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A methodology of large language model-driven dynamic Bayesian network for risk analysis of aircraft accidents

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Aircraft accidents tend to generate tremendous personal casualties and economic losses. Therefore, effective risk analysis is essential to manage and mitigate the catastrophic consequences of aircraft accidents. Nevertheless, insufficient and heterogeneous data pose a challenge for risk analysis. In this paper, we propose a methodology of large language model (LLM)-driven dynamic Bayesian network (DBN) for risk analysis. First, according to the collected aircraft accident cases, LLM is applied to identify risk-influencing factors (RIFs) through the designed prompt words. To improve the retrieval efficiency and accuracy of retrieval results, a hybrid model integrating Best Matching 25 and BAAI general embedding is employed to enhance the capacity of context retrieval and generation. Second, to quantify dependency relationships of RIFs, fuzzy set theory and domain knowledge are utilized to determine their probability distributions. Subsequently, a DBN-based risk assessment model is developed to analyze dynamic causal evolution and predict time-varying failure probability. Eventually, sensitivity analysis is conducted to capture crucial RIFs, and corresponding risk prevention and control strategies for aircraft accidents are constructed. The study results demonstrate that the proposed methodology is helpful to address the data limitations in the field of risk analysis.

Keywords: Risk analysis, large language model, dynamic Bayesian network, aircraft accidents.

1. Introduction

As modern aircraft systems continue to become increasingly integrated, the interdependencies among subsystems tighten, and their functional logic becomes more intricate[1]. In this context, the coupling of multiple failure modes in aircraft systems is unavoidable, which enhances the chance of causing disastrous events. The interplay of multiple risk-influencing factors (RIFs) arising from different components' failure mechanisms in aircraft flight processes is prone to leading to the occurrence of major accidents[2]. Such aviation accidents tend to cause huge economic losses and severe casualties. It is therefore imperative that a risk analysis be conducted to identify the causes of accidents and reduce risk to an acceptable level.

Traditional risk analysis methods, such as fault tree (FT), event tree (ET), and bow-tie model (BT), have been widely employed in aircraft accidents. However, due to their static structural nature, the aforementioned methods cannot update probabilities of RIFs and capture their conditional dependencies under changing conditions. Compared with these conventional methods, Bayesian networks (BNs) offer distinct advantages in modeling multistate variables, characterizing common-cause failures, and performing probabilistic reasoning under uncertainty[3]. In addition, BN is able to be flexibly combined with determined risk analysis techniques. For example, Guo et al. (2020)[4] integrated FT and BN to analyze a human error mechanism for pilots. Bauranov and Rakas (2024)[5] constructed a BN model based on integrated safety assessment model (ISAM) for the risk analysis of a mid-air collision. Pan et al. (2025)[6] proposed an FT–BN model with association rules to identify risk pathways in controller-induced aviation accidents.

Nevertheless, ordinary BN fails to describe the time-varying behavior of variables across discrete time-slices and capture the temporal relationships among node parameters. To address this issue, BN is extended as a dynamic Bayesian network (DBN) to model the time-dependent evolution of random variables and their probabilistic dependencies. Zhang and Wang (2024)[7] developed a DBN model to explore the coupling mechanism between aircraft takeoff attitude and flight operations. Wu et al. (2024)[8] constructed a DBN-based emergency disposal decision to improve the efficiency of civil aviation operations while reducing accident consequences.

The structure of DBN is commonly obtained from expert knowledge or via data-driven learning[9]. Knowledge-based construction relies heavily on domain experts and may suffer from subjectivity and inconsistency, whereas purely data-driven structure learning often requires large, high-quality datasets and can be sensitive to noise and missing information. The low-frequency and high-consequence characteristic of aircraft accidents results in a lack of relevant data. Thus, it is difficult to achieve a reliable risk analysis in aircraft accidents with heterogeneous and insufficient data. The development of large language models (LLMs) provides a promising solution for extracting potential RIFs and capturing their dependency relationships from heterogeneous textual and operational data to support DBN structure learning. To quantify dependency relationships of node variables, fuzzy set theory and domain knowledge are applied to establish their probability distributions.

In this study, we proposed a risk assessment methodology of predicting the failure probability of aircraft systems by combining LLM and fuzzy set theory to develop

DBN. In the proposed method, LLM is constructed to identify the RIFs of aircraft accidents. Fuzzy set theory is employed to quantify the prior probabilities of RIFs. Then, the LLM-driven DBN risk assessment model of aircraft systems is determined to capture dynamic risk evolution and predict time-varying failure probability. Eventually, sensitivity analysis is conducted to validate the effectiveness of the constructed model and identify crucial RIFs.

2. Methodology

In this section, we propose a methodology of LLM-driven DBN for risk analysis of aircraft accidents in limited and heterogeneous data. The details of each step are presented in the following.

(1) Phase one refers to data collection and processing. According to the obtained aircraft accident investigation report, relevant textual and operational information is extracted, cleaned, and stored in a structured manner.

(2) Phase two is to identify potential RIFs of aircraft accidents. Best Matching 25 (BM25) and BAAI General Embedding (BGE) are combined to improve the retrieval efficiency and accuracy of retrieval results. Based on the relevant documents retrieved and semantic embedding, the RIFs of aircraft accidents are captured.

(3) Phase three is to cluster different categories of the obtained RIFs and quantify their prior probabilities. We conducted the cluster analysis of RIFs based on global vectors for word representation (GloVe) and density-based spatial clustering of applications with noise (DBSCAN). Their prior probabilities are calculated by Type-2 fuzzy sets (T2FS).

(4) The final step is the construction DBN model. Based on the RIFs obtained from LLM and the clustering analysis results, a DBN-based risk assessment model for aircraft systems is developed. Through DBN probabilistic inference, the evolution of the failure probability of the aircraft system is established. The designed model is verified by the three axioms-based sensitivity analysis.

2.1. *Aircraft data collection and processing*

We collect the aircraft accident investigation report released by the National Transportation Safety Board (NTSB), Australian Transport Safety Bureau (ATSB), Federal Aviation Administration (FAA), and Air Accidents Investigation Branch (AAIB) as the primary sources of data. These reports were filtered, de-duplicated, standardized, and organized into structured records. Based on the collected accident information, the RIFs that contributed to the aircraft accident can be identified.

2.2. *Large language model-based risk-influencing factors mining*

In this section, BM25 and BGE are integrated for retrieval augmentation to support LLM-based extraction of RIFs, thereby improving the retrieval efficiency and accuracy of retrieval results.

2.2.1. *Best Matching 25*

BM25 is an improvement on the term frequency-inverse document frequency (TF-IDF) algorithm, and it overcomes the impact of the word frequency of keywords in the document on the score in the calculation of word frequency[10]. In the BM 25 algorithm, it is assumed that a word is more important to a document if it appears frequently within that document but infrequently across the entire document set. Accordingly, BM25 is adopted to perform efficient keyword-based retrieval, reducing the search space for subsequent semantic matching. The calculation process of the BM 25 algorithm is defined as[11]:

$$Score(D,Q)=\sum_{i=1}^{n} IDF\left(q_i\right)*\frac{f\left(q_i,D\right)*\left(k_1+1\right)}{f\left(q_i,D\right)+k_1*\left(1-b+b*\frac{|D|}{avgdl}\right)} \tag{1}$$

$$IDF\left(q_i\right)=\log\left(\frac{N-n\left(q_i\right)+0.5}{n\left(q_i\right)+0.5}+1\right) \tag{2}$$

where $Score(D,Q)$ indicates the correlation score between document D and query Q. q_i denotes the i-th word in the query. $f(q_i, D)$ means the frequency of the word q_i in document D. $IDF(q_i)$ stands for the inverse document frequency of the word q_i.

2.2.2. *BAAI General Embedding*

The core principle of BGE is to generate query and document embedding vectors using the bidirectional encoder and self-attention mechanism of the bidirectional encoder representations from transformers (BERT) model. The vector similarity scores of query and document vectors are calculated by the cosine similarity method. Finally, reliable text output can be obtained.

2.3. *Clustering analysis of risk-influencing factors*

This section aims to utilize GloVe and DBSCAN to carry out the cluster analysis of the obtained RIFs. T2FS is applied to compute the prior probabilities of these RIFs.

2.3. 1. *Global vectors for word representation*

GloVe belongs to an unsupervised learning algorithm that facilitates the acquisition of vector representations of words[12]. The core principle of GloVe is the notion that a word’s meaning is significantly influenced by the words that frequently appear in its context. By constructing a co-occurrence matrix, GloVe learns word embeddings that reflect semantic similarities among words, thereby generating word vectors. The co-occurrence matrix is optimized through the loss function so that the final word vector can more accurately reflect the semantic and grammatical relationships between words. Fig. 1 illustrates the framework of GloVe. In this study, the extracted RIFs are represented as word embeddings using GloVe to support subsequent clustering analysis.

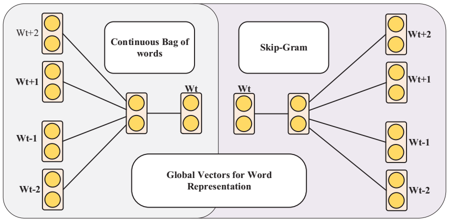

Fig. 1 Architecture of GloVe with CBOW and Skip-Gram Models[13].

2.3. 2. *Density-based spatial clustering of applications with noise*

Density-based spatial clustering of applications with noise (DBSCAN) is a commonly used clustering algorithm, which is capable of finding clusters of arbitrary shapes by two parameters as input: the radius (Eps) and the density threshold (MinPts)[14]. DBSCAN can form clusters of various shapes by concentrating on high-density regions that are distinct from low-density areas, while also automatically establishing the number of clusters. Thus, DBSCAN is used for clustering analysis of RIFs.

In DBSCAN, the *Eps* and *MinPts* can be evaluated by the Silhouette Coefficient Index(SCI) and Davies-Bouldin Index (DBI), and their calculation process is as follows[15]:

$$f(Eps, MinPts) = \max(SC) \cap \min(DB) \tag{3}$$

$$SC = \sum_{q_m=1}^{n} s(q_m) = \sum_{q_m=1}^{n} \frac{b(q_m) - a(q_m)}{\max\{a(q_m), b(q_m)\}} = \begin{cases} 1 - \dfrac{a(q_m)}{b(q_m)}, & a(q_m) < b(q_m) \\ 0, & a(q_m) = b(q_m) \\ \dfrac{b(q_m)}{a(q_m)} - 1, & a(q_m) > b(q_m) \end{cases} \tag{4}$$

$$DBI = \frac{1}{k} \sum_{i=1}^{k} \max_{j \neq i} \left(\frac{avg(C_i) + avg(C_j)}{d_{center}(C_i, C_j)} \right) \tag{5}$$

where $a(q_m)$ denotes the mean distance from sample q_m to other samples in the same groups. $b(q_m)$ refers to the mean distance from sample q_m to all samples in the other clusters. $avg(C_i)$ stands for the average distance between samples in groups. k indicates the number of clusters.

2.3. 3. *Type-2 fuzzy sets*

A T2FS denoted by $\tilde{T}$ within the universe of discourse M is described by a type-2 membership function (T2MF) $\varphi_{\tilde{T}}(m, u)$. $\tilde{T}$ is expressed[16]:

$$\tilde{T} = \{((m,u), \varphi(m,u)) | \ \forall m \in M, \forall u \in J_m \in [0,1]\} \tag{6}$$

where $0 \leq \varphi_{\tilde{T}}(m, u) \leq 1$. m indicates the domain variable. u stands for the secondary grade of $\tilde{T}$.

Let $\int_{u \in J_m} \varphi_{\tilde{T}}(m,u)/(m,u)$ be the secondary membership function of m, $\tilde{T}$ is rewritten as:

$$\tilde{T} = \int_{m \in M} \int_{u \in J_m} \varphi_{\tilde{T}}(m,u)/(m,u), \cdots\cdots J_m \in [0,1] \tag{7}$$

To mitigate application complexity, $\varphi_{\tilde{T}}(m, u)$ is set as 1 and $\tilde{T}$ is simplified:

$$\tilde{T} = \int_{m \in M} \left[\int_{u \in J_m} 1/u \right] / m, \cdots\cdots J_m \in [0,1] \tag{8}$$

where $\left[\int_{u \in J_m} 1/u \right] / m$ is the secondary membership function of m.

Assuming $\tilde{T}$ is an interval type-2 fuzzy number (IT2FN), and it can be described:

$$\tilde{T} = ((a_1^U, a_2^U, a_3^U, a_4^U; H_1(\tilde{T}^U), H_2(\tilde{T}^U)), (a_1^L, a_2^L, a_3^L, a_4^L; H_1(\tilde{T}^L), H_2(\tilde{T}^L))) \tag{9}$$

where $\tilde{T}^U$ stands for the upper membership function (UMF) and $\tilde{T}^L$ for the lower one (LMF).

By converting $\tilde{T}$ into $Ddf(\tilde{T})$, we calculate the probability of RIFs by equations[17]:

$$P = \begin{cases} 1/10^b, & Z \neq 0 \\ 0, & Z = 0 \end{cases} \tag{10}$$

$$b = \begin{cases} -0.72 \ln Ddf(\tilde{T}) + 2.839, & 0 \leq Ddf(\tilde{T}) < 0.2 \\ -\dfrac{1}{3} \times (\ln Ddf(\tilde{T}) - 14), & 0.2 \leq Ddf(\tilde{T}) \leq 0.8 \\ 3.705 \times ((1 - Ddf(\tilde{T})) / Ddf(\tilde{T}))^{0.445}, & 0.8 < Ddf(\tilde{T}) \leq 1 \end{cases} \tag{11}$$

where P represents the prior probability of RIFs.

2.4. *Dynamic Bayesian network*

DBN is a probabilistic graphical model that extends a Bayesian network (BN) to represent stochastic processes evolving over time[18]. DBN can model system behavior by discretizing the timeline into successive time slices t=1, 2, …, T, where each slice contains a set of random variables $X^{(t)}=\{X_1^{(t)}, \ldots, X_n^{(t)}\}$. Fig. 3 depicts the general structure of a DBN. Through giving a set of random variables $U=(X_1, X_2, X_3, \ldots, X_n)$, the joint probability can be calculated[19]:

$$P(X_{1:T}) = \prod_{t=1}^{T} \prod_{i=1}^{N} P(X_i^t | Pa(X_i^t)) \tag{12}$$

where X_i^t expresses the i th node at time t (i= 1, 2, …, N), $Pa(X_i^t)$ is the parent node of X_i^t, and T denotes the total time slice in DBN.

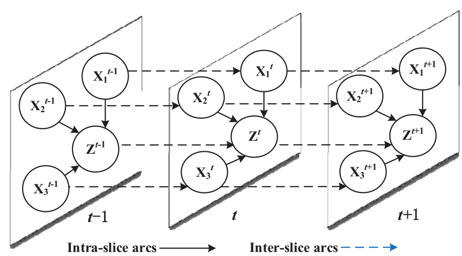

Fig. 3. The evolution of the DBN across different time slices[18].

3. Case study

3.1. *Risk-influencing factors mining*

Through this hybrid retrieval method, which integrates BM25 and BGE, RAG effectively combines the search results with the user's query to create an enhanced prompt. The cause of the aircraft accident is determined by invoking the gpt3.5-turbo model via the OpenAI API. LLM summarized the aircraft accident cases and the occurrence process during the generation process based on the relevant content or documents retrieved. The details regarding the partial cause of the aircraft accident are illustrated in Table 1.

We have unearthed the corresponding causes of accidents from different aircraft accident cases. For example, we learned that the cause of the aircraft accident was communication and coordination failure in case 1. In case 2, the aircraft accident was caused by plywood deck failure due to inadequate load-bearing capability and improper sheeting configuration. To gain a detailed understanding of the process of aircraft accidents, LLM also summarized the accident background and process corresponding to each accident case.

Table 1 The identified partial cause of aircraft accidents.

● Accident case 1>>Accident cause (communication and coordination failure)>>Summary>>The accident was caused by a failure in communication and coordination between the cabin crew and the flight crew, leading to the unauthorized re-opening of door DL2 without proper clearance.
● Accident case 2>>Accident cause (plywood deck failure)>>Summary>>The failure of the plywood deck due to inadequate load-bearing capability and improper sheeting configuration led to the helicopter's right main wheel penetrating the deck, initiating dynamic rollover.
● Accident case 3>>……

3.2. *Clustering analysis of risk-influencing factors for aircraft accidents*

Based on GloVe embeddings and the DBSCAN clustering algorithm, the extracted RIFs related to aircraft accidents are grouped according to their semantic similarity. As illustrated in Fig. 1, the clustering results yield six primary categories: engine failure, engine fuel system failure, landing gear failure, tail rotor failure, flight control failure, and other factors. For example, engine-related failures include engine ontology failure (X1), high-pressure compressor failure (X2), high-pressure turbine blade failure (X3), and fuel contamination (X4). Failures associated with the engine fuel system encompass engine-driven fuel pump O-ring seal failure (X5), engine fuel control unit failure (X6), and fuel line failure (X7). Landing gear failures consist of nose landing gear actuator failure (X8), landing gear drive shaft failure (X9), landing gear shock strut failure (X10), and landing gear brake disk failure (X11). The other clustering results of RIFs are shown in Fig. 1.

The results of cluster analysis of RIFs for aircraft accident

- **Engine failure:** engine ontology failure (X1), high-pressure compressor failure (X2), high-pressure turbine blade failure (X3), fuel contamination (X4)
- **Engine fuel system failure:** engine-driven fuel pump O-ring seal failure (X5), engine fuel control unit failure (X6), fuel line failure (X7)
- **Landing gear failure:** nose landing gear actuator failure (X8), landing gear drive shaft failure (X9), landing gear shock strut failure (X10), landing gear brake disk failure (X11)
- **Tail rotor failure:** tail rotor drive shaft failure (X12), tail rotor pitch change shaft bearing failure (X13)
- **Flight control failure:** horizontal stabilizer failure (X14), roll spoiler actuator failure (X15), pitch trim switch (X16)
- **Other factors:** main rotor blades failure (X17), clutch shaft failure (X18), propeller reduction gearbox failure (X19), design deficiency (X20), electrics failure (X21), electronic failure (X22), propeller failure (X23), battery failure (X24), power failure (X25), mechanical failure (X26)

Fig. 1. Cluster analysis results of RIFs for aircraft accidents.

3.3. *Dynamic Bayesian network-based aircraft system failure probability prediction*

According to equations (6)-(11), we calculated the prior probability of the obtained RIFs, and the results are demonstrated in Table 2. A DBN-based risk assessment model is constructed for aircraft systems on the basis of the established RIFs and their prior probabilities, as shown in Fig. 4. Based on the determined DBN model, we predicted the probability changes of the aircraft system's failure within a period of 360 days. This result indicates that as time increases, the probability of aircraft system failure gradually rises. On the 360th day, the probability of the aircraft system failure is 5.402E-01, seen in Fig. 5. By performing backward reasoning through the DBN, we obtained the posterior probabilities of the RIFs as shown in Table 2. By comparing the prior and posterior probabilities of RIFs, we identified the crucial RIFs that led to the failure of the aircraft system as X3 (high-pressure turbine blade failure), X12 (tail rotor drive shaft failure), X17 (main rotor blades failure), and X23 (propeller failure). The above four RIFs should be paid more attention to during the operation process of the aircraft.

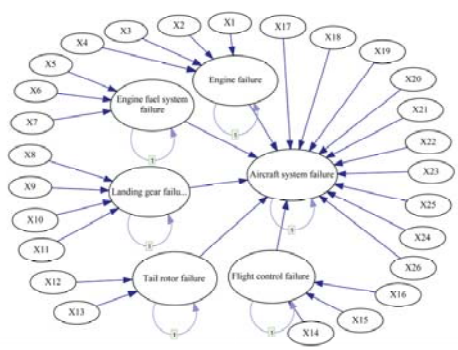

Fig. 4. The LLM-driven DBN model for aircraft system failure.

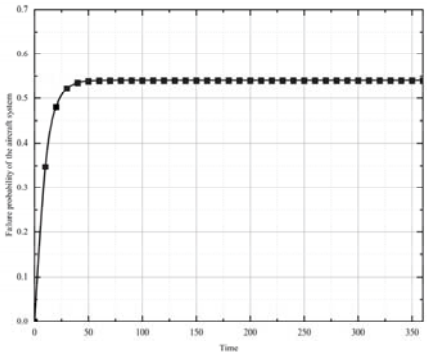

Fig. 5. Dynamic failure probability prediction with respect to the aircraft system.

Table 2 The prior probabilities of RIFs.

Symbol	Prior probability	Posterior probability
X1	6.738E-06	7.936E-04
X2	1.625E-05	2.406E-03
X3	1.849E-05	3.379E-03
X4	1.381E-05	2.066E-03
X5	1.099E-05	7.483E-04
X6	1.798E-05	2.537E-03
X7	1.499E-05	2.186E-03
X8	8.735E-06	5.354E-04
X9	1.737E-05	2.690E-03
X10	1.679E-05	2.395E-03
X11	1.394E-05	2.161E-03
X12	2.448E-05	3.587E-03
X13	9.892E-06	7.390E-04
X14	1.374E-05	2.103E-03
X15	1.365E-05	2.058E-03
X16	1.260E-05	1.904E-03
X17	8.936E-05	6.230E-03
X18	1.775E-05	2.452E-03
X19	1.823E-05	2.619E-03
X20	1.519E-05	2.364E-03
X21	1.403E-05	2.281E-03
X22	1.404E-05	2.076E-03
X23	1.810E-05	2.940E-03
X24	1.403E-05	2.281E-03
X25	1.357E-05	2.041E-03
X26	1.429E-05	2.430E-03

4. Discussion

By assuming physical relationships between system components, the failure probability change of the aircraft system is captured, as shown in Fig. 6. The original configuration represents the initial configuration of the system. Configuration 1 is the parallel configuration among the components of the engine and the engine fuel system. The results demonstrate that as the series connection of system components is changed to a parallel connection, the failure probability of the aircraft system decreases. We can conclude that by adjusting the redundant configuration design of system components, the reliability of the aircraft system can be enhanced.

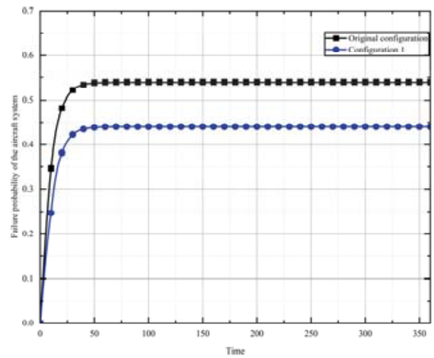

Fig. 6. A comparison between the original failure probability and the failure probability after changing the redundancy configuration of the system.

Take X1, X6, X12, X17, and X23 as an example, assuming the prior probability of nodes is subjected to a change of 80% and 120%, respectively. The variation of the prior probabilities of these nodes can affect the failure probability of the aircraft system, as indicated in Fig. 7. We found that when these RIFs are reduced by 80%, the probability of aircraft system failure decreased. Similarly, once these RIFs increased by 120%, the probability of the aircraft system failure increased. The three axioms reveal that a slight variation of the prior probability of root nodes can induce a variation of the failure probability in the aircraft system, thereby validating the effectiveness of the proposed model.

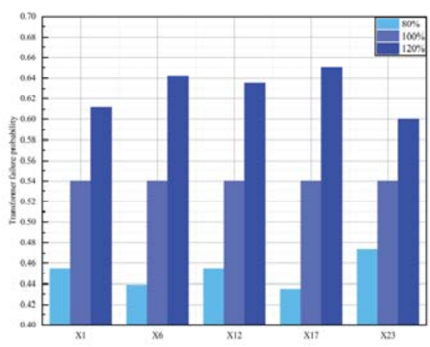

Fig. 7. Prior probability variation of RIFs affects the failure probability of the aircraft system.

5. Conclusion

In this paper, we propose a risk assessment model for analyzing aircraft system failures. Probabilistic risk assessment is conducted within an LLM-driven DBN framework. Aircraft accident investigation reports are used as the primary data source, and a LLM is applied to identify RIFs. To improve retrieval efficiency and ensure reliable contextual support for RIF extraction, a hybrid retrieval-augmentation approach integrating BM25 and BGE is adopted. T2FS combined with domain knowledge is employed to quantify the occurrence probability of RIFs. The proposed methodology is verified through an aircraft accident case study. The model considers the evolutionary characteristics of aircraft system risk and data heterogeneity, and the established DBN framework is capable of updating failure probabilities over time.

This study constructed a DBN-based risk assessment model to capture the dynamic evolution of aircraft accident risk and the probabilistic dependencies among RIFs. Considering the heterogeneity and scarcity of the data, LLM is used to extract RIFs of aircraft accidents from unstructured text. To quantify the extracted RIFs, fuzzy set theory is used to determine the prior probabilities of RIFs. The identified RIFs and their probabilistic relationships are transformed into the DBN to simulate the realistic operating conditions of aircraft systems and overcome the limitations of static risk analysis methods. Sensitivity analysis and diagnostic (backward) reasoning are performed to identify critical RIFs that contribute to aircraft system failure. The diagnostic results provide insights into system-level dependency mechanisms and support the formulation of targeted risk prevention and control strategies.

The results indicate that aircraft accidents are characterized by high safety requirements and limited availability of statistical data, which poses challenges for conventional risk assessment approaches. The proposed LLM-driven DBN methodology effectively overcomes data scarcity and heterogeneity by extracting RIFs from unstructured text and learning domain knowledge. This study provides support for dynamic risk analysis of aircraft systems in complex operational environments. However, detailed modeling of specific flight phases and physical failure mechanisms is not fully considered in this work. Future research will focus on extending the DBN framework to capture more detailed dynamic behaviors across different flight phases, thereby enabling a more comprehensive understanding of aircraft accident risk evolution.

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