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Contributing Factors of Fatal Commercial Air Accidents: Quantitative Approach

Prakayphet Chalayonnawin[1], Kamonchanok Suthiwartnarueput[2], Pongsa Pornchaiwiseskul[3], Chula Sukmanop[4]

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Abstract

The study examines the associations between accidents and contributing factors and the impacts of factors on accidents with fatalities using binary logistic regression and explores the effects of factors on the number of fatalities and aircraft damage. A total of 114 worldwide commercial aircraft accidents during 2014–2017 were collected from accident databases, final investigation reports, and various aviation communities. Correlation and post hoc tests, and binary logistic, censored, and ordered logistic regression, were adopted. Results revealed that aircraft manufacturer, aircraft model, aircraft size, flight phase, and State of occurrence's effective implementation (EI) are associated with accidents. The predicted model suggested that early morning flights, small-sized aircraft, and flying to/from/in a State with a lower EI signify the likelihood of an accident with fatalities occurring. Further, State of occurrence's EI was discovered to impact accidents with fatalities, number of fatalities, and aircraft damage, therefore it is the key to mitigating and preventing future mishaps.

Keywords: Fatal Accident, Commercial Air Transport, Binary Logistic Regression, Censored Regression, Ordered Logistic Regression

[1] *Corresponding Author,*
Logistics and Supply Chain Management Program, Graduate School, Chulalongkorn University, Bangkok 10330, Thailand. Prakayphet.c@student.chula.ac.th

[2] Faculty of Commerce and Accountancy, Chulalongkorn University, Bangkok 10330, Thailand. Kamonchanok.s@chula.ac.th

[3] Logistics and Supply Chain Management Program, Graduate School, Chulalongkorn University, Bangkok 10330, Thailand. Pongsa.p@chula.ac.th

[4] Office of the Permanent, Ministry of Transport, Bangkok 10100 Thailand. Chula.s@mot.go.th

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ปัจจัยที่ส่งผลต่อการเกิดอุบัติเหตุของอากาศยานพาณิชย์ที่มีผู้เสียชีวิต : การวิเคราะห์เชิงปริมาณ

ประกายเพชร ชลายนนาวิน[1], กมลชนก สุทธิวาทนฤพุฒิ[2], พงศา พรชัยวิเศษกุล[3] และ จุฬา สุขมานพ[4]

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บทคัดย่อ

การศึกษานี้มีวัตถุประสงค์เพื่อตรวจสอบความสัมพันธ์ระหว่างอุบัติเหตุและปัจจัยที่ส่งผลต่อการเกิดอุบัติเหตุ ตลอดจนศึกษาผลกระทบของปัจจัยที่ส่งผลต่ออุบัติเหตุที่มีผู้เสียชีวิตโดยใช้แบบจำลองการถดถอยลอจิสติกแบบทวิภาค และเพื่อสำรวจผลกระทบของปัจจัยดังกล่าวที่มีต่อจำนวนผู้เสียชีวิตและความเสียหายของอากาศยานโดยใช้การวิเคราะห์ด้วยแบบจำลองโทบิตโดยใช้แบบจำลองถดถอยแบบเซนเซอร์ และการวิเคราะห์ด้วยการถดถอยลอจิสติกแบบเรียงลำดับ งานวิจัยนี้ได้รวบรวมอุบัติเหตุของอากาศยานพาณิชย์จากทั่วโลกจำนวน 114 ครั้ง ในช่วง พ.ศ. 2557-2560 จากฐานข้อมูลอุบัติเหตุ รายงานฉบับสุดท้ายของการสอบสวนอุบัติเหตุ และหน่วยงานการบินต่างๆ โดยวิเคราะห์ข้อมูลจากการทดสอบสหสัมพันธ์ การทดสอบค่าเฉลี่ยรายคู่ การวิเคราะห์ด้วยแบบจำลองการถดถอยลอจิสติกทวิภาค แบบจำลองโทบิตโดยใช้แบบจำลองถดถอยแบบเซนเซอร์ และแบบจำลองการถดถอยลอจิสติกแบบเรียงลำดับ ทั้งนี้ ผลการวิจัยพบว่าผู้ผลิตอากาศยาน รุ่นของอากาศยาน ขนาดของอากาศยาน ช่วงการบิน และระดับประสิทธิผลของระบบกำกับดูแลความปลอดภัยและการรักษาความปลอดภัยของรัฐ มีความเกี่ยวข้องกับอุบัติเหตุ จากการวิเคราะห์พบว่าเที่ยวบินในช่วงเช้ามืด อากาศยานขนาดเล็ก และการบินไป/กลับจาก/ในรัฐที่มีระดับประสิทธิผลของระบบกำกับดูแลความปลอดภัยและการรักษาความปลอดภัยน้อย บ่งบอกถึงแนวโน้มที่จะเกิดอุบัติเหตุที่มีผู้เสียชีวิต ทั้งนี้ ระดับประสิทธิผลของระบบกำกับดูแลความปลอดภัยและการรักษาความปลอดภัยของรัฐที่เกิดอุบัติเหตุนั้น ถูกค้นพบว่ามีผลกระทบต่ออุบัติเหตุที่มีผู้เสียชีวิต จำนวนผู้เสียชีวิต และความเสียหายของเครื่องบิน ดังนั้น ระดับประสิทธิผลของระบบกำกับดูแลความปลอดภัยและการรักษาความปลอดภัยของรัฐ เป็นกุญแจสำคัญในการบรรเทาและป้องกันอุบัติเหตุในอนาคต

คำสำคัญ : อุบัติเหตุที่มีผู้เสียชีวิต, การบินเชิงพาณิชย์, การถดถอยลอจิสติกทวิภาค, การวิเคราะห์ด้วยแบบจำลองโทบิตโดยใช้แบบจำลองถดถอยแบบเซนเซอร์, การถดถอยลอจิสติกแบบเรียงลำดับ

[1] *ผู้รับผิดชอบบทความหลัก,*
สหสาขาวิชาการจัดการด้านโลจิสติกส์ บัณฑิตวิทยาลัย จุฬาลงกรณ์มหาวิทยาลัย กรุงเทพฯ 10330
Prakayphet.c@student.chula.ac.th

[2] ภาควิชาพาณิชยศาสตร์ คณะพาณิชยศาสตร์และการบัญชี จุฬาลงกรณ์มหาวิทยาลัย กรุงเทพฯ 10330
Kamonchanok.s@chula.ac.th

[3] สหสาขาวิชาการจัดการด้านโลจิสติกส์ บัณฑิตวิทยาลัย จุฬาลงกรณ์มหาวิทยาลัย กรุงเทพฯ 10330
Pongsa.p@chula.ac.th

[4] กระทรวงคมนาคม กรุงเทพฯ 10100 Chula.s@mot.go.th

Introduction

Air transport generates and supports employment, business transactions, connectivity, tourism, and social benefits (Air Transport Action Group [ATAG], 2020). When an accident occurs, it largely affects various stakeholders, including employers, airline companies, aircraft manufacturers, and other related stakeholders (Akyildirim et al., 2020; Coarsey-Rader, 1993). It incurs expenses, productivity losses, rehabilitation/long term care, property damages, property damage (aircraft), loss of quality of life, stock price changes, and effects on airline image and consumer trust (BITRE, 2006; Collings et al., 2022; Kaplanski & Levy, 2010; Krieger & Chen, 2015; Wang, 2013; Yang et al., 2018). Hence, the cooperation of aviation communities has continuously progressed to reduce the all-accident rate, improve and maintain aviation safety, and accomplish zero fatalities (EASA, 2022; IATA, 2022; ICAO, 2019a, 2020c).

Prior to the pandemic outbreak in 2020, 11 catastrophic accidents took hundreds of lives at a time during a 10-year period (2010-2019)(ASN, 2022; BBC News, 2021; Deka et al., 2022). According to Professor James Reason, “no defense is perfect”; therefore, despite the best efforts of aviation safety and advanced technology, the re-occurring accidents could signify that there are successive layers of defenses, barriers, and safeguards (Reason, 2016). Therefore, this study will investigate the contributing factors from past accidents during 2014-2017, particularly in the commercial operations using three response variables and statistical data analysis. Ultimately, this study is to identify the contributing factors signifying the likelihood of fatal accidents occurring for accident reduction.

This paper’s primary objective is to examine the associations between accidents and contributing factors (time of day, aircraft manufacturer, aircraft model by aircraft family, aircraft size by MTOW, flight phases, State of occurrence’s effective implementation (EI); Table 2 of the supplemental file), and the impact of contributing factors on accidents with fatalities. The secondary objective is to explore the effect of contributing factors on a number of fatalities and aircraft damage using censored and ordered logistic regressions. The ultimate goals are to detect early, predict, mitigate, and prevent accidents with fatalities, and identify critical factors for policy- and decision-makers in improving the safety of the aviation system.

Literature Review

The term causes and contributing factors are widely used synonymously. According to the ICAO (ICAO, 2020a), the definition of causes is “actions, omissions, events, conditions, or a combination thereof, which led to the accident or incident; whereas ‘contributing factors’ are actions, omissions, events, conditions, or a combination thereof, which, if eliminated, avoided or absent, would have reduced the probability of the accident or incident occurring, or mitigated the severity of the consequences of the accident or incident” (ICAO, 2020a). To reduce the likelihood of accidents with fatalities occurring, there are contributing factors considered in this study.

Regarding the *time of day*, a study found that early morning flights presented a higher risk of pilot error when compared with morning flights (Mello et al., 2008). Likewise, early morning start on pilot’s duties restricted the amount of sleep and contributed to higher fatigue level (Roach et al., 2012).

Regarding *aircraft manufacturer* and *aircraft model*, Boeing 737 and Airbus A320 were frequently discovered to be involved in avionics-related accidents, in which Boeing 737 had the highest proportion (Baidzawi et al., 2019). Moreover, the design of aircraft, air traffic management, and airport was identified as causal or contributing factors to the accident (Eurocontrol, 2004; U.K. CAA, 2013). Furthermore, the recent Boeing 737 Max accidents that occurred with Lion Air in 2018 and Ethiopian Airlines in 2019 presented the issue surrounding aircraft design and software that led to two fatal crashes, which grounded these aircraft models globally (Rhee et al., 2020; Topham, 2021).

Regarding the *size of the aircraft*, most accidents occurred in aircraft with a maximum takeoff weight (MTOW) between 27,001 and 272,000 kg; however, the aircraft with an MTOW between 5,701 and 27,000 kg have the highest fatality rate and lowest survival rate among all categories (Ekman & Debacker, 2018). Larger aircraft have a lower percentage of fatal injuries and a higher possibility of survival (Ekman & Debacker, 2018; RGW Cherry & Associates Limited, 2016).

Flight phases have an impact on fatality ratio (Tiabtiamrat & Wiriyacosol, 2010). The approach, takeoff, and en route phases were found as among the highest number of hull loss and fatal accidents (Airbus, 2022; U.K. CAA, 2013). Another study found that most accidents occurred during the landing phase, whereas the approach, takeoff, and en route phases were reported to yield the highest fatality rates (Ekman & Debacker, 2018).

The ICAO’s Universal Safety Oversight Audit Programme (USOAP) EI is generally used as a metric representing States’ safety oversight systems (ICAO, 2019b). Importantly, it is one of the Global Aviation Safety Plan’s targets to be achieved by 2022, 2036, and 2030 (ICAO, 2019a). A report found that inadequate regulatory oversight and inadequate regulation were among the top circumstantial factors that frequently contributed to fatal accidents worldwide (U.K. CAA, 2013). Africa had the highest number of human factor-related accidents and incidents from 2000 to 2014

(Kharoufah et al., 2018). Interestingly, Africa had the lowest State of occurrence's EI by critical elements and audit areas (ICAO, 2019b). Therefore, State of occurrence's EI is another interesting factor for this research.

According to the ICAO air transport statistics from 2006 to 2019, the volume of passengers increased from 2.257 billion in 2006 to 4.486 billion in 2019 (ICAO, 2020b). Despite advanced technology enhancing flight safety and accident prevention being continuously developed, there were still high fluctuations in the global rate of fatalities (see Figure 1; Table 1 of the supplemental file)) (ICAO, 2020b, 2021).

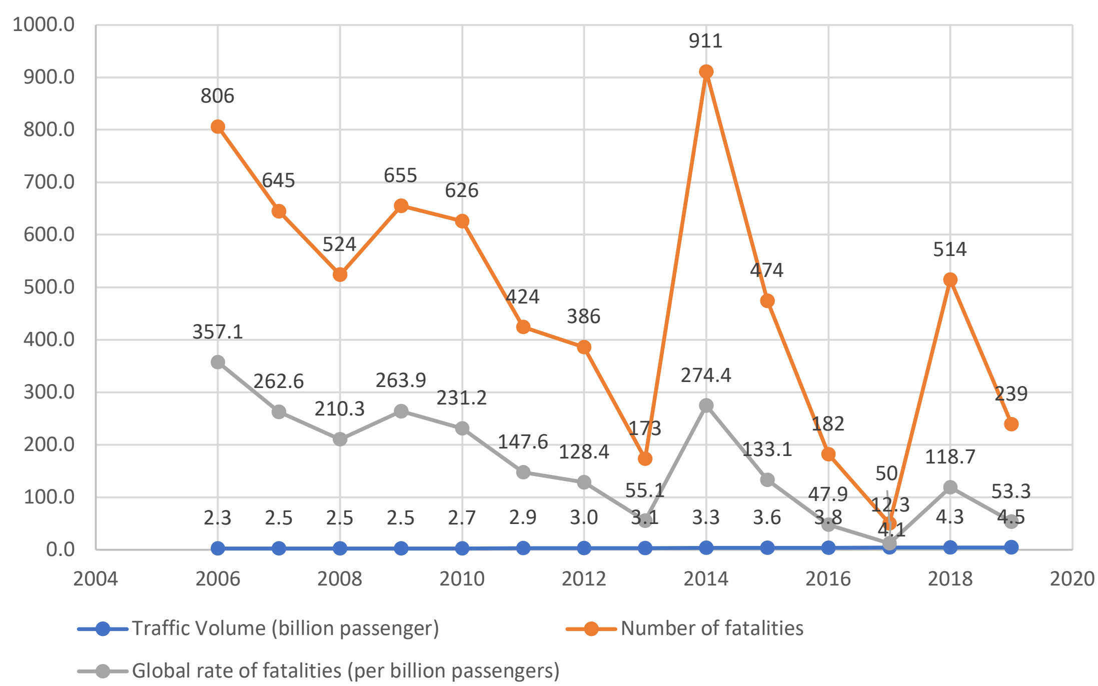

Figure 1 Passenger traffic volume, number of fatalities, and the global rate of fatalities.

According to an observation of the historical fatality record from 2006 to 2019, there was a similar pattern of accidents every three to five years, with some years showing a decreasing trend followed by a high increase in the following year. The number of fatalities sharply dropped from 911 to 50 in 2017 and suddenly increased by more than 900% in the latter year. Therefore, 2014–2017 was selected as the study period to examine the overall accidents of commercial operations which is the period before the COVID-19 pandemic that the traffic was under a normal operating condition. Moreover, the number of fatalities in 2017 reached its peak and gradually decline until 2017 before it rose up in 2018, which is the similar pattern to the observation in figure 1.

Logistic regression model is widely used for analyzing data when the outcome variable is discrete, with two or more possible values; also it is different from linear regression model where the outcome variable is dichotomous or binary (Hosmer & Lemeshow, 2000). Numerous studies relating to accidents or injury were using logistic regression which is a well-established model for evaluating probability between the outcome variables and independent variables. A binary logistic regression was primarily applied for estimating the likelihood between two outcome variables, for instances, mortality and severe injury; severely injured or dying and suffering minor or no injury; continue driving or changing lane; pedestrian's death (fatal and non-fatal); fatal or injured and property damage (Kwon et al., 2015; Moudon et al., 2011; Oh & Kim, 2010; Olszewski et al., 2015; Sze & Wong, 2007). Quite often the data collected from the accident report or database regarding severity was coded as an ordinal variable (Liu et al., 2020). Considering the nature of the variable being ordinal, the ordered logistic regression has been employed in previous studies to analyze in the model of dependent variable containing different levels, for example, injury severity, accident severity, reporting frequency, and crash severity (Feng et al., 2016; Moudon et al., 2011; Oltedal & McArthur, 2011; Rezapour et al., 2019). One study adopted censored regression for analyzing the non-negativity of the crash severity outcome, in which dependent variable was set to zero and the right limit was set to infinity (Ryan et al., 2022). This method is appropriate for the dependent variable that cannot be less than zero.

Methods

Study Design

This observational quantitative research study originated from the official accidents in the ICAO Safety Reports, in which selected accidents are those publicly available final investigation reports in English. The data were consolidated from Aviation Safety Network (ASN) aviation safety database, air accident investigation agencies, ICAO, EASA, EUROCONTROL, CAPA, civil aviation authorities, aircraft manufacturers, and aviation-related web pages (Table 3 and 4 of the supplemental file). The study variables were recorded in a Microsoft Excel spreadsheet and were then transferred to and analyzed in SPSS program version 28.0.0.0 (190) and Stata 17.0. There were three phases to this study. The primary outcomes were derived from Phase 1 by performing bivariate analysis, including correlation and post hoc tests between predictor and response variables, and in Phase 2, through multivariate analysis using binary logistic regression. Regarding secondary outcomes, Phase 3 involved other multivariate analyses, which were censored and ordered logistic regressions on the selected predictor variables from Phase 2. The last phase involved summarizing the key results, discussions, and major conclusions. The research process model is presented in Figure 2.

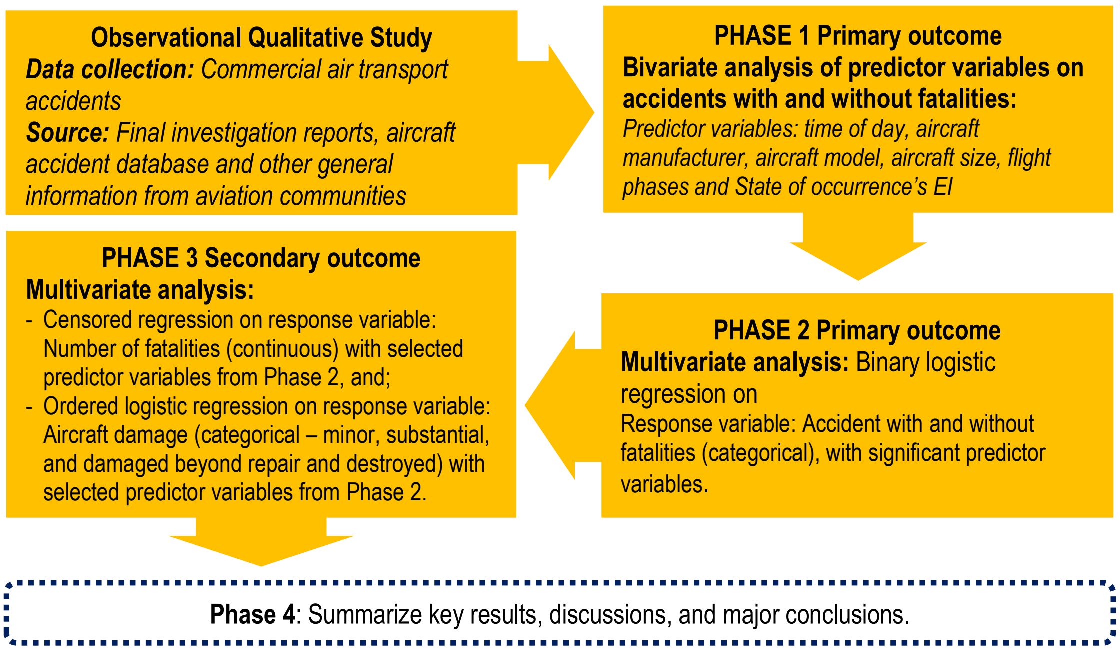

Figure 2 Research Process Model

Sample

The target population included 352 accidents in 2014-2017 (ICAO, 2021). All accidents reported are of those aircraft with at least a 5,700 kg MTOW. A total of 238 accidents were eliminated: 218 cases had not reached the final report stage (the accident investigation has not finalized), 14 cases did not publish a final report in English, and seven final reports could not be found. Therefore, the sample size was 114, which consisted of accidents with and without fatalities.

Procedures

The status of each accident was reviewed against the ASN database to select accidents that had concluded and for which a final investigation report was published. The characteristics of each accident were observed and recorded. Most reports provided all the information required for this study. However, some reports omitted information such as personnel and aircraft information. Therefore, some general information was collected from reliable external sources. The correlation tests were performed on predictor variables. Subsequently, Bonferroni's post hoc test was conducted on the significant predictor variables correlated with accidents with fatalities. Then, the predictor variable that had a statistically significant correlation with the response variable, was studied in other literature, or was recognized as one of the essential contributing factors was selected for regression. Multivariate analysis was performed to achieve the primary and secondary outcomes.

Data Analysis Approach

The data were input into an Excel spreadsheet and transferred to the SPSS program and Stata for analysis. There were nine study variables: 6 predictors and three responses. The predictor variables were a time of day, aircraft manufacturer, aircraft model, aircraft size, flight phases, and State of occurrence's EI. The response variables for the primary outcome were accidents with and without fatalities (categorical), whereas, for the secondary outcomes, they were a number of fatalities (continuous) and aircraft damage (categorical). The Kolmogorov-Smirnov test showed a p-value below .05; therefore, this study used nonparametric test because the data were not normally distributed. The correlations between predictor and response variables were identified using Spearman's rho, Pearson's chi-square, and Fisher's exact tests. The binary logistic regression assessed the impact on accidents with fatalities to derive the primary outcome, and censored and ordered logistic regressions were applied to study the effect on number of fatalities and aircraft damage. In this study, this study attempts to apply logistic regression to examine the probability of an occurrence of accident with or without fatalities, and the probability of the damages to the aircraft considering all contributing factors. The binary logistic regression fitted the nature of the binary outcome variable, and the ordered logistic regression suited the nature of the ordinal outcome variable. Further, the dependent variable for censored regression is the number of fatalities, which cannot be less than zero. For a linear regression, the dependent variable should be unbounded ($-\infty$ to $+\infty$), therefore it is inappropriate in this case. Therefore, the three data analysis methods are suitable for the types of collected data.

Results

Accidents with and without Fatalities

During 2014–2017, 114 accident cases met the criteria and were included in this study; of these, 14.9% were accidents with fatalities. The descriptive statistics between accidents with and without fatalities and six predictor variables: time of day, aircraft manufacturer, aircraft model by aircraft family, aircraft size by MTOW, flight phases, and State of occurrence's EI, are described (Table 5 of the supplemental file). Moreover, the bivariate analysis is illustrated in figure 3-8.

Time

The distribution of accidents by time of day was 39.5% (06:00–11:59), 31.6% (18:00–23:59), 21.9% (12:00–17:59) and 7% (00:00–05:59). The distribution of accidents with fatalities by time of day was 47.1% (06:00–11:59), 23.5% (12:00–17:59), 17.6% (00:00–05:59), and 11.8% (18:00–23:59). There was no statistically significant association between accidents and time of day (p = .094). However, 3 of 8 (37.5%) accidents were accidents with fatalities occurred in the early morning (00:00 – 05:59).

Aircraft

The distribution of accidents by aircraft manufacturer was 35.1% (Boeing), 13.2% (ATR), 12.3% (Airbus), 8.8% (de Havilland Canada), 5.3% (Embraer), 4.4% (Bombardier), 4.4% (McDonald Douglas), and 16.7% other (Fairchild/Swearingen, Fokker, Saab, Antonov, Beechcraft, British Aerospace, Let L, HESA, and Lockheed). The distribution of accidents with fatalities by aircraft manufacturer was 29.4% (ATR), 17.6% (Boeing), 11.8% (Airbus), 11.8% (Let L), 5.9% (Antonov), 5.9% (Bombardier), 5.9% (Fairchild/Swearingen), 5.9% (HESA), and 5.9% (McDonald Douglas). There was a statistically significant association between accidents and aircraft manufacturers (p = .018).

The distribution of accidents by aircraft model (family) was 20.2% (Boeing 737 Next Generation), 13.2% (ATR 42/72), 8.8% (Airbus 320 family), 8.8% (de Havilland Canada DHC-8 Dash 8), 7% (Boeing 737 Classic), 4.4% (McDonald Douglas DC-9/MD-80 series), 3.5% (Boeing 777), 2.6% (Bombardier CRJ-100 series), 2.6% (Embraer ERJ-145 family), 2.6% (Fairchild/Swearingen SA226/227), 2.6% (Saab 340/2000), and 23.7% other (Airbus A300, A330, A380; Antonov – An 26/140, An 74; Beechcraft 99/1900; Boeing 747,757,767; Bombardier CRJ-900; Embraer – ERJ-170, 190; Fokker 50, 100; British Aerospace Jetstream 31/41; Let L-410; Lockheed L-100 Hercules. The distribution of accidents with fatalities by aircraft model (family) was 29.4% (ATR 42/72), 11.8% (Airbus 320 family), 11.8% (An-26/140), 11.8% (Let L-410), 5.9% (Boeing 737 Next Generation), 5.9% (Boeing 747), 5.9% (Boeing 777), 5.9% (Bombardier CRJ-100 series), 5.9% (McDonald Douglas DC-9/MD-80 series), and 5.9% (Fairchild/Swearingen SA226/227). There was a statistically significant association between accidents and aircraft models (p = .046).

The distribution of accidents by aircraft size (MTOW) was 59.6% (27,001–272,000 kg), 34.2% (5,701-27,000 kg), and 6.1% (over 272,000 kg). The distribution of accidents with fatalities by aircraft size (MTOW) was 64.7% (5,701-27,000 kg), 23.5% (27,001-272,000 kg), and 11.8% (over 272,000 kg). However, 2 of 7 (28.6%) and 11 of 39 (28.2%) accidents were accidents with fatalities large-sized (over 272,000 kg) and small-sized aircraft (5,701–27,000 kg), respectively. There was a statistically significant association between accidents and aircraft size ($p = .007$).

Flight Phases

The distribution of accidents by flight phases was 43% landing, 12.3% en route, 10.5% taxi, 9.6% takeoff, 8.8% standing, 7% approach, 4.4% pushback/towing, and 4.4% initial climb. The distribution of accidents with fatalities by flight phases was 47.1% en route, 35.3% approach, and 17.6% initial climb. There was a statistically significant association between accidents with and without fatalities and flight phases ($p < .001$). However, there were no fatalities during the landing phase; whereas 6 of 8 (75%) accidents during the approach, 3 out of 5 (60%) during initial climb, and 8 of 14 (57.1%) during en route had fatalities.

Effective Implementation

The median (Quartile 1–Quartile 3) State of occurrence's EI of overall accidents was 92.2 (72.9–92.2), of which 92.2 (80.6–92.2) had no fatalities, and 71.7 (62–90.5) had fatalities. There was a statistically significant association between accidents with and without fatalities and State of occurrence's EI ($p = .045$).

The primary outcomes of the association between accidents and contributing factors were aircraft manufacturer, aircraft model, aircraft size, and flight phases. Bonferroni post hoc tests suggested that the proportion of accidents with fatalities in ATR; ATR 42/72; small-sized (5,701–27,000 kg); and during initial climb, en route, and approach phases, was greater than the proportion of accidents without fatalities ($p < .05$). However, the proportion of accidents without fatalities in medium-sized aircraft (27,001-272,000 kg) was larger than the proportion of accidents with fatalities ($p < .05$).

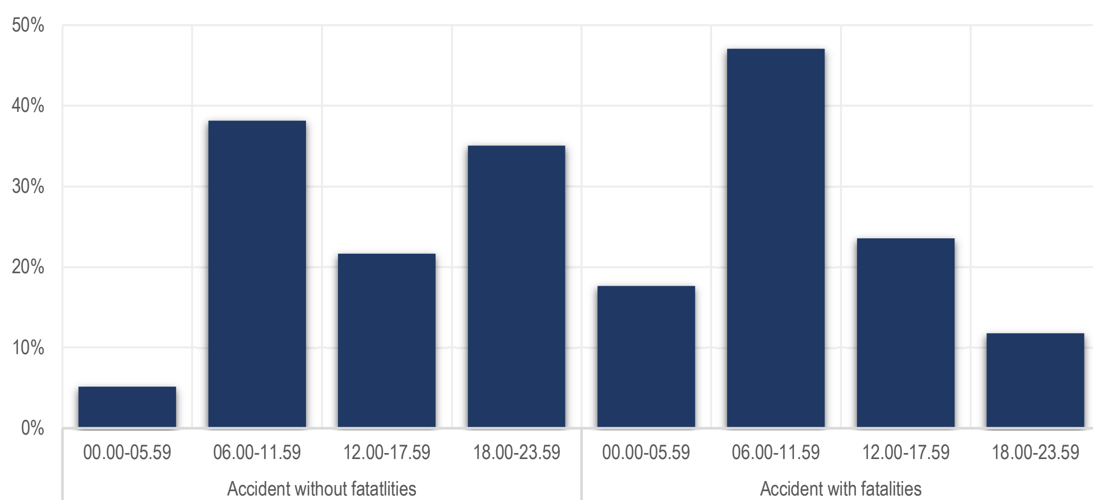

Figure 3 Bivariate analysis of time of day on accidents with and without fatalities.

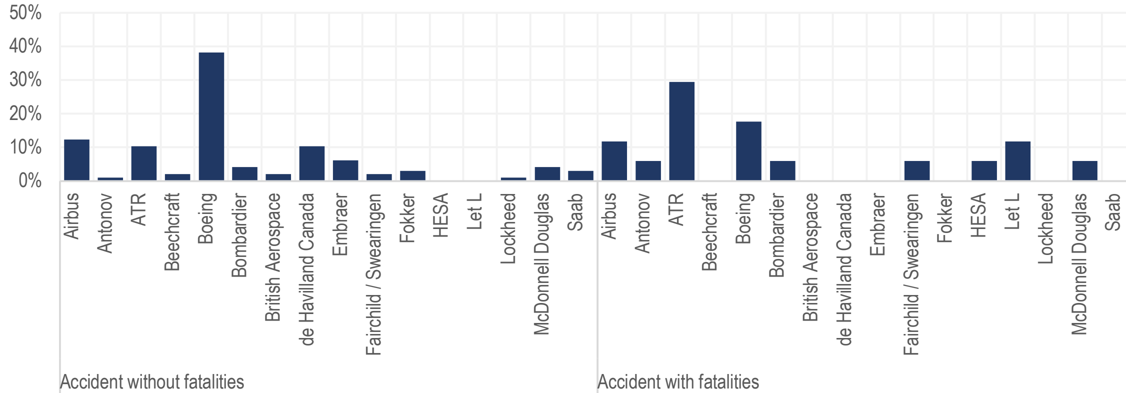

Figure 4 Bivariate analysis of aircraft manufacturers on accidents with and without fatalities.

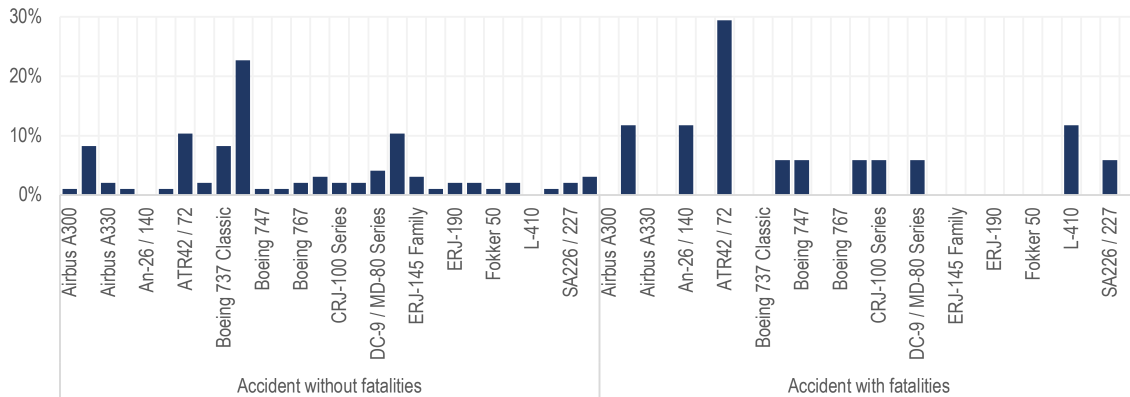

Figure 5 Bivariate analysis of aircraft models on accidents with and without fatalities.

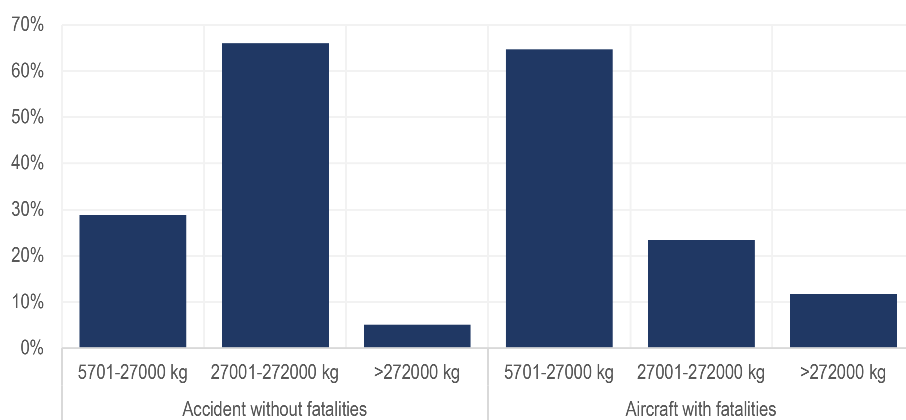

Figure 6 Bivariate analysis of aircraft size on accidents with and without fatalities.

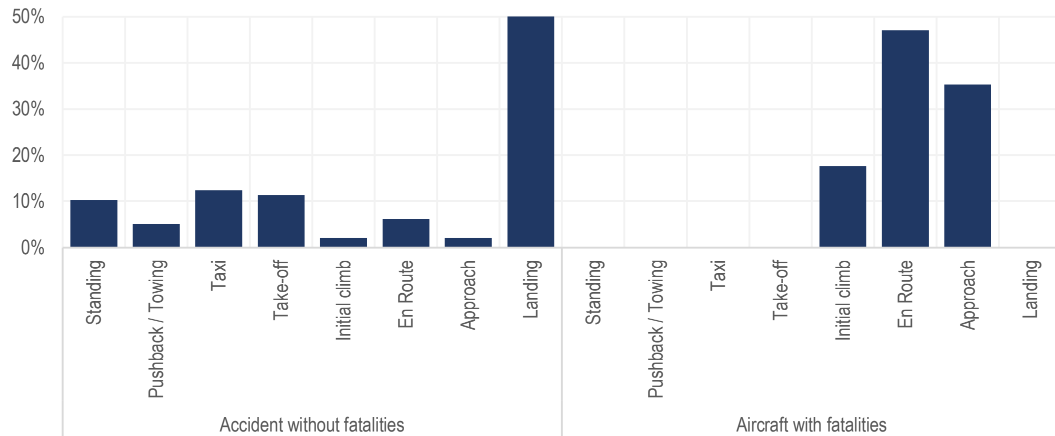

Figure 7 Bivariate analysis of flight phases on accidents with and without fatalities.

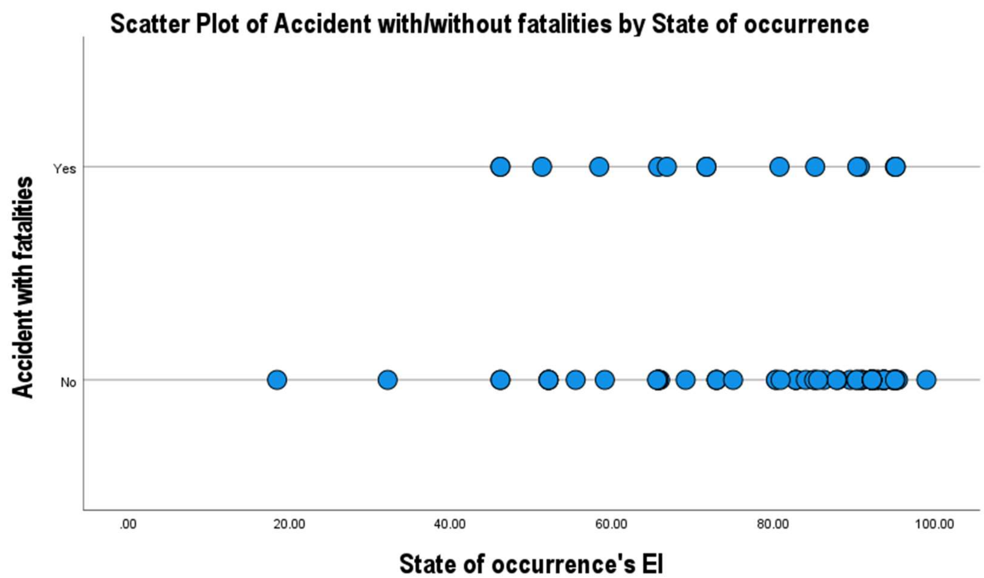

Figure 8 Bivariate analysis of State of occurrence's EI on accidents with and without fatalities.

Number of Fatalities

The descriptive statistics between a number of fatalities and predictor variables (time of day, aircraft size, and State of occurrence's EI), for which 17 cases with 981 fatalities are described (Table 6 of the supplemental file).

Time

The median (Quartile 1–Quartile 3) number of fatalities by time of day was 62 (32–89) for 00:00–05:09, 41.5 (3.5–156) for 06:00–11:59, 26.5 (4–50.5) for 12:00–17:59 and 24.5 (1–48) for 18:00–23:59. A minimum and a maximum number of fatalities during each period were 2 and 116 for 00:00–05:59, 2 and 239 for 06:00–11:59, 2 and 54 for

12:00–17:59, and 1 and 48 for 18:00–23:59. There was no statistically significant association between the number of fatalities and time of day (p = .338).

Aircraft

The median (Quartile 1–Quartile 3) number of fatalities by aircraft size (MTOW) was 133 (89–156) (27,001–272,000 kg), 121.5 (4–239) (over 272,000 kg), and 6 (2–45) (5,701 – 27,000 kg). The minimum and maximum numbers of fatalities by aircraft size (MTOW) were 1 and 54 (5,701–270,000 kg), 62 and 162 (27,001–272,000 kg), and 4 and 239 (over 272,000 kg). There was significant evidence of an association between number of fatalities and aircraft size (p = .007).

Effective Implementation

The median (Quartile 1–Quartile 3) of State of occurrence's EI (n = 17) was 71.7 (62–90.5). The minimum and maximum of State of occurrence's EI were 46.1 and 95.1. There was no statistically significant association between a number of fatalities and State of occurrence's EI (p = .203).

Aircraft Damage

The descriptive statistics are described between aircraft damage and predictor variables (time of day, aircraft size, and State of occurrence's EI; n = 113) (Table 7 of the supplemental file). There is one missing datum.

Time

The distribution of aircraft damage by time of day was 38.9% (06:00–11:59), 31.9% (18:00–23:59), 22.1% (12:00–17:59), and 7.1% (00:00–05:59). The distribution of aircraft damaged beyond repair and destroyed was 47.6% (06:00–11:59), 23.8% (12:00–17:59), 14.3% (00:00–05:59), and 14.3% (18:00–23:59). There was no statistically significant association between aircraft damage and time of day (p = .367). However, 3 of 8 (37.5%) accidents were aircraft damaged beyond repair and destroyed during the early morning (00:00–05:59).

Aircraft

The distribution of aircraft damage by aircraft size (MTOW) was 59.3% (27,001–272,000 kg), 34.5% (5,701–27,000 kg), and 6.2% (over 272,000 kg). The distribution of aircraft damaged beyond repair and destroyed was 61.9% (5,701–27,000 kg), 23.8% (27,001–272,000 kg), and 14.3% (over 272,000 kg). There was significant evidence of an association between aircraft damage and aircraft size (p > .001). However, 3 of 7 (42.9%) aircraft damaged beyond repair and destroyed were large-sized aircraft (over 272,000 kg).

Effective Implementation

The median (Quartile 1–Quartile 3) of State of occurrence's EI on overall aircraft damage was 92.2 (72.9–92.2), of which 92.5 (92.2–93.7) were minor, 92.2 (80.3–92.2) were substantial, and 71.7 (52.1–90.7) were damaged beyond repair and destroyed. There was significant evidence of an association between aircraft damage and State of occurrence's EI ($p = .002$).

Multivariate Analysis

Binary Logistic Regression

The response variable was accidents with and without fatalities, and significant predictor variables were aircraft manufacturer, aircraft model by aircraft family, aircraft size by MTOW, and flight phases. The time of day and State of occurrence's EI did not have a p-value less than .05. However, they were included in the regression because the p-value was close to .05 and it seems like the correlation result is contradicting with the previous study found that time of day contributed to pilot errors (Mello et al., 2008). Therefore, the author did not exclude time of day from the model. The Enter method was applied, and a model was developed. Though aircraft manufacturer, aircraft model, and flight phase were significantly associated with accident with fatalities, the variables were not statistically significant when generating the model with other variables. It appears that there is a multicollinearity.

Regarding the primary outcomes, the results revealed that the model was statistically significant compared with the null model, $\chi^2(6) = 23.79$, $p < .001$. At the time of day, aircraft size by MTOW and State of occurrence's EI explained 35.4% (Nagelkerke R2) of variance in the accidents with fatalities, and 88.2% of cases were predicted correctly. The reference category is 18:00-23:59 (time of day) and 5,701-27,000 kg (aircraft size by MTOW).

Table 1 demonstrates that early morning (00:00–05:59; $p = .006$), medium-sized aircraft (27,000 – 272,000 kg) ($p = .004$), and State of occurrence's EI ($p = .031$) are significant factors that contributed to the model. However, flights operated during 06:00–11:59 and 12:00–17:59 and large-sized aircraft with an MTOW of more than 272,000 kg were not significant and therefore did not have an impact on accidents with fatalities.

The OR indicates that accidents with fatalities are 48.8 times more likely to occur in early morning (00:00–05:59) than at night (18:00–23:59) (OR=48.77, 95% Confidence interval (CI) [3.1–772.1]). Additionally, the OR indicates accidents with fatalities are 0.10 less likely to occur when flying a medium-sized aircraft (27,000–272,000 kg) than when flying a small-sized aircraft (5,701–27,000 kg) (OR=0.10, 95%

CI [0.0-0.5]). Finally, every increase in State of occurrence's EI means the likelihood of accidents with fatalities occurring is 0.96 times lower (OR=0.96, 95% [CI 0.9-1]).

Table 1 Binary logistic regression results for assessing the impact between accidents with fatalities and contributing factors (time of day, aircraft size, and State of occurrence's EI).

Accidents with fatalities	β	*p*-value	Odds Ratio	95% CI	
Time of day					
00:00 - 05:59	3.887	.006	48.769	3.081	772.090
06:00 - 11:59	2.279	.052	9.764	.978	97.447
12:00 - 17:59	1.544	.205	4.685	.429	51.154
18:00 - 23:59 (reference)		.041			
Aircraft size (MTOW)					
5,701 - 27,000 kg (reference)		.009			
27,000 - 272,000 kg	-2.281	.004	.102	.022	.475
More than 272,000 kg	-.323	.755	1.382	.181	10.530
State of occurrence's EI	-.037	.031	.964	.932	.997
Constant	.207	.900	1.229		

Reference category: 18:00-23:59 and 5,701-27,000 kg

Censored Regression

The impact of time of day, aircraft size, and State of occurrence's EI on the number of fatalities was explored using censored regression. The minimum left-censored of 0 was assigned, and the upper limit was infinity. The reference category is 18:00-23:59 (time of day) and 5,701-27,000 kg (aircraft size by MTOW).

The secondary outcome is achieved by adopting censored regression. Table 2 suggested that early morning flight (00:00–05:59; $p = .018$) and State of occurrence's EI ($p = .047$) have a significant impact on the number of fatalities. All aircraft sizes were not significant factors in the model. The predicted number of fatalities was 199.6 times higher during the early morning flights (00:00–05:59) than at night (18:00–23:59). A 1% decrease in State of occurrence's EI was associated with an increase of about 3 fatalities in the predicted value of a number of fatalities.

Ordered Logistic Regression

Finally, ordered logistic regression was carried out to investigate the effect of time of day, aircraft size, and State of occurrence's EI on aircraft damage. The secondary outcome (see Table 3) obtained using ordered logistic regression, indicates that aircraft size ($p = .001$) and State of occurrence's EI ($p < 0.001$) have a significant impact on aircraft damage. No time categories were statistically significant; hence time categories cannot explain the level of aircraft damage. The reference category is 18:00-23:59 (time of day) and 5,701-27,000 kg (aircraft size by MTOW).

The odds of higher severity of aircraft damage for medium-sized aircraft (27,001–272,000 kg) was 0.14 lower than for small-sized aircraft (5,701 – 27,000 kg) (OR=.14, 95% CI [.04,.45]). Likewise, the OR of 0.95, suggested that, for a 1% increase in State of occurrence's EI, the severity of aircraft damage is expected to be 0.95 times lower (OR=.95, 95% CI [.92,.98]).

Table 2. Censored regression results for assessing the impact between the number of fatalities and contributing factors (time of day, aircraft size, and State of occurrence's EI).

Number of fatalities	β	Std. err.	t	P > t	95% CI	
Time of day						
00:00 - 05:59	199.600	83.306	2.400	.018	34.400	364.799
06:00 - 11:59	126.534	65.607	1.930	.056	-3.566	256.634
12:00 - 17:59	65.807	67.195	.980	.33	-67.443	199.056
Aircraft size (MTOW)						
27,001 - 272,000 kg	-94.119	97.750	-1.960	.053	-189.297	1.060
> 272,000 kg	-58.759	69.79	-.920	.362	-68.471	185.988
State of occurrence's EI	-2.138	0.88	-2.010	.047	-4.248	-0.028
Constant	-10.301	80.11	-.110	.916	-204.142	183.541

Reference category: 18:00-23:59 and 5,701-27,000 kg

Table 3. Ordered logistic regression results for assessing the impact between the aircraft damage and contributing factors (time of day, aircraft size, and State of occurrence's EI).

Aircraft Damage	Odds Ratio	Std. err.	z	P > z	95% CI	
Time of day						
00:00 - 05:59	5.654	5.398	1.810	.0700	.871	36.723
06:00 - 11:59	2.003	1.147	1.210	.225	.652	6.152
12:00 - 17:59	1.275	.824	0.380	.707	.359	4.524
Aircraft size (MTOW)						
27,001 - 272,000 kg	.138	.083	-3.280	.001	.043	.451
> 272,000 kg	2.116	2.250	.710	.481	.263	16.999
State of occurrence's EI	.946	.015	-3.550	<.001	.918	.976

Reference category: 18:00-23:59 and 5,701-27,000 kg

Discussions

The primary outcome of this study demonstrated that aircraft manufacturers, aircraft model, aircraft size, and flight phases have a statistically significant association with accidents. The post hoc test (Bonferroni) suggested that the proportion of accidents with fatalities in ATR, ATR 42/72, small-sized aircraft (5,701–27,000 kg), and initial climb, en route, and approach phases have higher proportion than accidents without fatalities, whereas medium-sized aircraft (27,001–272,000 kg) have a greater proportion of accidents without fatalities. Binary logistic regression conducted to achieve the primary outcome revealed the impact of time of day, aircraft size, and State of occurrence's EI on the accidents with fatalities, indicating that there is a high probability of accidents with fatalities occurring on an early morning flight (00:00–05:59), a small-size aircraft (5,701–27,000 kg), and flying to/from/in a State with a low EI. Furthermore, the secondary outcome from the censored regression suggested that operating flights during the early morning (00:00–05:59) and flying to/from/in a State with a low EI pose potential risks for an increasing number of fatalities, and the ordered logistic regression indicated that flying a small-sized aircraft (5,701–27,000 kg) and flying to/from/in a State with a low in EI pose a higher likelihood of higher severity of aircraft damage. The contributing factors are described and classified into four groups: time, aircraft, flight phases, and State of occurrence's EI.

Time

The past accidents revealed that flights in the morning flights had the most accidents. Time of day had no significant association with accidents. However, the proportion of accidents with fatalities was highest during early morning flights. The odds of accidents with fatalities occurring in the early morning flights are greater by approximately 49 times compared with night time operations. Likewise, the predicted number of fatalities in early morning flights is greater by approximately 200 times than in night operations. The results supported the previous literature indicating that pilots were exposed to a higher risk of attention issues and fatigue during early morning 00:00–05:59 (Mello et al., 2008; Roach et al., 2012). Therefore, the flights operating in the early morning (00:00–05:59) are at high risk.

Aircraft

The aircraft manufacturer is associated with accidents. Our study found that most accidents occurred with Boeing, ATR, and Airbus, and most accidents with fatalities occurred with ATR, Boeing, and Airbus, respectively. However, the Bonferroni test suggested that a higher proportion of accidents with fatalities occurred with ATR than in the proportion of accidents without fatalities. Boeing and Airbus were among the top three aircraft manufacturers with a high number of accidents and accidents with fatalities; however, their deliveries were higher and outsold ATR (ATR, 2022; O'Hare et al., 2022). However, ATR is a joint venture of Airbus and Leonardo (ATR, 2022), which sources Airbus design, technology, and production services (Airbus, 2021).

Likewise, the results of the aircraft model were consistent with those of the aircraft manufacturer in that most accidents occurred with Boeing 737 Next Generation, ATR 42/72, and Airbus 320 family, of which ATR 42/72 had the most accidents with fatalities. The results confirm the theory of the aircraft model in that the Boeing 737 and Airbus A320 were found to be related to accidents (Baidzawi et al., 2019). Similar to aircraft manufacturer results, more than 10,000 of these two aircraft models have been sold to date, making them the second and third largest fleets globally, in which Cessna 172 ranks first (Boeing, 2022; O'Hare et al., 2022). Interestingly, the post hoc test result also revealed that ATR 42/72 has the highest proportion of accidents with fatalities.

Our study exhibits that small-sized aircraft have the highest contribution to accidents with fatalities and aircraft damaged beyond repair and destroyed, as well as the higher proportion of accidents with fatalities than the proportion of accidents without fatalities, according to a post hoc test. Despite contributing to a large proportion of overall accidents, the post hoc test suggested that medium-sized aircraft (27,000–272,000 kg) represent the highest proportion of accidents without fatalities. This is consistent with the previous literature, which reported that a medium-sized aircraft of MTOW 27,001–272,000 kg had the most frequent accidents, whereas a small-sized aircraft of MTOW 5,701–27,000 kg had the highest fatality rate (Ekman & Debacker, 2018). Moreover, aircraft size has an impact on accidents with fatalities, as well as aircraft damage, but not on a number of fatalities. Furthermore, it is suggested that flying in a medium-sized aircraft represents a lower risk of being in an accident with fatalities and experiencing higher severity of aircraft damage than flying in a small-sized aircraft by 0.10 times and 0.14 times, respectively. Another study suggested that larger aircraft have a lower percentage of fatal injuries and a higher possibility of survival (Ekman & Debacker, 2018; RGW Cherry & Associates Limited, 2016). Our results indicate that large-sized aircraft have the most fatal accidents among overall accidents and the second-highest median number of fatalities; notably, this is significantly associated with a number of fatalities. However, the censored regression illustrated that the number of fatalities is not affected by the aircraft size. This could be due to the low number of fatalities in large-sized aircraft, as one of the two accidents involved only four-passenger fatalities.

ATR and ATR 42/72 could be related to accidents with fatalities due to the nature of their short-haul flying operation, which is linked to pilot fatigue that could contribute to accidents (Air Transport Action Group [ATAG], n.d.; ATR, 2014; Olaganathan et al., 2021). Interestingly, large-sized aircraft should be further explored among a larger sample to confirm if size has an impact on a number of fatalities.

Flight Phases

The correlation test showed a significant relationship between flight phases and accidents. The aviation community considers the approach and landing phases key safety issues and high risks (Flighy safety foundation, 2022). Our statistics also confirm that almost half of the accidents occurred during the landing phase; surprisingly, zero fatalities occurred during this phase. Although the en route contributed only 10.5% of overall accidents, this phase had the most accidents with fatalities, followed by approach and initial climb. The percentages of fatal accidents out of the overall accidents are very high in the approach, initial climb, and en route phases. Interestingly, the Bonferroni test showed that the proportion of accidents with fatalities was higher in the initial climb, en route, and approach. According to previous literature, the highest fatality rate and highest number of fatal accidents occurred in the approach, takeoff, and en route phases (Ekman & Debacker, 2018; U.K. CAA, 2013). Another report by Airbus suggested that en route, initial climb, and approach were the phases with the highest proportion of fatal accidents out of its hull loss accidents (Airbus, 2022).

The en route, initial climb, and approach phases are frequently reported to be involved potential risk of accidents with fatalities. However, a significant proportion of fatal accidents occur during the initial climb, which is fairly close to approach and landing. Therefore, this phase could be another interesting phase to further explore with a large sample size.

Effective Implementation

The ICAO's USOAP EI on State of occurrence does not have a significant relationship with accidents and the number of fatalities. However, there was a significant association with aircraft damage. This predictor variable was not excluded because it is a leading indicator and is one of the Global Aviation Safety Plan targets and a measure of State's safety oversight capability (ICAO, 2019a, 2019b). The global average EIs between 2014–2017 were 62%, 63%, 64.7%, and 60%, respectively (ICAO, 2021). This study found that the median overall State of occurrence's EI was 92.2 (IQR: 72.9–92.17), higher than the global average State of occurrence's EI. Accidents with fatalities have a lower median score than accidents without fatalities. According to observation, the median of State of occurrence's EI is 71.7, which is the same for accidents with fatalities, a number of fatalities, and aircraft damaged beyond repair and destroyed. Binary and ordered logistic regressions indicated that when State of occurrence's EI decreases by 1, the probability of accidents with fatalities and higher severity of aircraft damage increase by 0.96 times and 0.95 times, respectively. Correspondingly, a 1% decrease in State of occurrence's EI will increase the number of fatalities by approximately 3. Therefore, a higher state of occurrence's EI would signify a reduction in the likelihood of accidents with fatalities, number of fatalities, and higher severity of aircraft damage.

Conclusions and Recommendations

A total of 114 accidents were observed, and analyzed using binary logistic, censored, and ordered logistic regressions. Aircraft manufacturer, aircraft model, aircraft size, and flight phases are associated with accidents. Binary logistic regression suggested that time, aircraft size, and State of occurrence's EI are significant contributing factors to accidents with fatalities. Time of day and State of occurrence's EI were not excluded due to their importance to air accidents and safety. The secondary outcome revealed that specific time of day and State of occurrence's EI have an impact on a number of fatalities. In contrast, ordered logistic regression suggested that certain aircraft size and State of occurrence's have an impact on the severity of aircraft damage.

As a result, the policy- and decision-makers, including regulators and aviation professionals, should be aware that an early morning flight (00:00–05:59), a small-sized aircraft (5,701–27,000 kg), and flying to/from/in State with a low EI are at higher risks of having an accident with fatalities, higher severity of aircraft damage, and a higher number of fatalities. These characteristics should enable early detection, prediction, mitigation, and prevention of fatal accidents. Notably, State of occurrence's EI is the only factor that has an impact on all predicted models. According to the ICAO (ICAO, n.d.), "any change in the status of a protocol question for a State will lead to an update of the State's EI". Therefore, this contributing factor could be the key to improving State's aviation safety system considering the ICAO's USOAP critical elements and audit area.

Further studies should explore accidents with fatalities associated with the nature of small-sized aircraft, the impact of large-sized aircraft on a number of fatalities, and the impact of the initial climb phase on fatal mishaps with larger sample size.

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