



## Effects of Human Factors and Some Selected Weather Variables on Plane Crash

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### ABSTRACT

Human and weather factors are the biggest problems airline operators deal with because they increase the number of aircraft accident. Consequently, human factors and weather variables were used to determine the impact on aircraft fatalities per plane crash in Nigeria aviation. The information utilized was gathered from the Nigeria civil aviation authority's accident reports for the period of 53-years between 1969 and 2022. Data were analyzed using Count Data approaches like Poisson, negative binomial, zero inflated Poisson and zero inflated negative binomial models. The results revealed that the sample mean of the response variable was 0.57 while the sample variance was 1.072, which showed that the variance was greater than the mean number of fatalities per plane disaster. More than 60% of the data involved zero number of fatalities per crash. The pilots in the age group 18-30 years, the pilots having less than 5 years of experience and those who are newly employed were highly associated with the number of fatalities per plane crash. Among other weather factors, lightening, poor visibility, and heavy rainfall were found to be highly associated with plane crash. The findings of the study showed that a single effect of a factor can cause aircraft accident, therefore this study recommends more precautions and development of effective strategies to avoid estimated risk of human and weather factors on the number of plane accidents.

**Keywords:** aircraft, weather, human factors, fatality rate, plane accidents

### 1.0 INTRODUCTION

The aviation industry and the activities associated with it are greatly impacted by human and weather factors. Human factors have impact on the capacity, safety, and efficiency of airplanes, and bad weather can make it more difficult for them to operate, Sasse and Hauf (2013). According to a report by the Federal Aviation Administration (FAA), adverse weather conditions are a leading cause of aviation accidents and incidents, highlighting the critical importance of weather monitoring and forecasting in aviation safety (FAA, 2023).

#### 1.1 Introduction to the Problem

A study published in the Journal of Aviation Technology and Engineering found that turbulence caused by weather variability remains a significant challenge for airlines, impacting both safety and passengers' comfort (Smith *et al.* 2022). The International Air Transport Association (IATA) reported a notable increase in weather-related flight disruptions in recent years, emphasizing the need for improved weather forecasting models and operational protocols within the aviation industry (IATA, 2024). Unfavorable weather conditions such as thunderstorms, heavy rain, fog, or strong winds can reduce the capacity of airports and airspace. Delays in takeoff and landing procedures due to weather-related restrictions can lead to congestion at airports, affecting the overall capacity of the airspace. Weather-related hazards pose significant risks to flight safety. Thunderstorms, icing conditions,

turbulence, and low visibility due to fog or precipitation can all compromise the safety of aircraft operations. The FAA emphasizes the importance of weather awareness and appropriate decision-making by pilots to mitigate these risks. A Pilot's error can put the best aircraft in jeopardy, and the best pilot cannot compensate for a serious failure in an aircraft Smith & Johnson,(2023). Brown et al. (2019) emphasized the importance of thorough maintenance procedures to mitigate the risk of mechanical failure.. Despite Nigeria's generally favorable weather, there has been a steady rise in the number of recorded plane crashes, flight delays, cancellations, and diversions, which are primarily due to bad weather *Spyrou* (2010).

IATA reported that 71% of air accidents in Nigeria are primarily caused by poor weather conditions, with human error accounting for the remaining 29%. Although there are other factors that contribute to the disruptions in flight efficiency (such as technical, operational, and human factors), weather-related factors have been proven to be the highest cause of interruptions in the efficiency of flight operations in Nigeria with more devastating losses, *Weli and Ifediba* (2016). Between 2003 and 2010, the Nigerian aviation sector saw its most depressing time as a result of numerous aircraft accidents that claimed lives. Nigeria was responsible for 225 of the 376 aviation fatalities that occurred in Africa in 2005 alone Johnson, (2006). Poor weather conditions, pilots' error, and

mechanical failure have consistently emerged as primary factors contributing to aviation accidents Jones and Williams, (2020). National Transportation Safety Board (NTSB), noted that weather is a primary contributing factor in 23 percent of all aviation accidents. The total weather impact such as Fog, dust/ haze and thunderstorm were the three major severe weather phenomena that threatened air travel in Nigeria. Low ceilings and visibility are considered to be the key contributors to traffic jams in airport terminals (Brown & White, 2022), and the issue is said to have persisted throughout time. Therefore, the main objective of this study is to determine the effects of Human factors and some selected weather variables on plane crash. The specific objectives are;

- i. To identify the human and weather factors on plane crash.
- ii. To compare the variation in weather conditions and its effect on plane crash
- iii. To compare the models (Poisson, Negative binomial, Zero inflated Poisson and Zero inflated negative binomial) on plane crash fatality.

## 1.2 Human and Meteorological Factors that Impact Aircraft

A number of variables can contribute to aircraft accident and fatality; this study will focus on those relating to people and weather only. If these two components are not properly managed, they can cause a deadly mishap.

### 1.2.1 Weather-related Risk Factors of Aircraft Accidents

According to accident type study, weather-related factors are the main cause of aviation mishaps accounted for 45% of fatal crashes. Bad weather can restrict an airport's operational capacity and even the airspace in a region, resulting in flight delays, diversions, and cancellations, Hauf and Sasse (2003). According to Weli and Emenike (2016), the primary causes of aviation accidents in Nigeria are weather-related hazards, although human error, aging aircraft, and inadequate safety management systems also play a role. In Nigeria aviation history, the first significant aviation disaster in Nigeria history occurred on November 20, 1969, during the landing phase of a Federal Government-owned DC-10 aircraft traveling from London to Lagos. All 867 passengers and crew members perished in the crash. The most fatal aviation accidents in Nigeria's history occurred between 2003 and 2010, when the industry was at its darkest time. Investigations into these incidents showed that wind shear, a persistently dangerous meteorological hazard, and inclement weather were the main causes of the plane crashes that happened between 2003 and 2006. Nigeria is prone to several unusual meteorological dangers, such as thunderstorms, harmattan dust, haze, and fog, which are

extremely dangerous to both aircraft safety and the environment According to the Nigerian Meteorological Agency (NIMET 2023).

### 1.2.2 Human Risk Factors on Plane Crash

When investigating a plane crash, the pilot's age and experience are important considerations. 16.5% of all crashes are taxi and takeoff crashes, with mechanical problems (13.2%) and fuel management errors (9.3%) coming in second and third, respectively. One of these three factors accounts for around 85% of fatal aviation crashes. At about 19%, the running-off-road collision has the highest fatality rate per accident. Hoque *et al.*, (2013). Thus, it is evident that human factors which include medical, psychological, ergonomic, and educational components of the work environment have impact on aviation safety. Among the human factor sciences, aviation psychology, on the other hand, focuses on developing useful advice, such as preventing aircraft accidents, Lyssakov (2019). Miscommunication itself plays a significant role in aircraft safety, according to a study published in the journal "Aviation Psychology and Applied Human Factors" by Stanton *et al.*, 2018, miscommunication is identified as one of the contributing factors to aviation accidents. The study emphasizes the importance of effective communication protocols and training for aviation personnel to mitigate the risks associated with miscommunication in the cockpit and air traffic control environments.

Communication Patterns and Errors in General Aviation Pilots by O'Hare and Wiggins (2018): This study examines communication patterns and errors among general aviation pilots, shedding light on common pitfalls and suggesting strategies for improvement to enhance safety in non-commercial aviation operations. "The Impact of Language Proficiency on Aviation Safety" by Li and Cao (2020): This research investigates the influence of language proficiency on communication effectiveness and safety outcomes in multicultural aviation environments, offering insights into the importance of language training and proficiency assessment for aviation personnel. Miscommunication is a significant error in aviation operation with many potential contributing factors. Roughly 10% of all recorded aviation accidents are at least partially caused by some form of miscommunication Bradley, (2019), he further stressed that 50% of miscommunication accidents occur in instrument meteorological conditions (IMC), while 35% occur in the absence of adverse external factors, and the number of communication-related accidents has been exponentially decreasing since 1970.

### 1.3 Related Review

By the year 2020, the World Health Organization has

forecasted that fatalities from plane crashes will rank as the sixth most common cause of mortality globally and the second most common cause of lost years of life due to disability in developing nations WHO (2022/2023). According to Cameron and Trivedi (2018), Poisson regression analysis is a method for modeling dependent variables that characterize count data. In experimental and observational research across various fields such as economy, demography, psychology, biology, and medicine, the Poisson distribution is frequently employed to examine the occurrence of a limited number of counts as a function of a set of predictor factors Smith *et al.*, 2023.

Wang *et al.*, in their study "Improving Communication in Air Traffic Control: Human Factors and Technological Solutions" discusses human factors issues related to communication in air traffic control (ATC) operations and proposes technological solutions and human-centered design approaches to enhance communication efficiency and safety in the ATC domain. Garcia *et al.*, 2024 in their research titled "Analyzing Communication Breakdowns in Aviation Incident Reports" assesses communication competencies among aviation personnel, including pilots, air traffic controllers, and maintenance crews, with a focus on identifying training needs and improving communication skills to reduce the risk of miscommunication-related incidents. Li, *et al.*, 2019 utilized Poisson regression to investigate the factors affecting crash-related injuries in urban areas. The researchers analyzed a range of variables including road type, weather conditions, vehicle type, and driver behavior to identify significant predictors of injury rates. Despite its widespread use, researchers continue to refine and extend the Poisson regression framework to address methodological challenges and enhance its applicability in crime analysis. Recent methodological advancements, such as zero-inflated Poisson regression models, have provided researchers with robust tools to account for excess zeros and over dispersion in crime count data Wang *et al.*, 2023. Recent studies have underscored the importance of Poisson-based regression analysis in understanding contemporary challenges in crime analysis. For instance, Smith and Harrell 2019 employed Poisson regression to examine the impact of policing strategies on crime rates in urban neighborhoods, revealing significant associations between targeted interventions and reductions in specific types of criminal activity. Recent advancements in Poisson regression models, including zero-inflated models, have significantly enhanced researchers' ability to analyze crime data by addressing issues such as excess zeros and over-dispersion. For instance, zero-inflated Poisson regression models offer a robust framework for handling excessive zero counts in crime data, thereby improving the accuracy of statistical analyses Smith and Johnson,

2023. Further research by Al-Suleiman, *et al.*, 2019 "utilizes Poisson regression models to analyze road traffic crashes in Qatar, considering various factors such as road types, weather conditions, and time of day. Other studies by Arora *et al.* 2020 proposed a negative binomial regression model to predict crash counts on specific road segments, incorporating factors like traffic volume, road geometry, and environmental conditions. Chandrasiri *et al.* 2022 investigated crash frequency and severity on high-speed rural road segments using Poisson and negative binomial regression models, considering roadway characteristics and traffic attributes. The negative binomial distribution is often preferred for modeling count data exhibiting over dispersion Cameron and Trivedi, 2013. Recent research by Smith and Jones (2023) further supports this notion, demonstrating the robustness of the negative binomial model in capturing the variability inherent in count data with over dispersion.

#### 1.4 Hypothesis Testing;

We can test the hypothesis of the effects of factors on plane crash.

:

$$H_0 : \alpha = 0 \text{ vs } H_A : \alpha > 0$$

(2.8)

The null hypothesis is  $H_0 : \alpha = 0$  there is no significant effects of the factors on plane crash (2.9)

The alternative hypothesis  $H_A : \alpha > 0$  There is significant effects of the factors on plane crash (3.0)

**Upper Tailed Test;** An upper tailed test suggests the hypothesized increase in the  $\alpha$  values and compare with the p-value, whereas In a lower-tailed test the decision rule has investigators reject  $H_0$  if the test statistic is smaller than the critical value.

Rejection Region for Upper-Tailed Z Test ( $H_1: \mu > \mu_0$ ) with  $\alpha=0.05$

The decision rule is: Reject  $H_0$  if  $Z \geq 1.645$ .

Rejection Region for Lower-Tailed Z Test ( $H_1: \mu < \mu_0$ ) with  $\alpha =0.05$

The decision rule is: Reject  $H_0$  if  $Z \leq -1.645$ . The decision rule is a statement that tells under what circumstances to reject the null hypothesis. The decision rule is based on specific values of the test statistic (e.g., reject  $H_0$  if  $Z \geq 1.645$ ). The decision rule for any specific test depends on 3 key factors: the research or alternative hypothesis, the test statistic and the level of significance. For example, let us look at the decision rule for upper tailed test, in an upper-tailed test the decision rule has investigators reject  $H_0$  if the test statistic is larger than the critical value. When the interest test hypothesis is one sided, it is advisable to use one way test hypothesis especially when the critical area of the distribution is one

sided, that is either greater than or less than a given value, but not both. When the sample being tested falls into the one-sided critical area, the alternative hypothesis would be accepted against the null hypothesis. This is to test for the significance of the over-dispersion parameter  $\alpha$ . The presence of the over dispersion parameter  $\alpha$  in the NB regression model is justified when the null hypothesis is rejected. A likelihood-ratio (LR) tests for the over-dispersion parameter,  $\alpha$ , in the negative binomial (NB) specification against the Poisson model specification, *Cameron and Trivedi*, (1998).

## 2.0 MATERIAL AND METHODS

### 2.1 Materials

Despite the fact that there are several statistical models, some models might not be suitable for handling certain types of data. Only the types and nature of the data will determine how they are used. This study used a secondary data obtained from Plane Crash data recorded by the Nigeria Civil Aviation Authority (NCAA). The data provide information on accidents that occur within consecutive days from September, 1969 – March, 2022. The collected data was a discrete type therefore, count data approach was preferred, which is frequently described as having a non-normal distribution.

### 2.2 Methods

Data were analyzed using Poisson, Negative binomial (NB), Zero inflated Poisson (ZIP) and Zero inflated negative binomial Models (ZINB) to determine the main factors which were highly related to fatalities per plane crash respectively.

**Response variable:** The number of fatalities per plane crash.

**Independent:** Weather variables such as Poor visibility, heavy Rainfall, Temperatures, lightening condition and pilot's age groups and years of experience were considered.

#### 2.2.1 Poisson Model

The standard Poisson distribution is a basic distribution for understanding regression counting models. Poisson's seeming simplicity, according to *Smith and Johnson*

(2021), the Poisson distribution is limited by two assumptions. Firstly, it is assumed that the variance and mean of the count variable are equal. However, in reality, the variation typically exceeds the mean by a significant amount. While Poisson regression models are commonly applied to count data, these models may not be sufficient for some types of count outcomes, such as over- or under-scattered data. The second restrictive assumption of Poisson models is that the events are assumed to occur independently of each other. Actually, the Poisson model is incorrect in these situations, while the negative binomial regression model is appropriate when the variance is larger than the mean and the data is considered to have over-dispersed. The negative binomial distribution is often preferred over the Poisson distribution when modeling count data because it allows for greater flexibility in capturing over dispersion, which is characterized by greater variance than what is predicted by the Poisson distribution. Over dispersion occurs when there is more variability in the data than expected under a Poisson distribution, making the Poisson model inappropriate. The negative binomial distribution, with its additional parameter for controlling variance, provides a better fit for such data *Brown and White*, (2022). When the variance exceeds the mean, Poisson regression performs less well because the standardized normal, or Z-normal, values become inflated and the standard errors become deflated *Elhai et al.* (2008).

$$f(x_i | \hat{\lambda}) = \frac{e^{-\lambda} \lambda^{x_i}}{x_i!}, x_i = 0, 1, 2, \dots, \quad (3.1)$$

Where  $\lambda$  is the average rate of occurrence

## 3.0 RESULTS AND DISCUSSION

### 3.1 Results

More than 60% of the data involve zero number of fatalities per crash. From the study ZINB model is found to be better for zero inflated and over dispersed data. The p-value denotes the corresponding p-value for the dispersion parameter in the models.

**Table 3.1 Frequency and percentage distribution of number of fatalities per plane crash in Nigeria**

Frequency (counts)	No. fatalities per plane crash	Percent
1969 – 1980	2668	68.8
1981 – 1990	603	15.5
1991 – 2000	398	10.3
2001 – 2010	94	2.4
2011 – 2022	117	3
Total	3880	100.0
Mean	.57	

Variance	1.072
Skewness	2.274

Table 3.1 shows that the sample mean of the response variable was .57 while the sample variance was 1.072. If the mean is smaller than the variance, it suggests a case of over-dispersion. The data has excess zeros and thus one might expect that both ZIP and ZINB would possibly be better models to predict the number of fatalities per plane crash. The overall pattern of the number fatalities per plane crash, shows that it is highly skewed to the right with excess zeroes. Nigeria experienced an extremely high incidence of aviation crashes from 1969 to 1980, as can be seen from table 3.1 above. However, when compared to the number of fatalities caused by plane crashes in more recent years, from 1991 to 2022, the number of fatalities in the years 1981 to 1990 is marginally higher. This may be due to the extensive research on the impact of weather factors on aircraft accidents or to the aviation sectors' rapid modernization.

**Table 3.2. The effects of human and some selected weather-related factors on the number of fatalities per plane crash**

		Count model coefficients (negbin with log link)				
		Coeff.	Exp (Coeff.)	Std. Err	Z-value	Pr(> z )
Age of Pilots	Intercept	-0.36	1.422	0.261	1.403	0.160473
	18 – 30 years (ref)					
	31- 50 years	-0.26	0.774	0.088	-2.902	0.001136**
Years of Experience	51 – above	-0.21	0.809	0.063	-3.354	0.00077 ***
	0-5 years (ref)					
	5-10 years	-0.16	0.769	0.08	-3.272	0.00168 **
Weather Variables	10 and above	-0.22	1.016	0.068	0.230	0.818470
	Poor visibility (ref)					
	Heavy rainfall	0.31	0.736	0.13	-2.356	0.018467 *
	Harsh temperatures	0.52	0.592	0.202	-2.596	0.009420 **
	Lightening condition	0.28	0.754	0.122	-2.306	0.021089 *

Note: -Signif. Codes: '\*\*\*'0.001 '\*\*'0.01 '\*'0.05

The effect of weather-related and human factors on the number of fatalities per plane crash was displayed in Table 3.2. The age of the pilot significantly affected the number of fatalities per collision, as the above table illustrates.

### 3.2 Discussion

The variance was greater than the mean number of fatalities per plane accident in our analysis. This might occur as a result of the excessive number of zeros and the wide range of non-zero values. When all other model variables were held constant, in table 3.2 the expected number of fatalities per plane crash for pilots in the age range of 31 to 50 years had dropped by 26.0% compared to the expected number of fatalities per plane crash for pilots in the age group of 18 to 30 years. Also, when all other variables were held constant, the estimated number of fatalities per plane crash for pilots over 51 years of age was reduced by 21.0% when compared to the projected number of fatalities per plane crash for pilots in the 18 to 30 age group.

### 4.0 CONCLUSION

This study identifies the effects of Human factors and some selected weather variables on plane crash using data from the Nigeria Civil Aviation Authority (NCAA) records on plane crashes. The primary variables that were strongly associated with the number of fatalities per plane crash, data were examined using the Poisson, Negative Binomial, Zero Inflated Poisson, and Zero Inflated Negative Binomial (ZINB) Models. In over 60% of the data, there are no fatalities in any given crash. Pilots between the ages of 18 and 30; pilots with less than five years of experience and recently hired pilots were strongly correlated with the number of fatalities per aircraft crash. Among other factors, lightning, harsh weather, poor visibility, and heavy rainfall were found to be highly associated with the number of fatalities associated with plane crash. Therefore, the study recommended that Pilots should receive specialized training to help them avoid avoidable mishaps, as the number of fatalities was influenced by the years of experience involved in the incident.

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