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Posted Date: 17 February 2025

doi: 10.20944/preprints202502.1196.v1

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A Multi-Head Attention-Based Transformer Model for Predicting Causes in Aviation Incident

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Abstract: The timely identification of probable causes in aviation incidents is crucial for averting future tragedies and safeguarding passengers. Typically, investigators rely on flight data recorders, yet delays in data retrieval or damage to the devices can impede progress. In such instances, experts resort to supplementary sources like eyewitness testimonies and radar data to construct analytical narratives. Delays in this process have tangible consequences, as evidenced by the Boeing 737 MAX accidents involving Lion Air and Ethiopian Airlines, where the same design flaw resulted in catastrophic outcomes. To streamline investigations, scholars advocate for natural language processing (NLP) and topic modeling methodologies, which organize pertinent aviation terms for rapid analysis. However, existing techniques lack a direct mechanism for deducing probable causes. Bridging this gap, this study proposed a transformer-based model for predicting likely causes from raw text narrative inputs, leveraging advancements in long-input transformers. By training the model on comprehensive aviation incident investigation reports like those from the National Transportation Safety Board (NTSB), the proposed approach exhibits promising performance across key evaluation metrics, including Bilingual Evaluation Understudy (BLEU) with *(M=0.727, SD=0.33)*, Latent Semantic Analysis (LSA similarity) with *(M=0.696, SD=0.152)*, and Recall Oriented Understudy for Gisting Evaluation (ROUGE) with a precision, recall and F-measure scores of *(M=0.666, SD=0.217)*, *(M=0.610, SD=0.211)*, *(M=0.618, SD=0.192)* for rouge-1, *(M=0.488, SD=0.264)*, *(M=0.448, SD=0.257)*, *M=0.452, SD=0.248)* for rouge-2 and *(M=0.602, SD=0.241)*, *(M=0.553, SD=0.235)*, *(M=0.5560, SD=0.220)* for rouge-L, respectively. This demonstrates its potential to expedite investigations by promptly identifying probable causes from analysis narratives, thus bolstering aviation safety protocols.

Keywords: NLP in aviation safety; aviation incidents analysis; BERT; multi-head attention; transformers

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1. Introduction

Establishing the cause of an aviation incident or accident, to prevent it from re-occurring in the future, is the core goal of any aviation safety occurrence investigation and analysis. Hereafter, aviation accidents will be considered a subset of aviation incidents. Conventionally, whenever an investigation is deemed necessary in the event of an aviation incident or accident, the primary source of information is usually the Cockpit Voice Recorder (CVR) and Flight Data Recorder (FDR) devices [1]. Data from these two devices is vital in giving an account of what was happening within the cockpit and the input to the aircraft received from the pilot, respectively, minutes before and at the time of the incident. However, retrieving these two devices can take months or even years and in the worst case, the devices get severely damaged during or after the incident making the data irretrievable [2]. In such cases, where the data on the devices does not give conclusive findings or is not readily available for the investigations to start, the experts often divert their attention to other sources which can include eyewitnesses, pilot reports, air traffic controllers, satellite images, radar information, damaged aircraft

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components, and weather stations readings at the time of the incident [3]. This gathered information is often prepared and presented as a narrative describing the series of events and conditions under which the incident/accident occurred. This information is then analysed by experts to establish the likely cause of the incident [4], allowing them to suggest possible measures that can deter such incidents from happening again.

However, this entire process is time-consuming, and in the event of a design flaw, until the cause is established, and a preventative measure designed and implemented, the lives of passengers flying with such an aircraft model remain at risk. As an example, the flaw in the design of Boeing 737 MAX's Manoeuvring Characteristics Augmentation System (MCAS) feature which in certain circumstances counteract the pilots' input caused two fatal accidents including the crash of Lion Air (JT610) [5] flight followed, five months later, by Ethiopian Airlines Flight 302. Both aircraft crashed a few minutes after taking-off killing all 189 and 157 people on board respectively [5,6]. If the cause of the Lion Air accident had been established quickly and acted upon appropriately, the ET-302 [6] accident would likely have been avoided. With the aim of shortening aviation incident/accident investigation time, and allowing the quick establishment of the cause, researchers have proposed various natural language processing (NLP) and topic modeling-based approaches like Latent Dirichlet Allocation (LDA), Latent Semantic Analysis (LSA), Parallel Latent Dirichlet Allocation (PLDA), among others [7–11]. These proposed schemes analyse and group aviation terms with related meanings or that are connected to a given phase of flight, field of aviation, flight conditions, and/or causes into related topics. Such approaches could help the investigation team to establish the area of concentration and consequently, lead to quick establishment of the causes.

However, no previous study has proposed a scheme for generating the probable causes given the analysis narrative of the pre-incident conditions and activities. To this end, this work builds and deploys a transformer-based model to predict the probable cause of an aviation incident from the initial analysis narrative. Transformer models like Bidirectional Encoder Representations from Transformers (BERT) [12] and its variants [13–18] have demonstrated cutting-edge performance across various challenging NLP tasks. Since the analysis narratives often contain long textual paragraphs, The researchers hypothesized that the resulting model would produce enhanced performance if based upon recent studies on long-input transformers [19–22] which have revealed that increasing the Transformer's input length positively correlates with model performance.

The training approach for the transformer model deployed in this work aligns with the fundamental principles of a language translation transformer. However, it deviates in that, instead of setting the masked input to the transformer's decoder as the target language during training, it utilizes the target probable cause. Upon evaluation on the NTSB dataset, the model showcased the potential for transformers to accelerate aviation incident investigations by generating the probable causes based on the analysis narrative. The contribution of this study is two-fold:

1. A new generative model based on multi-head attention transformer is proposed and trained for generating the probable cause of an aviation incident when given as input the raw text narrative of series events before, during or after the accident. The model accepts both long and short input narratives which should expedite the investigation process enhance air transport safety.
2. Many aviation incident dataset have instances with analysis narratives but with no corresponding entry for the probable causes. This leads to eliminating many instances during model training and consequently leads to poor model performance in terms of generalization to new instances. With the ability to generate missing probable cause, instances with missing values can be retained, likely leading to better model performance and generalization.

The rest of this paper is organized as follows: Section 2 presents a review of prior related work followed by Section 3 where a detailed description of the our approach is presented. In Section 4 the findings of this study are presented. In Section 5 a detailed discussion of the findings is presented, highlighting the contributions and limitations of our study and finally section 6 gives concluding remarks, highlighting the direction of future work.

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2. Related Work

The utilization of machine learning and deep learning methods and techniques in aviation analysis and prediction has garnered increasing attention from aviation safety researchers. This interest is driven by objectives such as expediting aviation incident investigations, promptly determining the causes of incidents for swift mitigation of future occurrences, predicting incidents, and extracting knowledge to enhance air transport safety. This section delves into key prior studies that have employed AI-based techniques in alignment with aviation safety.

Burnett et al., [23] trained four conventional ML classifiers, including Decision Trees, KNN, SVM, and ANN with back propagation for prediction of aviation injuries and fatalities. The authors employed a cross validation training approach with 10 folds and looked at how factors like pilots' accumulated flight hours and age impacted the rate of injuries and fatalities. Experimental results revealed ANN to be superior for the task when evaluated on datasets sourced from Federal Aviation Administration (FAA) between 1975 and 2002 inclusive.

Nanyonga et al., [24] utilized NLP and other AI to analyze text narratives, aiming to determine aircraft damage levels from safety incidents. Four learning models: Long Short-Term Memory (LSTM), Bidirectional LSTM (BLSTM), and Gated Recurrent Units (GRU), Simple recurrent Neural Network (sRNN) and hybrid architecture models including GRU+LSTM, sRNN+BLSTM+GRU, etc, were assessed on 27,000 NTSB reports. Results indicated all models achieved over 87.9% accuracy, surpassing random guessing (25%) for a four-class problem.

Another study [25], assessed the risk created by various anomalies in aviation events using of a hybrid classifier constituting proposed a hybrid model comprising a SVM and and several neural networks. The four-step method involved all events being categorized into five risk-level groups, followed by application of a SVM model to determine the link between textual event synopses and the resulting consequences. Next the hybrid model was trained to capture the correlations between contextual event attributes and risk-level groups. A fusion rule was then proposed to combine outcomes from the two models and finally, a stochastic-base decision tree was used to predict the risk level.

Both [26] and [27] deployed Bayesian inference-based techniques for aviation incident modeling and analysis. Study [27] aimed to forecast aircraft safety incidents by employing an inventive statistical method. This method utilized Bayesian inferences and hierarchical structures to build learning models of varying complexities and goals. In contrast, [26] focused on analyzing commercial aviation accidents spanning the period between 1982 and 2006, as documented by the NTSB. This second study proposed a four-phase approach to build a Bayesian network capable of capturing the relationship between the sequence of events that led to the accidents. The methodology encompassed creating a graphical representation for visualizing aviation accident events, forming a Bayesian network representation by amalgamating the graphical representations of all accidents, while accounting for the causal and dependent relationships between aircraft damage and personnel injury.

In their study [13], trained and evaluated two models, *ResNet* and simple RNN, to classify the phase of flight during which the incident happened. Various NLP-based techniques were sequentially deployed including word tokenization, punctuation, unwanted characters and stopword removal, lemmatization operations and *word2vec* transformation of the unstructured textual analysis narratives extracted from the NTSB aviation incident investigation reports. The models recorded a classification accuracy of more than 68% on a 7-class classification problem.

In study [28], Nanyonga et al., carried out a comparative study of two topic modeling analysis techniques: LDA and Non-negative Matrix Factorization (NMF) regarding aviation accident reports. Using Coherence Value for performance evaluation the quality of generated topics was evaluated with LDA, displaying superior topic coherence and indicating its robustness in extracting semantic connections among words within topics. NMF, on the other hand, showcased exceptional performance in line with generating unique and detailed topics, facilitating a more targeted examination of particular aspects of aviation accidents.

 doi:10.20944/preprints202502.1196.v1

Their study [29] showcased an automated text classification approach, utilizing machine learning, that could enhance analysts' efficiency by accurately categorizing "Occurrence" in aviation incident reports, thereby enabling more precise querying of reporting databases. Using a Random Forest algorithm to classify more than 45,000 textural reports, an accuracy of 80-93% was recorded based on the ICAO "Occurrence" Category. The authors also conducted text cleaning that encompassed use of standard NLP techniques including stemming, removal of irrelevant words and symbols like stop words, punctuation characters and other special symbols, and then deployed the *n-gram* techniques including bi-gram, tri-gram, etc for feature extraction prior to passing the reports to the ML algorithm for classification.

Studies including [30–32] deployed NLP-based techniques including topic modelling, and text classification, for information extraction from, and analysis of, aviation incident reports and have reported competitive results regarding causal factor analysis like human factors analysis, and aviation incident risk classification, aircraft damage classification, aviation report clustering and grouping, and many other AI-based tasks.

One research gap revealed in our literature review concerns attention-based transformers. Despite the attention-based transformer models achieving outstanding performance on various NLP tasks, including machine translation [33–35], text summarization [36,37], text simplification [38,39], grammatical error correction [40,41] and question answering [42], little-to-no attention has been paid to their deployment in the field of aviation safety to establish the likely causes of an aviation incident given the raw text analysis narrative. The work in this study aims to close this knowledge gap by proposing and training a transformer-based model for such tasks.

3. Proposed Approach

3.1. Dataset

Several aviation, and transport safety agencies, such as the Australian Transport Safety Bureau (ATSB), Aviation Safety Reporting System (ASRS), and the NTSB, actively gather and release reports detailing aviation incident investigations. This research utilized aviation incident reports provided by the NTSB. These reports, along with accompanying metadata, are available on the NTSB's website in a variety of formats, such as monthly-published *.pdf* documents, *.json* files, or by querying individual reports through their online platform. A summarized version in *.csv* format can also be obtained. For this study, the researchers focused on *.json* files containing detailed incident investigations from the years 2001 to 2020. Importantly, the only included incidents where investigations that had been concluded, resulting in a dataset comprising 29,676 cases. From each report, the *analysisNarrative* were extracted and *probableCause* sections to facilitate model training and validation processes. Additionally, a comprehensive statistical analysis was carried out to assess the distribution of text lengths within these fields. It was found that the average length of the *analysisNarrative* was 1,116 words, while the *probableCause* field averaged 165 words, with standard deviations of 858.36 and 93.12, respectively. Further examination revealed that the shortest *analysisNarrative* entry contained only 4 words, while the longest reached 36,544 words. In comparison, the *probableCause* field ranged from 7 to 1,600 words. Figures 1 and 2 visually represent the distribution of text lengths for both the *analysisNarrative* and *probableCause* fields.

3.2. Data Pre-Processing

Data pre-processing involved removing HTML tags and urls, transforming wrongly-encoded characters; that is, characters encoded with the ASCII equivalent codes were decoded to their natural language characters. Also, reports whose *analysisNarrative* entries were longer than 10,000 words, and *probableCause* entries longer than 1,000 words, were treated as outliers and discarded for this study.

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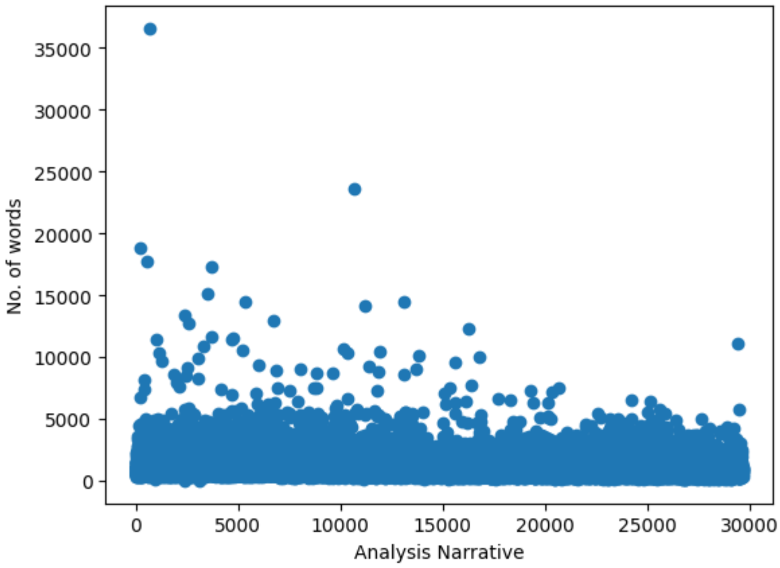

Figure 1. Text length distribution of the *analysisNarrative* field entries

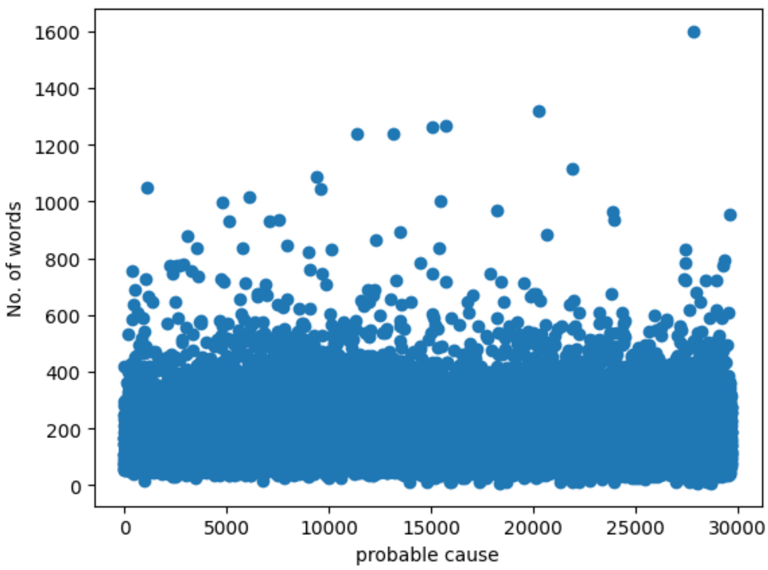

Figure 2. Text length distribution of the *probableCause* field entries

3.3. The Transformer

The Transformer architecture, introduced in study [43], represented a revolutionary advancement in the NLP domain, yielding remarkable outcomes. Departing from traditional RNN models, the Transformer employs multi-head self-attention, enabling parallel processing and overcoming the limitations of sequential training inherent in conventional RNNs. This self-attention mechanism not only enhances computational efficiency but also captures intricate dependencies among various text components. As described by the authors, the attention process involves associating a given query, Q, with key(K)-value(V) pairs for sequence generation. Within this framework, Q, keys K, V, and the prediction are expressed as vectors. The resulting sequence is computed through a weighted summation of the V entries, with each value's weight determined by a passing a scaled-dot product of Q and K vectors through a softmax function as depicted in Eq.(1). Figure 3 shows the architecture of the transformer model and the architectural components of its encoder, decoder and output blocks.

$$Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V \quad (1)$$

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Where;

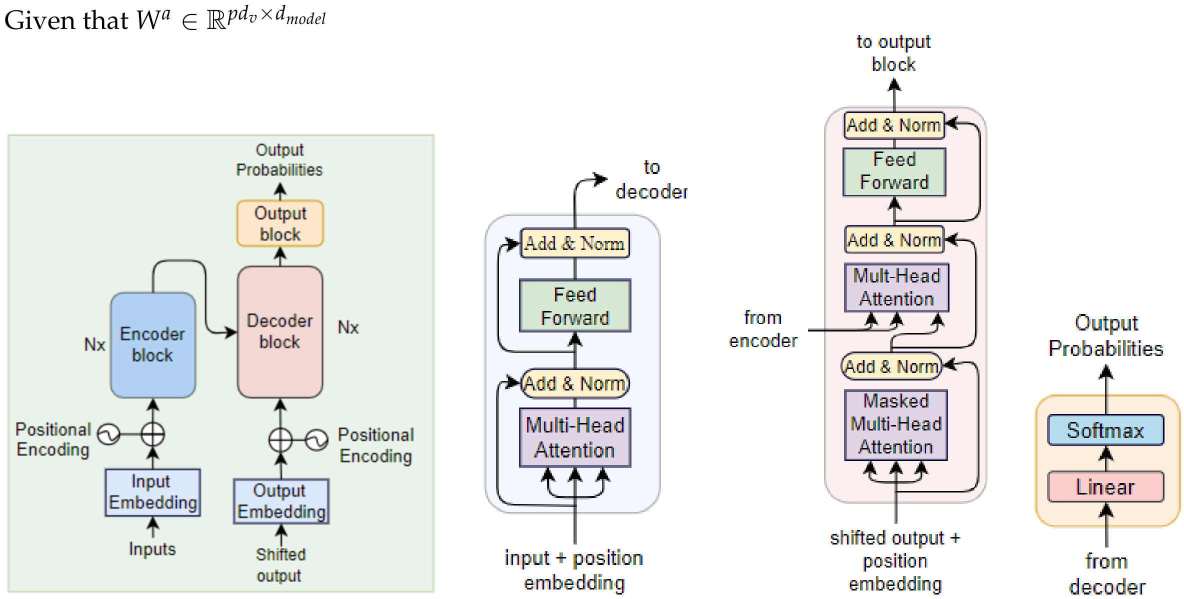
d_k is the dimensional size of K.
T transposes K to allow matrix multiplication.

.

In order to facilitate concurrent processing, the multi-head self-attention mechanism utilizes several linear projections of Q, K, and V, each mapped to dimensions d_k, d_k and d_v respectively. These parallel operations generate outputs within the d_v-dimensional space, which are combined and mapped again to derive the ultimate V entries. This approach results in a model capable of simultaneously attending to information across many representational vector subspaces at various locations. The multi-head self-attention mechanism, featuring p heads, is defined as presented in Eq.(2).

$$MultiHead(Q, K, V) = cancat(head_i, \ldots, head_p)W^a \tag{2}$$

Given that $W^a \in \mathbb{R}^{pd_v \times d_{model}}$



(a) (b) (c) (d)

Figure 3. Transformer model architecture and and a break down of its architectural components-(a): Full transformer block architecture; (b) Architectural components of the encoder block; (c) Architectural components of the decoder block; (d) Components of the transformer output block.

3.4. Experimental Setup

For our experiments, the model constituted 8 encoder and decoder layers and its embedding dimension was set to 1024 to enable long inputs. For multi-head attention, 8 attention heads were employed, while a dropout of 0.1 was used at each Batch normalization layer, and Feed-forward layer for regularisation and to prevent model over-fitting. In addition, the input sequence length was set to 1024 and the dimension of the Feed-Forward network's inner-layers was set to 2048, both the "analysisNarrative" and"probableCause"'s vocabulary sizes were set to 100,000.

The model was trained on 90% of the dataset while the remaining 10% was used for testing following study [44] in which this split ratio produced the best prediction results. Training was done for 50 epochs using a learning rate of 0.001 with Adam optimizer, betas were set to $(0.95, 0.96)$, epsilon set to $1e - 10$, batch-size set to 64, and cross-entropy as the loss function.

3.5. Performance Metrics

To evaluate the quality of generated probable cause, three metrics commonly used tasks involving natural language generation problems such as text summarizing, machine translation, question answering and grammatical error correction are used in this study.

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3.5.1. Bilingual Evaluation Understudy (BLEU)

BLEU [45] deploys an *n-gram* based evaluation metric approach that is extensively utilized in Machine Translation assessment. It is precision-centric and assesses the degree of overlap between n-grams from the target and generated texts. This overlap is insensitive to word position, except for *n-gram* term associations. However, BLEU imposes a brevity penalty when the generated text is substantially shorter than the reference text. Besides Machine Translation, BLEU finds application in problems where the input and output use the same natural language, including grammatical error correction [46,47], summarization [48,49], and text simplification [39,50], which involves rewriting a sentence into one or more simpler sentences. The BLEU score can be computed using Eq.(3) [45].

$$BLEU = BP \cdot \exp\left(\sum_{i}^{N}(w_i \cdot \ln p_i)\right) \tag{3}$$

where;

BP $\rightarrow$ Brevity Penalty, calculated using Eq.(4)
w_i $\rightarrow$ order *i* *n-gram* precision's weight.
p_i $\rightarrow$ *n-gram's* modified precision score of order *i*
N $\rightarrow$ maximum *n-gram* order to consider

$$BP = exp(1 - \frac{l_p}{lr_{avg}}) \tag{4}$$

l_p $\rightarrow$ length of predicted cause
lr_{avg} $\rightarrow$ average length of reference cause.

3.5.2. Recall Oriented Understudy for Gisting Evaluation (ROUGE)

ROUGE [51] applies a definition similar to that of BLEU. However, unlike BLEU which emphasizes precision, ROUGE's emphasis is on recall. ROUGE comes in three main versions [52,53]: *n-rouge*, primarily examining *n-gram* overlap (such as 2-rouge and 1-rouge for 2-grams, and 1-gram respectively); *L-rouge*, which evaluates the Longest Common Text Sub-sequence; and *s-rouge*, emphasizing skip grams. Like BLEU, ROUGE finds application in both machine translation and in problems where the input and output use the same natural language, including summarizing [54–56], grammatical error correction [53,57], and text simplification [58–60], which involves rewriting a sentence into one or more simpler sentences. For each of *rouge-1*, *rouge-2* and *rouge-L*, the precision, recall, and F-measure are calculated using Eqs.(5), (6), (7) [51].

$$Precision = \frac{Count_{mn-gram-ap}}{Count_{n-gram-p}} \tag{5}$$

$$Recall = \frac{Count_{mn-gram-ap}}{Count_{n-gram-a}} \tag{6}$$

$$F1 - Score = 2 \times \frac{precison \times recall}{precison + recall} \tag{7}$$

where'

$Count_{mn-gram-ap}$ is the number of n-grams from the target probable cause matching with the predicated probable cause.
$Count_{n-gram-p}$ is the count of n-grams in predicted probable cause
$Count_{n-gram-a}$ is the count of n-grams in actual probable cause

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3.5.3. Latent Semantic Analysis (LSA)

LSA [61], presented in 1997 by Landauer and Dumais in [62], calculates the semantic similarity between a reference sentence and the model's generated sentence. It relies on pre-computed word co-occurrence counts from a large corpus. Employing the bag of words (BOW) approach, it treats word order as irrelevant. Unlike ROUGE and BLEU, LSA is lenient on variations in word choice, such as "hard" versus "difficult." In essence, LSA encodes sentences or documents into vectors using a bag of words technique. These vectors enable the computation of similarity metrics, such as cosine similarity, to assess the likeness between generated and target texts. Like BLEU and ROUGE, LSA has seen application in measuring the output quality of various natural language generation models including text summarizing, grammatical correction, translation, and text simplification [63–67]. The cosine similarity between sequences, s_1 and s_2, can be obtained by converting the sequences to numeric vectors, v_1 and v_2, and then using Eq.(8) for similarity calculation [68].

$$Similarity(v_1, v_2) = \frac{dot(v_1, v_2)}{||v_1|| \times ||v_2||} \tag{8}$$

4. Results

For model inference, instances from the test were fed into the model and it generated a probable main cause for each analysis narrative. The example of training cases are shown in Figure 4, where random samples of analysis narratives from the test set are passed to the model. The model generated almost semantically perfect probable causes concerning each input narrative.

```
--------------------------------------------------------------------------------
    SOURCE: According to the pilot, he made a precautionary landing on a road to investigate a possible airplane malfunctio
n. During the landing, he noted that the wind was out of the north and about 25 to 35 mph. After troubleshooting, the pilot
attempted to take off from the road to the east. According to the airplane manufacturer, the airplane's maximum demonstrated
crosswind is 20 knots at 90 degrees. During the takeoff roll, the pilot lost directional control of the airplane, and the ai
rplane departed the road. Subsequently the right main landing gear collapsed, and the right wing impacted the ground. The pi
lot reported no preimpact mechanical malfunctions or failures with the airplane or engine that would have precluded normal o
peration.
    TARGET: The pilot’s decision to take off in a crosswind that exceeded the airplane’s maximum demonstrated crosswind capa
bility and his subsequent inability to maintain directional control.
 PREDICTED: The pilot ' s failure to maintain directional control during takeoff in crosswind conditions .
--------------------------------------------------------------------------------
    SOURCE: The pilot reported a loss of engine power while on an instrument approach to an airport. He was unable to reach
the airport, and collided with a tree short of the runway. Postaccident inspection disclosed no evidence of any preimpact me
chanical anomalies with the airplane or its engine. Initial responders to the accident site noted an absence of fuel smell o
r visible fuel at the site, although one wing containing fuel tanks had separated during the accident. No evidence of any fu
el stains were discovered anywhere on the airplane.
    TARGET: The pilot’s inadequate in-flight planning/decision, which resulted in a loss of engine power during an instrumen
t approach to land, and an in-flight collision with a tree and terrain.
 PREDICTED: The pilot ' s failure to follow the published instrument approach procedure , which resulted in a collision with
trees .
--------------------------------------------------------------------------------

    SOURCE: The airplane experienced a total loss of engine power during cruise flight, and struck a tree during a forced
landing. After the accident, the passenger reported the engine driven fuel pump failed. Review of a flight manual for the
make and model airplane revealed that a fuel gauge was incorporated into the fuselage (header) fuel tank cap. Fuel flowed
from the wing tanks, via the engine driven fuel pump, to the fuselage tank. Once in the fuselage tank, fuel was gravity fe
d into the engine. Further review of the manual revealed that in case of engine driven fuel pump failure, the engine would
continue to function until the 6-gallon fuselage tank was drained. During an examination of the wreckage, the fuselage tan
k was observed to be empty, except for some residual fuel. The fuel was clear, consistent with 100LL aviation gasoline, an
d no contamination was observed. The engine driven fuel pump was removed from the engine for inspection. When the pump was
actuated by hand, there was no movement or continuity to its mechanical linkage that connected into the engine. The inoper
ative pump was re-attached to the engine to prevent oil leakage, and 5 gallons of gasoline was added to the fuselage tank.
The engine then started on the first attempt, without hesitation, and ran continuously at idle power and partial power.
    TARGET: A total failure of the engine driven fuel pump, and the pilot's failure to recognize a diminishing fuel supply
in the fuselage (header) fuel tank, which resulted in a total loss of engine power during cruise flight and subsequent col
lision with trees during a forced landing.
 PREDICTED: A loss of engine power due to fuel starvation as a result of the pilot ' s improper fuel management . Contribu
ting to the accident was the pilot ' s failure to comply with the airplane manufacturer ' s recommended flight procedures
for the fuel system .
---------------------------------------------------------------------------------

    SOURCE: The pilot said that he normally flew the airplane with the fuel selector positioned to the right main fuel tan
k during skydiving operations. However, on the day of the accident, maintenance was performed on the airplane, and three e
ngine run-ups were performed using the left main fuel tank. The pilot ferried the airplane back to its home base uneventfu
lly with the left main fuel tank selected. Before the accident flight, the pilot verified that there was adequate fuel in
the right main fuel tank; however, he did not reposition the fuel selector to the right main fuel tank. During climb, abou
t 800 feet above ground level, the airplane experienced a total loss of engine power. The pilot was unable to restart the
engine and performed a forced landing. Subsequent examination revealed that the airplane’s right main fuel tank had been c
ompromised and was leaking fuel, whereas the left main fuel tank was intact and devoid of fuel. Additionally, data downloa
ded from the airplane's engine monitor revealed that the engine power loss was preceded by a loss of fuel flow. Postaccide
nt examination did not reveal any preimpact mechanical malfunctions or failures that would have precluded normal operatio
n.
    TARGET: The pilot's inadequate preflight preparation and fuel management, which resulted in a total loss of engine pow
er due to fuel starvation.
 PREDICTED: The pilot ' s improper fuel management , which resulted in a total loss of engine power due to fuel starvation
.
---------------------------------------------------------------------------------
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Figure 4. Some examples of analysis narratives with corresponding probable causes as presented in the original report and the model's predicted probable causes

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4.1. Model Performance Based on the BLEU Score

The BLEU Score was used to measure how closely the predicted probable cause matched the reference probable cause. For each pair of sentences, BLEU gives a value between 0 and 1, with 1 indicating a perfect match. The minimum n-gram order was set to 1 while N was set to 4 for this work. After a series of evaluations with various random samples of size 500 from the test set, in comparison with results from other metrics, the weight vector, w was set to $(0.1, 0.1, 0, 0)$.

For each instance in our test set, the BLEU score was computed, recording a mean score of 0.727 with a standard deviation of $-/+0.330$. A scatter distribution of the obtained BLEU scores between the first 1000 (probable cause, predicted probable cause) pairs is shown in Figure 5.

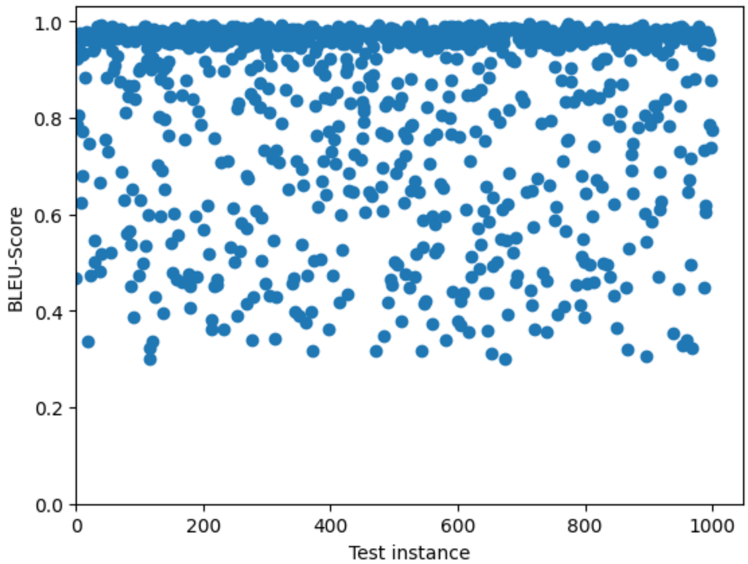

Figure 5. BLEU scores for the first 1000 test instances

4.2. Model Performance Based on the LSA Similarity Score

LSA Similarity gives the semantic similarity between vector representations of the output probable cause and target probable cause. It represents the semantic similarity rather than lexical similarity. A high similarity score implies that the sequences have closer meanings. Like the case of BLEU scores, for each instance in the test set obtained the (probable_cause, predicted_probable_cause) pair.

Each component of the pair was then converted into its numeric vector representation using Google's pretrained Universal-Sentence-Encoder Version 4, which is the latest version at the time of writing this paper. Universal-sentence-Encoder models were introduced by Google Researchers in study [69] where the cosine similarity was deployed consequently placing vector embeddings of semantically similar words close to each other. The pretrained Universal-Sentence-Encoder model used in this work can be downloaded from the TensorFlow hub [1]. Our model recorded a mean LSA similarity score of 0.697 with a standard deviation of $-/+0.153$. A distribution of the obtained Similarity scores is visualized in Figure 6

[1] https://tfhub.dev/google/universal-sentence-encoder/4

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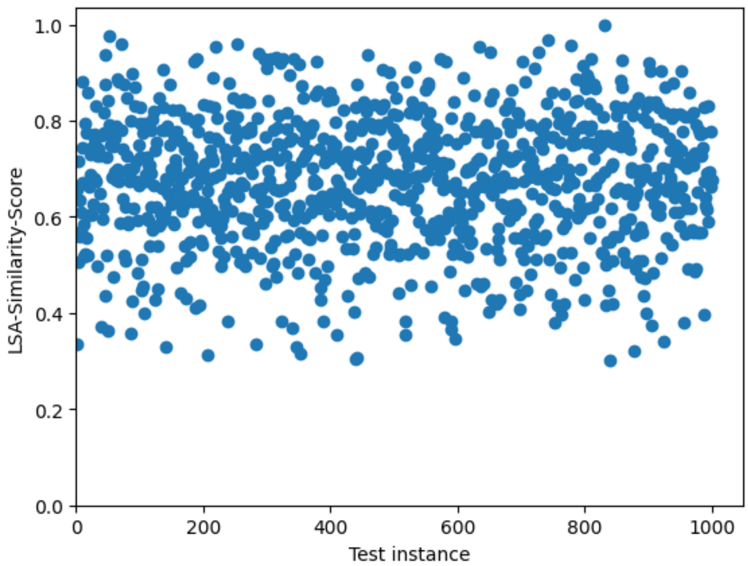

Figure 6. LSA-similarity scores for the first 1000 test instances

Table 1. ROUGE Results: Precision, Recall, and F-measure from Rouge-1, Rouge-2, and Rouge-L

Metric	Precision		Recall		F-measure	
	Mean	Stddev	Mean	Stddev	Mean	Stddev
rouge-1	0.666	0.217	0.610	0.211	0.618	0.192
rouge-2	0.488	0.264	0.448	0.257	0.452	0.248
rouge-L	0.602	0.241	0.553	0.235	0.560	0.220

4.3. Model Performance Based on the ROUGE Scores

For ROUGE Scores, this study considered *n-rouge*(rouge-1, rouge-2) and *L-rouge*(rouge-L). These scores measure the overlap of *n-grams* between the candidate and reference sentences. *Rouge-1* gives score from unigrams, *rouge-2* gives score from *bi-grams*, while *rouge-L* gives score from the longest common sub-sequence. Higher scores indicate better overlap between the sentences.

4.4. AnalysisNarrative Length Vs BLEU/LSA Scores

Further investigations were carried out on how the length of the input analysis narrative impacted the model's output in terms of the BLUE and LSA similarity scores. The results revealed that the analysis narrative length had no direct correlation with the model's BLUE score as shown in Figure 7. On the other hand, the LSA similarity score shows no correlation with the length of the input analysis narrative for shorter inputs. However, it tends to converge to the mean score as the length of the analysis pattern increases as shown in Figure 8. This finding emphasizes the researchers' hypothesis which stated that working with long input sequences would enhance the model's predictive performance. This also emphasises the finding of prior studies on long-input transformers including [19–22] which revealed that increasing the Transformer's input length positively correlates with model performance.

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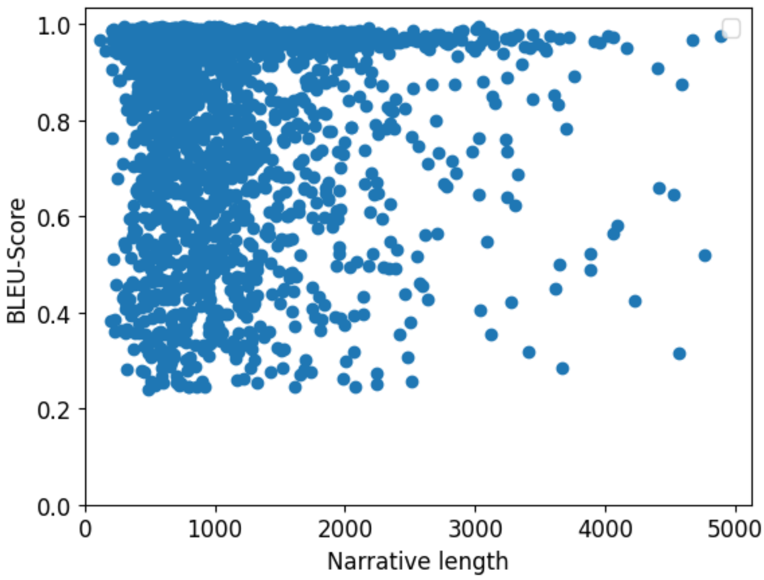

Figure 7. Impact of Analysis narrative's length on the model's BLEU score.

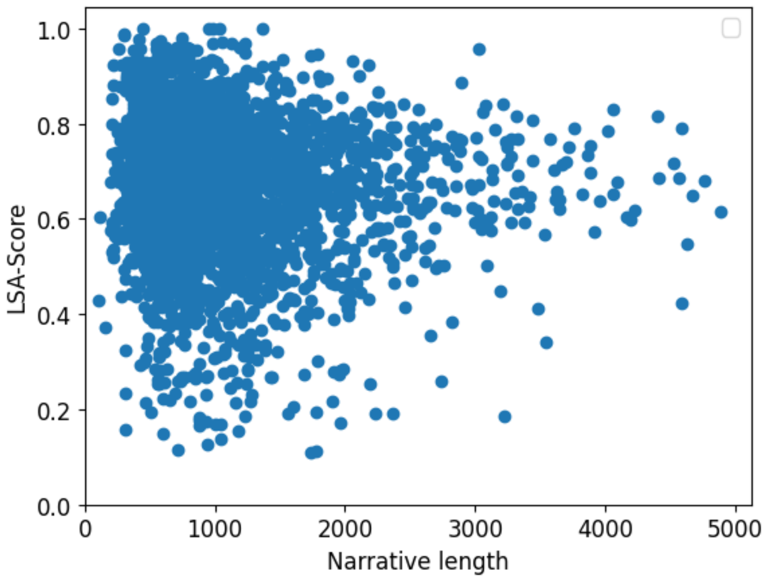

Figure 8. Impact of *analysisNarrative* length on the model's LSA similarity score.

5. Discussion

Having the ability to predict the probable causes of an aviation incident can greatly expedite the investigation process. The results from this study revealed that a multi-head attention-based transformer model is a tool for solving this problem. However, although the model recorded commendable results across all metrics, by their formula, the LSA similarity score is more reliable compare to BLEU and ROUGE metrics. This is because the model's output and reference sentence can constitute a different set words for the same semantic content. Since the LSA similarity score computes the overall semantic similarity between the sentences, it will more likely produce a high score if the two sentences are similar and vice-versa. On the other hand, the BLEU score requires that the weight vector, w for each n-gram is manually determined. This means that the final BLEU score greatly depends on the accuracy of the values of w which requires human expert and if wrongly determined can lead to misleading results. Also, the computation of BLUE and ROUGE scores like the uni-gram, bi-gram, etc, depend on the overlap of words between the reference and predicted sentence, that is, observed probable cause and predicted probable cause for this study.

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For instance, considering the output in the screenshot in Figure 9, the reference probable cause as given in the dataset is:

```
--------------------------------------------------------------------------------
    SOURCE: The pilot reported that, while on short final for landing, he heard a "high pitched whine" and that the helicopt
er's tail rotor authority subsequently degraded. He immediately initiated a full autorotation to landing. During the landing
in a field with uneven terrain, the helicopter was substantially damaged.Postaccident examination revealed that, during the
flight, the tail rotor driveshaft (TRDS) had become uncoupled from the drive assembly and main rotor belt transmission. The
forward TRDS retention nut was found safety wired; however, it was less than hand tight. The main rotor transmission input a
ft pinion nut was found backed off the pinion; the nut and pieces of its fractured cotter pin were found captured in grease
contained in the TRDS fitting grease cavity. The nut was intact, but it exhibited thread wear. The cotter pin was shorter an
d thinner than the cotter pin specified in the helicopter manufacturer's illustrated parts catalog. The grease in the aft pi
nion splines was discolored, caked, and dry, indicating that it had not been serviced in a long time.The main rotor transmis
sion input pinion exhibited significant wear on the forward spline set and the aft spline set that engaged the driving splin
e, which was normally retained by the aft pinion nut. The aft upper H-frame bearing was displaced on the driving spline. The
driving splines' interior spline teeth exhibited severe wear matching the wear on the pinion, and rotation damage was found
on the spline ends. Other areas of the pinion exhibited fretting corrosion.According to the helicopter manufacturer's Handbo
ok of Maintenance Instructions, during the 1,200-hour inspection, the mechanic was required to remove the upper pulley, insp
ect the pinion, and torque and safety wire the aft pinion nut during reassembly. The mechanic who performed the 1,200-hour i
nspection (and others) stated that, during the inspection, he had "never gotten into" the drive assembly, had not checked th
e torque on the aft pinion nut, and had not inspected the cotter pin.
    TARGET: The mechanic’s improper maintenance of the main transmission aft pinion nut and belt drive system, which resulte
d in the uncoupling of the tail rotor driveshaft and the subsequent loss of helicopter control.
 PREDICTED: The failure of the main rotor drive belts due to a loss of belt tension on the main rotor drive system as a resu
lt of maintenance personnel s failure to properly secure the - nut and the helicopter s main rotor drive belts .
```

Figure 9. Reference model output screenshot for discussing the BLEU, ROUGE and LSA Similarity scores: The model's output constitutes a slightly different word set from the reference probable cause

"The mechanic's improper maintenance of the main transmission aft pinion nut and belt drive system, which resulted in the uncoupling of the tail rotor driveshaft and the subsequent loss of helicopter control".

While the model's prediction given the same analysis narrative, is:

"The failure of the main rotor drive belts due to a loss of belt tension on the main rotor drive system as a result of maintenance personnel s failure to properly secure the - nut and the helicopter s main rotor drive belts."

Although the semantic meanings of the two narratives are close and would both draw the incident investigator's attention to the same component and attribute the failure to the maintenance personnel's not properly securing the nut and belt drive system, BLEU scores differed across different weight vector values as shown in Table 2.

Table 2. BLEU-scores for various weight vector values

Weight vector	BLUE-Score
$[0.1, 0.1, 0.1, 0.1)]$	8.67×10^{-32}
$[0.01, 0.01, 0.01, 0.01]$	7.83×10^{-4}
$[0.25, 0.25, 0, 0]$	0.459
$[0.1, 0.1, 0, 0]$	0.732
$[0.01, 0.01, 0, 0]$	0.969

On the other hand, the ROUGE scores were **rouge-1:** precision=0.476, recall=0.606, Fmeasure=0.533, **rouge-2:** precision=0.146, recall=0.188, Fmeasure=0.164 and **rouge-L:** precision=0.310, recall=0.394, Fmeasure=0.347. As it can be seen, the results from the BLEU score largely depend on the values of vector w. It is also clear that the score greatly degrades when w contains entries for the tri-gram and quad-gram which correspond to the third and fourth entries of w respectively. The value is also, misleading for very small entries of the uni-gram and bi-gram as seen when w is set to $(0.01, 0.01, 0, 0)$.

Generally, the recorded scores in the case of ROUGE metrics are relative more reliable for the *rouge-1* and *rouge-L*. The *rouge-2* has recorded poor performance due to the fact that the word sequence in the reference text does not always overlap with the word sequence in the model's output. For the example output in Figure 9, the recorded ROUGE scores are poor in terms of *precision*, *recall*, and *F-measure* for all the three n-grams used in this study despite the semantic meaning being very similar. On the other hand, because the LSA returns the semantic similarity between two text sequences, its

 doi:10.20944/preprints202502.1196.v1

output is considerably high (0.757) for this particular example indicating that despite the discrepancies in the used set of words, the semantic meaning is greatly similar.

Finally, the LSA Similarity score's input length-model performance analysis indicated that training the model with long inputs can result in stable model performance as the score converged to the mean score with increasing input length (See Figure 8). It is worth noting that training a highly efficient transformer model requires huge amounts of training data which was a great limitation for this study.

6. Conclusion

Identifying potential causes in aviation incidents quickly is crucial for preventing future tragedies. While flight data recorders are commonly used, delays or damage can obstruct their effectiveness. The Boeing 737 MAX accidents with Lion Air and Ethiopian Airlines highlight the impact of such delays. To improve investigation efficiency, this study developed a transformer-based model for predicting the probable cause of an aviation incident given an analysis narrative of the pre/post incident series of events that can be collected from sources including eyewitnesses, radar systems, Air traffic controllers that were in charge of the flight under investigation, maintenance history/logs, etc. The model was trained on extensive NTSB aviation incident reports and allows short- and long-input narratives. This approach shows promise in expediting investigations and enhancing aviation safety through key metrics like BLEU, ROUGE, and LSA.

The assumption is that the model's output can improve with a larger training dataset. Therefore, as a direction for future work, analysis narratives from other aviation investigation bureaus, such as the ATSB, can be combined with the NTSB narratives, and the model can be retrained on a larger dataset for improved predictions.

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