Incident Pattern Recognition Analysis

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Abstract

The aviation industry is proactively trying to strengthen their understanding of flight safety and focused on implementing new standards to prevent the rare occurrence of aviation mishaps. Machine Learning (ML) and analytics are bridging the gap through advanced artificial intelligence (AI) systems being used for the collection and analysis of pertinent data related to flight safety. The use of analytical tools and processes are shaping the aviation industry's ability to be able to interpret insights from previous mishap data and form standards consistent with preventing future mishaps from occurring. Building analytical dashboards made up of data visualizations help interpret results within seconds. Creating data visualizations is done through manipulating and preparing data that results in a reduction of observations to gain further insight and narrow the scope to specific features of flight safety. The aviation mishap area of focus for the analysis is specifically aimed at identifying and predicting if there is a trend in mishaps occurring in the landing phase during personal flight types. In-depth analysis through machine learning pipelines will help us identify outputs conducive to our aim of trend and prediction recognition in personal flight types and the landing phase of flight. Personal flight types are the specific category of flight types the analysis focuses on due to uncovering that most incidents occur during personal flights. In this study, we will reveal a comprehensive report that uncovers facts such as 58.78% of mishaps result from personal flight types and acknowledges that 58.75% of mishaps occur from aircrafts operated by pilots with a private pilot certification. An important piece of the analysis report will center around the connection between mishaps occurring in personal flight types during the landing phase of flight. Combining the personal flight types and landing phase mishap data will allow us to understand and identify trends within mishap data so that we can build models through machine learning pipelines to effectively predict outputs for inputs related to mishap risks.

Keywords: Analytics, Machine Learning, Artificial Intelligence, Data Visualizations

1. Introduction

In FAA's records, by the number of flights, the majority of the flights are happening on personal flights (Harvard University, 2023). Also, by the incident numbers, personal flights are the leading flights by flight type. The US has an aviation culture that many people choose to get personal pilot licenses and enjoy making personal flights. In these personal flights, the landing phase is the most chaotic and risky. In this research paper, we will examine the reasons for landing incidents for personal flights.

Table 1: Data Overview

Variable	Explanation	Data Type	Descriptive Statistics*	**Prc Mss
Event Type	Type of Event	N	Incident	0
Flight Conduct Code	Flight Conduct Code	N	General Operating Rules	0.39
Flight Phase	Period Within Flight	N	Level Off Touchdown	0.33
Flight Plan Filed Code	Flight Rules	N	Unknown	45.24
PIC Cert Type	Pilot Cert	N	Private Pilot	18.26
PIC Flight Time Total Hrs	Pilot Flight Time Total Hrs	N	4,016.50	21.09
PIC Flight Time Total Make-Model	Pilot Make-Model Flight Times Hrs	N	795.61	24.03
Primary Flight Type	Flight Type	N	Personal	48.62

*Descriptive Statistics: Nominal- mode; Numeric- mean (standard deviation)
** Percent Missing

The data preparation proved to be extensive due to the 20-year time span of FAA incident data evaluated. Through cleaning and manipulating the data, we found key variables associated with our focus related to incidents caused by personal flight types. Variables such as Flight Conduct Code, PIC Certification Type, PIC Flight Time Total Make-Model, and Primary Flight Type served to provide us with data that made an incident pattern recognizable in the personal flight type. Throughout the report, we identify key findings from the study through data visualizations that provide an in-depth insight.

The data scrubbing process reveled another key variable congruent with interest in identifying incident data related to phase of flight. We see from Table 1 that the mode statistic measure in the flight phase variable is LEVEL OFF TOUCHDOWN. From this finding, we can hypothesize that the landing phase of flight contains most of the incident data. The report will contain a detailed analysis that dives into the incident data related to phase of flight during personal flight types.

The aim for this analysis is to evaluate aircraft incidents and analyze the patterns associated with the incidents happening on personal flights during the landing phase of flight. Analyzing trends within the Flight Phase variable will provide the study with insight to identifying a potential pattern with the landing phase during personal flight types. The results from the data preparation and use of business intelligence (BI) tools will allow us to prepare the variables of interest for modeling. Once our data is properly cleaned and evaluated, we will aim to find an algorithm that facilitates the capability to predict incident indicators.

2. Literature Review

Aviation has always been considered an inherently dangerous activity. Upon the discovery of flight and increased rate of air travel, government officials started to recognize the need for an agency to oversee the safety of aerospace transportation. For almost 50 years, the Federal Aviation Administration has served to enforce regulations and standards that encompass operating, maintaining, and manufacturing aircraft (Federal Aviation Administration, 2023).

The evolution of analytics over the past decade has rapidly developed our ability to analyze historical and real-time data. Previously, historical data collection was the focal point for understanding real-time events and played a significant role in the interpretation of results. While historical data still provides insight, powerful analytics through machine learning algorithms has significantly enhanced the ability to draw interpretation from a combination of historical and real-time data collection (Davenport, 2017). An increased presence of analytical methods has changed the way aviation uses descriptive, predictive, and prescriptive analytics to reduce mishaps and gain more insight toward overall optimization.

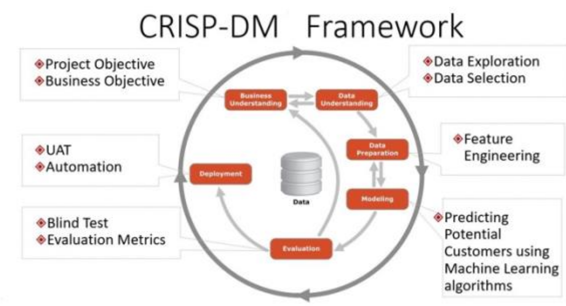
The advancements in analytics technology have changed the way the aviation industry conducts business processes. Machine learning has become a powerful technology that has optimized business processes to give aviation companies more insight and comprehension to key performance indicators (KPIs). Revenue management, fuel consumption optimization, facial recognition security controls, airfield image processing, and predictive maintenance are examples of how powerful analytics technologies work to automate and speed-up business processes (Santosh, 2021). A critical element of aviation success is the efficiency and accuracy within intelligent machine learning algorithms that work to track real-time technical aircraft states and detect anomalies that help curb unexpected costs. The transformation that has occurred within the aviation industry sets the stage for machine learning to become even more useful in ensuring aviation mishaps stay a rarity.

The reputation that aviation has gained through the years has not been easy but worked to improve from devastating incidents such as 9/11. Since 9/11, the FAA has adopted a strict policy standpoint that makes the aviation experience for customers one that can be trusted. We often think of the aviation experience being filled with unknown anxiety and timely delays, but we rarely think about the occurrence of an aviation mishap. The FAA stands as an administration to bridge the gap between possibilities of aviation mishaps and travelers' anxiety. "Between 2001 and 2007, aviation witnessed one of its safest periods for scheduled air carriers. Not counting the terrorist activities of September 11, 2001, there were only three fatal accidents in 2001; none in 2002; two in 2003; one in 2004; three in 2005; two in 2006; and none in 2007. Fatal accidents became rare events with only .01 accidents per 100,000 flight hours or .018 accidents per 100,000 departures" (Federal Aviation Administration, 2023). The FAA continues to be the administration that oversees air travel and enforce a mentality where safety is always prioritized. As we research incidents within aviation, we will identify trends and be able to understand where most incidents are occurring in aviation today.

3. Methodology and Data

The analysis conducted required in-depth knowledge of aviation operations and deployed a familiar data mining process in developing our data mining project. In academia, the use of the CRISP-DM methodology is becoming widely used due to benefits in data mining solutions that deliver value and meet business goals. Our data mining solutions focused on generalizations that are conclusive in finding the balance between overfitting and underfitting. The data mining procedures produced a high correlation between training and testing accuracy.

Figure 1



The analysis uses a widely known CRISP-DM methodology in developing a data mining project that can use the FAA data to generate and validate variables. Through six steps, (1) business understanding, (2) data understanding, (3) data preparation, (4) modeling, (5) evaluation, and (6) deployment, we emphasized the use and combination of both aviation operations knowledge and FAA data (Hotz, 2023). The study aimed to experiment with different algorithms and evaluate their performance using various metrics such as accuracy, precision, ROC, life, etc. Some common algorithms that we examined during the study were linear regression, logistic regression, decision trees, random forests, naive bayes, and neural networks. Choosing the correct algorithm was significant due to the understanding that an algorithm can drastically impact the performance of the model and the accuracy of the predictions.

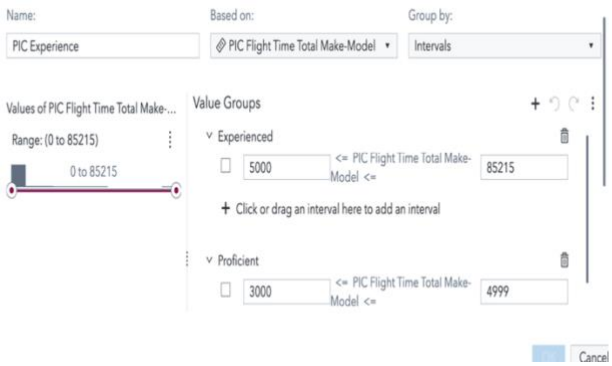
4. Data Preparation

The first data preparation transform used to enhance the dataset was removing variables from the dataset that contained unnecessary information pertaining to our analysis. The variables removed from the dataset were Aircraft Engine Make, Aircraft Engine Model, Engine Group Code, Total Fatalities, Total Injuries, Flight Plan Filed Code, and Aircraft Registration Nbr. The reasoning behind removing these variables was due to this information not contributing to significant pattern recognition in flight types and flight conduct codes. Another reason behind the removal of the variables discussed was Engine Group Code, Flight Plan Filed Code, Aircraft Engine Make, and Aircraft Engine Model all contained high percentages (nearly 50%) of Null data points. The two factors, unnecessary data and high Null percentage, contributed to the decision to ultimately remove this data.

Figure 2

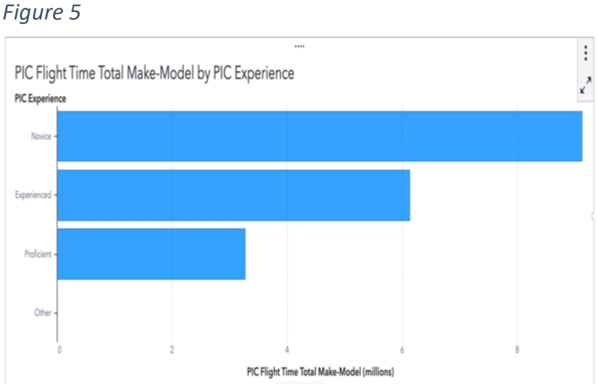
The next data preparation step performed was to add a new data item in efforts to examine pilot-in-command (PIC) experience by PIC Flight Time Make-Model. Adding this data item to the data set will give us the advantage in examining what level of experience in make-model occur in the dataset most. The construction of this new category within the data consisted of three interval value groups: Experienced, Proficient, and Novice. The interval for Novice classification were pilots who conducted flights with 1-2999 hours in make-model. Proficient pilots in make-model were classified in the interval of 3000-4999 hours in make-model. Experienced pilots in make-model were classified in the interval of hours in make-model over 5000 hours.

Figure 4



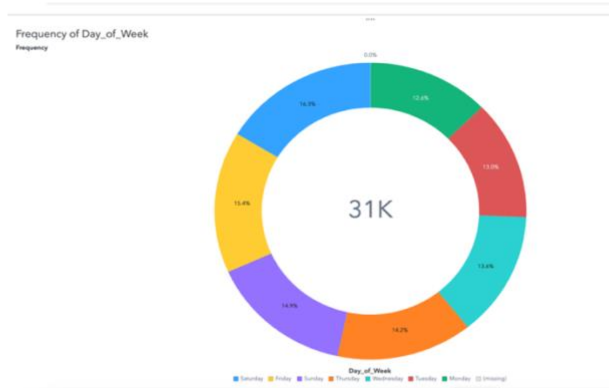
When we create a quick bar chart of the data with the category being PIC Experience and measure being PIC Flight Time Total Make-Model, we observe that the Novice category accounts for the most PIC Flight Time Total Make-Model hours in the dataset. This provides us with the insight that a lot of flights are piloted by pilots who have 1-2999 hours of flight time in make-model. Later in the analysis, this

Figure 5



could serve as a focal point to observing the root cause behind any uncovered significant incident patterns in flight types.

Figure 3



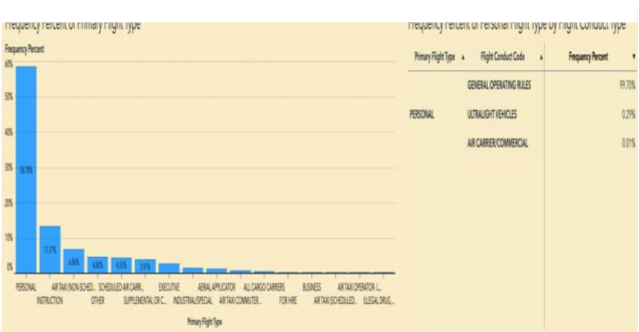
The last data preparation step performed was aimed at creating a calculated field for days of the week. The data field, Days_of_Week serves to help better understand what day of the week incidents occur most frequently. To make this possible, I had to create a calculated item based on Local Event Date. The new calculated item, Days_of_Week, was manipulated to be a Date type item and formatted as DOWNAME11(Day of Week). The new data item facilitated the ability to be able to create different charts that allow us to examine data according to the day of the week. *Figure 5* shows an example of a pie chart that helps us analyze the days of the week that incidents occur most frequently. Included in the design of the pie chart is a legend that specifies the colors for specific days of the week. A conclusion can be made from this pie chart that incidents occur most frequently (16.3% of the time) on Saturday. This is an example of how creating a new calculated field item based on Local Event Date can give access to insights that might have otherwise gone unknown. As we conduct the analysis, the

Days_of_week variable will help us uncover potential patterns and trends in the data.

3.1 Data Preparation Findings and Supplementary Research

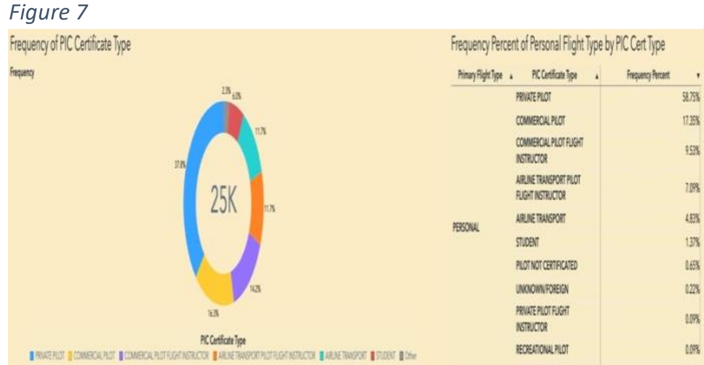
The next step in the analysis process is going back to the prepared flight incident data and looking for enhancements that can be made to improve the probability of valuable findings. Along with making changes to the data, supplementary research was conducted to explore the available information regarding flight types in relation to incidents. We're at the point in the data preparation step that allows us to analyze what flight type results in the greatest number of incidents and other variables relating to that flight type.

Figure 6



Data transformation methods were performed in the last step to examine unique characteristics of the data such as PIC experience levels and days of the week that incidents occur most on. This step of the analysis presents figures that were created by manipulating and filtering data to represent the answer to a specific question. The first question, "What flight type is responsible for the greatest number of incidents?". If we examine the bar graph in the top left corner of the report presented in *Figure 6*, we observe that Personal flight types make up nearly 59% of the incident data. This visualization provides the insight that Personal flight types make up most of the incident report data. The next question, "What flight conduct code is filled most pertaining to Personal flight types?". If we examine the crosstab table in the top right corner of *Figure 6*, we see that nearly 100% of the time General Operating Rules apply. From the data visualizations in *Figure 6*, we can conclude that most incidents in the flight dataset result from Personal flight types that are filed under General Operating Rules.

Figure 7



Continuing the data manipulation and filtering process we continue to ask questions pertaining to the flight incident data. We know that Novice experienced PIC pertaining to hours in make-model, Personal flight types, and General Operating Procedures pertaining to Personal flight types account for most of the data. The next question we ask is, "What PIC Certificate Type appears most in the data?". If we look at the pie chart titled, "Frequency of PIC Certificate Type", we observe that almost 38% of the incidents occur when a PIC has a Private Pilot certification type. Our interest now shifts to analyzing if there is a connection between Personal flight types and Private Pilot certification types. The question, "What PIC Certification Type is most common under the personal flight type category?". If we examine the crosstab table in *Figure 7* titled, "Frequency Percent of Personal Flight Type by PIC Cert Type", we see that a connection does exist in that Private Pilot certification types account for nearly 59% of the incident data pertaining to Personal flight types.

Figure 8

A unique part of the data manipulation process aimed to examine the variable Phase of Flight. Our interest in observing incidents occurring in the landing phase of flight in Personal flight types led us to create this bar chart in Figure 8. Data preparation consisted of ensuring that Primary Flight Type was filtered to only show Phase of Flight characteristics within Personal flight types without the presence of missing values. As we can see from the resulting bar chart in figure 8, we observe that the top Phase of Flight incident category is Level-Off Touchdown. Level-off touchdown refers to the phase of flight where the nose of the aircraft transitions from low to level-altitude, referred to as flaring, until the landing gear makes permanent contact with the ground (ECCAIRS Aviation, 2013). The finding that Level-Off Touchdown is the top incident category within Personal flight types contributes to our wanted comprehension of when incidents occur within Personal flight types. The landing phase of flight proves to be the cause of most incidents within Personal flight types due to most of the incidents occurring from Level-Off Touchdown.

The findings from these visualizations help support the belief stated in the introduction that Personal flight types account for many incidents. Additionally, our increased comprehension of the most frequent Phase of Flight category within Personal flight types helps us determine that Landing accounts for most of the incidents. Insights from the visualizations show that many PIC are Private Pilot certified and conduct personal flights that result in the greatest number of incidents according to the dataset. According to the Aircraft Owners and Pilots Association (AOPA), the cause of most general aviation incidents can be traced directly back to the pilot (RedBird Pro, 2022). In other words, the Pilot-in-Command is most often the reason for an incident occurring. As we have revealed in Figure 8, the landing phase of flight proves to be the phase of flight where incidents occur most frequently. This could be due to many factors such as poor proficiency due to limited flying time and reduced oversight in terms of maintenance and planning. Other factors that may contribute to Personal flight types and Private Pilot certifications resulting in a higher incident rate include fewer safety regulations compared to commercial aircrafts and the fact that not all private pilots are certified to fly IFR. Fewer safety regulations and decreased ability to fly in weather conditions that require proficiency IFR can contribute to more incidents occurring with Private Pilot certification types (Lyons Simmons, 2022).

5. Statistical Analysis

We know that almost 59% of aircraft incidents result from personal flight types. This suggests that personal flight types are associated with a higher risk of incidents compared to other flight types in the dataset. Additionally, we know that almost 59% of the personal flight type incidents are made up of pilots with private pilot certifications. This suggests that pilots with private pilot certifications are overrepresented in the group of pilots involved in aircraft incidents related to personal flights. If we observe Figure 7 above, we see that nearly 38% of the entire incident data is represented by private pilot certifications and almost 59% of the pilot certifications within personal flight type incidents are representative of private pilot certifications.

From our descriptive statistics descriptions in Table 1, we observe that our nominal and numeric values are consistent with our findings from the research. For example, nominal variables, such as PIC Cert Type and Flight Phase, contain a descriptive statistics feature that showcases the mode, Private Pilot and Level-Off Touchdown. Every variable provided in Table 1 showcases descriptive statistics consistent with our findings from the research. It's important that we continue to conduct statistical tests, such as Chi-Squared and Regression Analysis, to assess the degree of interdependence between variables. It's important to note that statistical tests alone cannot prove causation, only correlation. Therefore, it's important to interpret the results of these tests with caution and consider other factors that may be affecting the relationship between the variables.

6. Visualization of Findings

Figure 9

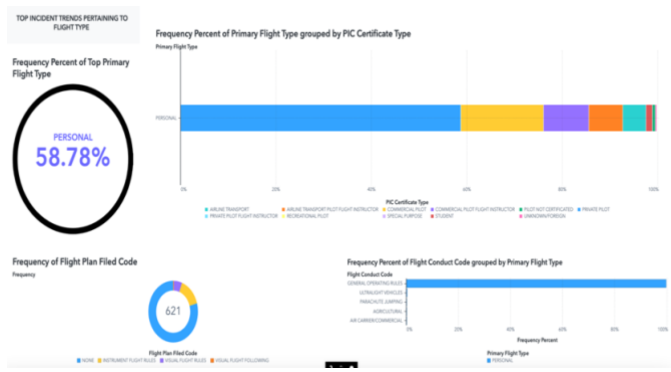


Figure 9 represents a static dashboard containing key metrics pertaining to the significant incident trend pattern in a specific flight type. It's important to note that all the data fields have been filtered to represent visualizations with no missing value within data fields. The importance of *Figure 8* in comparison to other figures is the emphasis put on the flight type with a pattern and supporting data fields. We also examine a new data field that shows we started to think more in depth of our Flight Type pattern recognition efforts.

If we move to the top left-hand corner of *Figure 9*, we see Frequency Percent of Top Primary Flight Type and acknowledge that 58.78% of the incident data occurs during a Personal flight type. This is no surprise as we have already defined the personal flight type as being the most common, frequent occurring flight type involving incidents as previously represented in *Figure 6*.

Next, we move to represent the most frequent percentage of PIC Certificate types by Personal flight types in the chart Frequency Percent of Primary Flight Type grouped by PIC Certificate Type. The top right of *Figure 9* shows that Private Pilot certifications represent 58.75% of Personal flight types. The results of Personal flight types and Private Pilot certifications representing over half of the incident data provide us with a strong pattern between these two variables and incidents reported.

The bottom right-hand bar chart in *Figure 9* represents the frequency percent pertaining to Flight Conduct Code filled by Personal flight types. Again, we see that General Operating Rules make up almost all the Flight Conduct Codes filed. Frequency of Flight Plan Filed Code is the pie chart in *Figure 9* that provides a visual of the most frequent flight plan filed code where an incident occurs. Missing values and UNKNOWN values were filtered out of the dataset to gain a more accurate understanding about which flight plan code was filed most. As we can see, the flight plan code filed most was NONE. Out of 621 flight plans filed that resulted in an incident, flight plan code NONE was filed most in the dataset. Flight plan code NONE occurring most frequently in the dataset is significant because private pilots flying personal flight types are not required to file a flight plan under VFR conditions if they do not fly into restricted airspaces (Aviation StackedExchange, 2022).

The static dashboard, Top Incident Trends Pertaining to Flight Type, in *Figure 9* provides us with data visualizations that clearly define an incident pattern within Personal flight types. Identifying high frequency in Private Pilot certifications, General Operating Procedures flight conduct code, and NONE as the flight plan filed code help support that Personal flight types show a significant trend in incidents.

Figure 10

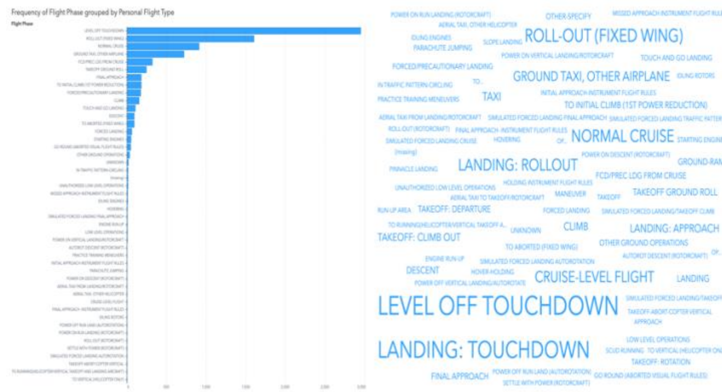


Figure 10 provides us with a new visualization that we aimed to introduce to this analysis to increase our awareness of when incidents occur most. As represented above in the data manipulation section (Figure 8), we determined that Level-Off Touchdown was the most frequent Phase of Flight of when incidents occur most in Primary flight types. This was an important observation for our understanding of when incidents occur most within Personal flight types. Figure 10 provides a word cloud that provides a unique data visualization by using the size of words to help us visualize the occurrence of incidents in different phases of flight. The unique takeaway from the word cloud in Figure 10 is that it not only includes data from Personal flight types, but all primary flight types within the FAA incident dataset. We already know that Level-Off Touchdown is the most frequent Phase of Flight within Personal flight types, but what about the Phase of Flight that accounts for most of the incidents within all flight types? The word cloud on the right side of Figure 10 provides us with an understanding that Level-Off Touchdown and Landing: Touchdown account for most incidents throughout all flight types. Figure 10 provides us with an additional pattern recognition that makes our conclusion that most incidents occur in the landing phase of flight to be an accurate one.

Figure 11

7. Sentiment Analysis

The sentiment analysis consisted of a sample of flight incidents from the incident flight dataset. Each unique ADIS Report Number consisted of a hidden free-from text column that provided an expert's incident comment. Through using advanced analytics to create text topics pertaining to the incident comments, a sentiment analysis was conducted to help define what type of sentiment existed within the incident comments.

The size of each word is typically determined by its frequency or count in each text or dataset. This count can be either positive or negative, depending on the context in which it is used. Positive counts refer to the number of times a word appears in a text with a positive connotation or meaning. For example, the word "love" in a word cloud about romantic relationships would likely have a positive count. Negative counts, on the other hand, refer to the number of times a word appears in a text with a negative connotation or meaning.

If we examine *Figure 11,* we can observe the chart in the upper-left corner that identifies topic names and shows the top two topics: approach, +landing, privacy data, privacy and +propeller, engine, +contact, right. The word cloud in the upper-right corner identifies terms that appear most frequently throughout the incident comments. The graph and word cloud at the top of *Figure 11* allow for deeper analysis to occur by clicking on any of the Topic Names or Terms. Clicking a specific Topic Name, or Term, will change the visualization to represent findings within the selected data field. The *Documents* list table in the center of *Figure 11* showcases each document with the ADIS Report Number and Sentiment value. The sentiment value helps determine which documents contain a positive sentiment (over 0.50), negative sentiment (under 0.50), or neutral sentiment (equal to 0.50). Finally, a table presented at the bottom of *Figure 11* allows for an observation of how many negative, neutral, and positive documents are within each Topic Name.

The findings from this small sample of incident comments allow for us to conclude that a large amount of negative document counts exist. While this is expected due to analyzing incident related data, we see a connection in the top topic: approach, +landing, privacy data, privacy. As this category results in a high negative document count, we can conclude that there is certainly negative sentiment toward incidents involving the words within the topic category. If we examine the word cloud itself, we see those larger sized words such as aircraft, pilot, damage, landing, runway, etc. contributing to our understanding of sentiment. Additionally, we can examine the document comments themselves and observe a sentiment score (0-1) that allows us to determine the positive and negative sentiment of the document.

8. Discussion

The data and research depict there have been several incidents involving private pilots flying personal flight types under general operating rules resulting in incidents and sometimes fatalities. While some of these incidents may have been caused by mechanical issues or other factors outside of the pilot's control, many of them have been attributed to pilot inexperience and pertained to landing incidents specifically.

This highlights the importance of proper training and experience for private pilots, especially when it comes to landing. Pilots need to be prepared to handle a variety of challenging conditions, such as crosswinds, gusty winds, and short runways. They also need to know when to abort a landing attempt and try again later, rather than attempting to force a landing that may be unsafe.

Additionally, there may be a need for increased regulatory oversight or requirements for private pilots to ensure that they are properly trained and qualified to handle challenging landing conditions. This could include mandatory training programs, recurrent training requirements, or stricter licensing requirements for certain types of aircraft or landing conditions. While private aviation can be a rewarding and enjoyable experience for many pilots, it is important to prioritize safety and ensure that pilots are properly trained and equipped to handle the unique challenges that come with flying in personal aircraft, particularly during the landing phase of flight.

9. Conclusion

The analysis produced insightful interpretations that utilized data visualizations to help reveal and further raise awareness about an incident trend. The report provides a contextual and comprehensive understanding towards recognition in an incident pattern occurring in Personal Primary Flight Types and Landing phases of flight. It’s very clear that the variables PIC Experience, Flight Type, Flight Conduct Code, PIC Certification Type, Flight Plan Filed Code, and Phase of Flight are contributing variables in incidents within Personal Primary Flight Types. The research revealed that NOVICE flying experience (< 3,000 Hrs.) of pilots in make-model was the most observed experience level throughout the dataset. The analytical processes used helped uncover that almost 60% of the incident data was related to the Personal Primary Flight Type. In almost all cases of Personal Flight Type incidents, General Operating Rules (GOR) was the flight conduct code filed. The incident pattern conclusion in Personal Flight Type is strengthened through examining that Private Pilot certifications accounted for almost 40% throughout the entire dataset and nearly 60% of incidents involved in Personal Flight Types. The plan filed code observed most was NONE. Flight plan filed code NONE was an insightful finding due to understanding that Private Pilots flying Personal Flight Types do not need to file a flight plan under most VFR conditions. Private pilots flight personal flight types need to re-focus their effort and standards pertaining to aviation safety. The landing phase of flight was uncovered to be the phase of flight where incidents occur most frequently. The use of bar charts and word clouds helped us visualize the frequency of incidents occurring during the landing phase of flight. Complacency within the private sector of aviation safety should be spot-lighted to ensure the FAA and regulating officials are taking proper action in reversing this incident trend. A few actions that need to be implemented are cracking down on private sector filed flight plan standards and incorporating controls that set higher standards for maintenance and weather reporting according to the flight plan.

9.1 Future Research

Machine learning has great potential in our future research pertaining to incident trend recognition in the aviation industry. It can help to identify patterns and predict future trends, enabling the industry to take proactive measures to prevent incidents. Future research in this area could focus on developing more sophisticated algorithms that can analyze large and complex datasets, including audio and visual data from cockpit voice and flight data recorders. We could also use machine learning algorithms to explore the use of natural language processing to analyze incident reports and other written documentation. The use of machine learning and expertise from professionals within the industry will help to shape a hybrid-model that focuses on human factors and other non-quantifiable factors that affect aviation safety. The application of machine learning in aviation safety has great potential, and future research in this area could make significant contributions to the field.

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