Uncovering hidden patterns in flight safety data through statistical analysis

by

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Abstract

This research aims to identify trends in data that indicate a potential increase in the risk of aviation accidents. By analyzing aviation incident historical data, we look at the relationship between incidents on the ground and those in flight, as well as minor incidents and major incidents within an Army aviation unit. Machine learning algorithms applied to data sets involving crew experience and mishap reports may determine whether indications exist that forecast a higher risk of an aviation incident for an aviation organization within the U.S. Army. Achieving zero preventable mishaps regarding aviation operations requires a proactive approach to hazard identification and risk management, which is explored in the methods of this project. The results from the analyzed data determine if any consistencies exist in the conditions within an aviation unit leading up to recordable mishaps.

Keywords: aviation, safety, incident, accident, risk, mitigation, machine learning, army

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Chapter 1 - Introduction

Introduction

Aviation incidents occur on the ground and in flight and are categorized accordingly. They are separated for reporting procedures as “flight”, “flight-related”, and “ground”. Generally, flight-related incidents are likely more substantial, causing more damage or loss of life. Aviation incidents are classified based on the severity of damage caused or loss of life, from the most significant “class A” incidents to the least substantial “class E” incidents (Headquarters, Department of the Army, 2023a). US Army incidents are rated as “class A” if an incident involves the loss of life or greater than $2.5 million in damage. Incidents are rated as a “class E” if greater than $5,000 but less than $25,000 in damages occur (Headquarters, Department of the Army, 2023a). Incidents that range between these two classifications vary by the value amount of damage done in dollars (Headquarters, Department of the Army, 2023a).

US Army Aviation units are organized by type of airframe and individual qualifications. Lower echelon units are meant to operate independently and complement the Combat Aviation Brigade (CAB), which comprises all the smaller organizations and incorporates all three main US Army airframes. These airframes are the AH-64 Apache, UH-60 Blackhawk, and CH-47 Chinook. An aviation “company” is the smallest organization and is homogeneous in the type of airframe. An aviation “battalion” may comprise one or more types of airframes and consist of several companies. Typically, three companies in a battalion contain aircraft, and three other companies comprise ground support elements. Multiple battalions make up a CAB (Sherman, 1991). This research consolidates aviation incidents at the battalion level and focuses on incidents rated between class A and class D.

As a learning organization, the Army continuously develops methods to increase combat efficiency and maintain combat power (Richard, 1997). One way that the US Army accomplishes this is by ensuring the longevity of its personnel and equipment. The Army recognizes this concept formally as a force preservation function of warfighting that enables commanders with the ability to employ the maximum amount of lethality to accomplish a mission (Headquarters, Department of the Army, 2019). With this knowledge of incident trends, commanders can identify a baseline of risk and develop mitigation strategies that reduce the likelihood of future mishaps. The purpose of this research is to determine the feasibility of identifying those trends that indicate an increased probability of future aviation mishaps.

Information showing a pattern of conditions historically linked to units with class-A mishaps helps a unit commander assess their current status. With this data, the commander can see if similar conditions exist and better evaluate the risk of a major aviation mishap. If the commander believes such an event is possible, they can take steps to prevent incidents that might lead to a class-A or B mishap. This research will help the US Army better understand how to predict mishap chances based on the conditions within aviation units. It will support safety researchers in exploring more connections between diverse data and deepen the understanding of aviation incident prediction. If a relationship is found, it could save lives and protect equipment worth millions. If no relationship is found, then time and resources can be redirected to other research areas. At a minimum, this study will eliminate some assumptions about data correlations and give future researchers new avenues to explore different data sets.

Research Goals

This research aims to identify whether patterns in the available data suggest future aviation accidents. Additionally, it uses current predictive algorithms to analyze trends. Finally, it evaluates the effectiveness of these predictive models when applied to the specific dataset.

Hypotheses

H_0: There is no statistical significance between dates, individual battalions, and the severity of aviation incidents.

H_1: If there is a relationship between lower classifications of aviation incidents and higher classifications of aviation incidents within an army unit, then this correlation can be used to identify units with a higher risk for subsequent incidents.

H_2: If there is a relationship between ground incidents and flight incidents within an army unit, then this correlation can be used to identify units with a higher risk for subsequent incidents.

Chapter 2 - Background and Theories

In 2022, the US Naval Safety Command (NSC) conducted similar analytics to forecast US Navy units that are at a higher risk for mishaps. After a spike in class-A mishaps involving surface ships in 2017, involving 17 deaths and 8 injuries, the Department of the Navy mandated a review of data available to determine if future mishaps can be prevented based on conditions within naval organizations. The NSC research identified four trends that were common in all the incidents analyzed (Orender, 2022). These trends were a lack of experience, high operational tempo (OPTEMPO), crew turnover, and a lack of personnel in key positions (Orender, 2022). The NSC researchers developed metrics to quantify these factors and built models that predicted when combinations of these factors would increase the likelihood of an organization experiencing a significant impending safety incident. The output of their research was a cross-plot that depicts changes from the previous month and represents the compounding effects of crew experience and operational volatility (OPVOL). Ships with low experience and high operational volatility (which is an aggregate of crew turnover and OPTEMPO) are plotted in the top right quadrant, while high-experience ships with low levels of OPVOL are represented in the bottom left quadrant. While explicitly stating that this model does not predict the future, the NSC research purports to represent the similarity of the condition of the ship that has experienced a class-A mishap (Orender, 2022).

This research project intends to take a similar approach to safety research as the NSC and apply similar concepts to the aviation enterprise, rather than maritime. There are similarities between metrics of crew experience; however, they are calculated differently and will require a different approach than the classification of ship crew experience. Additionally, this research project will merely determine if a relationship exists between specific data. This will inform the

USACRC of the need to conduct further analysis in the focus area to determine measures to represent such data for senior leaders.

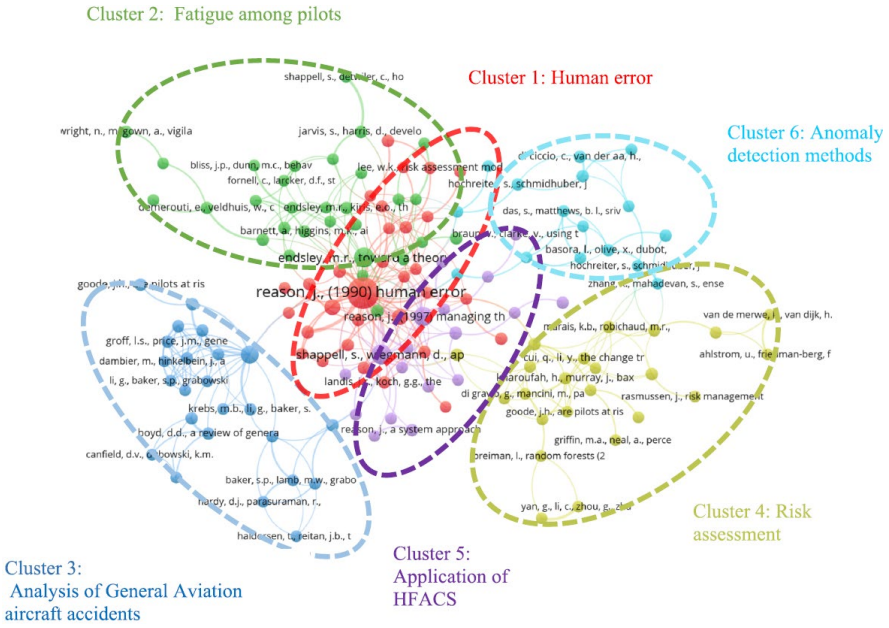
Aerospace is a monthly journal published online by the Swedish MDPI with the latest information on research about aerospace and astronautics. An article from 2020 provided an analysis of the application of machine learning to understand risks associated with flight operations and incident causal chains. The authors of this article explain a system that they developed a system named Safety Analysis of Flight Events (SAFE) as a method to process data, interpret correlations, and visualize outputs. The outcome of their research identifies and ranks a list of critical events regarding specific safety events and demonstrates the contribution of machine learning to the human conceptualization of incidents and their associated precursors (Lee et al., 2020).

Pritchard et al. (2024) applied machine learning techniques to evaluate aviation fleet monitoring practices, with a particular emphasis on the role of automation in operational analysis. While the focus of their study differs from the central research question of the present investigation, their methodological framework offers relevant insights into data-driven approaches within aviation systems research. Specifically, their use of Principal Component Analysis (PCA) to identify standard operational characteristics within a fleet dataset illustrates how machine learning can effectively distill complex quantitative data into interpretable performance indicators. This study thereby establishes a useful precedent for the integration of similar analytical methods in aviation-focused research contexts.

The aviation industry has a rich history of incident research and industry adaptations, continually improving safe operations and keeping pace with the evolving risks associated with technological advancements (Lofquist, 2010; National, 2018; Olaganathan, 2024). The

Department of Safety Science at Embry-Riddle Aeronautical University conducted a comprehensive bibliometric review spanning the past century (1923-2023) to examine the evolution of this field and identify the multidisciplinary nature of the literature involved in aviation risk management. Analyzing these trends in aviation safety research highlights specific milestones and shifts in research focus over time. “By pinpointing areas that require further investigation, the research provides a roadmap to maximize the impact of future aviation safety studies” (Okine et al., 2024, p. 1). This research evaluates historical trends in aviation risk research and can determine where there are any gaps in safety procedures. Okine conducted a co-citation analysis of aviation publications by determining how frequently pairs of articles were referenced in single-source articles. As authors reference specific articles (in pairs) within their works, clusters of research emerge, which can be seen in Figure 1. These citations indicate trends of topics referenced by authors, and those categories are labeled according to their color.

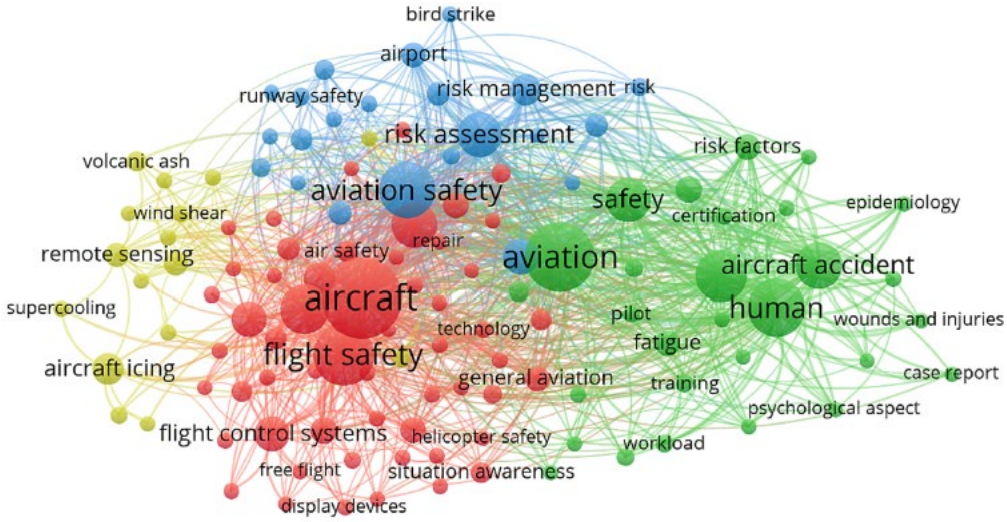
Figure 1. Okine’s document co-citation network map



Note. Seven broad categories of aviation safety research

Additionally, the Embry-Riddle researchers conducted a co-occurrence analysis to determine focal trends in aviation safety. By scrubbing more than 10,000 aviation documents for topics that appeared more than 50 times in a single article, the researchers produced a network map of 123 keywords. Using a color pattern that differs from the previous figure, patterns emerge in the similarities of the keywords, which can be seen in Figure 2. They may be broadly categorized into four focal areas of aviation safety research: environmental (yellow), aircraft (red), management (blue), and human (green).

Figure 2. Okine's Network visualization of co-occurrence keywords



Note. Four broad categories emerge based on repetitive themes within aviation research

Comparing these two network maps shows a particular pattern of focus on human factors. According to Wiegmann and Shappell, this is to be expected. "As aircraft have become more reliable, humans have played a progressively more important causal role in aviation accidents, resulting in the proliferation of human error frameworks and accident investigation schemes." (Wiegmann & Shappell, 2001, p. 341). This thematic focus of aviation safety research may prove valuable because it illuminates patterns of aviation incidents that require more attention than other areas. As themes of rising concern are addressed, their appearance in professional literature

decreases. Okine's 2012 study observed this occurrence in the discussions involving aircraft icing:

> In the early years of the aviation industry, aircraft icing was a major concern. Between 1975 and 1988, there were a total of 803 icing-related aviation accidents, and the majority of these were fatal. According to ICAO statistics, between 1986 and 1996, 42 aircraft icing accidents resulted in a 39% passenger fatality rate. Although they were once considered to be the primary external cause of accidents, aircraft icing-related accidents have drastically decreased in recent years as a result of the studies done on aircraft icing (Okine et al., 2024, p. 16).

Assuming this focus on human errors continues to be addressed through research and technological development, it is possible to expect a decrease in the appearance of this category, and presumably, some new pattern will emerge with a different focus.

The *Science Direct* journal recently published an article that explains the benefit of using a text-based approach to analyze aviation incident reports. The framework in this paper provides a four-step modeling approach to structure the data, identify the topics, produce a co-occurrence network, and pinpoint causal factors through a quantitative analysis. The motivations for this research are based on the potential for enormous loss of life in an aviation incident and the economic cost to corporations involved in the aviation business. The correlation among topics such as "weather", "turbulence", and "aircraft crash" is consistent with previous findings and provides a macro perspective of the underlying mechanisms of aviation safety. This research demonstrates the importance of text-based analysis when understanding the underlying causes of narratives or discussions involving specific topics. The cultural relevance of discussions is highly important when recognizing the underlying themes involved (Xing et al., 2024).

The “High-Reliability Organization” (HRO) theory may be compared to the Army’s approach to organizational efficiency (Shipman, 2021; Cantu et al., 2021). The HRO theory was originally adopted by the army but failed to gain momentum (Malish, 2019). HRO theory comprises five principles: preoccupation with failure, reluctance to simplify, sensitivity to operations, commitment to resilience, and deference to expertise. According to these authors, the army retains only some semblance between these principles and the tenets in which it operates, regarding aviation safety. The authors identify these five tenets adopted in Army aviation: vigilance to vulnerability, regimented communication for key transactions, Mishap investigation, analysis, and action, Standardization and surveillance of safety protocols, and Leadership accountability for the performance and treatment of teams. While none of the vocabulary remains the same, there are some parallels behind the foundations of each principle. These principles illuminate an enterprise-level narrative of the army, and the authors contrast it with the realities of the army’s execution (Malish & Sargent, 2019).

Chapter 3 - Methods

3.1. Data Collection

The United States Army Combat Readiness Center (USACRC), located at Fort Rucker, Alabama, serves as the Army's source of safety-related analytics and is the key source of data for this research (*USACRC Home*, n.d.). Data provided by the USACRC includes two datasets consisting of 2,898 and 1,582 mishap reports covering the past decade from aviation units throughout the army. The reports range from class D to class A mishaps, including ground and in-flight incidents. Additional data is available from the US Army's Centralized Aviation Flight Record System (CAFRS), which details specific crew experience, including flight hours and the type of flight conducted (night, night-vision device, day, instrument, etc.). The mishap report dataset will be the focal point of this research. Any crew-related data and actual mishap-reported data used necessitate the removal of all personally identifiable information before analysis to protect individual privacy. Machine learning algorithms applied to this clean data will determine trends that can be used to identify units at a higher risk of aviation mishaps.

This research project uses regression analytics to predict relationships between tiers of aviation mishap reports within aviation units. The result will be some form of plot that visually represents whether a relationship exists or not. Some variables that will be analyzed include the classification of mishaps (class A through class D) and the category of the incidents (whether ground or in-flight). Two predictors will be the lower-tier incidents (class C and D) to be tested with the outcome of higher-tier incidents (class A and B) to determine if a relationship exists. Additionally, ground mishaps will be the predictor that may have a relationship with in-flight mishaps. The dataset provided by the USACRC includes the date of the incident, mishap

classification code, mishap category level, type of aircraft, location of the incident, primary cause factors, and the organization that the aircraft belonged to at the time of the incident.

3.2. Data Preparation

Ordinal variables may be ranked in a specific order to demonstrate the importance of one value over another to create a scale (Christensen et al., 2015). On the other hand, nominal variables consist of categorical data, where the value of the variable does not imply importance over any other variables, only that it is different (Christensen et al., 2015). In this research, I determined that the ordinal variables were the mishap classification code and the mishap category level. The mishap classification code represents the severity of the mishap according to the US Army's definition of mishaps, explained in Appendix A. In short, a "Class A" accident is far more severe than a "Class D accident". The mishap category level defines whether the incident was aviation-related or not. They could either be an "aircraft ground" mishap, a "flight-related" mishap, or a "flight" mishap. A "flight" mishap occurs while an aircraft is either in flight or intending to fly, and the aircraft is damaged (Headquarters, Department of the Army, 2023b). A "flight-related" mishap occurs when there is an intent to fly, and there is some form of injury to the crew but no damage to the aircraft (Headquarters, Department of the Army, 2023b). This can occur if someone fell while pre-flighting the aircraft since there was an intent to fly. Lastly, the "aircraft ground" mishap is when an aircraft is damaged without the intent to fly (Headquarters, Department of the Army, 2023b). For example, a vehicle is accidentally backed into the side of an aircraft, causing airframe damage. These are defined in more detail in Appendix A. The scale from least to greatest for mishap classification codes is class D, class C,

class B, and class A. The ordinal scale from least to greatest for the mishap category level is aircraft ground, flight-related, and flight.

The independent variables are those that are not influenced by other variables, but rather are assumed to be the cause of another variable. The dependent variables are expected to convey the effect or the outcome of the independent variables (Christensen et al., 2015). In this research, the dependent variables take the form of the mishap classification code and mishap category level.

Microsoft Structured Query Language (SQL) Management Studio was used to format and classify the data. Python coding was utilized through the "Spyder" interface to conduct the analysis. The data was retrieved from the Army Safety Management Information System (ASMIS) and formatted as a .csv file. To make the data usable in a quantitative study, the text was first converted into numerical values via data classification. Every variable was assigned a numerical value through SQL for analysis. An example of this is seen in Figure 3.

Figure 3. Sample of classified data

weekday	weekday	mishap_class	mishap_class	mishap_categ	mishap_categ	aircraft_mtds	aircraft_mtds	bn_uic	bn_uic
Monday	1	A	1	Flight	1	C-147A	1	W027	1
Tuesday	2	B	2	Flight-Related	2	AH-64D	2	W04W	2
Wednesday	3	C	3	Aircraft Ground	3	AH-64E	3	W04X	3
Thursday	4	D	4			AH-6M	4	W0CT	4
Friday	5					B350/KA350	5	W0FY	5
Saturday	6					C-12A	6	W0H9	6
Sunday	7					C-12C	7	W0MU	7

Note. Classified values are listed to the right of each textual description

Based on a recommendation from the USACRC, the dataset was refined by focusing on aircraft mishaps caused specifically by human error, excluding environmental or mechanical failures, for example. Out of the total 1,615 accidents in this report, 1,378 were due to human error, representing 85.3% of the data. Material failure accounted for 85 mishaps (5.3%), environmental factors for 50 mishaps (3.1%), and there were 102 mishaps with unknown or unrecorded causes, making up 6.3% of the dataset. Since this research aims to subtly analyze the

organization's safety climate, including data related to material failures, environmental causes, or unknown reasons, it could have skewed the results away from the focus. For instance, if an aircraft is struck by lightning while tied down during a storm, it is classified as an "environmental mishap". Natural events or genuine mechanical failures do not accurately reflect the safety climate in an organization for identifying trends in aviation mishaps. Therefore, these mishaps were excluded, leaving 1,378 data points for further analysis.

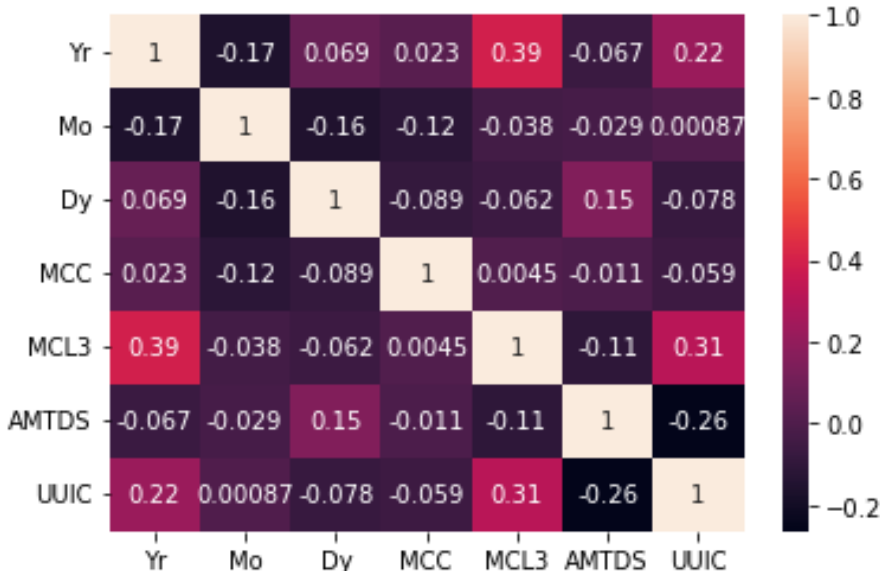
148 mishaps involved fixed-wing aircraft (airplanes). Because of the nature of rotary-wing aircraft and their mission types, there is a clear difference between these types of airframes. Typically, fixed-wing aircraft are used mainly for high-altitude personnel transportation, while rotary-wing aircraft operate tactically near the ground to transport personnel and equipment or fight enemy forces. Additionally, there are far fewer fixed-wing aircraft in the US Army compared to rotary-wing aircraft. Because of these differences, the 148 fixed-wing accidents were removed from the dataset, and the remaining 1,230 mishaps were analyzed.

3.3. Analysis

Using the classified data, the first step was to determine if a simple correlation existed. Using Spyder to analyze Python coding, the first run was not promising. Figure 4 shows nearly no correlation between any of the variables. Some potential soft correlations might be seen in comparing the "MCL3" and "yr" columns, as well as the "MCL3" and the "UUIC" columns. The abbreviations are fully explained in Appendix B. The "MCL3" represents the "mishap category level 3", which was previously defined as "flight", "flight-related", or "aircraft ground". The "UUIC" variable represents the organization that the aircraft belonged to at the time of the mishap. There is a total of 273 units that were analyzed during this study, which represent army

aviation battalions. Battalions generally consist of one to three types of airframes and usually have a similar mission focus. Typically, a battalion has three companies with approximately 10 helicopters each. Each battalion was given a numerical identifier and can be seen in the two right-most columns in Figure 3. “bn_uic”, “UUIC”, and “buic” are all synonymous for this research.

Figure 4. First correlation plot iteration in Spyder



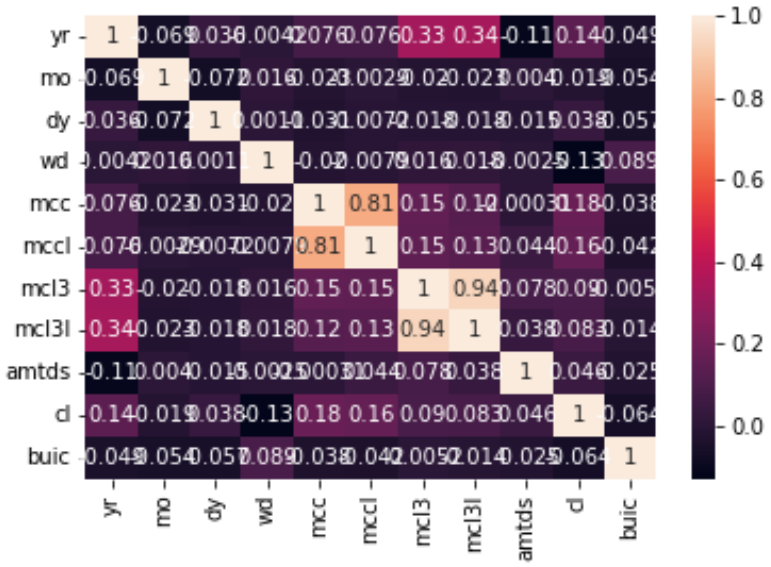
Note. The initial correlations were very low

Several correlation plots were developed, and no significant correlations were identified. There is a training organization accounted for in this dataset, which may have skewed the data because it comprises 190 of the incidents listed. These data points were excluded in Figure 5, yet there were still no significant correlations depicted. The correlation plot trends with and without the training organization’s data remained essentially the same, with less than 0.1 variation in every comparison.

An “L” at the end of the column names indicates a logistic derivative field that was developed to simplify the comparisons. Since this research sought to compare lower

classifications of incidents to higher classifications of incidents, the variables were grouped as such. For example, “mccl” combined “Class A” and “Class B” mishaps into one category, and “Class C” and "Class D” into a second category. This way, higher and lower classified mishaps could be compared. We would expect to see high correlations between the field and its respective logistic derivative, indicated by an “L” at the end.

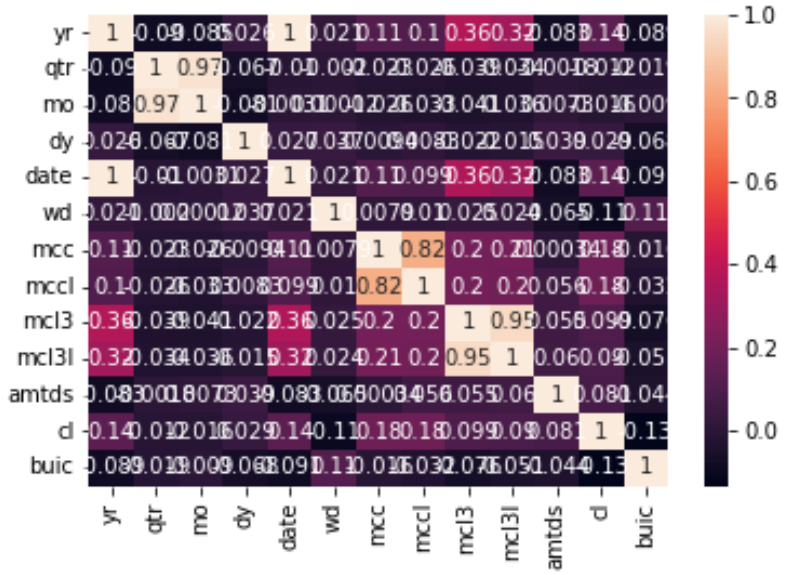
Figure 5. Eighth correlation plot with more variables



Note. Despite removing the training battalion, no correlations were identified

The next correlation plot in Figure 6 corrects some misspelled information among the data points. For example, the field listed as “cl” indicates whether the mishap location was a combat location or not. To do this, the program searched for known combat locations at the time. Iraq and Afghanistan were the primary locations assessed to be combat locations; however, there were fourteen cases where the location Afghanistan was found to be misspelled as “Afhganistan”, so the algorithm was not accounting for them. Even with the grammatical correction, there was no noticeable correlation between the variables.

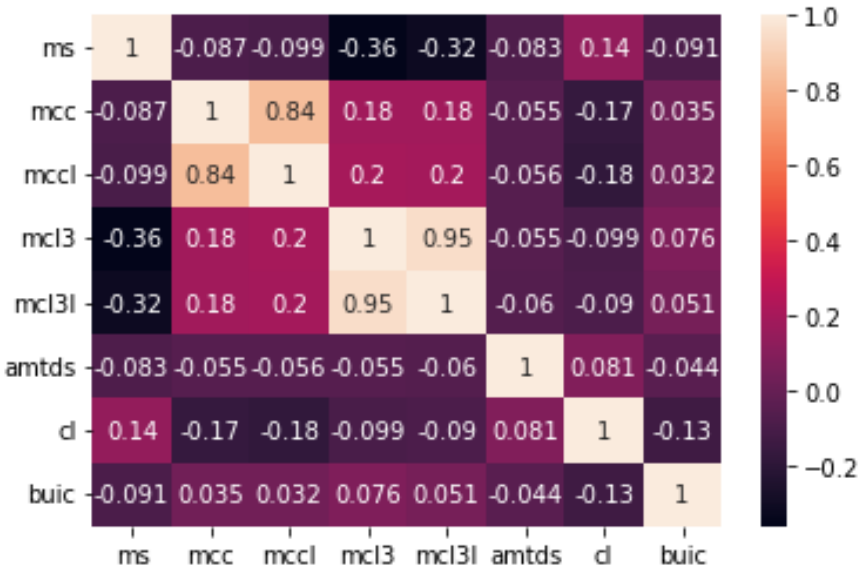
Figure 6. Eleventh correlation plot with more variables and corrections



Note. The training battalion was added back into the analysis

The final correlation plot in Figure 7 below organizes the months in sequence and scales the mishap classification to the monetary value assigned to each class of accident. There was a total of 136 months during which accidents occurred between October 2012 and January 2024. This ensured comparison among successive months along a chronological axis and transitioned trends from one year to the next. Rather than comparing incident trends within the same year or same months throughout the years, this mapped the mishaps along a continuous axis. This field was given the name “month sequence” and shortened to “ms”. Additionally, the fourteenth correlation plot (Figure 7) scaled the classes of accident by the monetary value assigned to each. “Class A” accidents were assigned the value of ‘100’, “Class B” accidents were assigned the value of ‘24’, “Class C” accidents were assigned the value of ‘2.4’, and “Class D” accidents were assigned the value of ‘1’. This introduced the accident severity into the analysis as defined by the US Army.

Figure 7. Fourteenth correlation plot, using "ms" and scaled accident classifications



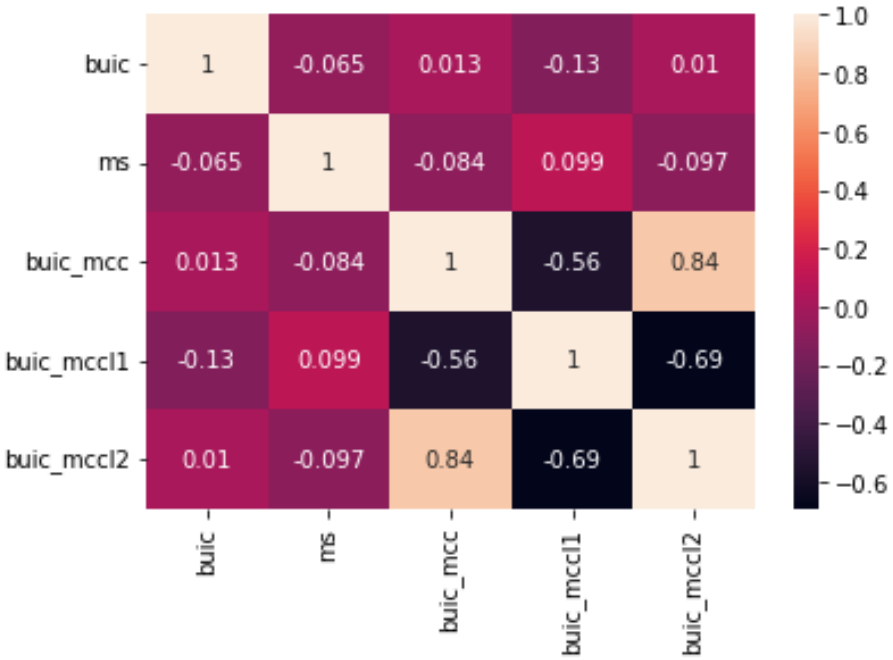
Note. An insignificant trend emerges between “ms” and “mcl3”

The Principal Component Analysis (PCA) was the next tool to assess the correlation between variables in a more complex and comprehensive manner. Principal Component Analysis (PCA) is a statistical technique used to reduce the dimensionality of large datasets while retaining the most significant sources of variance within the data. By transforming correlated variables into a smaller set of uncorrelated components, PCA enables researchers to identify underlying patterns and relationships that may not be immediately apparent in the raw data. In the context of aviation safety research, PCA is particularly valuable for analyzing complex, multivariate datasets such as flight operations, maintenance records, or sensor data from aircraft systems (Li, 2015; Ning, 2021). Its ability to highlight dominant operational trends and detect deviations from standard performance parameters makes it a powerful tool for identifying potential safety risks, optimizing maintenance schedules, and improving overall fleet reliability (Savolainen, 2024). PCA allowed a reduction in the dimensionality of the dataset to two principal components that capture the aggregate of information within the dataset. The target was

selected to be “mcc”, and the features varied between the remaining fields (mcl3, buic, ms, date, wd, and amtds).

The next analysis used in this research methodology was to group the data to compare any potential progression from lower accident classifications to higher classifications. To do this, SQL was used to group when “mccl” = 1 (class C or D accidents) and when “mccl” = 2 (class A or B accidents) by “buic” and “ms”. New data fields were created and labeled as “buic_mccl1” and “buic_mccl2”, respectively. The resulting fields grouped the severity of the accident (“mccl”) by the unit where the accident occurred (“buic”), in chronological order (“ms”).

Figure 8. Correlation plot of newly grouped data



Note. There are potential correlations within the data.

The newly grouped data were used in a PCA to generate the graph in Figure 15. The target was “buic_mcc”, and the features were “ms”, “buic”, “buic_mccl1”, and “buic_mccl2”. The legend on the right indicates the severity of accident classification, ranging from 10 to 1000 and representing class D to class A accidents accordingly. Following the PCA, the newly

grouped data were used to generate linear and multiple linear regressions. Similarly, the grouping of flight and non-flight incidents was grouped into “buic_mcl311” and “buic_mcl312”. Accidents that were considered “ground mishaps” were grouped into the new field labeled “buic_mcl311”, while “flight mishaps” and “flight-related” were grouped into “buic_mcl312”. This grouped data was used in the multiple regression seen in Figure 17. In both linear regressions seen in Figures 16 and 17, the independent variables used were time, unit identifier, and less severe or ground accidents. The dependent variables used were higher-severity or flight-related accidents.

One other analysis conducted involved converting the dataset to a series of pivot tables. The intent with this analysis was to draw out general relationships between time and overall accident sums. These are listed below in Figures 9 through 13. Figure 9 shows the total number of accidents between 2012 and 2024 that occurred in those months.

Figure 9. Pivot table of accident data organized by quarter and month

Quarter	Number of Incidents
Q1	**296**
January	96
February	83
March	117
Q2	**294**
April	85
May	107
June	102
Q3	**366**
July	113
August	136
September	117
Q4	**274**
October	109
November	98
December	67
Grand Total	**1230**

Note. Quarters are broken down by calendar year, with Q1 starting in January.

The table in Figure 10 further refines the analysis from the previous table. This is a visual representation used to compare the data contained within the “mccl” field.

Figure 10. Quarterly accident data, by severity

Row Labels	Class A-B	Class C-D
Q1	**42**	**254**
January	11	85
February	12	71
March	19	98
Q2	**41**	**253**
April	12	73
May	15	92
June	14	88
Q3	**55**	**311**
July	18	95
August	21	115
September	16	101
Q4	**46**	**228**
October	13	96
November	18	80
December	15	52
Grand Total	**184**	**1046**

Note. Quarters are broken down by calendar year, with Q1 starting in January.

Similarly, Figure 11 refines the accident data by parsing out flight-related and non-flight-related accidents. This is a visualization of the data in the “mcl3l” field. The non-flying incidents are defined as those represented as “ground mishaps” within the datasets. Within the data, both “flight-related” and “flight” mishaps are classified as flight incidents.

Figure 11. Quarterly accident data, by type of mishap

Row Labels	Non-Flying Incidents	Flight Incidents
Q1	**109**	**187**
January	41	55
February	30	53
March	38	79
Q2	**110**	**184**
April	28	57
May	45	62
June	37	65
Q3	**138**	**228**
July	44	69
August	49	87
September	45	72
Q4	**86**	**188**
October	35	74
November	28	70
December	23	44
Grand Total	**443**	**787**

Note. Quarters are broken down by calendar year, with Q1 starting in January.

Rather than the normal analytical process throughout the study up to this point of broad trends, the table in Figure 12 aims to determine if there is a trend based on the day of the week. This table shows the total number of accidents as they occurred Monday through Sunday, regardless of the year or month.

Figure 12. Accident data by weekday

Weekday	Number of Incidents
Monday	184
Tuesday	262
Wednesday	269
Thursday	230
Friday	140
Saturday	89
Sunday	56
Grand Total	**1230**

Note. Most accidents occur on Tuesdays and Wednesdays.

The last pivot table aggregates accident data by calendar year, spanning from 2013 to 2023. 2012 and 2024 were excluded due to incomplete data for those years. In 2012, accident data were collected from October to December, and in 2024, only information for January existed at the time of this study. This analysis is conveyed in Figure 13.

Figure 13. Accident data by year

Year	Number of Incidents
2013	145
2014	93
2015	123
2016	94
2017	101
2018	102
2019	88
2020	121
2021	135
2022	98
2023	102
Grand Total	**1202**

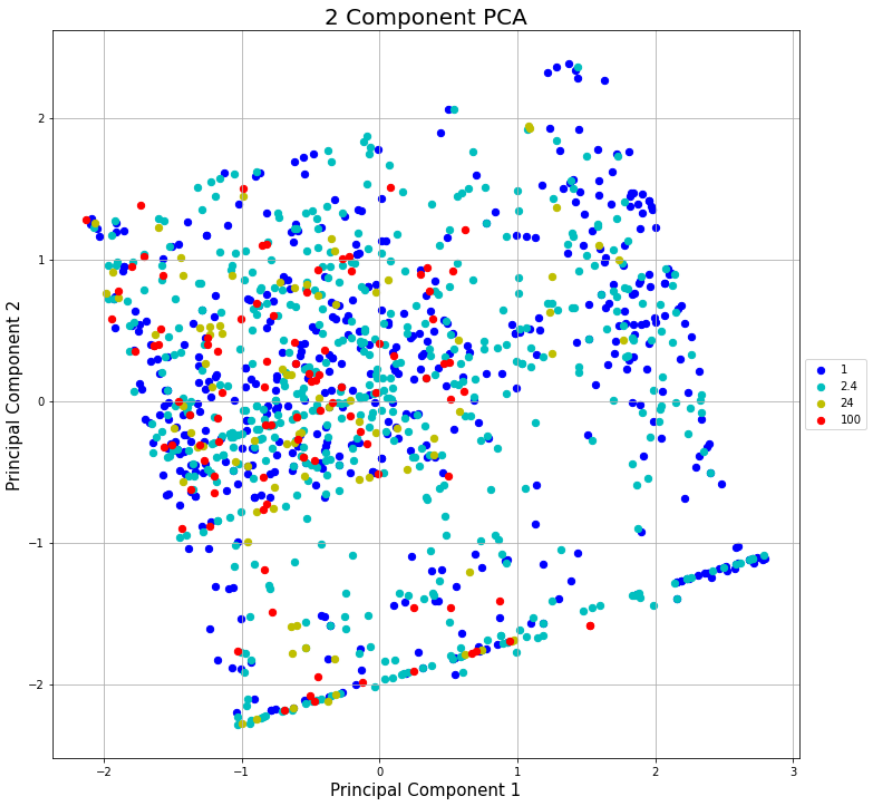
Note. 2012 and 2024 are excluded because the data is incomplete in those years.

Chapter 4 - Results

4.1. Discussion.

Initial correlation plots did not indicate an underlying relationship within the dataset. The first indication of possible correlations arose through PCA. During the 22 combinations of targets and features, and several iterations, the Total Variance Explained (TVE) ranged from 0.611 to 0.787. Combinations of ms, date, buic, mcl3, and mcc indicated the highest TVE, while including wd, amtds, and more than 3 features produced a lower TVE. Figure 14 shows the general trend of the PCA results and specifically reflects using mcc as the target with features ms, buic, and mcl3. The TVE in this iteration was 0.787.

Figure 14. PCA with target “mcc” and features “ms”, “buic”, and “mcl3”

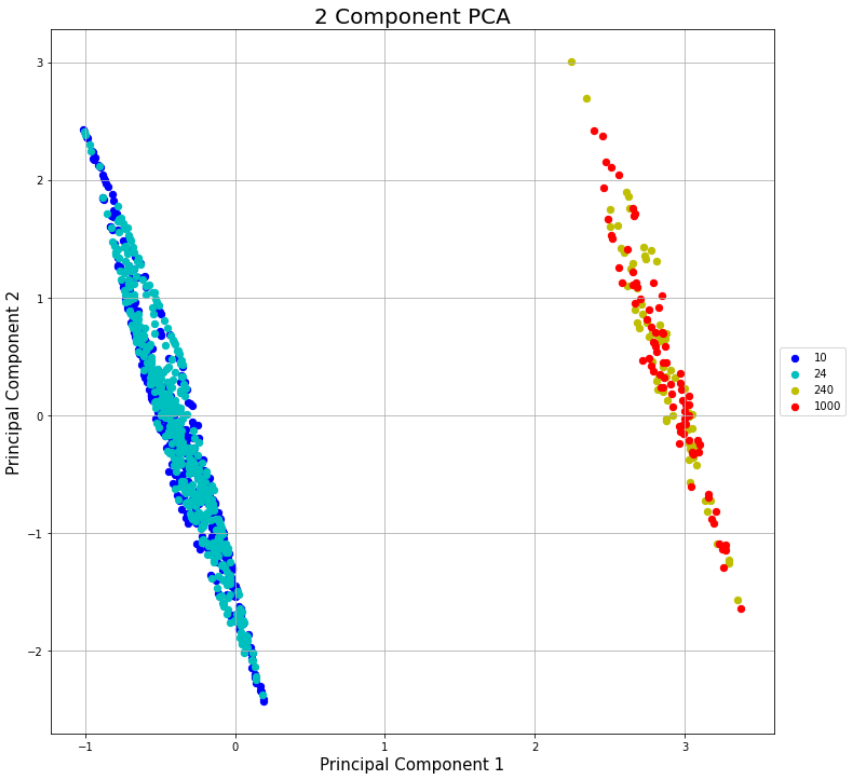


Note. The TVE in this iteration was 0.787, indicating a suitable model.

Further correlations were explored by grouping the data. The intent was to analyze trends of accident severity within units chronologically. The correlation plot of the new dataset, as seen in Figure 8, shows a possible negative relationship between low and high accident classifications at each unit over time. The -0.69 may indicate that, as class C/D accidents increase at a unit, class A/B accidents do not increase, and in fact generally decrease overall. The 0.84 rating may indicate that, as accidents of any severity increase, severe accidents ("buic_mccl2") tend to increase at a unit. Likewise, the -0.56 seems to imply that, as accidents of any severity increase, less severe accidents generally decline.

The PCA conducted for the newly grouped data also indicates potential trends within the dataset. The most severe accidents were distinct from the less severe accidents in the resulting PCA chart in Figure 15, likely due to the scale at which the accidents occur. The target in this PCA was "buic_mcc". The features were "ms", "buic", "buic_mccl1", and "buic_mccl2". The resulting TVE for this PCA was 0.692.

Figure 15. PCA conducted with newly grouped data



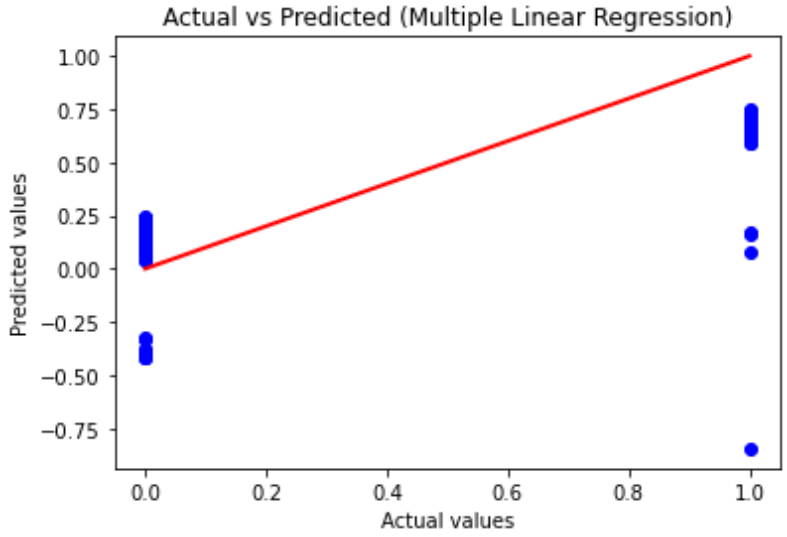
Note. The TVE for this iteration was 0.692.

Finally, linear regressions and multiple linear regressions were executed with no significant indications. While identifying “ms”, “buic”, and “buic_mccl1” as the independent variables, with “buic_mccl2” as the dependent variable, R-squared values range from 0.013 (linear regression) to 0.517 (multiple linear regression). When testing ground and flight incidents as the independent and dependent variables, respectively, the R-squared value increased to 0.650 on a multiple linear regression. P-values remained below 0.05 in every case except for “ms” in the multiple linear regressions, which ranged from 0.07 to 0.12. These results are shown below in Figures 16 and 17, respectively.

While generally higher TVE describes more suitable models as a fit for the data set being examined, P-values below 0.05 indicate potential statistical significance. It is important to note that just because there is some semblance of statistical significance during this analysis, that

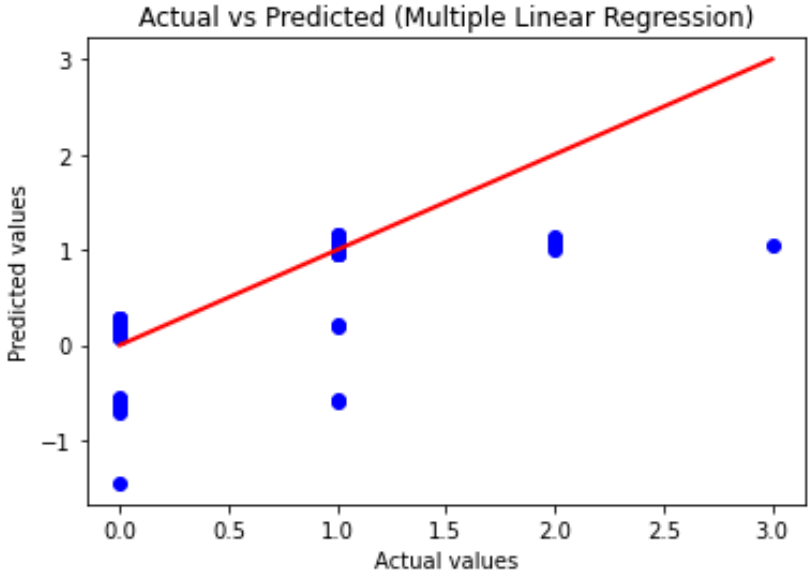
doesn't mean that a correlation exists. Due to the unsupervised nature of PCAs, it is unclear how the variables interact with one another, so a correlation cannot be conclusive.

Figure 16. Multiple linear regression comparing accident severity



Note. The R-Squared value for this iteration was 0.517.

Figure 17. Multiple linear regression comparing accident type



Note. The R-squared value for this iteration was 0.650.

The pivot table analysis illuminated a few trends throughout the data overall that neither support nor refute the hypothesis. 68% of accidents in Q4 are flying accidents (32% are non-flying), which is notably higher than Q1-Q3, which range from 62% to 63%. While the ratio of class C and D incidents to class A and B incidents remains consistent throughout all four quarters, there is a clear spike in accidents that occur in Q3. Accidents that occur in Q3 account for 30% of all accidents, while Q1, Q2, and Q4 range between 22% to 24%. Lastly, 43% of accidents occur on either Tuesday or Wednesday, and 19% occur on Thursday. While potentially interesting at face value, the data is not likely relevant without comparing the total number of flights conducted on each day of the week. The pivot table analysis highlighted aspects of the dataset that are valuable and noteworthy, but not relevant to this research.

4.2. Findings.

This study drew out potential trends within the data when grouped or analyzed appropriately; however, this study was unable to link direct and concise correlations explored in the hypotheses. Initial correlation plots did not indicate relationships among the various fields; however, resultant TVEs from PCAs peaking at 0.787 indicate a valuable model to assess the data. P-values within the PCAs below 0.05 indicate statistical significance for the feasibility of underlying relationships. Additionally, relatively higher R-squared values may indicate a fair possibility of the dependent variables relying on the presence of the independent variables.

While this study indicates potential statistical significance exists within the dataset, it does not conclusively demonstrate the way the variables interact; therefore, further research is necessary to determine if H_1, H_2, and H_0 are true or false.

Chapter 5 - Conclusion

5.1. Limitations.

This research was limited in two primary ways: access to data and sample size. This research incorporated a large sample size of generally quantitative data. While several fields within the dataset consisted of words, the information contained in those fields was discrete and easily translated into numeric values. For example, there is a threshold when a mishap is declared as flight, or flight-related (category "mcl3" in this research), which is established in the accident report. Once that threshold is met, it is categorized discretely and is essentially quantitative data. The same goes for the class of accident. Once the dollar value exceeds a specific threshold, it is categorized as a specific class of accident, ranging from A, B, C, or D. This was categorized as "mcc" in this research.

The sample size in this study was not tested to determine if it was optimal. A sample size that is too large may not attribute characteristics relevant to trends that occur within specific units. In other words, the large sample size of this dataset may attribute too many generalizations that do not illuminate individual unit particularities surrounding an accident. Zooming in to analyze trends within specific units may draw out trends that could not be demonstrated at the macro scale of this research.

Additionally, this research does not account for the consistency of the battalions identified. Occasionally, units are disbanded. In this case, personnel and equipment are redistributed to different units within the Army. Likewise, units are occasionally established. This dataset does not recognize when units are stood up or shut down. While this occurs very infrequently, if there were trends that began to emerge at a unit before shutting down, the personnel would be redistributed, and trends would not be carried over to other units. This is not

likely to be significant, due to the infrequency that this occurs, and that units will not likely engage in flights for several months leading up to the deactivation, or not consistently fly for a period following unit activation.

5.2. Future work.

Future work expanding on this research could incorporate qualitative data and analyze trends within individual units during targeted months. Reviewing accident reports would provide qualitative data attributed to each accident. Since contributing factors are attributed to each mishap during investigations, categories can be derived from the reports. This qualitative data could facilitate a mixed-method research strategy to provide context behind the data points. From there, qualitative data could be classified and analyzed to determine if trends exist.

An approach rooted in grounded theory, or a theory of high hazard (HHT), could develop coding categories that appear within mishap data of specific units within a given amount of time (Ferroff et al., 2012; Ghaith & Huimin, 2025). A specific threshold can be established to determine suitability for further analysis if a unit exceeds a specified number of recorded mishaps within a specified amount of time. Trends that may appear through this approach may become repetitive across several different units that scale up to the macro-level, which could then be generalized across the enterprise. The combination of qualitative data being analyzed at the individual unit level provides additional context that could enhance understanding for subsequent accident occurrences.

Further research could also assess the intriguing Q3 spike in aviation mishaps and whether this increase in accidents translates to a higher level of operational readiness. The logic is as follows: an increase in accidents could be a relatively consistent number of accidents

occurring during a period of an increase in overall flight hours. This overall increase in flying could lead to a temporary increase in operational readiness and demonstrate that there is no increase in accident rates. When overlayed with similar data from various branches within the Army, this could provide insight into strategic implications for seasonal operational readiness.

5.3. Conclusion.

This research demonstrates some potential for statistical significance between dates, individual battalions, and the severity of aviation incidents, while not conclusively resolving a correlation between mishap severity or mishap types. This research cannot demonstrate that a relationship exists between lower and higher severity of incidents within a unit. Additionally, this research cannot demonstrate that a relationship exists between ground and flight incidents within a unit. However, a focused study using qualitative data could extract trends within individual units through a grounded theory approach that demonstrates applicability throughout the Army Aviation enterprise.

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Appendix A - Glossary

Flight mishaps
Those mishaps in which intent for flight exists (as defined in this glossary) and for which there is reportable damage to the aircraft itself. (Explosives, chemical agents, or missile events that cause damage to an Army aircraft with intent for flight are categorized as flight mishaps to avoid dual reporting.) (Headquarters, Department of the Army, 2023b).

Flight-related mishaps
Those aircraft mishaps in which there is intent for flight and no reportable damage to the aircraft itself, but the mishap involves a fatality, injury to aircrew, ground crew, passengers, other injury, and/or property damage (Headquarters, Department of the Army, 2023b).

Ground mishap
Any mishap exclusive of aviation (for example, Army motor vehicle, Army combat vehicle, privately-owned vehicle, marine) (Headquarters, Department of the Army, 2023b).

Intent for flight (unmanned aircraft system)
Intent for flight begins when power is applied or brakes released (if so equipped), or unmanned aircraft is hand released by the operator, or the launcher is released, for the purpose of moving an aircraft under its own power to commence authorized flight (including ground taxi/hover) by an authorized crew. Intent for flight ends when the aircraft is at a full stop and power is completely reduced and/or stopped Intent for flight begins for Aerostat balloons when all of the mooring lines are removed for the purpose of deployment and ends when all of the mooring lines are attached (Headquarters, Department of the Army, 2023b).

Intent for flight (unmanned aircraft system/manned aircraft)
Intent for flight begins when power is applied or brakes released to move the aircraft under its own power, for the purpose of commencing authorized flight with an authorized crew. Intent for flight ends when the aircraft is at a full stop and power is completely reduced. Intent for Flight is the physical act of applying power to move the aircraft, not the thought process of the crewmember as to what is going to occur in the future (Headquarters, Department of the Army, 2023b).

Investigation
A systematic study of a mishap, incident, injury, or occupational illness circumstances (Headquarters, Department of the Army, 2023b).

Mishap
An unplanned event that causes personal injury or illness, or property damage (Headquarters, Department of the Army, 2023b).

Mishap classification (Headquarters, Department of the Army, 2023a)
Use mishap classes to determine the appropriate safety investigation and reporting requirements. Mishap classes are listed in paragraphs 3–9a through 3–9f.

a. Class A mishap. An Army mishap in which—

(1) An injury and/or occupational illness results in a fatality or permanent total disability (as defined in the glossary); or

(2) A manned Army aircraft is either destroyed, missing, or abandoned, or

(3) The resulting total cost of property damage to Government and other property is $2.5 million or more.

b. Class B mishap. An Army mishap in which—

(1) An injury and/or occupational illness results in permanent partial disability (as defined in the glossary); or

(2) Three or more personnel are hospitalized as inpatients as a result of a single occurrence; or

(3) The resulting total cost of property damage to Government and other property is $600,000 or more but less than $2.5 million.

c. Class C mishap. An Army mishap in which—

(1) A nonfatal injury or occupational illness results in 1 or more days away from work or training beyond the day or shift on which it occurred; or

(2) Temporary disability ensues at any time thereafter, resulting in days away from work and does not meet the definition of class A or B; or

(3) The resulting total cost of property damage to Government and other property is $60,000 or more but less than $600,000.

d. Class D mishap. An Army mishap in which—

(1) A nonfatal injury or illness which results in days of restricted work, or transfer to another job, or medical treatment greater than first aid; or

(2) Medical/clinical duties result in needle stick injuries or cuts from medical instruments contaminated by blood or other potentially infectious material; or

(3) Medical removal is required under medical surveillance requirements of an OSHA standard; or

(4) Occupational hearing loss exceeds the threshold shift established by 29 CFR 1910.95 and DoDI 6055.12; or

(5) Tuberculosis is contracted associated with work; or

(6) The resulting total cost of property damage is $25,000 or more but less than $60,000.

e. Class E mishap. An Army mishap in which total cost of property damage is $5,000 or more, but less than $25,000.

f. Class F aviation incident. An aviation incident confined to aircraft turbine engine and drone engine damage due to unavoidable internal or external foreign object (does not include installed aircraft auxiliary power units).

g. Class G mishap. Biological mishaps are classified as an Army class G biological mishaps, see paragraph 20 – 12.

h. Class H mishap. Chemical mishaps are classified as an Army class H chemical mishap, see paragraph 21 – 5.

i. Reporting. Report events meeting the definition of an Army mishap using established mishap reporting methods, see figure 3 – 1.

Appendix B - Definition of Terms

mishap_class: classification of the mishap based on the Army's class A, B, C, D definition in Army Regulation 285-10. Class 'A' is the most severe, and class 'D' is much less severe.

mishap_category: categories of the mishap, as defined in Department of the Army Pamphlet 385-40. This differentiates incidents that occur on the ground, in flight, or flight-related.

aircraft_mtds: categorizes the type of aircraft based on its Mission, Type, Design, and Series (MTDS) designation. Some examples are fixed-wing aircraft such as the C-12 and rotary-wing aircraft such as the AH-64 or UH-60.

bn_uic: this is an alpha-numeric code assigned to an organization, used to identify individual battalions in this research.

weekday: day of the week, starting with Monday and ending with Sunday.

yr: identifies the year that the mishap occurred, from 2013-2024.

qtr: identifies the quarter that the incident occurred, based on the fiscal year. The first quarter is from October through December.

mo: identifies the month that the incident occurred, from January through December.

dy: identifies the day of the month that the incident occurred.

date: identifies the date that the incident occurred, formatted as yyyymmdd.

wd: identifies the day of the week that the incident occurred, starting with Monday.

ms: months in sequential order, with October 2012 being #1 and January 2024 being #136.

mcc: mishap classification category. This identifies Class A, B, C, and D incidents.

mccl: a logistic derivative of "mcc" that groups class "A" and "B" incidents together, and class "C" and "D" together.

mcl3: mishap category level 3. This identifies flight, flight-related, or ground incidents.

mcl3l: a logistic derivative of "mcl3" by categorizing "flight" and "flight-related" together to distinguish ground incidents.

amtds: type of airframe (AH-64, CH-47, UH-60, etc.).

cl: combat location identifies if an incident occurred in or near a combat location, but does not identify if the incident was combat-related.

buic: this is the abbreviation for the "bn_uic" defined above.

buic_mcc: sum of all ‘mcc’ incidents that occurred in a given month according to the unit.

buic_mccl1: number of occurrences that are class C or D incidents in a given month by unit.

buic_mccl2: number of occurrences that are class A or B incidents in a given month by unit.

buic_mcl3l1: number of occurrences that are not flight incidents in a given month by unit.

buic_mcl3l2: number of occurrences that are flight incidents in a given month by unit.