profitability (Wang, Hofer, & Dresner, 2013) and the general operational problems and challenges facing airlines (Oster et al., 2013). Those recent aviation studies used airline accidents, or a variation on them, to represent airline safety. Cui and Li (2015) used airline accidents as a measure of safety. Oster et al. (2013) used fatal accidents as the measure of safety, stating that the globally reliable and consistent nature of fatal airline accident data allows safety comparison across aviation segment and regions.

Table 2

Transport Accident Studies Using Accidents to Measure Safety Outcomes

Transport model	Examples of research studies
Shipping	Bak & Gucma, 2016; Eleftheria, Apostolos, & Markos, 2016; Li et al, 2014; Mou et al., 2016
Buses	Goh, Currie, Sarvi, & Logan, 2014; Nirupama & Hafezi, 2014
Trucks	Guest, Boggess, & Duke, 2014; Mooren, Grzebieta, Williamson, Oliver, & Friswell, 2014
Transit	Liu & Moini, 2015
Trams	Naznin, Currie, Logan, & Sarvi, 2016a; Naznin, Currie, Logan, & Sarvi, 2016b
Taxis	Wang, Li, Du & Mao, 2015
Bicycling	Schepers, Twisk, Fishman, Fyhri, & Jensen, 2017; Vanparijs, Panis, Meeusen, & de Geus, 2015
Motor vehicles, road, and road traffic	Blattenberger, Fowles, & Loeb, 2013; Commandeur et al., 2013; Mehmandar, Soori, & Mehrabi, 2016; Silla et al., 2017; World Health Organization, 2015; Yannia et al., 2013; Yeo, Jang, Skabardonis, & Kang, 2013
Road design	Barbosa, Cunto, Bezerra, & Nodari, 2014; Farid, Abdel-Aty, Lee, Eluru, & Wang, 2016
Rail	Evans, 2013; Madigan, Golightly, & Madders, 2016

Accidents and fatal accidents have also been the measure applied when comparing safety performance between transport modes such as trains, buses, airlines, and cars (Karimi et al., 2013; Liu & Moini, 2015; Savage, 2013). Both the World Health Organization (WHO) and the European Union measure road safety performance based on fatal accidents (fatality numbers) and set global and European road safety targets around reduction of fatal accidents (WHO, 2015).

Accident-based metrics are commonly used in aviation safety studies as accident data is readily available in the public domain, particularly when the accidents are major or fatal. The ICAO (2016c) provides definitions of accidents, incidents, and serious incidents which ensures a high level of consistency across countries and regions when reporting aviation accidents. ICAO also applies its filter to accidents when they publish their annual accident review (ICAO, 2016a).

Both the ICAO and the IATA use airline accidents and accident rate (per million sectors) as their fundamental measures of airline safety performance (IATA, 2017; ICAO, 2016a). ICAO (2016c) stated that its primary indicator of safety in global air transport is the accident rate of scheduled commercial aircraft. Both Airbus and Boeing use accidents (hull loss and fatal accidents) and accident rates as their primary measures of aviation safety performance (Airbus, 2016; Boeing, 2017). Boeing (2017) use flight sectors or departures as the basis for calculating accident rates because there is a stronger correlation between accidents and departures than between accidents and flight hours or miles flown. Airbus (2016) supported Boeing's findings, basing accident rates on the number of flights (departures), as flight hours are neutral to accident probability. Almost

80% of aircraft accidents occur during the take-off (taxi, take-off, and initial climb) and landing (approach and landing) phases, whereas cruise accounts for only 6% of accidents (Airbus, 2016).

Safety indexes. Airline accidents are rare, and due to their rarity, they are not good predictors of safety. Proactive metrics of minor incidents can determine the level of safety and the likelihood of an accident outcome (Li et al., 2014). Outputs such as accidents and incidents can provide information on the underlying distribution of accident probability because safety is difficult to observe directly (Li et al., 2014). Safety indexes and composite indexes use a range of individual safety performance indicators to arrive at an overall safety score (Neves, 2015; Commandeur et al., 2013). Safety indexes and safety performance indicators have been used to compare safety performance in the fields of shipping (Li et al., 2014), road safety (Aarts & Houwing, 2015; Commandeur et al., 2013; Wang, et al., 2016; Yannia et al., 2013) and aviation (Chen & Li, 2016; Neves, 2015; Pacheco, Fernandes, & Domingos, 2014). Even though safety indexes can overcome the limitation of solely using accidents to measure safety, most safety indexes still place the highest weighting on accidents (Aarts & Houwing, 2015; Chen & Li, 2016; Neves, 2015). Thus, accidents are the fundamental measure of safety. Aarts and Houwing (2015) noted that accidents and fatalities are the baselines for most comparisons of safety performance and for exploring the strength and directions of significant relationships between the safety performance indicators and accident outcomes. Pacheco et al. (2014) developed an airport safety index based on weather and terrain factors, but the authors verified the index by using aircraft accident and incident data from the airports. These studies highlight that accidents are at the core of safety indexes.

The limitation of safety indexes and safety performance indicators is that index constructs must be replicable and readily available across business units, countries, and regions. For example, the reliable comparison of reportable injuries between companies or countries requires the same definition of reportable injuries. However, the regulatory definition of reportable injuries is not the same, ranging from one to seven days depending on the country. Without a common standard, comparisons of safety performance indicators or safety indexes are invalid. Finally, Kaspers et al. (2016) argued that smaller events and incidents are only accident precursors in simplistic linear safety models, and do not reflect safety outcomes in complex, socio-technical systems such as aviation.

Determining the safety performance of airlines requires a valid and reliable measurement of safety. Airline safety data must meet three criteria for inclusion in this doctoral study. Firstly, the safety data must be equally and consistently available for all airlines globally. Secondly, the safety data must be available historically and consistently to evaluate long-term trends. Thirdly, the safety data must be equally available for and applicable to both LCCs and FSCs.

The IATA's annual list of global airline accidents meets the requirements of global consistency, historical consistency, and global availability. Thus, the annual IATA accident list is the database for all the accidents used in this study.

Regional Safety Performance

The ICAO, IATA, and OAG divide the world into regions, allowing for more consistent and relevant management and oversight of those regions. Although, the regional breakdowns are not consistent between the IATA, ICAO, and OAG, as highlighted in Table 3. While the IATA and OAG have the same regional headings, there are some differences between the countries within each region. I used OAG regional definitions this study.

Table 3

Comparison of Regions Between IATA, ICAO, and OAG

IATA	ICAO	OAG
Africa	Africa	Africa
Middle East North Africa	Middle East	Middle East North Africa
CIS	Europe	Eastern Europe/CIS
Europe		Western Europe
Latin America	Pan America	Latin America
North America		North America
Asia Pacific	Asia Pacific	Asia Pacific
North Asia		North Asia

Airline safety performance differs across the various regions of the world (Hodgson, Siemieniuch, & Hubbard, 2013; IATA, 2017; ICAO, 2017; Oster et al., 2013; Savage, 2012). The effectiveness of safety regulation and oversight between countries reflects the different attitudes towards aviation safety between countries (Gilbey et al., 2016; Herrera & Vasigh, 2009; Savage, 2012). The IATA calculates regional safety performance based on the annual accident rate within each region. Developing regions, such as Africa and Asia consistently have higher accident rates than developed regions, such as North America and Europe (Savage, 2012).

Table 4

IATA Regional Aviation Safety Performance Measured by Aircraft Accident Rate

	Aircraft accident rate per million flights		
	2017	5-year average (2012-2016)	8-year average (2009-2016)
Africa	6.9	8.1	9.6
Middle East/North Africa	0.5	3.3	5.0
CIS	4.1	3.4	4.7
Latin America	1.9	2.2	2.9
Asia Pacific	1.5	2.8	2.7
Europe	0.7	1.8	1.8
North America	0.6	1.2	1.3
North Asia	0.0	0.6	0.8

Note. The IATA has only published overall accident rate in each region since 2009; hence a 10-year average sine 2007 cannot be determined.

Table 4 notes the 2017 accident rates (per million departures), as well as five-year and eight-year accident rate averages. I derived the data from the regional accident rate published annually in the IATA Safety Report published between 2004 and 2018. The data in Table 4 highlights the differences in regional safety performance, with Africa, the CIS, and the Middle East having accident rates five to ten times worse than those in Europe, North America, and North Asia.

Regulatory factors. The aviation safety regulator and its regulations are an organizational factor and defense in the Swiss cheese model. All airlines within a country must meet the same minimum regulatory standards of safety and security set by the national regulator (Yadav & Nikraz, 2014). Thus, within a country, both LCCs and FSCs should have similar levels of safety performance. National aviation regulators have varying levels of sophistication to implement, assure, and enforce safety regulations and programs, resulting in different safety performance between countries and regions (Faure, 2014; Herrera & Vasigh, 2009; Gilbey et al., 2016; Oster et al., 2013).

Reason (2000a) noted that the growing public intolerance for third-party risk, environment damage, accidents, and work-related injury have heavily reduced accident rate in many domains (such as aviation). This public intolerance has resulted in increasingly comprehensive safety legislation in most industrialized nations. Even in the least responsible organizations in industrialized nations, merely keeping up with regulatory requirements results in the implementation of robust safety measures (Reason, 2000a). Reason deliberately highlighted the emphasis and expectation of safety in industrialized nations; a difference reflected in the IATA regional safety data.

Airline safety is heavily dependent on the local country implementation and enforcement of safety regulations. Industrialized nations are more developed and sophisticated in this regulatory role than developing nations. The result of this is that airline safety levels are very similar within a country or region (Savage, 2012), but differ between countries, particularly industrialized and non-industrialized countries, and regions (Xu, 2015).

National culture factors. Culture is the collective mental programming and conditioning shared with other members of a group (Hofstede, 1983, 2003). Shared beliefs and values that guide behavior and distinguish one group from another are fundamental to any definition of culture (Casey, Riseborough, & Krauss, 2015). National culture is a complex phenomenon due to multiple influencing factors and the large variations in national culture within a country. Substantial research exists on the topic of national culture and cultural traits and dimensions (Hofstede, 1983, 2003). Cultural traits and their impact have been studied in the aviation industry, including airline crew (Al-Wardi, 2016; Chow, Yortsos, & Meshkati, 2014) and air traffic controllers (Noort, Reader, Shorrock, & Kirwan, 2016; Reader, Noort, Shorrock, & Kirwan, 2015). Cultural traits influence crew operational and safety performance in several critical ways and have been cited as a contributing factor in airline and shipping accidents, such as Asiana Airline in San Francisco (Chow et al., 2014) and multiple accidents involving China Airlines and Korean Air (Hodgson et al., 2013).

National culture influences risk perception and plays a role in important antecedents of safety behavior. Cultural traits also influence the relationships between leaders and team members, including the exchange of information, which impacts safety. (Starren, Hornikx, & Luijters, 2013). Safety climate, and ultimately safety performance, is impacted by safety communication and the extent to which there is an open exchange of safety-related information (Barbaranelli, Petitta, & Probst, 2015).

Gert Hofstede's seminal research on cultural traits is the most widely cited and influential (Casey et al., 2015; Starren et al., 2013). Hofstede classified national culture along six dimensions: (1) Individualism vs. collectivism, (2) Power distance, (3) Uncertainty avoidance, (4) Masculinity, (5) Long-term orientation, and (6) Indulgence (Hofstede, 2003). Three dimensions of power distance, uncertainty avoidance, and individualism-collectivism have repeatedly shown a relationship with safety outcomes and the safety culture environment (Casey et al., 2015; Hodgson et al., 2013; Noort et al., 2016).

***Power distance*.** Power distance refers to the degree of acceptance by individuals within a group to an unequal distribution of power (Hofstede, 1983, 2003). In a low power distance culture, the degree of inequality is low, and there is interdependence between subordinates and superiors, providing an opportunity for coordination, consultation, and if necessary, questioning and challenging of the superior by subordinates (Al-Wardi, 2016; Levitt, 2014). High power distance cultures more easily and unquestioningly comply with instructions and demands from supervisors, even when those demands compromise safety (Casey et al., 2015; Starren et al., 2013). The high power distance crews have decisions made by the Captain, with little or no input from the crew, and commands are carried out unquestioningly by the junior crew (Barbaranelli et al., 2015; Chow et al., 2014). While this can speed up the decision-making process and bring time efficiencies, it has the negative effects of not including other opinions or ideas and crew are less likely to raise issues and safety concerns, both of which can result in the implementation unsafe or wrong decisions (Hodgson et al., 2013).

High power distance and collectivism may act as a barrier to effective safety communications (Casey et al., 2015). Teams from high power distance, collectivist cultures are less likely to communicate openly with leaders about safety issues (e.g., hazards, risks, incidents) or report performance-related issues (e.g., errors, mistakes). High power distance and authoritarian cultures result in junior crew failing to communicate openly with senior crew or raise errors and mistakes, and senior crew unwilling to share information (Chow et al., 2014; Noort et al., 2016).

High power-distance impacts risk-tasking behavior, as senior staff may not even be willing to admit mistakes and errors, seeing them as a sign of incompetence (Prati & Pietrantoni, 2014). The cultural trait of 'face' can result in taking greater risk-taking, due to crew not wanting to lose face or senior crew not wanting to admit mistakes or inability (Levitt, 2014). Chow et al. (2014) cited the example of the Korean Air accident in San Francisco, where the Captain elected to conduct a non-precision visual approach because other airlines were conducting a visual approach and the Korean captain did not want to lose face and admit that he could not conduct a non-precision visual approach.

Individualism–collectivism. Individualism–collectivism relates to the degree of responsibility that people are ready to take in looking after themselves and their connections within a group (Hofstede, 1983, 2003). In a high individualism culture, individuals are expected to look after themselves, and self-satisfaction is valued (Al-Wardi, 2016; Levitt, 2014). In the workplace, the task achievement is more important than maintaining harmony and relationships. A collectivist culture stresses the importance of loyalty, deep relationships, and harmony within the team. Personal connections override the task (Al-Wardi, 2016).

Collectivism and high power distance have been associated with an unwillingness to voluntarily report errors and incidents (Barbaranelli et al., 2015; Casey et al., 2015; Noort et al., 2016). Collectivist cultures predispose team members to avoid reporting errors and safety concerns so as not to bring shame or embarrassment to the team and maintain harmony (Casey et al., 2015).

Uncertainty avoidance. Uncertainty avoidance focuses on the experience when faced with risk or uncertainty and the way of managing the situation (Hofstede, 1983, 2003). People in a high uncertainty avoidance culture need structure in their environment and relationships so that they can predict situations and outcomes. A high uncertainty avoidance society use controls, structure, rules, and regulations to reduce uncertainty (Al-Wardi, 2016) and employees prefer to follow standard procedures, with guidance and instruction given. In low uncertainty avoidance cultures, there are fewer rules and procedures, and individuals are encouraged to develop new views and practices and act outside the procedures if necessary (Al-Wardi, 2016). Low uncertainty avoidance cultures are more comfortable with ambiguity and flexibility in operational situations (Barbaranelli et al., 2015). Noort et al.’s (2016) study of over 13,600 air traffic controllers across 21 European countries found that high uncertainty avoidance was negatively associated with safety culture. High uncertainty avoidance was associated with less innovation in decision making, greater reliability on formal procedures and protocols, less flexibility to act on new or emerging information and risk, reduced tolerance for diverse opinions, and reduced willingness to report errors and incidents.

Employees from national cultures with higher uncertainty avoidance are highly focused on rules and procedural compliance (Starren et al., 2013). While procedural compliance is positive, it can also result in crew rigidly following procedures, commands, and decisions even when it is clear the crew should reconsider or reframe the procedure, command, or decision (Hodgson et al., 2013). The result is slow decision-making and slow decision change in the face of new information.

In summary, the cultural traits of high power distance, low individualism, and high uncertainty can have a negative impact on safety behavior, safety culture, and ultimately safety performance and accidents. Thus, national and regional cultures displaying these traits might encounter higher accident rates.

Socioeconomic factors. In comparison to developed regions, safety in less developed countries and regions is not as high a priority due to less mature approaches to safety management, an emphasis on production over safety, and a lack of resources to invest in safety initiatives (Casey et al., 2015). In response to several studies that found a correlation between national scores of power-distance and accident rates, Hofstede (2003) re-examined the data with the addition of gross national product (GNP) per capita, and found the GNP per capita was the dominant variable, rather than power-distance. Hodgson et al. (2013) updated Hofstede’s (2003) research with an additional 17 years of accident data and found that GNP per capita was the largest single factor in airline accident rates. High power distance, low individualism (high collectivism), and high uncertainty avoidance all had a negative correlation with GNP per capita. Although, some 'Asian tiger' countries such as Korea, Taiwan, and Singapore are outliers due to the high GNP per capita.

Xu (2015) also found correlations between a country's GDP per capita and its airline accident rate, with higher GDP per capita resulting in better safety performance. Xu noted that industrialized countries have stronger economic performance, more stringent regulatory standards, and stronger law enforcement, which correlated with better airline safety performance. Savage (2012) noted that countries within the same region, and thus having similar socio-economic situations, usually have indistinguishable airline safety records. However, the differences in airline safety performance between regions is significant (Savage, 2012). Safety studies in other transport modes such as driving have found increased accident and fatality rates related to less developed countries for reasons such as poorly designed and maintained roads, older or unsafe vehicles, poor infrastructure, and poorly developed and enforced safety regulations (Sengoelge, Laflamme, & El-Khatib, 2018). The reasons for poor road safety in less developed countries are like the reasons for poor airline safety in the same countries and regions.

The relationships and interactions between a country's economic wealth, dominant cultural traits, and the geopolitical situation are complex and beyond the scope of this study. However, safety performance and safety culture differ between countries and regions. A country's economic wealth, dominant cultural traits, and the geopolitical situation, all impact the effectiveness of the aviation safety regulatory system.

Fleet factors. Another possible reason for the difference in safety performance between regions is operational fleet factors. Turbine-propeller (turbo-prop) and Eastern-built aircraft (e.g., Sukhoi, Mikoyan MiG, Tupolev, Ilyushin, Yakovlev Yak) are over-represented in aircraft accidents (IATA, 2017). Eastern-built aircraft are also more common in Africa, Middle East, CIS/Eastern Europe, and Latin America compared to North America, Europe, and Asia. Further, fleet age impacts airline safety performance (Herrera & Vasigh, 2009). First, second, and third generation aircraft are less safe than modern fourth generation aircraft as they are over-represented in airline accidents (Airbus, 2016; Boeing, 2017). Older generation aircraft are more common in less developed regions such as Africa and Latin America, impacting safety performance in those regions (Herrera & Vasigh, 2009).

Transition

Section 1 covered the foundation of this study. In this section, I started with a description of the background of the study and I followed with the problem statement, the purpose statement, and the nature of the study. I then presented the research questions, hypotheses, and theoretical framework that guided the study. Section 1 also defined the relevant terms, the assumptions, limitations, and delimitations underlining the study, as well as the significance of the study. Finally, Section 1 contained a critical analysis and synthesis of the literature related to the study and the study variables.

Section 2 covers the nature and structure of the research study and its design, including the steps involved in collecting, validating, and analyzing the data. I justify the population and sampling method, and description of the survey instrument, techniques, and analysis methods. Finally, in Section 2, I examine the reliability and validity. Section 3 contains the presentation and analysis of the results and findings. I discuss the application to professional practice, implications for social change, and recommendations for action and future research. Finally, I provide the study summary and conclusions.

Section 2: The Project

In Section 2, I discuss the purpose of the study, the role of the researcher, and the selected research method and design. I provide information on the collection and analysis of data, as well as addressing any ethical issues. Finally, I discuss the reliability and validity of the study.

Purpose Statement

The purpose of this quantitative correlational study was to examine the relationship between airline category, geographical region, and safety performance. The independent variables were the category of an airline classified as an LCC or FSC and the regional geographic base of the airline. The dependent variable was the safety performance measured by aircraft accidents. The target population comprised archival data records of global passenger airlines. The implications for positive social change include the potential for airline leaders to improve the safety image of their airline and provide passengers a better understanding of airline safety. Providing passengers with information on airline safety performance is beneficial for nervous flyers (Graham & Metz, 2017) and may allow passengers to make more informed choices on using different categories of airlines in different geographical regions. The research may result in new travel opportunities for travelers that were previously unrealized due to safety concerns.

Role of the Researcher

The role of the researcher in the data collection and analysis process in a quantitative study is to ensure an adequate sample size, as well as consistency, reliability, and validity of the data and the analysis (Kyvik, 2013). Castellan (2010) summarized that in quantitative research, the researcher is an external observer exploring relationships between variables, remaining detached and independent and thus has a neutral role. My role in the data collection and analysis for this study was the retrieval and analysis of archived airline and safety data from publicly available websites and publications. My research method was the quantitative analysis of archived data, and I did not use any surveys, interviews, or participants. Maintaining independence in data collection and analysis is important. During the data collection process, the researcher should mitigate any bias to avoid influencing the outcome (Daigneault, 2014). Although, Fassinger and Morrow (2013) cautioned that regardless of the objectivity of the research methods and efforts of the researcher to remove bias, the cultural background, attitudes, and values of the researcher will permeate the research. Acknowledging and identifying any potential research bias is a step towards mitigating any potential researcher bias.

At the time the study was conducted, I was not employed in the airline industry, reducing any potential bias. Conducting quantitative research with archived data ensured that I remained independent of the variables as I determined the relationship between them. The Belmont Report ethical protocols did not impact my research as the archival data was all publicly available and there were no participants in the study.

Participants

No airlines, organizations, or individuals took part in the study. I used publicly available archive data from the IATA, ICAO, and OAG. Thus, I did not require any participants for this study.

Research Method and Design

Research Method

I chose a quantitative methodology for this study. Airline accident rates are the most common measure of safety performance (Cui & Li, 2015; Neves, 2015; Oster et al., 2013), and the use of accident numbers and rates lends itself to quantitative analysis. Quantitative studies allow the identification of statistical results to describe or detect changes in numerical characteristics of the population under study, explore relationships between the variables, and test hypotheses (Castellan, 2010; Paul & Garg, 2014; Yilmaz, 2013), which was the purpose of my study. The goal of quantitative analysis is to establish valid and reliable facts and to predict and test hypotheses (Castellan, 2010; Yilmaz, 2013), which was the goal of my research. Yilmaz (2013) noted that the statistical data in quantitative research allows for the succinct and parsimonious summary of major patterns across broad scales and situations. In my study, the population was all passenger airlines categorized as LCC or FSC across all global regions, and the numerical characteristic was safety performance measured by accidents. The quantitative method was appropriate for this study because the purpose of the study was to analyze objective numerical safety data and determine statistical relationships between variables that I could generalize across the airline industry. Further, quantitative statistical analysis is suited to my broad, global data set of all passenger airlines in the world.

Quantitative methods are used to test a theory deductively rather than developing a theory inductively, as would be the case with qualitative research (Guetterman et al., 2015; Yilmaz, 2013). Qualitative methods are appropriate when the research intent is to explore the human side of business practice and process in their natural setting, how people make sense and meaning, and what their lived experiences, perceptions, and attitudes represent (Gergen, Josselson, & Freeman, 2015; McCusker & Gunaydin, 2015; Yilmaz, 2013). Qualitative methods do not allow the determination of statistically significant variable relationships. A mixed methods study contains the attributes of both quantitative and qualitative methods (Guetterman et al., 2015). The intent of my study was the statistical analysis of numerical data, making qualitative and mixed-method approaches inappropriate.

Research Design

Nonexperimental research compares differences and explores relationships between variables (Castellan, 2010; Cor, 2016). Correlation is the statistical measure of how closely and in what direction two variables are related (Emerson, 2015). Researchers use Pearson correlational analysis to explore linear relationships between variables (Altman & Krzywinski, 2015a; Sari et al., 2017). A correlation design allows the examination of the relationship between or among two or more variables, rather than to assume or determine cause and effect (Altman & Krzywinski, 2015a; Prion & Haerling, 2014). Studies using archival data employ correlation designs (Kilduff, Galinsky, Gallo, & Reade, 2016). The use of a correlational design with Pearson's *r* allows for the measurement of variable strength and relationship (Prion & Haerling, 2014; Puth, Neuhauser, & Ruxton, 2014). The objective of my study was to determine the relationship between the nominal independent variables of airline category categorized as LCC or FSC and airline geographical location, and a ratio dependent variable of safety performance measured by accidents. Hence, a correlation design was appropriate for this study.

Other designs, such as experimental and quasi-experimental designs are appropriate for assessing cause and effect (Castellan, 2010; Cor, 2016; Froman & Owen, 2014). Experimental researchers have control over one or more of the variables and manipulate the variables to test hypotheses (Brouwers, Wiggins, Helton, O'Hare, & Griffin, 2016; Castellan, 2010). The objective of this study was to examine the differences and relationship between variables, not to assess cause and effect. Further, I had no control or influence over any of the variables. Thus, the experimental and quasi-experimental designs were not appropriate.

Case study and phenomenological research designs are used to study the human complexity of real-life issues and processes through individuals and small group interviews (Gee, Loewenthal, & Cayne, 2013; Hampshire, Iqbal, Blell, & Simpson, 2014; Sutton & Austin, 2015). Case study and phenomenological research are qualitative methods, using interviews and observations in naturalistic settings to understand complex people-based managerial issues and organizational processes (Gee et al., 2013; Sutton & Austin, 2015; Yilmaz, 2013). Lalor et al. (2013) noted that case study research is appropriate when exploring *how* and *why* questions. Researchers can rarely generalize case study research beyond the cases under study (Lalor et al., 2013). Thus, case study and phenomenological research designs were not appropriate for the quantitative analysis of airline safety using archival accident data.

Population and Sampling

Population

A population does not necessarily refer to people but can also refer to the total quantity of things or cases that are the subject of the research (Etikan, Musa, & Alkassim, 2016). The dependent variable in this study was safety performance measured by airline accidents. Thus, the population was all airlines that have had accidents, for which the IATA airline accident data archives were the most relevant and appropriate records. The IATA's accident data archive is highly reliable and is consistent across time and regions. I used ICAO's (2017) list of LCCs to categorize the airlines as LCC or FSC. Based on the airline's country of registration, I placed the airlines into regions based on the OAG's (2018) regional breakdown. The OAG regional breakdown is in Appendix B. These archived records were the primary data I used for the quantitative analysis of this study. Thygesen & Ersboll (2014) noted that archive and register-based populations and data are well-suited to total population sampling.

The airline accident data consisted of all the passenger airline accidents listed by the IATA in their annual safety reports for the 14-year period from 2004 to 2017. I excluded cargo and ferry flights, as those aviation operations are not passenger operations and were not relevant to this study.

Sampling

A sample is a subset of the population (Acharya, Prakash, Saxena, & Nigam, 2013). I used a nonprobabilistic sampling technique called total population sampling, which is a subset of purposive sampling. Nonprobabilistic purposive sampling occurs when researchers select subjects from the target population based on their fit with the purpose of the study and specific inclusion and exclusion criteria (Acharya et al., 2013; Etikan et al., 2016; Suen, Huang, & Lee, 2014). Total population sampling is a type of purposive sampling where the researcher examines the entire population that has the attribute or trait (Etikan et al., 2016; Thygesen & Ersboll, 2014). Total population sampling is appropriate and possible when the population size is relatively small, and the total population pool is known and accessible, allowing a researcher to use the total population as the sample (Etikan et al., 2016; Thygesen & Ersboll, 2014). In this study, the traits of the airline population were passenger airlines that have had an accident, which provided a relatively small population of about 70 subject airlines per year.

Nonprobabilistic sampling is more common in qualitative research than quantitative research, where probability-based sampling is the preferred sampling method and the sample size is based on statistical power rather than data saturation (Catania, Dolcini, Orellana, & Narayanan, 2015; Etikan et al., 2016; Suen et al., 2014). Probability sampling requires random sampling of the population, whereas randomization is not important in selecting a sample from the population in nonprobability sampling (Etikan et al., 2016). Nonprobabilistic sampling is acceptable for research that involves a specific and targeted population sample (Stern, Bilgen, & Dillman, 2014). Acharya et al. (2013), Etikan et al. (2016), and Wilson (2014) stated that nonprobability sampling has the limitation of researcher bias and sample selection bias, resulting in difficulties in generalizing the results beyond the sample. However, these limitations are more applicable to convenience sampling, which is the most common form of nonprobabilistic sampling (Acharya et al., 2013).

The American Association for Public Opinion Research noted that under certain conditions, nonprobability sampling is appropriate for making statistical inferences (Baker et al., 2013). Buseh, Kelber, Millon-Underwood, Stevens, and Townsend (2013) used nonprobabilistic sampling in their quantitative study that included correlation and multivariate linear regression analysis. Daigneault (2014), Palinkas et al. (2015), and Thygesen and Ersboll (2014) all concluded that a nonprobabilistic, purposive sampling strategy could generate quantitative data, and purposive sampling is becoming an increasingly popular sampling technique in quantitative research. Quantitative methods emphasize the breadth of understanding, as opposed to qualitative methods, which emphasize the depth (Palinkas et al., 2015). Using the entire population as the sample ensures research breadth, as the knowledge gained represents the population from which it was drawn (Palinkas et al., 2015).

Probability sampling is without bias and subjectivity as every element or subject in the population has an equal and known probability of sample selection (Wilson, 2014). Using the total population as the sample for my study removed any sampling bias and subjectivity and made statistical inferences appropriate (Thygesen & Ersboll, 2014). All subjects in the population of airlines that have had accidents had the same 100% chance of being selected, which is a sampling trait more aligned with probability sampling. Indeed, calling the population in this study a sample is misleading, because a sample is a subset of a population, whereas the subjects in this study were the entire population.

Statistical analysis of sampling error, effect size, and power analysis are not relevant when the sample is the entire population (Thygesen & Ersboll, 2014). Although, Millis (2003) suggested that when faced with a fixed sample or population size, a power analysis can help researchers select outcome measures and values with maximum sensitivity.

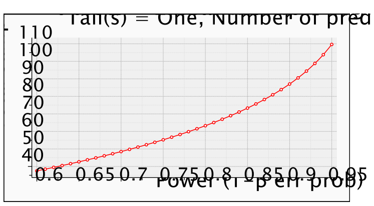

Figure 6. Power as a function of sample size for multiple linear regression.

Statistical power refers to a statistical test's sensitivity to differences and relationships between groups or conditions. I used Faul, Erdfelder, Lang, and Buchner's, (2007) G*Power 3.1 program to conduct an a priori calculation of sample size. The sample size required to achieve an effect size of $f = 0.10$, $\alpha = 0.05$, and power $\beta = 0.90$ was 88, as shown in Figure 6.

Ethical Research

I did not use participants and organizations in the study; thus, I did not require informed consent. The data on airline category (LCC or FSC), geographical region, and safety performance measured by accidents were archival data in the public domain. The data did not contain names of individuals or other confidential or sensitive information. No ethical concerns existed with data used in my analysis. Due to the public nature of the archival data used in my research, I submitted a simplified version of IRB submission for public archive research. My Walden IRB approval number was 03-01-18-0665148.

Data Collection Instruments

I used public archive data from the IATA, ICAO, and OAG in this study. No surveys, interviews, or participants were used, nor were any pre-existing instruments for the data collection. I measured all the study variables with public archive data accessible online.

The dependent variable in the study was airline safety performance. The independent variables were the type of airline (LCC or FSC) and geographic region of registration. Both dependent variables were nominal data. Airline acccidents are a common measure of airline safety performance (Boyd, 2016, 2015; Cui & Li, 2015; Knecht, 2013; Oster et al., 2013). I used passenger airline accidents (ratio data) as defined by the IATA and listed in the IATA annual safety reports. I excluded cargo and ferry flights from the data. The IATA cross-references and harmonizes its accident list with the ICAO to ensure that all airline accident that occurred in the world each year are reliably and consistently captured (ICAO, 2013b). I chose the IATA accident list as the historical accident data covered the 14-year period of the study and can be updated for future studies. ICAO has published the accident database in their annual safety report since 2012. Thus, ICAO accident data could not be used for this research as it did not cover the 14-year period of the study dating back to 2004. The IATA accident data is historically stable as they have used the same definition of accident throughout the study data. Changing definitions and criteria is a data reliability issue identified in other archival studies on aviation safety (Zavila et al., 2016).

Airline categorization as LCC or FSC (nominal data) was based on ICAO's (2017) list of LCCs. The database contained all current and defunct airlines in all countries that ICAO categorized as LCC. As the global regulator, ICAO is a valid and reliable source of LCC categorization data applied to the global fleet. If an airline changed category from LCC to FSC (e.g., Virgin Blue to Virgin Australia) or FSC to LCC (e.g., Hong Kong Express to HK Express), it was categorized as LCC or FSC for the relative period that it was an LCC or FSC. The ICAO LCC list contains notes on the history and changes to the airlines listed.

A common denominator of operational scale is required to enable a comparison of safety between LCC and FSC, as well as between regions. The number of flights, miles flown, or passengers carried is often used to compare airline safety performance (Airbus, 2016; IATA, 2017; ICAO, 2017; Oster et al., 2013). I used the number of aircraft flights, commonly referred to as departures, to normalize the accident data as accidents per million departures. Accidents per million departures are the primary measure of airline safety by Airbus (2016), Boeing (2017), IATA (2017), and ICAO (2017), as well as being a common measure in the academic literature (Oster et al., 2013). Aircraft flight data was obtained from OAG, which was broken down by airline category and region. Thus, I calculated both LCC and FSC accidents per million departures in all regions, providing ratio data for robust statistical analysis.

I allocated airlines to countries according to their aircraft registration. Countries, and hence airlines, were placed in geographical regions (nominal data) according to OAG definitions of regions. OAG regional definitions were used instead of IATA or ICAO definitions as I based the airline departures data for regions on the OAG data. Thus, I allocated airlines (LCC and FSC) to geographical regions according to OAG definitions (refer to Annex B for regional definitions)

Data Collection Technique

Archival data is considered public record data (Tesar, 2015) or any existing information collected by others, amenable to systematic study (Jones, 2010; Simnett, Carson, & Vanstraelen, 2016). Through the growth of the internet and electronic media, public and company records, and electronic and online databases, archived data are increasing in quantity and quality, resulting in the increasing popularity of archival research (Onyancha, Ngoepe, & Maluleka, 2015; Rhee, 2015; Tesar, 2015). Archival research is also becoming more common in university research settings. Daniels and Yakel (2013) and Defond and Zhang (2014) called archival research a burgeoning line of research. Archival research is a common research method in many fields including economics, astronomy, anthropology, history, sociology, organisational and industrial psychology, health care, and auditing and assurance (Cheng & Phillips, 2014; Clary-

Lemon, 2014; DeFond & Zhang, 2014; Ivanov, 2017; Jones, 2010; Simnett et al., 2016). Dikolli et al. (2013) described the advantages of using archival research to supplement and complement experimental research, as demonstrated by Kilduff et al. (2016).

There are other advantages to using archival data for research; the data already exists, the dataset may be the total population, and the data were collected independently of the study reducing researcher bias (Shultz, Hoffman, & Reiter-Palmon, 2005; Simnett et al., 2016; Thygesen & Ersboll, 2014). Use of archival data can save time, resource, and costs (Cheng & Phillips, 2014). Archival data can overcome the problem that many organizations are conservative about having outsiders conduct research within or on their organization, avoiding the potential issues of resources, interruption, and challenging findings (Shultz et al., 2005). Archive datasets are often larger than a single researcher can collect, and they can include international and longitudinal data (Shultz et al., 2005), like the14-year period of global airline accident data used in this study. Further, archival data has the advantages that it does not require participants for the study and public archive data can be obtained and analyzed with minimal ethical issues.

The disadvantages of using archive and register data are that the data is limited to the variables recorded, data may be missing or incomplete, and the data cannot be added to or tailored to any current research (Cheng & Phillips, 2014; Shultz et al., 2005). The data and archive may not be set-up for academic research purposes (Simnett et al., 2016). The availability and quality of the data may be questionable in some instances, with errors difficult to detect (Shultz et al., 2005). However, the data in some official and widely-used archives can be considered highly reliable due to the professional data entry and multiple checks to minimize errors, omission, and duplications (Cheng & Phillips, 2014; Simnett et al., 2016). International archive data may have endogeneity concerns, with a multitude of cultural, institutional, and regulatory factors contributing to endogenous results (Simnett et al., 2016). Although, the international data for my research came from the single IATA database, cross-checked against the ICAO database, thus minimizing endogeneity factors.

I collated several data sources (IATA accidents, IAG regions and departure frequency, and ICAO airline categorization) to overcome the challenge that no single data source contained all the information I required for my analysis. Cheng and Phillips (2014) described the advantages of cross-linking information from different archive data sources, such as I did.

My research aim was to explore the relationship between airline category (LCC or FSC), geographical region, and safety performance measured by accidents. I sourced data on aircraft accidents from IATA's annual safety reports, which provided a list of all airline accidents each year from 2004 to 2017. The IATA accident data is publicly available and historically stable as the definition of an accident did not change. The IATA accident data covered all airlines in all countries for the 14-year period of my analysis. Finally, the IATA data is valid and reliable as IATA and ICAO harmonize and cross-check their accident data against each other to ensure a complete and harmonious record of airline accidents. The OAG makeup of geographical regions was sourced directly from OAG and is listed in Appendix B. Combing the OAG regional information with the IATA accident data allowed for geographical data analysis. The ICAO LCC list was also added to the IATA airline accident lists, allowing for LCC and FSC accident analysis. Airline departures data for regions and airline category was obtained from OAG, allowing accident data to be normalized as accidents per million departures. The safety performance data classified by airline category and geographical region is in Appendix A.

Data Analysis

RQ: What is the relationship between airline category, geographical region, and safety performance?

H_0: There is no statistically significant relationship between airline category, geographical region, and safety performance.

H_1: There is a statistically significant relationship between airline category, geographical region, and safety performance.

Airline category (LCC or FSC) and geographical region were both nominal data. Variables in each category were mutually exclusive; an airline is either or LCC or FSC but cannot be both. An airline can only be registered in a single country, and hence was exclusive to a single region.

Correlation is the statistical measure of how closely and in what direction two variables are related (Emerson, 2015), and Pearson correlations explore linear relationships between variables (Altman & Krzywinski, 2015a; Sari et al., 2017). A correlation design allows the examination of the relationship between or among two or more variables (Altman & Krzywinski, 2015a; Prion & Haerling, 2014; Uyanik & Guler, 2013). Correlation designs analyze the relationship between multiple independent variables and a continuous dependent variable (Green & Salkind, 2017). Regardless of the correlation strength between the variables, correlation does not imply causality (Froman & Owen, 2014). The objective of this study was to determine the relationship between the nominal independent variables of airline category categorized as LCC or FSC and airline geographical location, and a ratio dependent variable of safety performance measured by accidents (per million departures) Hence, I chose a correlation design for this study.

Regression analysis is a statistical technique for estimating the correlations or relationship among variables (Altman & Krzywinski, 2015b). Regression provides a means of predicting one dependent variable from the other independent predictor variables (Crawford, 2006). Regression models with one dependent variable and two or more independent variables are called multilinear or multiple regression (Uyanik & Guler, 2013). To address the research question in my study with a quantitative correlational design, I used multiple linear regression to examine the relationship between the independent variables (also known as the predictor or regressor variables) of airline category and geographical region and the dependent or response variable of airline safety performance (accidents per million departures). In multiple linear regression, rejection of the null hypothesis implies that the independent or predictor variables (airline category and geographical region) have a significant effect on the dependent or response variable (airline safety performance). Uyanik and Guler (2013) stated that multiple linear regression analysis could answer such research questions as, are there any relationships between independent and dependent variables, and if there are relationships, what is the power of the relationship, and is it possible to make predictions regarding the dependent variable. Due to the predictive qualities of regression analysis and ability to describe relationships between variables (Uyanik & Guler, 2013), the regression analysis was the optimal statistical method to test my hypothesis and answer my research question.

The objective in testing the null hypothesis was to determine if a linear relationship exists between the independent or predictor variables of airline category (LCC or FSC) and geographical region, and the dependent or response variable of airline safety performance measured by accidents and normalized per million departures. Simple univariate linear regression and logistic regressions are an alternative form of regression analysis. Simple univariate linear regression is suitable for use with a single independent and single dependent variable (Altman & Krzywinski, 2015b; Uyanik & Guler, 2013). Logistic regression is suitable for determining nonlinear relationships between variables and for studies with multiple or categorical dependent variables (Lever, Krzywinski, & Altman, 2016). Neither of these conditions was relevant or applicable to my study. Hence, I did not use tests for simple univariate and logistic regression.

This research study also explored whether there is a difference in safety performance between LCCs and FSCs, as well as any differences between the safety performance of global regions. Thus, the study examines the difference between the independent groups of airline category (LCC and FSC) and global region (eight global regions). The dependent variable is safety performance measured by accident rate per million departures. These research conditions are the required elements for using independent samples *t*-test analysis (comparing two groups) and ANOVA (comparing three or more groups) (Green & Salkind, 2017; Rietveld & van Hout, 2015). The purpose of the independent samples *t* test and ANOVA is to determine if there is a statistically significant difference between the mean scores of the independent groups (Pandis, 2015).

There was no missing data in my study, as all airline accidents for the 14-year period were captured, all airlines were categorized as LCC or FSC, and all airlines were allocated to a geographical region. The number of airline departures was available for each region for the entire period. Thus, there was no missing data in the variables. The data from the IATA, ICAO, and OAG was entered into an MS Excel file, then transferred to SPSS for statistical analysis. SPSS is a statistical software program commonly used for data analysis, including correlation analysis in aviation safety studies (Chen & Li, 2013; Kolmos, 2017; Saleh, Suwandi, & Hamidah, 2016). The safety performance data classified by airline category and geographical region is in Appendix A.

Study Validity

Research validity is a requirement for scientific rigor (Morse, 2015). Validity refers to the accuracy of research data (Yilmaz, 2013) and the ability to draw justifiable and accurate inferences and conclusions about a population from the data (Ellis & Levy, 2009; Govaerts, 2015; McKibben & Silvia, 2016; Morse, 2015). Heale and Twycross (2015) noted that validity is the extent to which a concept is accurately measured in a quantitative study; in my study, that concept is airline safety. This research used a nonexperimental design, exploring correlation, not causation. Thus, threats to internal validity were not applicable (Ellis & Levy, 2009; Yilmaz, 2013; Zhou, Jin, Zhang, Li, &

Huang, 2016). However, threats to the validity of the statistical conclusions were of concern.

Statistical Conclusion Validity

Statistical conclusion validity is concerned with systematic and random errors and the appropriate use of data and statistical tests. Conclusion validity indicates whether there is a relationship between the independent and dependent variables that is not explainable by chance (Ellis & Levy, 2009; Cor, 2016; Yilmaz, 2013). Cor (2016) noted that the general questions of statistical conclusion validity relate to the appropriateness of the statistical tests chosen, and for the data and tests to meet the relevant statistical assumptions for the chosen tests.

Threats to statistical conclusion validity can inflate Type I and Type II errors (Ellis & Levy, 2009). Type I errors (alpha (α) errors) result in rejecting the null hypothesis when it is true (Gu, Hoijtinik, & Mulder, 2016; Kim, 2015), or falsely concluding that a relationship or difference exists between subject groups or variables when it does not (Trafimow & Earp, 2017). Low statistical power may lead to type I errors. Type II errors (beta (β) errors) result in failing to reject the null hypothesis when it is false (Gu et al., 2016; Kim, 2015), or falsely concluding that a relationship or difference does not exist between groups or variables when it does (Trafimow & Earp, 2017).

Minimizing type I and II errors requires balancing the alpha (statistical significance) and beta (statistical power) levels because as the probability of committing type I error increases, the probability of committing a type II error decreases (Kim, 2015;

Trafimow & Earp, 2017). To achieve a balance between type I and II errors, it is common to set the alpha (α) level, or level of statistical significance at 0.05 and the beta (β) level, or level of statistical power at 0.8 - 0.9 (Ioannidis, Hozo, & Djulbegovic, 2013; Kim, 2015; Trafimow & Earp, 2017). Setting statistical significance at 0.05 and statistical power at 0.8 – 0.9 maximizes the chance of the researcher making correct inferences and minimizes the chances of making the wrong inferences (Ioannidis et al., 2013). Although, Chen, Chen, and Chen (2013) and Cho and Kim (2015) commented that in some studies it may be desirable to minimise either type I or type II errors at the expense of the other, depending on of the nature of the research question and the implications of accepting or rejecting the null hypothesis.

The three conditions that can threaten the validity of the statistical conclusions are: (a) reliability of the instrument, (b) data assumptions, and (c) sample size (Karpinski, Kirschner, Ozer, Mellot, & Ochwo, 2013; Venkatesh, Brown, & Bala, 2013). Rutkowski and Delandshere (2016) suggested that using a large enough sample size, a proven research instrument, and appropriate statistical tests with data that meets the required data assumptions, will minimize threats to statistical conclusion validity.

While I did not use a published instrument, I did use accident categorization and data based on that published by the IATA and the ICAO. Accident data is the most common metric in aviation safety studies (e.g., Boyd, 2016; Chen & Li, 2016; Cui & Li, 2015; Di Gravio et al., 2015; Knecht, 2013; Oster et al., 2013; Zavila et al., 2016), and transport safety studies in general (e.g., Eleftheria et al., 2016; Goh et al., 2014; Guest et al., 2014; Liu & Moini, 2015; Schepers et al., 2017; Wang et al., 2015). Face validity is achieved when expert opinion agrees on whether an instrument measures the intended concept (Heale & Twycross, 2015). Aircraft accidents are the primary measure of airline safety by global bodies such as the ICAO (2017), the IATA (2017), and aircraft manufacturers such as Boeing (2017) and Airbus (2016), all of whom use the metric of accidents per million departures. Thus, the approach and data can be considered valid and reliable.

The data assumptions of homoscedasticity, linearity, and normal distribution should be met. Regression analysis with data that violates the assumptions of linearity and normal distribution can result in biased results and confidence intervals (Crawford, 2006; Uyanik & Guler, 2013). Green and Salkind (2017), Parra-Frutos (2013), and Uyanik and Guler (2013) all recommended that the data assumptions of homoscedasticity, linearity, and normal distribution can be verified by examining the normal probability plot of the standardized regression residuals, standardized residual scatter plots, and determining the skewness and kurtosis coefficients. Thus, I performed those three tests on my data to determine if the required data assumptions of homoscedasticity, linearity, and normal distribution were met. Finally, bootstrapping can be used within correlation and regression analysis to overcome issues of parameter dependency and produce robust test results (Barker & Shaw, 2015; Chang, Sickles, & Song, 2015; Green & Salkind, 2017). Thus, I used the bootstrapping feature of SPSS on my data.

Regarding the threat to conclusion validity of an insufficient sample size, both Gu et al. (2016) and Sari et al. (2017) noted sample size could impact statistical significance when sampling is limited. However, error probabilities for large sample sizes are usually not a problem, because as the sample size grows the probability of both type I and type II errors are reduced (Gu et al., 2016; Kim, 2015). The sample in my study was the total global population of all passenger airlines involved in accidents; thus, sample size should not impact statistical conclusion validity. An *a priori* calculation of sample size required to achieve an effect size of $f = 0.10$, $\alpha = 0.05$, and power $\beta = 0.90$, required a minimum sample of 88, as shown in Figure 6. My sample size was 222. Further, the population used was the total population (N=890), removing any threats to sampling bias.

External Validity

Threats to external validity were also of concern. External validity reflects the extent to which the research results can be generalized to situations and populations beyond the sample population and the study itself (Cor, 2016; Yilmaz, 2013; Zhou et al., 2016). External validity also addresses the ability to generalize the sample results across different measures, settings, or times (Cor, 2016; Ellis & Levy, 2009). The concept of longitudinal time validity is relevant to my study as I used 14 years of historical data to explore long-term relationships between the independent variables and safety performance.

Threats to external validity include sampling bias, where many participants inadvertently share an important trait or many the population decline to participate (Zachariadis, Scott, & Barrett, 2013). The sample population of this research study is the total population, avoiding any threats of sampling bias. The second threat to external validity is temporal validity, or the impact of unique or temporary circumstances or time on the variables, and the validity of the results over future time periods (Cor, 2016). To minimize temporal validity threats, I used 14 years of accident data from 2004 to 2017. A third threat is the interaction of unknown factors or influences on the variables (Zachariadis et al., 2013). Using the entire global population over a 14-year period minimizes the threat of unknown and uncontrollable factors and influences. Threats to ecological validity refer to the ability to generalize results from the controlled research environment to the real, authentic world (Cor, 2016). My research did not take place in a controlled environment but used the archival accident data of airlines from the real world.

Transition and Summary

Section 2 contained information on the purpose statement to assess the relationship between airline category, geographical region, and safety performance. In Section 2, I elaborated on the research method and design, explaining why I selected a quantitative method to examine the relationship between the variables. The role of the researcher and the research ethics of this study were discussed. I justified the use of a non-probability, total population sampling technique, and explained the data collection techniques, analysis methods, reliability, and validity. I obtained the archival data from the IATA, the ICAO, and OAG for data analysis.

In Section 3, I analyze the data and interpret the results to present the study findings. My results and findings are applied to the professional practices of the airline industry, and implications for positive social change are considered. Finally, I discuss recommendations and action for future research, along with the study summary and conclusions.

Section 3: Application to Professional Practice and Implications for Change

Introduction

Poor safety performance in the airline industry impacts airline economic performance, as airline accidents can result in direct costs of over US$500 million per accident (Walker et al., 2014). The purpose of this quantitative correlational study was to examine the relationship between airline category, geographical region, and safety performance. The implications for positive social change include the potential for airline leaders to improve the safety image of their airline and provide passengers a better understanding of airline safety. Providing passengers with information on airline safety performance is beneficial for nervous flyers (Graham & Metz, 2017) and may allow passengers to make more informed choices on using different categories of airlines in different geographical regions.

A correlational design was appropriate for the study because my goal was to understand relationships between the variables. ANOVA and *t* tests were appropriate for determining differences between the variables.

Airline category (LCC or FSC) had no statistically significant difference in safety performance (accident rate per million departures) at a global level. When regional differences in LCC and FSC safety performance were examined, LCCs were significantly safer than FSCs in Africa and North America. Geographical region (eight regions) had a statistically significant difference in safety performance (accident rate per million departures), but only between the best performing region (North America) and the worst performing region (Africa). The regression model was not able to predict safety performance significantly. The null hypothesis was accepted, and the alternative hypothesis was rejected.

Presentation of the Findings

In this section, I discuss the testing of the assumptions, present descriptive statistics, present inferential statistic results, provide a theoretical conversation related to the findings, and conclude with a concise summary. I employed bootstrapping, using 1,000 samples, to address the possible influence of assumption violations. Thus, bootstrapped 95% confidence intervals are presented where appropriate.

The research question and purpose of this quantitative correlational study was to examine the difference and relationship between airline category, geographical region, and safety performance. I hypothesized that there is no statistically significant difference or relationship between airline category, geographical region, and safety performance. The independent variables were the category of an airline classified as LCC or FSC and the geographic region in which the airline was based. The dependent variable was the safety performance measured by aircraft accidents, normalized per million departures. Data for all variables consisted of archival data from the IATA, ICAO, and OAG, and aircraft accidents were normalized to a rate per million departures. The target population comprised all passenger airlines globally that had an accident (as defined by IATA) in the 14-year period from 2004 to 2017.

Due to the ratio level data of accident rate (per million departures) and the nominal data of airline category (LCC or FSC) and geographical region (eight separate regions), *t* tests and ANOVAs were used to determine if any significant differences existed between the mean safety performance scores of the variables. Multiple linear regression analysis was used to determine the nature of the relationship between the variables of airline category. I utilized bootstrapping, using 1,000 samples to address the possible influence of assumption violations.

Evaluation of Statistical Assumptions

Parametric tests such as *t* tests, ANOVAs, and correlations with data that violates the assumptions of independent observations, normal distribution, and homogeneity of variance can result in biased results and confidence intervals (Ahad & Yahaya, 2014; Rana, Singhal, & Dua, 2016; Singh, Roy, & Tripathi, 2013). All observations were independent of each other. An airline can only be allocated to one category (LCC or FSC) and one region. The skewness score for the dataset was $\gamma = 4.05$ ($\gamma = 4.10$ for LCC and $\gamma = 2.54$ for FSC), and both the Shapiro-Wilk and Kolmogorov-Smirnov tests were significant, $p < 0.001$. A visual inspection of the normal probability plot (Q-Q plot) (Figure 7) also indicates a nonnormal distribution. Thus, the dataset was nonnormal and positively skewed. It is good that the data was positively skewed to zero accident rate as this highlights that aviation is a safe form of transport. Levene's test for homogeneity of variance showed that the variance of accident rates in regions was not equal, $F(7, 214) = 6.86$, $p < 0.001$.

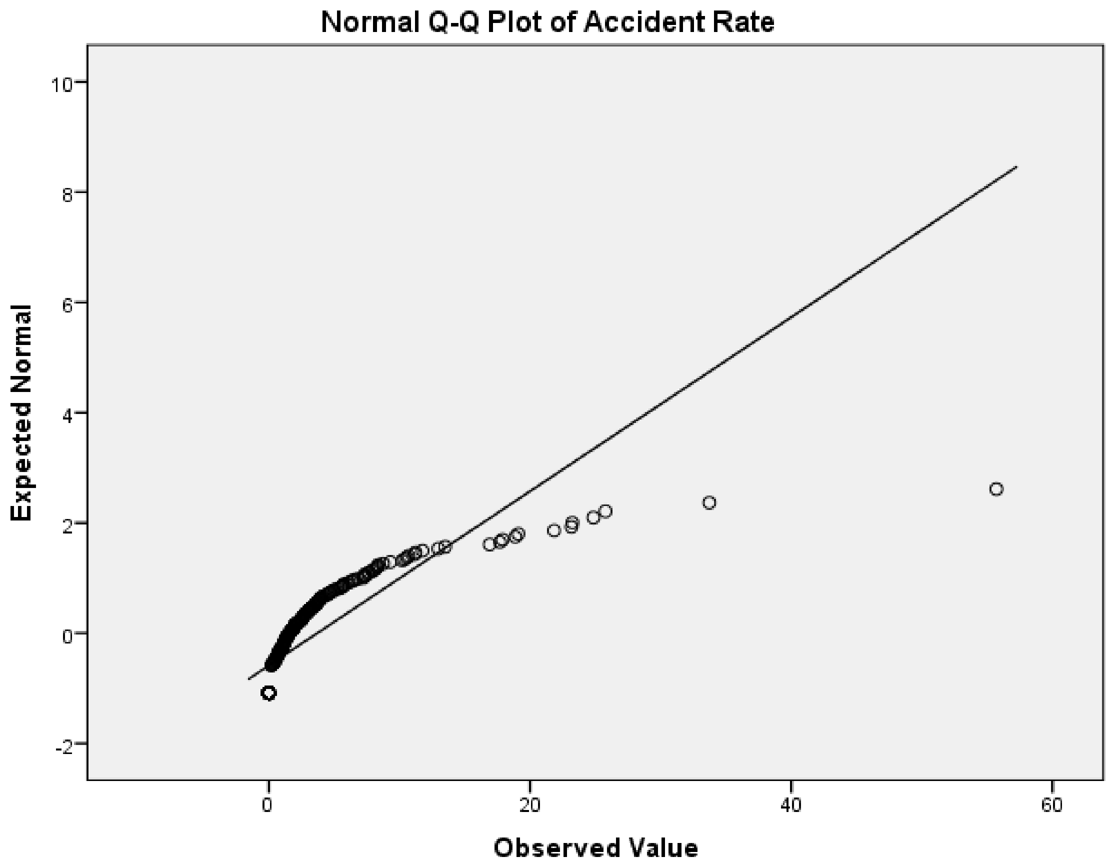

Figure 7. Normal probability plot (Q-Q) of the dependent variable (accident rate).

Ensuring equal sample size (or balanced cells) assists to mitigate any violations of homogeneity of variance and nonnormality (Ahad & Yahaya, 2014; Osborne, 2013; Parra-Frutos, 2014; Skidmore & Thompson, 2013). My independent variables of airline categories (LCC and FSC) and the eight regions all had equal cell sizes. Large sample sizes assist to mitigate violations of normality (Marcinko, 2014; Williams, Grajales, & Kurkiewicz, 2013), although there is no agreed upon definition of a large sample size, and large sample size has been nominated as greater than 20 samples (Rana et al., 2016), 25 samples (Erceg-Hurn & Mirosevich, 2008), 30 samples (Seco, Garcia, Garcia, &

Rojas, 2013; Sullivan et al., 2016), 48 samples (Skidmore & Thompson, 2013), 80 samples (Sainani, 2012), and 100 samples (Lumley, Diehr, Emerson, & Chen, 2002). Saki and Tabesh (2014) recommended an increase in sample size by up to 30% of that required for a sample that meets all assumptions (note: G*Power calculations required for my conditions required a sample size of 88). Thus, my dataset of N = 222 (with 890 airline accidents underpinning the accident rate calculations) can be considered sufficiently large, exceeding all the requirements.

Bootstrapping can be used to overcome issues of parameter dependency and produce robust test results (Chang et al., 2015; Seco et al., 2013; Green & Salkind, 2017; Williams et al., 2013). Thus, I used bootstrapping with 1,000 samples, as recommended by Parra-Frutos, (2014) and Seco et al. (2013), to address the possible influence of assumption violations, and 95% confidence intervals based upon the bootstrap samples are reported where appropriate. In summary, the large size of my dataset, equal sample size, and use of bootstrapping are sufficient to mitigate the violations of normality and homogeneity of variance; which ensured the *t* test, ANOVA, and regression were appropriate and relatively robust to the assumption violations (Parra-Frutos, 2014; Sainani, 2012; Seco et al., 2013).

Descriptive Statistics

The original IATA dataset of all airline accidents from 2004 to 2017 consisted of 1181 accidents. I removed all the cargo flights and ferry flights, as these are not passenger airline operations, leaving 890 accidents included in the analysis. The frequencies and percentages of the nominal level independent variables of airline category and region are in Table 6. The means and standard deviation of the ratio level dependent variable (accident rate) are in Table 7. Table 8 displays the mean accident rate for LCCs and FSCs across all eight global regions. The regions of Africa and North America had statistically significant differences in the safety performance of LCCs and FSCs.

Table 5

Frequency and Percentage of Accidents for Airline Category and Region

	Airline accidents (Total)	
Variable	*N*	%
Airline category		
LCC	108	12.1
FSC	782	87.9
Global region		
Africa	100	11.2
Asia Pacific	183	20.6
Eastern Europe/CIS	78	8.8
Latin America	113	12.7
MENA	80	9.0
North America	154	17.3
North Asia	35	3.9
Western Europe	146	16.4

Note. *N* = 890

Table 6

Mean and Standard Deviation of Accident Rates for Airline Category and Regions

Variable	Accident rate (per million departures) M	SD	Bootstrapped 95% CI (*M*)
Airline category			
LCC	3.26	7.74	[1.96, 4.88]
FSC	4.15	4.53	[3.34, 5.06]
Global region			
Africa	6.17	8.19	[3.35, 9.23]
Asia Pacific	4.81	3.99	[3.45, 6.53]
Eastern Europe/CIS	4.37	5.40	[2.51, 6.70]
Latin America	2.87	3.66	[1.71, 4.30]
MENA	4.98	5.92	[2.98, 7.28]
North America	0.76	0.63	[0.52, 1.00]
North Asia	4.27	12.27	[0.48, 9.41]
Western Europe	1.61	0.89	[1.28, 1.91]

Note. $N = 222$.

Table 7

Accident rate of Airline Category across Regions

Region	Accident rate (per million departures)			
	LCC		FSC	
	M	SD	M	SD
Africa*	0.00	0.00	11.46	7.53
Asia Pacific	5.99	5.36	3.62	1.18
Eastern Europe/CIS	3.05	6.81	5.69	3.24
Latin America	2.49	4.97	3.26	1.69
MENA	4.18	4.18	5.78	5.78
North America*	0.34	0.54	1.18	0.40
North Asia	7.95	16.83	0.58	0.41
Western Europe	1.58	1.04	1.64	0.75

Note. $N = 222$. * $p < 0.05$

Table 8

Frequency and Percentage of Aircraft Characteristics in Accidents by Airline Category

	Airline accidents			
	LCC		FSC	
	N	%	N	%
Total	108	12.1	782	87.9
Aircraft origin				
Western built	107	0.9	687	12.1
Eastern built	1	99.1	95	87.9
Aircraft type				
Jet	82	75.9	467	59.7
Turboprop	26	24.1	315	40.3

Note. $N = 890$.

Inferential Statistical Analysis

My quantitative research question was:

RQ: What is the relationship between airline category, geographical region, and safety performance?

H_0: There is no statistically significant relationship between airline category, geographical region, and safety performance.

H_1: There is a statistically significant relationship between airline category, geographical region, and safety performance.

A Pearson product-moment correlation was run to determine the relationship between the number of airline accidents and the number of airline departures. There was a moderate positive correlation between accidents and departures, which was statistically significant ($r = 0.553$, $N = 222$, $p < 0.001$). The greater the number of departures, the greater the number of accidents.

I conducted an independent-samples *t* test (two-tailed), $a = 0.05$, to assess whether LCCs differed significantly from FSCs in a measure of safety performance. The assumptions of equal variances (Levene's test, $p = 0.061$) were evaluated with no violations noted. The results were not significant, $t(220) = -1.05$, $p = 0.329$ (two-tailed). There were no significant differences in accident rates per million departures between LCCs ($M = 3.26$, $SD = 7.74$) and FSCs ($M = 4.15$, SD = 4.53) at a global level. The 95% CI of the mean difference (-0.89) was -2.57 to 0.78**.** Table 6 depicts the descriptive statistics of the variables. The safety performance of LCCs was significantly better than FSCs in Africa $t(13) = -5.70$, $p < 0.001$ (two-tailed) and North America $t(26) = -4.46$, $p < 0.001$ (two-tailed).

To explore any differences between the safety performance of the eight regions, I used a one-way ANOVA analysis to compare the means of regional accident rates per million departures. I conducted a one-way ANOVA, $a = 0.05$, to assess whether there was a statistically significant difference in safety performance (accident rate per million departures) for the eight regions. The results were significant, $F(7, 214) = 2.40$, $p < 0.05$. The measure of effect size measured by η^2 was .07 indicating that 7% of the variance in the accident rate is accounted for by region. Post hoc analysis, using the Tukey HSD test, indicated that the accident rate (per million departures) for Africa (*M* = 6.17, *SD* = 8.19) was significantly different (p = 0.03) from North America (*M* = 0.76, *SD* = 0.63). No other regions differed significantly from each other. Table 9 depicts the ANOVA summary.

I conducted a two-way ANOVA that examined the effect of airline category and global region on the accident rate. There was a statistically significant interaction between the effects of airline category and region on accident rate, $F(7, 206) = 5.59$, $p < 0.001$. Simple main effects analysis showed North America was safer than Africa ($p < 0.02$), but there were no differences between any other regions.

Table 9

ANOVA Summary Table for the Impact of Region on Accident Rate

Source	*df*	*SS*	*MS*	*F*	*η2*	*p*
Between-group	7	643.92	91.99	2.40	0.07	0.02
Within-group	214	8210.59	38.37			
Total	221	8854.51				

I used standard multiple linear regression, α = 0.05 (two-tailed), to examine the efficacy of airline category in predicting safety performance. The independent variable was airline category (LCC or FSC), and the dependent variable was safety performance (accident rate). The null hypothesis was that airline category is not significantly related to safety performance. The alternative hypothesis was that airline category is significantly related to safety performance. The regression model was not able to significantly predict airline safety performance *F*(1,220) = 1.10, *p* > 0.05, *R*2 = 0.005. The *R2* (0.005) value indicated that less than 1% of the variation in safety performance is accounted for by the linear combination of airline category. In the final model, airline category did not explain any significant variation in safety performance. Table 10 depicts the regression analysis summary.

Table 10

Regression Analysis Summary for Predictor Variables

Variable	*B*	*SE B*	*β*	*t*	*p*	*B* 95% Bootstrap CI
Airline category	0.90	0.87	0.07	1.75	0.32	[-0.94, 2.43]

Note. *N* = 222.

Analysis summary. The purpose of this study was to examine the difference and relationship between airline category (LCC and FSC), global region (eight regions), and safety performance (accident rate). I used standard multiple linear regression to examine the ability of airline category to predict safety performance (accident rates). The model was unable to significantly predict airline accident rates *F*(1,220) = 1.10, *p* > 0.05, *R*2 = 0.005. The conclusion from this analysis is that airline category (LCC or FSC) is not related to safety performance.

To explore any differences between the safety performance of LCCs and FSCs, I used independent samples *t*-test analysis to compare the means of LCC and FSC accident rates per million departures. There were no significant differences in accident rates per million departures between LCCs and FSCs, *t*(220) = -1.05, *p* = 0.329 (2-tailed). To explore any differences between the safety performance of the eight regions, I used a one-way ANOVA analysis to compare the means of regional accident rates per million departures. The results were significant, $F(7, 214) = 2.40$, $p < 0.05$. The accident rate for Africa ($M = 6.17$, $SD = 8.19$) was significantly larger ($p = 0.03$) than North America ($M = 0.76$, $SD = 0.63$). No other regions significantly differed from each other.

Both *t*-test and regression analysis found no relationship with or difference between airline category (LCC/FSC) and safety performance on a global level. LCCs were statistically safer than FSCs in Africa and North America. A statistically significant difference in safety performance was found between global regions, but only between the Africa and North America regions. The finding of no significant difference between the safety performance of LCCs and FSCs is supported by the Swiss cheese model of organizational accidents. Accidents in complex sociotechnical systems such as airlines are impacted by multiple latent and organizational factors; regulations and regulators, cultural attributes, and socio-economic conditions. These latent, organizational conditions are relatively constant across airlines within the same country or region. The safety standards that any airline must meet in a given country or region are the same for both low-cost and full-service airlines.

While latent issues are relatively constant within a country or region, they are different between regions, with the greatest differences between the most and least developed regions. The results of such latent, organizational differences are different levels of safety performance, with the biggest safety differences between regions with the largest latent, organization differences (national culture, socioeconomic conditions, regulatory effectiveness) such as comparing Africa to North America. The airline category of low-cost or full-service is not an organizational factor that impacts airline accidents globally, but the geographical region does impact airline accidents.

Airline operations in different countries and regions have different levels of safety performance (Hodgson et al., 2013; IATA, 2017; ICAO, 2017; Oster et al., 2013; Savage, 2012), and my research findings supported those differences. However, the finding that airline category was not related to safety performance at a global level contradicts traveler perceptions that the aggressive operational cost cutting of LCCs impacts safety. While LCCs offer a reduced level of service, they do not offer a reduced level of safety. On the contrary, in the regions of Africa and North America, LCCs had superior safety performance to FSCs.

Table 11

Accident & Incident Rate of US carriers (Flores & Reyes, 2006)

	Accident rate (per million sectors)	Incident rate (per million sectors)
US mainline (FSC)	5.0	31.3
US LCC	2.4	13.9
US Regional	3.9	22.9

Note: Accident and incident defined as per FAA. Excludes 9/11 events.

My results of LLC and FSC safety performance in North America are similar to those of Flores and Reyes (2006) who have conducted one of the few studies comparing LCC and FSC safety. Flores and Reyes (2006) compared the accident and incident rate of

U.S. mainline carriers (FSCs), LCCs, and regional carriers over a five-year period (2000-2004). The results (shown in Table 11) indicate that U.S. LCCs had better safety performance than their mainline (FSC) and regional counterparts, with the accident and incident rate for LCCs less than half that of mainline (FSC) carriers. Flores & Reyes (2006) concluded that strategic choices and organizational cultures were key to safety performance, citing the LCCs' choice of single-type fleets of third-generation jets, and simpler organizational structures.

Applications to Professional Practice

Passengers rank airline safety as one of the most important factors in airline choice selection (Desai et al., 2014; Jeeradista et al., 2016; Jiang, 2013; Min & Min, 2015). Thus, safety performance impacts an airline's ability to attract and maintain customers (Sandada & Matibiri, 2016). The research may be of value to leaders in the LCC airline sector as the findings suggest there is no statistically significant difference between LCC and FSC safety performance at a global level. In most regions, the LCC accident rate is lower than the FSC accident rate, but it is only statistically significant in Africa and North America, where LCCs have a lower accident rate. Thus, it can be suggested that LCCs have the same, if not lower accident rates than FSCs, and LCCs are at least as safe as FSCs. LCCs can use this information to counter negative media reports, industrial arguments, and traveler perception on the LCC sector's safety performance.

It is well-accepted that developing regions have worse safety performance than developed regions, hence the focus of bodies like the IATA and ICAO to improve safety in developing regions. Thus, the finding that airlines in North America have statistically significant lower accident rates than airlines in Africa is not surprising. It may be more surprising that the differences between regional safety performance were not more common. The results do confirm that airlines in developing regions, regardless of airline category, need to be conscious of their safety performance and take steps to improve it. An improvement in the safety performance of airlines in developing regions may attract new customers.

One possible reason for the equal or better safety performance of LCCs to FSCs is that FSCs operate more eastern-built aircraft and more turboprop aircraft. Both eastern-built aircraft and more turboprop aircraft are over-represented in accident rates. There are positive safety implications and hence, positive business implications for the LCC sector in operating a fleet of a predominantly western-built jet aircraft. LCC managers may consider sharing this fleet information more widely, using it to their advantage. Avoiding or minimizing the exposure to eastern-built aircraft and turboprop aircraft should be a consideration in future fleet decisions for both LCC and FSC.

Passengers are often willing to pay more to fly with airlines they perceive as safe (Molin et al., 2017), and passengers are more loyal to safe airlines, avoiding unsafe airlines, particularly in regions with historically poor airlines safety performance (Sandada & Matibiri, 2016). Passengers have previously chosen to fly FSCs over LCCs due to the better safety image of FSCs (Lu, 2017). However, the findings of this current study can be used by LCC airline management to positively change the safety image of the LCC sector. Information related to airline safety performance might be used by airline managers to shape airline image and influence passenger airline choice, which may impact business performance. Fleischer et al. (2015) noted that when objective safety information is available, passengers will discount their subjective opinions and perceptions and incorporate that objective information into their decision making on airline choice, and that includes paying a premium to travel on airlines with high safety performance. In summary, there is a potential business benefit through increased knowledge of airline safety performance.

Implications for Social Change

There is no significant difference in the safety performance of LCCs and FSCs, but there is a significant difference between regional safety performance. The category of the airline (LCC or FSC) had no relationship with airline accident rates, whereas the regional origin of the airline did. Safety is one of the most important considerations in airline choice, and these findings provide passengers a better understanding of airline safety performance, presenting greater opportunities for passengers to make informed choices about airline selection. Information that can reduce the safety concerns of travelers, particularly nervous flyers or those with flight phobias is of benefit to those travelers (Graham & Metz, 2017). Travelers with a fear of flying more strongly avoid airlines perceived as having poor safety performance. Up to 30% of the adult population has a fear of flying (Fleischer et al., 2015) and providing airline safety information to that population allows a more rationale airline choice. Removing barriers to air travel, especially those around safety, may result in new travel opportunities for travelers that were previously unrealized due to their safety concerns. Travelers are now able to alter their perceptions of LCC and FSC safety performance, as there is no global difference in accident rates, and indeed, LCCs had lower accident rates in Africa and North America. LCCs should be viewed to be as safe, if not safer, than FSCs. Travelers may now also make more informed decisions about the safety performance of airlines from different regions. For example, if flying between North America and Africa, it is statistically safer to travel on the North American based airlines rather than the African based airlines.

Recommendations for Action

The first recommendation is for airlines to reduce their exposure to eastern-built aircraft and turboprop aircraft due to the higher accident rates of such aircraft types. There are often sound economic and operational reasons for operating turboprops on certain routes, which needs to be balanced against safety risks.

The second recommendation is for the LCC management to more proactively promote the safety performance of the LCC sector. LCC managers need to counter the misperceptions about LL safety performance and inform travelers and the broader public of the safety performance of LCCs. Industry bodies such as the IATA and associated regional airline bodies should promote this safety knowledge to expand and grow the airline industry as a whole. IATA can release safety information about LCC safety performance through its website, press releases, and its annual safety report.

Finally, it is recommended that the ICAO provides greater assistance to regulators in developing regions, particularly Africa. ICAO's assistance could include resources and training to develop and mature the airline regulatory systems in developing regions. The theory of organizational accidents in complex sociotechnical systems reinforces the need for effective regulatory systems to improve aviation safety.

I aim to present this work at the Flight Safety Foundation International Airline Safety Summit (IASS), as it is considered by airline safety professionals to be the premier safety conference. I will submit the research for publication in a journal such as Safety Science, Journal of Airline Management, or Accident Analysis and Prevention, as these were the three most commonly cited journals in my literature review. However, passengers and the travelling public do not read academic safety journals or attend airline professional conferences, so it is most important to consider how to ensure my research findings reach a broader public audience, who can benefit from the social change. Thus, I will use social media and connections to spread a broader message of my findings.

Recommendations for Further Research

A lack of flight sector data for all airlines individually in the accident database does not permit the calculation of accident rates for individual airlines. Future researchers might explore specific airline accident rates by examining airline's annual reports and other reliable sources of flight frequency data. The accident data set is limited to the 14-year period 2003 to 2017. Thus, future researchers could update the dataset. With the global growth of LCCs, continuing research is relevant. Safety performance was measured by accidents which are retrospective and limited in number. No globally consistent, proactive safety metric was available at the time I conducted this study. In the future, such a measure may be applied to all airlines in all regions, thus allowing global safety performance to be examined consistently by metrics other than accidents.

I examined the relationship and differences between LCCs and FSCs safety performance in different global regions. I provided suggestions why there was not a difference or relationship between LCC and FSC safety performance and suggestions why there was a difference in safety performance between some regions but did not empirically examine the research question of why or how. Thus, future researchers may examine why there is or is not a relationship or difference between the variables

Reflections

As someone with a deep interest in aviation, I entered this DBA doctoral research with the assumption that LCCs should be as safe as FSCs in any given region, a view I was criticized for by many of my aviation colleagues. I remained conscious of my bias to ensure neutrality and conducted multiple statistical tests to explore and confirm relationships and differences between the variables in different ways. Given the ongoing discussion in the aviation industry about the poor safety performance of the developing regions, I did expect to find significant safety differences between more regions. My findings have reinforced to me the power of data over opinion, and to keep an open mind and not be swayed by influential voices or popular opinion. Finally, I was concerned about using the Swiss cheese model of organizational safety as it has not been updated for over 20 years and has come under recent criticism. Despite this, Reason’s Swiss cheese model and the theory of organizational accidents in complex sociotchnical systems was still able to correlate with my findings. Old does not always mean outdated.

Conclusion

Although travelers perceive FSCs to be safer than LCCs, this research study found that LCCs are as safe, if not safer than FSCs based on accident rates. Based on the theory of organizational accidents, LCCs and FSCs have similar levels of safety performance within any country or region they operate within the same organizational system, within the same cultural, socioeconomic, and regulatory environments. However, those same systems and environments differ between countries and region. There are regional differences in airline safety, with North America being the safest region and Africa being the least safe region based on accident rates.

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Appendix A: Safety Performance by Airline Category and Geographical Region

Table A12

Safety Performance: World

Year	Departures		Accidents		Accident rate (per million departures)	
	FSC	LCC	FSC	LCC	FSC	LCC
2004	24,521,979	2,294,184	61	6	2.49	2.62
2005	25,074,538	2,680,231	82	7	3.27	2.61
2006	25,044,538	3,207,405	47	8	1.88	2.49
2007	25,610,598	3,915,356	61	9	2.38	2.30
2008	25,270,855	4,383,125	62	8	2.45	1.83
2009	24,095,806	4,481,244	55	11	2.28	2.45
2010	24,951,163	5,007,486	64	5	2.57	1.00
2011	25,377,501	5,578,045	74	5	2.92	0.90
2012	25,267,687	5,989,334	54	4	2.14	0.67
2013	25,231,689	6,440,899	56	7	2.22	1.09
2014	25,419,695	6,942,039	44	10	1.73	1.44
2015	25,772,545	7,640,241	49	7	1.90	0.92
2016	26,543,805	8,348,397	37	12	1.39	1.44
2017	27,384,227	9,099,350	25	9	0.91	0.99

Table 13

Safety Performance: Western Europe

Year	Departures		Accidents		Accident rate (per million departures)	
	FSC	LCC	FSC	LCC	FSC	LCC
2004	5,375,502	557,746	13	2	2.42	3.59
2005	5,452,401	702,896	11	1	2.02	1.42
2006	5,490,683	833,913	7	1	1.27	1.20
2007	5,598,905	1,065,989	15	2	2.68	1.88
2008	5,504,913	1,212,523	6	3	1.09	2.47
2009	5,071,798	1,239,477	10	4	1.97	3.23
2010	5,158,182	1,342,764	4	1	0.78	0.74
2011	5,146,594	1,441,358	8	2	1.55	1.39
2012	4,926,516	1,515,758	10	3	2.03	1.98
2013	4,762,056	1,581,407	12	0	2.52	.00
2014	4,697,163	1,762,880	4	2	0.85	1.13
2015	4,706,631	1,948,592	11	0	2.34	.00
2016	4,837,584	2,147,944	6	3	1.24	1.40
2017	4,837,240	2,344,341	1	5	0.21	1.71

Table 14

Safety Performance: Eastern Europe and CIS

Year	Departures		Accidents		Accident rate (per million departures)	
	FSC	LCC	FSC	LCC	FSC	LCC
2004	676,385	18,328	4	0	5.91	.00
2005	730,265	39,890	5	0	6.85	.00
2006	799,796	57,040	7	0	8.75	.00
2007	864,876	76,170	3	0	3.47	.00
2008	962,877	89,045	8	1	8.31	11.23
2009	893,973	86,094	2	2	2.24	23.23
2010	953,769	91,815	7	0	7.34	.00
2011	1,036,934	91,722	14	0	13.50	.00
2012	1,027,334	106,682	4	0	3.89	.00
2013	1,038,685	122,230	8	1	7.70	8.18
2014	1,078,810	140,299	3	0	2.78	.00
2015	1,067,343	178,352	3	0	2.81	.00
2016	1,091,329	211,608	3	0	2.75	.00
2017	1,204,052	251720	3	0	3.32	.00

Table 15

Safety Performance: North America

Year	Departures		Accidents		Accident rate (per million departures)	
	FSC	LCC	FSC	LCC	FSC	LCC
2004	10,120,329	1,476,666	8	0	0.79	.00
2005	10,159,268	1,581,845	19	3	1.87	1.90
2006	9,606,789	1,764,759	6	0	0.62	.00
2007	9,700,893	1,950,046	14	1	1.44	0.51
2008	9,221,909	2,028,577	10	0	1.08	.00
2009	8,546,586	1,927,913	9	0	1.05	.00
2010	8,447,920	1,994,028	13	0	1.54	.00
2011	8,326,224	2,100,826	16	0	1.92	.00
2012	8,173,862	2,049,095	9	0	1.10	.00
2013	8,11,0711	2,002,903	10	1	1.23	0.50
2014	7,955,135	2,011,167	8	1	1.01	0.50
2015	7,816,557	2,111,644	10	1	1.28	0.47
2016	7,802,160	2,236,085	6	2	0.77	0.89
2017	7,793,837	2,362,087	6	0	0.77	.00

Table 16

Safety Performance: Latin America

Year	Departures		Accidents		Accident rate (per million departures)	
	FSC	LCC	FSC	LCC	FSC	LCC
2004	2,267,573	118,252	4	2	1.76	16.91
2005	2,276,328	138,993	13	0	5.71	.00
2006	2,288,348	195,862	7	2	3.06	10.21
2007	2,298,096	263,295	8	0	3.48	.00
2008	2,280,286	328,154	15	0	6.58	.00
2009	2,140,504	407,013	8	0	3.74	.00
2010	2,349,156	511,100	9	1	3.83	1.96
2011	2,363,559	631,466	13	2	5.50	3.17
2012	2,426,825	684,895	3	1	1.24	1.46
2013	2,263,799	854,250	6	0	2.65	.00
2014	2,333,849	897,077	7	0	3.00	.00
2015	2,365,994	935,770	3	0	1.27	.00
2016	2,381,857	904,354	6	2	2.52	.00
2017	2,366,215	947,018	3	0	1.69	.00

Table 17

Safety Performance: North Asia

Year	Departures		Accidents		Accident rate (per million departures)	
	FSC	LCC	FSC	LCC	FSC	LCC
2004	2,524,638	12,822	4	0	1.58	.00
2005	2,716,227	17,953	1	1	0.37	55.70
2006	2,972,400	29,644	2	1	0.67	33.73
2007	3,181,037	55,906	2	1	0.63	17.89
2008	3,279,096	62,617	1	0	0.30	.00
2009	3,412,733	110,487	1	0	0.29	.00
2010	3,699,978	163,150	2	0	0.54	.00
2011	3,922,009	211,394	2	0	0.51	.00
2012	4,188,010	264,959	5	0	1.19	.00
2013	4,496,400	317,208	3	0	0.67	.00
2014	4,711,155	394,071	2	1	0.42	2.54
2015	4,898,475	534,325	4	0	0.82	.00
2016	5,167,571	687,045	1	1	0.19	1.46
2017	5,5470,94	810,541	0	0	.00	.00

Table 18

Safety Performance: Asia Pacific

Year	Departures		Accidents		Accident rate (per million departures)	
	FSC	LCC	FSC	LCC	FSC	LCC
2004	2,407,634	105,967	11	2	4.57	18.87
2005	2,502,115	189,192	12	2	4.80	10.57
2006	2,586,543	308,518	8	4	3.09	12.97
2007	2,570,385	467,866	13	5	5.06	10.69
2008	2,544,260	602,132	12	3	4.72	4.98
2009	2,467,341	626,231	9	4	3.65	6.39
2010	2,646,129	772,033	7	3	2.65	3.89
2011	2,801,241	940,894	10	1	3.57	1.06
2012	2,709,185	1,192,164	12	0	4.43	.00
2013	2,744,073	1,371,254	9	4	3.28	2.92
2014	2,747,525	1,521,263	11	6	4.00	3.94
2015	2,945,960	1,655,682	12	5	4.07	3.02
2016	3,162,188	1,851,534	5	4	1.58	2.16
2017	3,365,078	2,048,140	4	5	1.19	2.44

Table 19

Safety Performance: Middle East and North Africa (MENA)

Year	Departures		Accidents		Accident rate (per million departures)	
	FSC	LCC	FSC	LCC	FSC	LCC
2004	631,970	4,403	5	0	7.91	.00
2005	674,543	9,462	7	0	10.38	.00
2006	748,107	16,018	6	0	8.02	.00
2007	820,349	22,545	6	0	7.31	.00
2008	874,189	38,802	5	1	5.72	25.77
2009	967,433	56,531	9	1	9.30	17.69
2010	1,055,075	101,313	8	0	7.58	.00
2011	1,088,991	112,752	8	0	7.35	.00
2012	1,099,928	132,030	3	0	2.73	.00
2013	1,112,066	159,046	4	1	3.60	6.29
2014	1,181,613	177,655	3	0	2.54	.00
2015	1,21,4325	215,749	2	1	1.65	4.64
2016	1,308,310	240,684	8	1	6.11	4.15
2017	1,364,720	257,655	1	0	0.73	.00

Table A920

Safety Performance: Africa

Year	Departures		Accidents		Accident rate (per million departures)	
	FSC	LCC	FSC	LCC	FSC	LCC
2004	517,948	0	12	NA	23.17	NA
2005	563,391	0	14	NA	24.85	NA
2006	551,872	1,651	4	0	7.25	.00
2007	576,057	13,539	11	0	19.10	.00
2008	603,325	21,275	5	0	8.29	.00
2009	595,438	27,498	7	0	11.76	.00
2010	640,954	31,283	14	0	21.84	.00
2011	691,949	47,633	3	0	4.34	.00
2012	716,027	43,751	8	0	11.17	.00
2013	703,899	32,601	4	0	5.68	.00
2014	714,445	37,627	6	0	8.40	.00
2015	757,260	60,127	4	0	5.28	.00
2016	792,806	69,143	3	0	3.78	.00
2017	905,991	77,848	5	0	5.52	.00

Appendix B: Global Regions (per OAG definitions)

Region	Countries
Africa	Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Chad, Comoros, Congo, Congo DRC, Cote D'Ivoire, Djibouti, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius,, Mayotte, Mozambique, Namibia, Niger, Nigeria, Reunion, Rwanda, Saint Helena, Sao Tome & Principe, Senegal, Seychelles, Sierra Leone, Somalia, South Africa, South Sudan, Swaziland, Tanzania, Togo, Uganda, Zambia, Zimbabwe
Asia Pacific	Afghanistan, American Samoa, Australia, Bangladesh, Bhutan, Brunei Darussalam, Cambodia, Christmas Island, Cocos & Keeling Islands, Cook Islands, Fiji, French Polynesia. Guam, India, Indonesia, Kiribati, Lao, Malaysia, Maldives, Marshall Islands, Micronesia, Myanmar, Nauru, Nepal, New Caledonia, New Zealand, Niue, Norfolk Island, Northern Mariana Islands, Pakistan, Palau, Papua New Guinea, Philippines, Samoa, Singapore, Solomon Islands, Sri Lanka, Thailand, Timor Leste, Tonga, Tuvalu, Vanuatu, Vietnam
Eastern Europe &	Albania, Armenia, Azerbaijan, Belarus, Bosnia and

CIS	Herzegovina, Bulgaria, Croatia, Czech Republic, Estonia, Georgia, Hungary, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Macedonia, Moldova, Montenegro, Poland, Romania, Russia, Serbia, Slovakia, Slovenia, Tajikistan, Turkmenistan, Ukraine, Uzbekistan
Latin America	Anguilla, Antigua and Barbuda, Argentina, Aruba, Bahamas, Barbados, Belize, Bermuda, Bolivia, Bonaire and Saba, Brazil, Cayman Islands, Chile, Colombia, Costa Rica, Cuba, Curacao, Dominica, Dominican Republic, Ecuador, El Salvador, Falkland Islands, French Guiana, Grenada, Guadeloupe, Guatemala, Guyana, Haiti, Honduras, Jamaica, Martinique, Mexico, Montserrat, Nicaragua, Panama, Paraguay, Peru, Puerto Rico, , Saint Kitts and Nevis
MENA	Algeria, Bahrain, Egypt, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Libya, Morocco, Oman, Qatar, Saudi Arabia, Sudan, Syria, Tunisia, UAE, Yemen
North East Asia	Hong Kong, Japan, Macao, Mongolia, North Korea, South Korea, Taiwan
North America	Canada, Greenland, Unite States of America
Western Europe	Austria, Belgium, Cyprus, Denmark, Faroe Islands, Finland, France, Germany, Gibraltar, Greece, Iceland, Ireland, Italy, Luxembourg, Malta, Monaco, Netherlands, Norway, Portugal,

Spain, Sweden, Switzerland, Turkey, United Kingdom