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Modeling Interdependencies in Human Error: A HFACS Based Study of Loss of Control-Inflight Accidents

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DEPARTMENT OF MECHANICAL AND AEROSPACE ENGINEERING

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The undersigned certify that they have read and recommended to the Institute of Engineering for acceptance, a project report entitled **"MODELING INTERDEPENDENCIES IN HUMAN ERROR: A HFACS BASED STUDY OF LOSS OF CONTROL-INFLIGHT ACCIDENTS"** submitted by **Aditya Pant, Chanakya Aryal, Saurav Sen Khawas, Saurya Shrestha** in partial fulfillment of the requirements for the Bachelor's Degree in Aerospace Engineering.

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Abstract

Loss of Control In-Flight (LOC-I) remains a critical challenge in aviation, where a sequence of human failures from organizational levels to unsafe acts often leads to catastrophic outcomes. This study conducts a systematic review of accident reports and develops a complex network model to examine underlying causal structures. Using the Human Factors Analysis and Classification System (HFACS), data from 90 LOC-I investigation reports were categorized and mapped into a directed, weighted network consisting of 85 unique nodes and 316 edges.

The network demonstrated an average degree of 3.718, placing the system firmly in the supercritical regime where a giant component of failure dominates. Topological analysis revealed that the system is scale-free, following a power-law distribution where $\log_{10}(wd) = 0.45\log_{10}(i) + \log_{10}(185.76)$, identifying high-intensity hubs as the primary drivers of accident evolution. Visualization via the Fruchterman-Reingold layout and the application of a modularity algorithm identified five distinct community structures, segmenting the network into specialized failure clusters. Results show that Loss of Situational Awareness emerged as the most critical hub with a weighted degree of 92, serving as a central bridge for risk propagation. These findings suggest that safety mitigations should transition from broad-spectrum interventions to targeted attacks on these identified high-centrality hubs to effectively disrupt causal chains in LOC-I scenarios.

Keywords: *Loss of Control In-Flight (LOC-I),HFACS, Complex Network Analysis, Human Factors, Network Centrality, Modularity Analysis*

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A special mention goes to our friends, whose companionship turned long nights of coding and analysis into shared memories. Their encouragement was the steady rhythm that kept us moving forward when the complexity of the network felt overwhelming.

Beyond the halls of our college, we carry a deep sense of gratitude for our families. They were the silent pillars of our endurance, offering comfort when the research felt overwhelming and celebrating the small victories that eventually built this project. Their sacrifices provided the foundation upon which we stand.

Finally, we dedicate this work to our country, Nepal. In a land defined by its challenging skies, the pursuit of aviation safety is more than a study; it is a necessity for our future. We hope this research contributes in some small way to the safety of our mountains and the protection of those who fly over them. This work is a reflection of the wisdom of our mentors and the spirit of our home, and we carry the lessons learned with a deep, lingering sense of gratitude. As we reach the conclusion of this journey, we find ourselves looking back at the long hours and quiet doubts, realizing that this path was never traveled alone. The weight of ninety stories of loss has stayed with us throughout this process, transforming an academic requirement into a profound responsibility.

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Abbreviations

ASN	Aviation Safety Network
CFIT	Controlled Flight Into Terrain
CFR	Code of Federal Regulations
FAA	Federal Aviation Administration
HFACS	Human Factor Analysis and Classification System
HFACS-BN	Human Factor Analysis and Classification System – Bayesian Network
HFACS-MA	Human Factor Analysis and Classification System – Maritime Accidents
HFACS-RA	Human Factor Analysis and Classification System – Railway Accidents
HFACS-YA	Human Factor Analysis and Classification System – Yachting Accidents
IATA	International Air Transport Associations
ICAO	International Civil Aviation Organization
LOC-I	Loss of Control-In Flight
NTSB	National Transportation Safety Board
SME	Subject Matter Expert
SOP	Standard Operating Procedure

CHAPTER 1 INTRODUCTION

1.1 Background

Over the past few decades, technological advancements in aircraft design, avionics, and safety systems have significantly improved aviation safety and reduced the overall rate of accidents. Modern aircrafts are equipped with advanced navigation systems, automated flight controls, and warning technologies that help pilots detect and avoid potential hazards. However, despite these improvements, accidents can still occur due to a variety of operational, environmental, and human-related factors. Some common accident types include Controlled Flight Into Terrain (CFIT), where a functioning aircraft is unintentionally flown into terrain; Runway Excursions, where an aircraft veers off or overruns the runway; and Mid-Air Collisions between aircraft. Among these categories, Loss of Control In-Flight (LOC-I) stands out as the most fatal, as shown by statistical studies done by Airbus [1] and Boeing[2]. According to IATA [3], 94% of Loss of Control-Inflight(LOC-I) accidents results in crew or passenger fatality.

Loss of Control In-Flight (LOC-I) occurs when pilots are no longer able to maintain control of the aircraft or keep it on its intended flight path. This can happen for several reasons, including aerodynamic stalls, mechanical failures, severe weather conditions, or human factors such as spatial disorientation or incorrect responses to abnormal situations. When an aircraft enters an uncontrolled state, recovering stable flight can be extremely difficult, especially during critical phases such as takeoff or landing. Because of the severe consequences and the complex mix of factors involved, LOC-I remains a major concern for aviation safety researchers and industry professionals who continue to work on improving pilot training, aircraft systems, and safety procedures to reduce its occurrence.

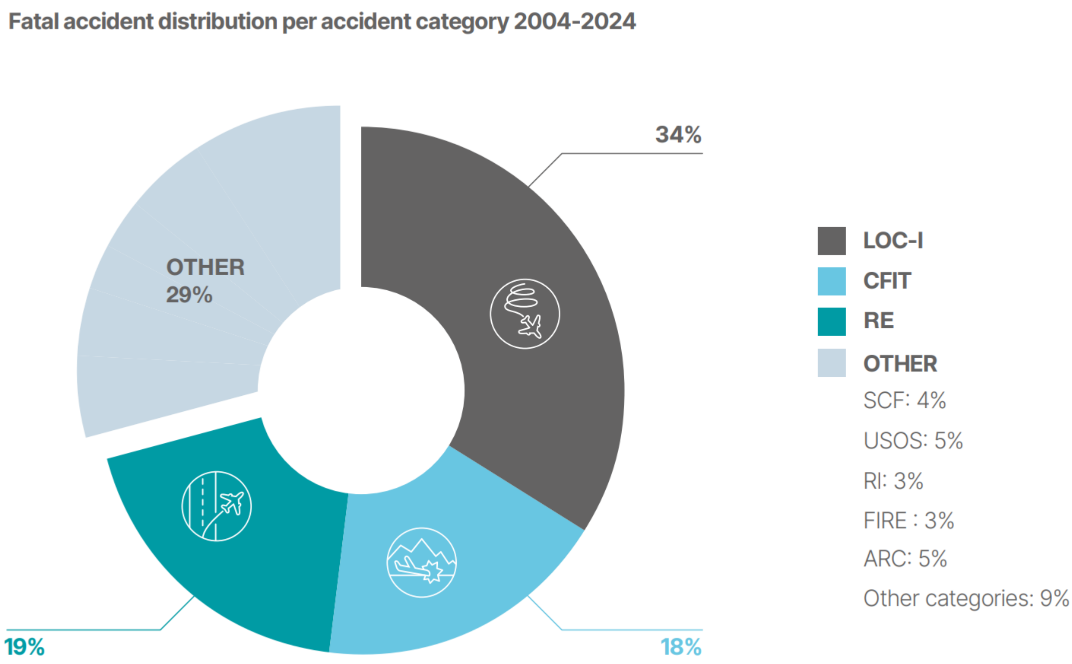


Figure 1.1: Accident distribution per catogory(Airbus)

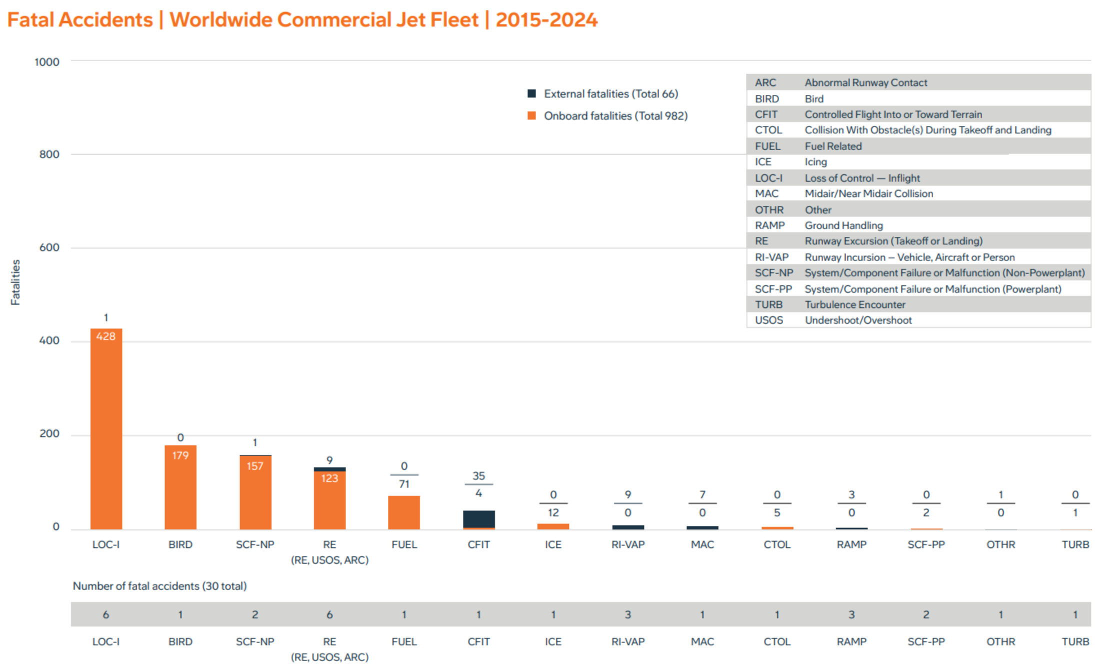


Figure 1.2: Accident distribution per category(Boeing)

1.1.1 Human Factors in Aviation

Human error has long been recognized as a major contributor to aviation accidents. According to Shappell and Wiegmann [4] 60% to 80% of aviation accidents are caused by some form of human error. These findings highlight the importance of understanding and analyzing human performance within the aviation industry.

Human factors in aviation encompass the psychological, physiological, and organizational aspects that influence human performance during flight operations. Factors such as fatigue, high workload, stress, inadequate communication, poor decision-making, and insufficient situational awareness can significantly affect pilot performance and increase the likelihood of errors. In addition, external pressures such as time constraints, environmental conditions, and operational demands may further complicate the decision-making process for flight crews.

Because aviation is a highly complex and dynamic system involving interactions between humans, machines, and the environment, even small errors can have significant consequences. As a result, modern aviation safety efforts increasingly focus on identifying, analyzing, and mitigating human-related risks. This has led to the development of structured frameworks and safety models that help investigators and researchers systematically classify and analyze human errors in aviation accidents.

1.1.2 Accident Causation Models

Accident causation models are developed to explain how accidents occur by identifying the interactions between human errors, technical failures, and organizational factors within complex systems. In aviation, accidents are rarely the result of a single failure; rather, they usually arise from a chain of contributing factors that combine over time. Accident causation models help researchers and investigators understand these interactions by providing structured frameworks to analyze the underlying causes of accidents and identify potential weaknesses within the aviation system.

Over the years, several models have been proposed to better understand accident mechanisms and improve safety management. These models aim to move beyond blaming individual operators and instead focus on the broader system in which humans operate, including technological, environmental, and organizational influences. By applying such models, investigators can systematically identify contributing factors and develop more effective safety measures to prevent similar accidents in the future.

One of the most widely used frameworks in aviation human factors analysis is the SHELL Model. The SHELL Model emphasizes that aviation safety depends not only on individual human performance but also on how effectively humans interact with other components of the aviation system. The term SHELL represents five interacting elements within the aviation environment:

1. **Liveware(L)**
   Liveware refers to the human operator, such as pilots, air traffic controllers, maintenance technicians, and ground crew. Humans are considered the central element of the system because they interact with all other components. However, human performance can be affected by factors such as fatigue, stress, workload, training level, and situational awareness.

2. **Software(S)**
   Software represents the non-physical elements of the aviation system, including operational procedures, checklists, manuals, regulations, standard operating procedures (SOPs), and training programs. Poorly designed procedures or unclear documentation can create confusion and increase the likelihood of human error.

3. **Hardware(H)**
   Hardware refers to physical equipment and technological systems, such as aircraft instruments, cockpit displays, control systems, and maintenance tools. Human–hardware interaction is critical; poorly designed interfaces or confusing instrument layouts can increase pilot workload and lead to operational mistakes.

4. **Environment(E)**
   Environment includes both physical and organizational surroundings in which aviation operations occur. This may involve weather conditions, airport infrastructure, cockpit noise, lighting, temperature, and even organizational culture. Environmental stressors can significantly influence human performance and decision-making.

5. **Liveware-Liveware Interaction(L-L)**
   This component focuses on human-to-human interaction, such as communication between pilots, coordination between pilots and air traffic controllers, and teamwork among maintenance crews. Effective communication, leadership, and coordination are essential to maintaining safe operations.

A key concept of the SHELL model is the interface between components. Safety issues often arise not because one element fails completely, but because there is a mismatch at the interface between elements. For example, when a pilot (Liveware) struggles to interpret a confusing instrument display(Hardware) or when unclear procedures (Software) conflict with operational demands.

Another widely used framework used in study of human error is the ’Swiss Cheese’ model proposed by James Reason [5] in 1990. This model explains accidents as the result of multiple failures across different layers of a system. Each of these layers in represented in the model as a slice of swiss cheese in which holes represent weakness of failure points within that layer. These failure points can active failures or latent conditions. Active failure refer to unsafe acts committed by frontline operators. These errors have immediate consequences and occur close to the operational level. Latent conditions, on other hand, originate within an organizational structure and remain unnoticed for long period. This model shifted the paradigm of investigations in the direction of analysis and study of the latent failures that were involved in the causal sequence of failures [5]. According to Swiss Cheese Model, an accident occurs when the holes in multiple defense layers momentarily align, allowing hazards to pass through the system and lead to a failure event.

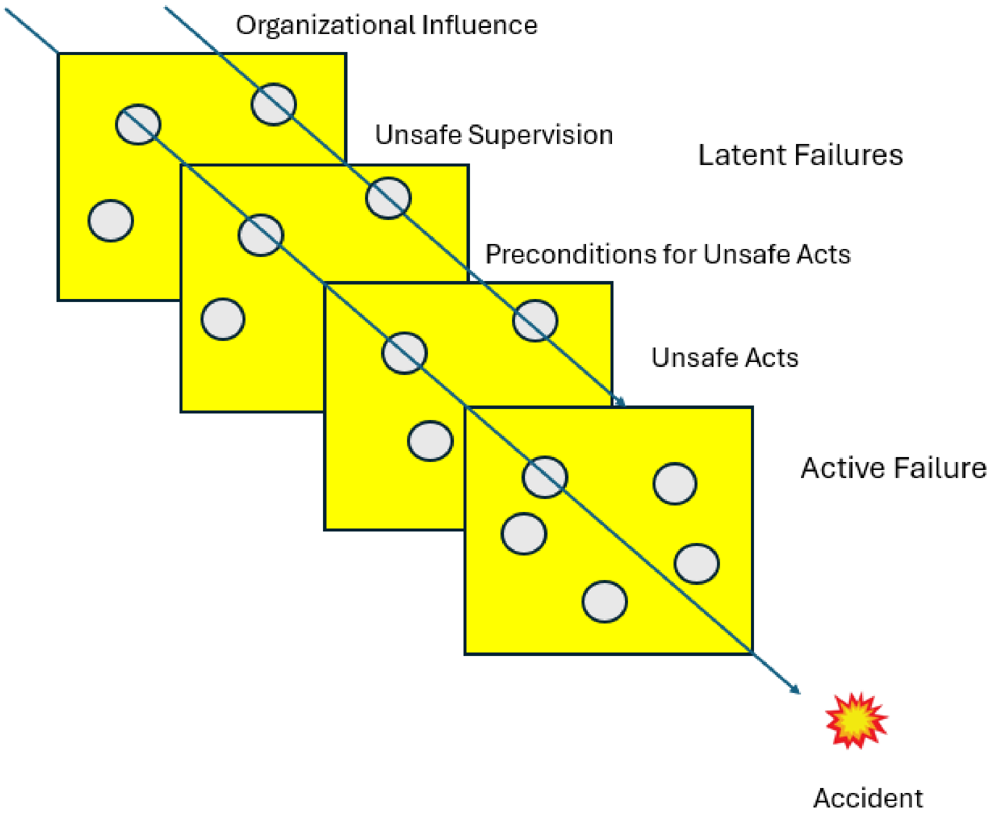


Figure 1.3: Swiss Cheese Model(adapted from Shappell and Wiegmann[6]

Although Swiss Cheese Model provides a strong conceptual framework for analyzing accident causation, it does not provide detailed method for systematically categorizing human errors. To address this limitation, Dr. Scott Shappell and Dr. Douglas Wiegmann developed the **Human Factor Analysis and Classification System** (HFACS) which is based on principles of Swiss Cheese Model. It transforms the layered defense concept to a structured taxonomy that can be used to classify human factors. The HFACS framework classifies human error into four levels: Unsafe Acts, Preconditions for Unsafe Acts, Unsafe Supervision and Organizational Influences. One of the major strengths of HFACS is that it enables researchers and investigators to trace human error across multiple layers, rather than focusing solely on the actions of operator. By understanding how latent conditions propagate through layers of HFACS framework to produce unsafe acts, HFACS provides a comprehensive framework for accident investigation and safety improvement.

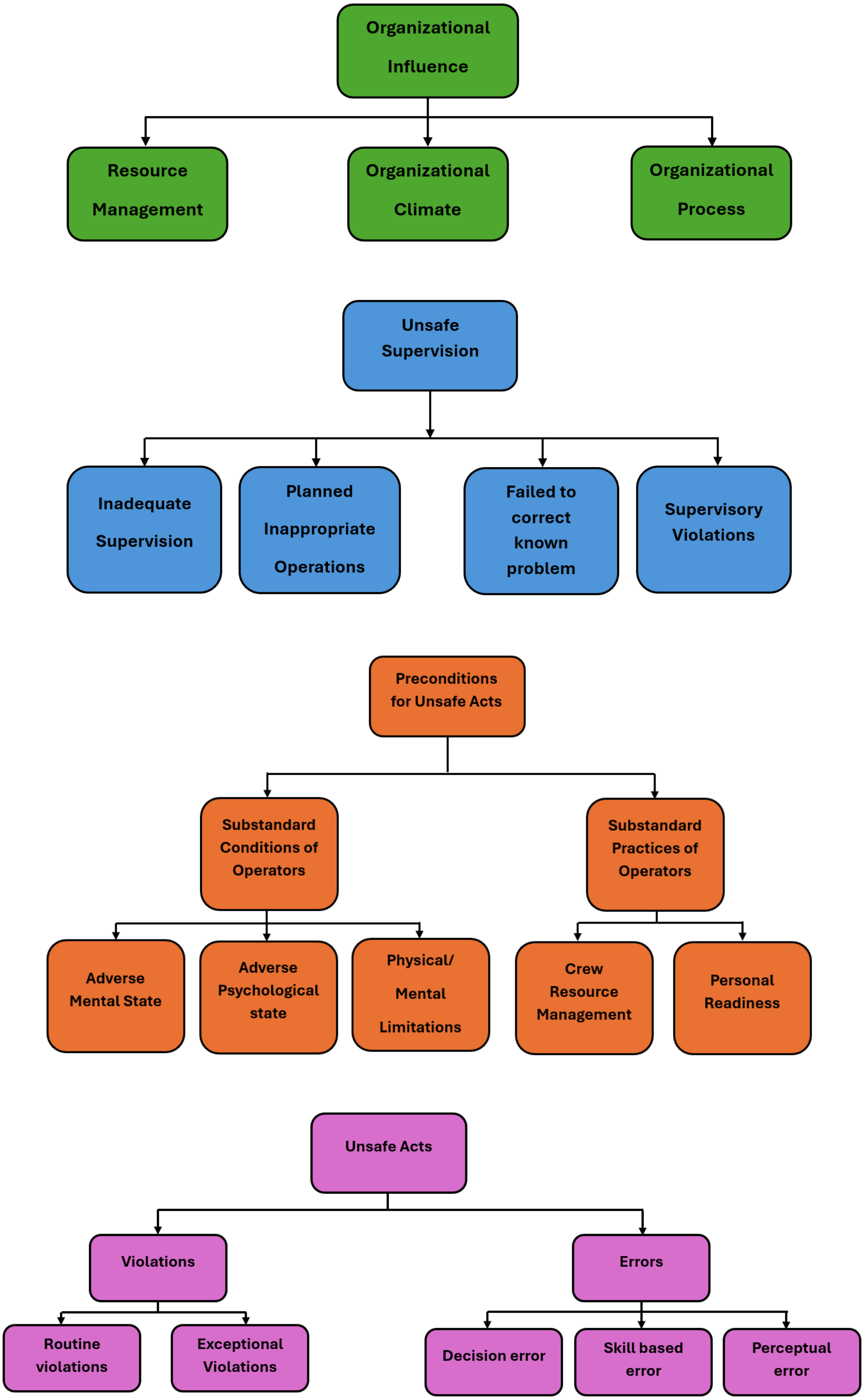


Figure 1.4: HFACS Framework (adapted from Shappell and Wiegmann [6]

Each level of HFACS is further categorized into different causal categories as shown in Figure 1.4. A brief description of each level of HFACS and the causal categories is given below.

1. **Organizational Influence**

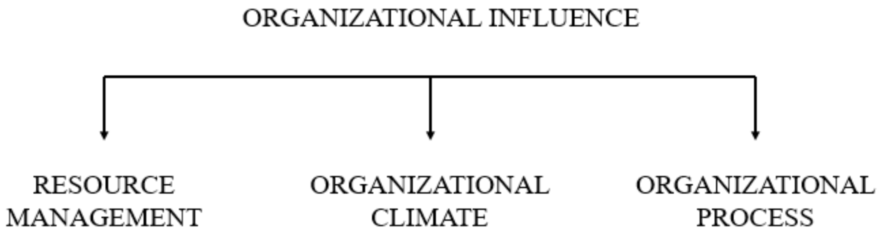


Figure 1.5: Organizational Influence (adapted from Shappell and Wiegmann [6])

Organizational Influences are the highest and the most foundational level in the HFACS framework. It refers to the broad, systematic factors within an organization that shapes the working environment and indirectly contribute to unsafe supervision, preconditions for unsafe acts and unsafe acts. Organizational Influences are categorized as:

- **Resource Management**: Failure in Resource Management occurs when corporate level decisions favor cost reduction over safety, leading to unsafe operational conditions, under-trained personnel and outdated equipment.
- **Organizational Climate**: Organizational Climate refers to the working environment shaped by communication, policies and culture. When unclear or poorly enforced it can create confusion and weaken communication and coordination across the organization.
- **Organizational Process**: Organizational Processes involve corporate rules and procedures that govern daily operations. When poorly designed or lacking oversight it can increase the risk of accident.

2. **Unsafe Supervision**

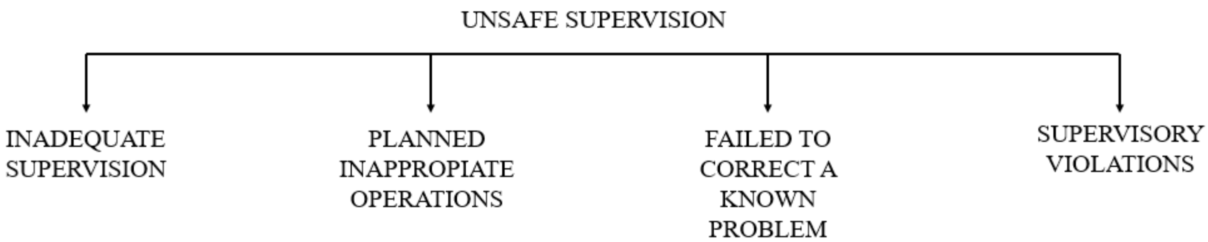


Figure 1.6: Unsafe Supervision (adapted from Shappell and Wiegmann [6])

Unsafe Supervision is the third level of HFACS framework. It refers to the decisions, actions and omission of supervisors and management in contributing to safety degradation. It links organizational influences (policies, culture, resources) to preconditions and unsafe acts, so it is where many "fixable" latent conditions. Unsafe supervision are categorized as:

- **Inadequate Supervision**: Supervisors must provide proper training, guidance and should have leadership skills to ensure smooth operations. Failure to do so through lack of oversight or support can degrade crew performance, improper crew manning which increases likelihood of errors.
- **Planned Inappropriate Operations**: Planned Inappropriate Operations refers to poor operational decisions like improper crew manning, jeopardizing crew rest, scheduling unsafe flights, etc. that compromise safety and performance, contributing indirectly to accidents.
- **Failure to Correct a Known Problem**: The instances when supervisors are aware of the deficiencies among individuals, equipment, training and other related safety areas, yet allowed to continue unabated.
- **Supervisory Violations**: Supervisory violations are the instances when existing rules and regulations are willfully disregarded by supervisors, such as allowing unqualified aviator to operate aircraft or failing to enforce safety protocols.

3. **Preconditions for Unsafe Acts**

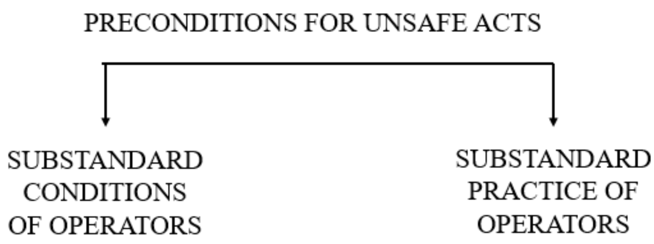


Figure 1.7: Preconditions for Unsafe Acts (adapted from Shappell and Wiegmann [6])

Preconditions for Unsafe Acts are the underlying conditions that influence crew performance and increase the likelihood of unsafe acts. The preconditions are further categorized into two divisions: Substandard Conditions of Operators and Substandard Practices of Operators

- **Substandard Conditions of Operators**

– **Adverse Physiological States**: Adverse Physiological States refers to the medical and physiological states like physical fatigue, illness or medication side effects that can impair pilot performance and increase risk of poor decision making.

– **Physical/Mental Limitations**: Physical and/or Mental limitations refers to the instances like sensory limits, cognitive overload, lack of aptitude, etc. mission requirements exceeds the capabilities of the individual at the controls.

- **Substandard Practice of Operators**

  – **Crew Resource Micromanagement**: Crew resource mismanagement refers to poor coordination and communication among aviation personnel, which can lead to confusion, overlooked tasks, and accidents.

  – **Personal Readiness**: Personal readiness failures occur when individuals are not physically or mentally prepared for duty, leading to poor performance and increase risk of error, even if no rules are violated.

4. **Unsafe Acts**

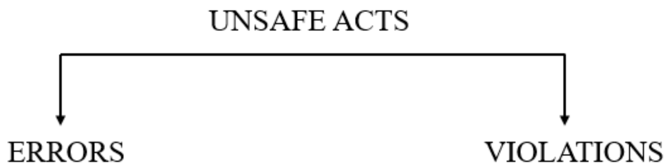


Figure 1.8: Unsafe Acts (adapted from Shappell and Wiegmann [6])

The Unsafe acts of aircrew can be classified into two categories: Errors and Violations. Errors refers to the mental or physical activities of individuals that fail to achieve their intended outcome. Violations refers to the willful disregard of rules and regulations that govern the safety of the flight.

- **Errors**

  – **Skill-Based Errors**: Skill-Based errors occur without significant conscious thought. The skill based actions are particularly vulnerable to failure of attention and memory. In context of aviation it is best described as ”stick-and-rudder” and other flight skills [6].

- **Decision Errors**: Decision Errors represents the intentional behavior that proceeds as intended, yet the plan proves inadequate or inappropriate for the situations. It is often referred to as an ”honest mistakes” [6].
- **Perceptual Errors**: Perceptual errors are unsafe acts committed by pilots when their perception of the environment differs from reality, often due to degraded or unusual sensory input such as visual illusions or spatial disorientation. Importantly, the perceptual error is not the illusion or disorientation itself, but the pilot's erroneous response to it. [6]

- **Violations**
  - **Routine Violations**: Routine Violations are habitual by nature, often enabled by a tolerance of such departures from rules by a system of supervision [5].
  - **Exceptional Violations**: Exceptional violations appear as isolated departures from authority which does not indicate individual's typical behavior pattern nor condoned by management [5].

The Human Factors Analysis and Classification System (HFACS) framework has been widely recognized as a powerful and systematic tool for analyzing human factors in aviation accidents. Its structured approach enables researchers to identify and classify human and organizational contributions to accident causation across multiple levels of the aviation system. Consequently, HFACS has been extensively applied in aviation safety studies to investigate the role of human error. Materna et al. [7] applied HFACS to analyze 101 aviation accidents in Slovakia, identifying total of 217 causal factors among which 166 were attributed to human factors which makes up 77% of all occurrences. Shappell and Wiegmann [8] analyzed 119 commercial aviation accidents using HFACS framework and extracted 319 human causal factors associated. The analysis highlighted differences between carrier types: Part 121 carriers (larger airlines) had a higher proportion of accidents involving organizational factors while Part 135 carriers (smaller scheduled operators) had more supervisory failures.

While the Human Factors Analysis and Classification System (HFACS) is widely regarded as one of the most powerful tools for analyzing human error in aviation, it is important to recognize its limitations. HFACS is primarily a qualitative framework that focuses on categorizing and describing human and organizational factors rather than quantifying their relations. Although it provides a hierarchical structure for identifying causal factors, it does not capture the dynamic interactions and inter-dependencies that exist among the factors.

In real-world aviation accident scenarios, contributing elements rarely act in isolation. Instead, accidents typically arise from complex, nonlinear interactions among multiple factors across different system levels. For example, organizational decisions may influence supervisory practices, which in turn affect operational conditions and ultimately shape frontline human performance. These interrelated factors form a network of dependencies, rather than a simple linear chain of causation.

To address this limitation, recent research has explored the integration of the Human Factors Analysis and Classification System (HFACS) with Complex Network Theory. In this combined approach, the causal factors identified through HFACS are represented as nodes within a network, while the relationships or interactions between these factors are modeled as edges. This representation enables accident data to be transformed into a structured network, allowing the application of quantitative techniques to analyze system behavior and uncover hidden patterns of interaction.

For example, Yang et al. [9] applied an HFACS–complex network approach to analyze 109 chemical industry accidents, while Yao et al. [10] developed a tailored HFACS-YA (Yachting Accidents) framework combined with complex network analysis to examine 179 yachting tourism accidents. In both cases, the integration of HFACS with network modeling enabled the visualization of accident causation as a weighted and directed graph constructed using Gephi. These network representations highlight the relative importance of different factors through node weights and reveal the strength of interactions through edge weights, providing deeper insight into the complex, interconnected nature of accident causation.

1.1.3 Complex Network Analysis

A complex network is a graphical representation of a complex system consisting of nodes and edges. Nodes represent the individual components of the system, while edges represent the relationships or interactions between these components. Complex network analysis goes beyond simple linear causeeffect models by representing a system as a network of multiple interconnected elements rather than a sequence of isolated events. Complex network theory therefore provides a powerful framework for analyzing human factors in complex socio-technical systems. It recognizes that human behavior and system safety are influenced by a web of interconnected elements, including individuals, equipment, environment, and organizational management, as well as the complex coupling effects among them.

Compared to traditional accident analysis approaches, complex network methods emphasize the structural relationships between multiple factors rather than focusing only on hierarchical classifications or individual causal chains. Frameworks such as the HFACS model categorize human errors within predefined hierarchical levels, while statistical methods typically focus on identifying correlations or trends within accident datasets. Similarly, AcciMap model analyze accidents from a systems perspective by examining interactions across different organizational levels. However, complex network approaches differ in that they represent accident factors as interconnected nodes within a network, allowing researchers to quantitatively analyze relationships such as influence, connectivity, and centrality among contributing factors. This network-based perspective makes it possible to identify key factors that play central roles within the system and better understand how multiple contributing elements interact to produce accidents.

- **Nodes:** Nodes represent individual factors within a system. These can include human elements, technical elements, environmental elements, and organizational elements.
- **Edges:** Edges represent the connections, dependencies, and flow of information or influence between these nodes.

The key nodes and pathways in the complex network are identified using various network metrics which includes centrality and clustering measures. In our research we will be using the following metrics:

1. **Degree Centrality**: Degree centrality is a metric in that quantifies the number of direct connections interactions, edges, or links a node has within a graph. A node with high degree centrality is a hub and is directly connected to other nodes
2. **Betweenness Centrality**: Betweenness Centrality is measure of how often a node appears on the shortest path between other nodes. Nodes with highest betweenness centrality control the flow of information in the network. Betweenness Centrality is calculated by the following formula:

$$b_m = \sum_{j,h \in N, j \neq h} \frac{n_{jh(m)}}{n_{jh}} \tag{1.1}$$

where betweenness cenrality b_m of nodes express the proportion of the number of paths passing through node m to the total number of shortest paths among all shortest paths, n_{jh} represents the number of all shortest paths connecting nodes j and h in the network, and $n_{jh(m)}$ stands for the number of passing nodes m in all shortest paths connecting nodes j and h in the network [9]

3. **Clustering Coefficient**: Clustering coefficient is measure of the extent to which a node's neighbors are also connected to each other. High clustering means a tightly knit neighborhood like sub-systems or teams that are independent.

$$\overline{C} = \frac{1}{N} \sum_{i=1}^{N} \frac{2M_i}{D_i(D_i - 1)} \tag{1.2}$$

where M_i represents the number of connections between nodes connected to node i; D_i is the node degree of node i; N is the total number of complex network nodes.

4. **Modularity**: Modularity is a indicator which quantifies the strength of division of network into communities. High modularity indicates well defined clusters with dense internal connections and sparse external ones.

$$Q = \frac{1}{2m} \sum_{ij} \left(W_{ij} - \frac{d_i d_j}{2m} \right) \delta(C_i, C_j) \tag{1.3}$$

where Wij is the number of edges between nodes i and j; m is the total number of edges of the network or the sum of weights in the weighted network; di is the degree of the node i; Ci is the community category to which node i belongs; Cj is the community category to which node j belongs; $\delta(Ci, Cj)$ is an indicator function, such that if Ci = Cj is 1; otherwise, it is 0.

5. **PageRank**: PageRank measures relative importance of nodes based on the number and quality of the connections. High PageRank value indicates the nodes that are more influential in the overall network structure.

$$P_i = \frac{s}{n} + (1 - s) \sum_{P_j \in E(P_j)} \frac{P_j}{G(P_j)} \tag{1.4}$$

1.1.4 Loss of Control-Inflight (LOC-I)

Loss of Control – Inflight (LOC-I) is the most significant cause of fatal accidents in commercial aviation [1]. LOC-I occurs when an aircraft deviates from the intended flight path or an adverse flight condition places an aircraft outside the normal flight envelope, with the pilot unable to maintain control of the aircraft[3]. Loss of Control-Inflight causes aircraft to depart from normal flight and possibly reach altitudes or encounter situations from which it can be difficult or impossible to recover, such as a stall or a spin. LOC-I can result from factors affecting piloting performance, engine failures, adverse meteorological conditions, stalls/upsets or other circumstances that interfere with the ability of the pilot to control the flight path of the aircraft.

LOC-I is one of the most complex accident categories, involving numerous contributing factors that act individually or, more often, in combination. These contributing factors include latent conditions in the system, external threats to the flight crew, errors in the handling of those threats, and undesired aircraft states resulting from deficiencies in managing threats and errors. LOC-I accidents are almost always catastrophic; 94% of the accidents analyzed involved fatalities to passengers or flight crew. This category of accident resulted in more fatalities than any other category (2,462 of 4,075) in the reporting period (2009 through 2018) [3]. Due to high severity , LOC-I accidents have been assessed by IATA and industry representatives as one of the highest priorities for safety intervention and risk mitigation [3].

1.2 Problem Statement

The application of the Human Factors Analysis and Classification System (HFACS) in aviation safety research has enabled the systematic classification of human errors across multiple hierarchical levels. However, the majority of existing studies have largely been limited to descriptive analyses, such as frequency distributions and statistical summaries of contributing factors. While these approaches provide valuable insights into the prevalence of different error types, they often fail to capture the interdependencies and interactions among contributing factors that characterize complex aviation accident scenarios.

Although HFACS has enabled the categorization of errors across multiple levels, it's full analytical potential, particularly in integration with Complex Network Theory remains underexplored in aviation industry. Such integration offers the capability to model accident causation as an interconnected system, enabling a data-driven, systems-level analysis of how human errors interact and propagate within Loss of Control In-flight (LOC-I) incidents.

Furthermore, the development of automated and scalable analytical tools for HFACS-based network modeling presents significant research potential. These tools can be used in the identification of hidden critical patterns, key influencing factors, and dominant error pathways within large accident datasets. Ultimately, this approach can support the formulation of more effective safety interventions by enabling targeted mitigation strategies focused on the most influential contributors to accident occurrence.

1.3 Objectives

1.3.1 Main Objective

To analyze Loss of Control-Inflight (LOC-I) occurrence reports by applying HFACS combined with network theory to identify key human factor interactions, uncover hidden interdependencies and provide insights to improve aviation safety

1.3.2 Specific Objectives

- To extract and categorize causal factors from 90 LOC-I occurrence reports using the HFACS framework, identifying a unique node set across four hierarchical levels.
- To establish and validate directed causal relations among these factors, constructing a dataset of edges and verifying these interactions with a Subject Matter Expert (SME).
- To model the system as a Complex Network and determine the Average Degree , ensure the network exceeds the critical transition threshold for a stable giant component.
- To quantify node importance using topological metrics through Weighted Degree and Betweenness Centrality to pinpoint critical risk propagation points.

- To analyze the network's structural organization by calculating the Power Law exponent for scale-free properties and employing a modularity algorithm to segment the system into specialized failure communities.

1.4 Scope

- This project can help identify human factors in Loss of Control-Inflight (LOC-I) occurrences, helping airlines and regulators improve safety training, procedures, and policies.
- The project will offer analytical tools and methodologies for researchers and safety consultants to study accident causation and enhance safety management.
- It will enable software developers to automate incident analysis and create intelligent safety management tools, using network models to simulate accidents and teach risk mitigation strategies.
- The methods and knowledge are transferable to other high-risk industries (maritime, rail, energy, etc.), providing a scalable framework for risk assessment and safety improvement.

1.5 System Requirements

1.5.1 Hardware Requirements

No special hardware is necessary for standard accident report analysis and network modeling. Standard computing equipment is sufficient for this project.

1.5.2 Software Requirements

The following software tools are required for this project:

- **Gephi** - For network construction, visualization, and analysis
- **MongoDB** - For data storage and management

- **Python** - For data processing and csv file generation
- **LaTeX** - For document preparation and typesetting
- Code editors for coding and analysis (Visual Studio Code and Jupyter Notebook)

CHAPTER 2 LITERATURE REVIEW

The introduction of Reason's Swiss Cheese Model [5], which conceptualizes accidents as the result of failures across multiple layers of system defenses, has significantly influenced the study of human factors in accident analysis. Building upon this concept, the Human Factors Analysis and Classification System (HFACS), developed by Shappell and Wiegmann [6], introduced a structured framework for classifying human errors into hierarchical levels, including Organizational Influences, Unsafe Supervision, Preconditions for Unsafe Acts, and Unsafe Acts. A key strength of HFACS lies in its ability to distinguish between active failures and latent conditions, thereby providing a comprehensive perspective on accident causation.

Since its inception, HFACS has been widely applied in the analysis of human factors within the aviation industry. Materna et al. [7] applied HFACS to 101 aviation accidents in Slovakia and reported that approximately 77% of causal factors were related to human error. Among these, unsafe acts were identified as the primary contributors, with skill-based errors being the most frequent, followed by decision errors. Similarly Shappell et al. [11] analyzed accidents under 14 CFR Part 121 and Part 135 operations and found that the majority of causal factors were associated with aircrew performance and environmental conditions, with comparatively fewer linked to supervisory and organizational levels. The reliability of their analysis was assessed using Cohen's kappa, yielding a value of 0.71, indicating substantial agreement. Gaur [12] analyzed civil aviation accidents in India (1990–1999) and concluded that human factors contributed to 77.1% of incidents, with organizational influences accounting for 52.1% of cases. Furthermore, Li et al. [13] extended the application of HFACS to a dataset of 523 aircraft accidents, employing Lambda statistics to quantify the proportional reduction in error.

Beyond aviation, HFACS has demonstrated considerable versatility across other high-risk industries. Wang et al. [14] applied an extended HFACS framework to chemical industry accidents to examine relationships between hierarchical levels. Liu et al. [15] developed an HFACS-based classification system for coal mine accidents, while Zhan et al. [16] utilized HFACS-RAs to identify human factor influences in railway accidents. In the healthcare domain, Jalali et al. [17] applied HFACS to classify medical errors and found that preconditions for unsafe acts were the dominant contributors. Patterson and Shappell [18] adapted the original HFACS to a mining specific version(HFACS-MI) and analyzed 508 mining accidents in Queensland, Australia. In their study skill based errors were most common followed by decision errors. Preconditions were associated with 81.9% of the cases with physical environment and technical environment being major contributors. These studies highlight the adaptability and robustness of HFACS across diverse operational environments.

Despite its widespread application, most HFACS-based studies are limited to descriptive and statistical analyses, primarily focusing on the frequency and distribution of contributing factors. Such approaches often treat causal elements as independent variables and fail to capture the interdependencies and nonlinear interactions that characterize complex accident systems. Although HFACS enables multi-level analysis, its conventional implementation does not fully support the modeling of system-wide interactions and dynamic relationships, particularly in complex accident scenarios.

To address these limitations, recent research has explored the integration of HFACS with advanced analytical approaches. For instance, Yang and Mott [19] developed an HFACS-based Bayesian Network (HFACS-BN) to analyze aviation accidents and estimate probabilistic relationships among contributing factors. Similarly, Li et al. [20] combined HFACS with Bayesian networks to investigate unsafe behaviors in hazardous chemical accidents, identifying environmental and mechanical factors as key influences. Yıldırım et al. [21] applied a modified HFACS framework (HFACS-MA) to maritime accidents, using statistical techniques such as the Chi-square test and correspondence analysis to identify relationships among factors. Wang et al. [14] further identified multiple failure pathways in chemical accidents by evaluating associations between adjacent HFACS levels using Fisher's exact test.

In addition to HFACS-based analyses, several system-oriented accident models have been proposed to better capture the complex interactions among technical, organizational, and human factors in safety-critical systems. One such approach is the AcciMap framework, developed by Jens Rasmussen, which represents accidents as multi-level causal structures spanning different layers of a socio-technical system, including government policy, regulatory bodies, organizational management, and operational processes. Thoroman et al. [22] applied the AcciMap method to analyze 16 near-miss incident reports obtained from the French aviation accident investigation authority. Their study examined the common cause hypothesis, which suggests that similar networks of contributing factors may underlie both near-miss events and actual accidents. The findings largely supported this hypothesis, indicating that the reports exhibited comparable patterns of causal interactions. On average, each report contained a similar number of contributory and protective factors.

More recently, the application of Complex Network Theory has emerged as a promising approach for modeling accident causation as a system of interconnected factors. Rentian et al. [23] analyzed 257 aviation accidents using complex network analysis, constructing a network consisting of 45 nodes and 304 edges representing relationships among accident factors. Their study concluded that complex network analysis provides better applicability for understanding aviation accident causation compared to conventional analytical approaches. Similarly, Zhang et al. [24] investigated gas explosion accidents by modeling safety systems as complex networks composed of human, equipment, environmental, and management elements. Their results demonstrated that minor failures can propagate through interconnected pathways, ultimately triggering large-scale disasters through cascading effects.

Building upon this network-based perspective, researchers have increasingly integrated HFACS with complex network theory to enhance accident analysis. In this combined approach, causal factors identified through HFACS are represented as nodes, while their interactions are modeled as edges, enabling the construction of a structured network representation of accident systems. For example, Yang et al. [9] and Yao et al. [10] applied HFACS combined with complex network analysis to study accident causation in chemical and yachting tourism contexts, respectively. Their studies resulted in the development of weighted and directed network models, where node importance and interaction strength were quantified, and accident mechanisms were visualized as interconnected graphs. This approach enables the identification of key influencing factors, critical interaction pathways, and dominant risk propagation mechanisms, providing deeper insights beyond traditional analytical methods.

However, a notable gap remains in the literature regarding the application of HFACS combined with network analysis to Loss of Control In-Flight (LOC-I) accidents. Given the high severity and complex, multi-factor nature of LOC-I events, there is a need for research that integrates HFACS with network-based approaches to capture the interactions among human, technical, and organizational factors. Addressing this gap can provide deeper insights into accident causation mechanisms and support the development of more effective safety mitigation strategies.

Table 2.1: Summary of foundational literature on human factors and HFACS-based analysis

Category	Author(s)	Key Methodology	Core Findings / Metrics	Identified Research Gap
Foundational Models	Reason [5], Shappell & Wiegmann [6]	Swiss Cheese & HFACS Framework	Established 4 levels of human error; distinguished active vs. latent failures.	Lacks a quantitative method to model system-wide interactions.
Aviation Statistics	Materna et al. [7], Shappell et al. [11], Gaur [12]	Frequency & Descriptive Analysis	Human factors in ∼77% of cases. Found high frequency of skill-based errors.	Treats causal factors as independent; fails to capture non-linear interdependencies.
Cross-Industry Adaptation	Patterson and Shappell [18], Jalali et al. [17], Wang et al. [14]	HFACS-MI (Mining), HFACS-Healthcare	Preconditions and physical environment identified as dominant contributors.	Primarily descriptive; focused on distribution rather than propagation.
Probabilistic Modeling	Yang and Mott [19], Li et al. [20], Yıldırım et al. [21]	Bayesian Networks, Chi-Square Test	Estimated probabilistic relations; identified multiple failure pathways	Often limited to adjacent levels or predefined paths; lacks global topology
System-Oriented Models	Thoroman et al. [22]	AcciMap Framework	Mapped socio-technical layers; validated “common cause” hypothesis	Qualitative in nature; difficult to identify mathematical hubs in large data sets
Complex Network Theory	Rentian et al. [23], Zhang et al. [24]	Network Analysis (45 nodes and 304 edges)	Proven small failures can propagate via cascading effects; better applicability than traditional statistics	Not integrated with specific hierarchical rigor of HFACS
Integrated Network-HFACS	Yang et al. [9], Yao et al. [10]	Weighted and Directed Network Models	Quantified node importance and visualized accident mechanisms	No specific application to Loss of Control-Inflight accidents

CHAPTER 3 METHODOLOGY

This study adopts a structured multi-phase methodology to investigate the human factors associated with Loss of Control In-Flight (LOC-I) accidents by integrating the Human Factors Analysis and Classification System (HFACS) with Complex Network Theory. A total of 90 LOC-I accident reports obtained from the Aviation Safety Network database were systematically examined to identify the underlying human and organizational factors contributing to these events. Each accident report was carefully reviewed and coded using the HFACS framework, which enabled the classification of contributing factors into hierarchical categories, including organizational influences, unsafe supervision, preconditions for unsafe acts, and unsafe acts. This structured classification process allowed for a consistent and systematic identification of human-factor-related elements present in the accident investigations.

Based on the findings reported in each accident investigation, causal relationships between the identified factors were established to construct causal chains that represent how failures propagate across different HFACS levels. These causal chains capture the interaction between organizational conditions, supervisory actions, environmental and psychological preconditions, and operator-level errors or violations that ultimately contribute to LOC-I accidents. To ensure the accuracy and reliability of the identified relationships, the constructed causal chains were subsequently reviewed and validated by a Subject Matter Expert in aviation safety. This expert evaluation provided an additional layer of verification to minimize potential misinterpretations and improve the credibility of the dataset.

Following this validation process, the verified causal relationships were used to construct a complex network model using Gephi software, where individual HFACS factors were represented as nodes and their causal interactions were represented as edges. The resulting network structure enabled the visualization and quantitative analysis of the interconnections among different human factors contributing to LOC-I accidents. Several network analysis metrics, including Degree Centrality, Betweenness Centrality, Clustering Coefficient, Modularity, and PageRank, were applied to the constructed network to identify the most influential factors and key interaction pathways within the system. Through this integrated analytical approach, the study aims to reveal critical patterns of human-factor interactions and highlight the underlying mechanisms that contribute to LOC-I accident causation.

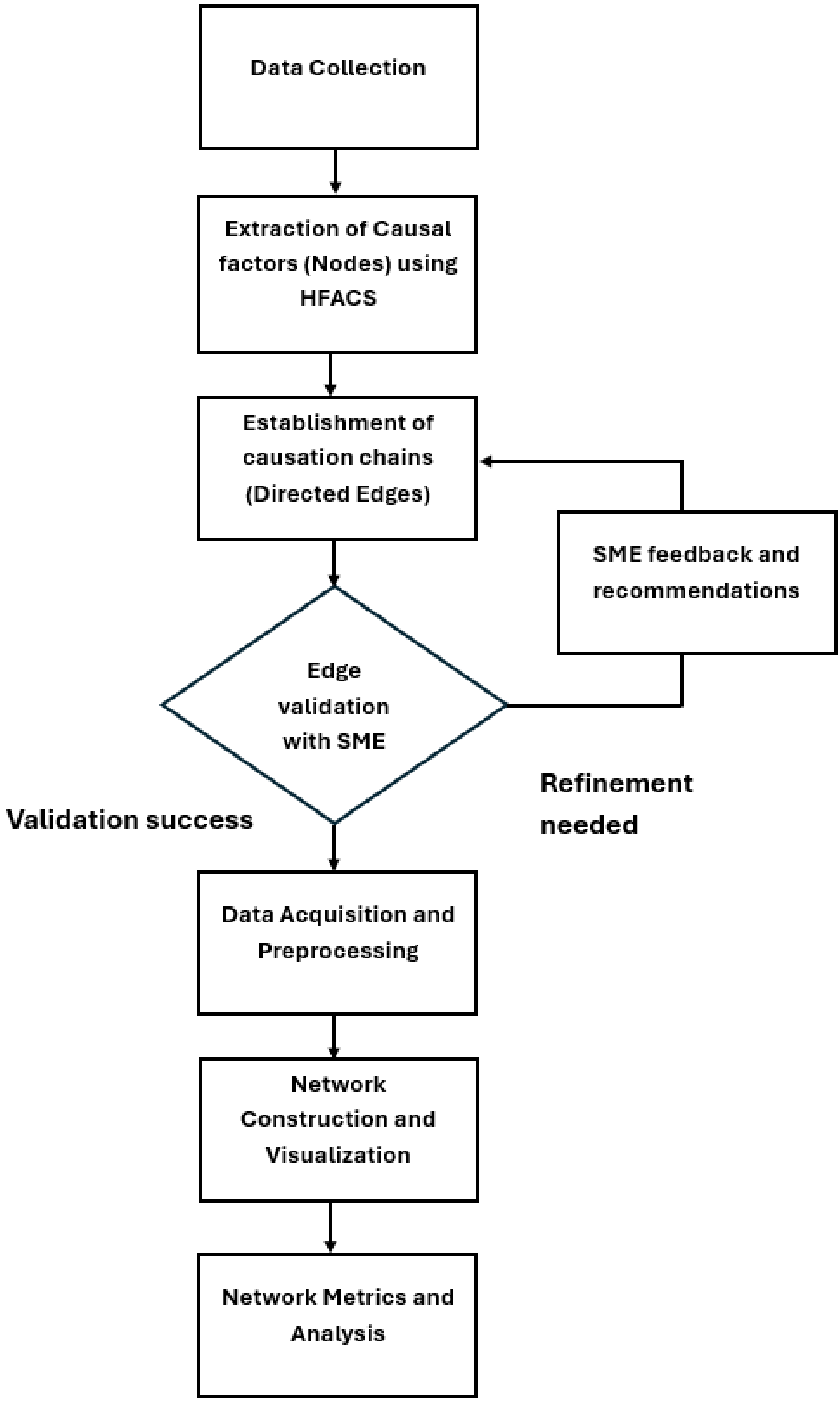
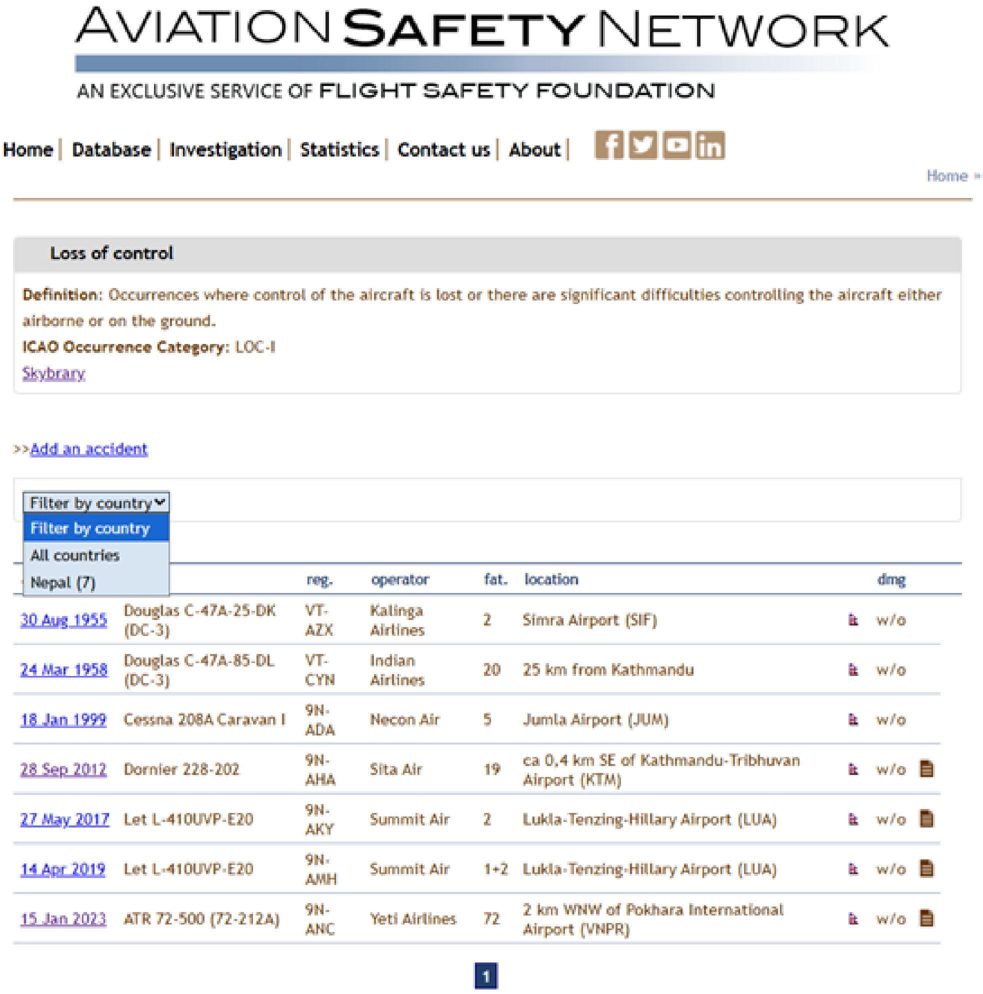


Figure 3.1: Methodology Flowchart

3.1 Data Sources

Accident reports from Aviation Safety Network (ASN) under ICAO Occurrence Category Loss of Control-Inflight (LOC-I) was to construct our dataset.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Home »

Loss of control

Definition: Occurrences where control of the aircraft is lost or there are significant difficulties controlling the aircraft either airborne or on the ground.

ICAO Occurrence Category: LOC-I

Skybrary

>>Add an accident

Filter by country

Filter by country

All countries

Nepal (7)

	type	reg.	operator	fat.	location		dmg	
30 Aug 1955	Douglas C-47A-25-DK (DC-3)	VT-AZX	Kalinga Airlines	2	Simra Airport (SIF)		w/o	
24 Mar 1958	Douglas C-47A-85-DL (DC-3)	VT-CYN	Indian Airlines	20	25 km from Kathmandu		w/o	
18 Jan 1999	Cessna 208A Caravan I	9N-ADA	Necon Air	5	Jumla Airport (JUM)		w/o	
28 Sep 2012	Dornier 228-202	9N-AHA	Sita Air	19	ca 0,4 km SE of Kathmandu-Tribhuvan Airport (KTM)		w/o	
27 May 2017	Let L-410UVP-E20	9N-AKY	Summit Air	2	Lukla-Tenzing-Hillary Airport (LUA)		w/o	
14 Apr 2019	Let L-410UVP-E20	9N-AMH	Summit Air	1+2	Lukla-Tenzing-Hillary Airport (LUA)		w/o	
15 Jan 2023	ATR 72-500 (72-212A)	9N-ANC	Yeti Airlines	72	2 km WNW of Pokhara International Airport (VNPR)		w/o	

1

Figure 3.2: Aviation Safety Network [25]

The finding from Figure 3.3 shows there is decrease in fatal accidents and increase in number of flights. Even as the number of fatal accidents has decreased the severity of LOC-I is still very high with 94% of the accidents involving fatalities to passengers or flight crew [3]. Thus it is necessary to carry in-depth accident analysis for LOC-I.

The accident reports for this research was publicly sourced from Aviation Safety Network (ASN) database. Only reports with explicit mention of LOC-I as primary event was included. To ensure sufficient coverage, a sample size of 100 LOC-I occurrence reports was established.

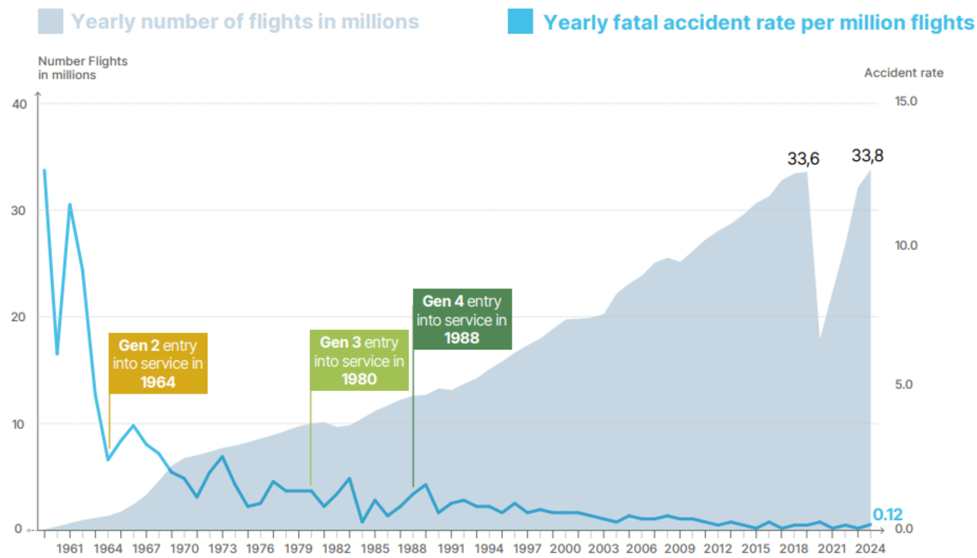

Figure 3.3: Fatal accident rate per million flights [1]

3.2 Development of Website for data entry and storage

A custom web-based application was developed to support the data logging pipeline using a MongoDB database as the backend storage system. The application was designed to simplify the process of recording and managing the causal factors identified from LOC-I occurrence reports during the HFACS analysis. Through this platform, the extracted nodes and edges representing causal factors and their relationships were systematically entered and stored in the database. In addition to these causal elements, the system also records key contextual information for each accident, including the date of occurrence, flight number, continent or region, airline operator, and a direct link to the original accident investigation report. This additional information helps maintain traceability and provides useful context for the dataset. The use of a web interface made data entry and retrieval more organized and efficient, while MongoDB's flexible document-based structure allowed the storage of accident reports with varying numbers of causal factors. Overall, the platform served as a centralized repository for organizing the extracted accident data, which was later used to construct the complex network model for further analysis in Gephi. A snippet of data logging website in given in appendix D.

A snippet of accident nodes and edges in JSON format is given in Appendix E.

3.3 Human Factor Analysis and Classification System

HFACS is a comprehensive classification framework for human factors in accidents. According to HFACS, this study uses a four-level hierarchy: Organizational Influences, Unsafe Supervision, Preconditions for Unsafe Acts, and Unsafe Acts. Each category is further decomposed and coded.

The HFACS-based model qualitatively analyses the internal elements in terms of direct and indirect causes. The holistic and integrated perspective of the HFACS analysis result can then be utilized to identify the risk factors and root causes of incidents. After this, it is possible to develop a quantitative and comprehensive statistical analysis using a complex network.

3.3.1 Extraction of Causal Factors(Nodes) using HFACS

The Loss of Control In-Flight (LOC-I) accident reports sourced from the Aviation Safety Network (ASN) was systematically analyzed using the Human Factors Analysis and Classification System (HFACS) framework to identify and extract causal factors. The HFACS taxonomy employed in this study comprises a total of 99 causal factors, distributed across four hierarchical levels: Organizational Influences (27 factors), Unsafe Supervision (18 factors), Preconditions for Unsafe Acts (27 factors), and Unsafe Acts (27 factors).

The identified causal factors (nodes) was validated by a subject matter expert (SME) to ensure accuracy and consistency in classification. Also, a cross-validation approach was adopted, wherein the extracted factors were compared against previously annotated accident reports and findings from relevant studies in the literature. An illustrative example of the node and edge extraction process is provided in Appendix B.

3.3.2 Establishment of Causation chain(Directed Edges)

Analysis of accident reports indicates that contributing factors do not exist in isolation; rather, they exhibit complex interactions and interdependencies within the system. These interactions may remain latent or undetected, allowing abnormal conditions to evolve into hazardous states, ultimately leading to a loss of system control. Therefore, it is essential to examine the causal chains of events that contribute to accident occurrence in order to gain a deeper understanding of underlying mechanisms.

Accordingly, causation chains, represented as directed edges, was established between the identified nodes derived from the Human Factors Analysis and Classification System (HFACS) analysis. These relationships was determined based on evidence from accident reports, supplemented by informed analytical judgment. To ensure the reliability and validity of the constructed network, the identified edges was cross-validated through comparison with existing literature and findings from related studies.

3.4 Validation of Directed Edges with a Subject Matter Expert

To ensure the reliability and validity of the constructed network, the identified nodes and directed edges derived from a subset of 30 accident reports was reviewed and verified by a subject matter expert (SME) in aviation safety. This validation process is required to ensure the accuracy of both the classification of causal factors and the establishment of causal relationships between them.

Based on the feedback, necessary corrections, refinements, and recommendations provided by the SME was applied into the dataset. This validation approach enhances the credibility of the network model and ensures that the identified relationships accurately reflect real-world accident causation mechanisms.

3.5 Python script to process the data and generate csv file for nodes and edges

A python program was used to extract the data from MongoDB, preprocess the data and generate csv file. These files are then imported into Gephi, where the complex network is constructed and further analyzed through visualization and computation of network metrics.

1	id	weight	category	level
2	ORMBR2	3	Organizat	O
3	OOPO1	3	Organizat	O
4	USIS3	16	Unsafe Su	US
5	USPIO1	1	Unsafe Su	US
6	USPIO5	4	Unsafe Su	US
7	USFCKP3	12	Unsafe Su	US
8	USFCKP4	7	Unsafe Su	US
9	PUSCAM4	4	Preconditi	P
10	PUSPCR2	21	Preconditi	P

Figure 3.4: Snippet of nodes.csv

1	source	target	weight	category
2	USPIO5	PUSCAM4	3	US-P
3	PUSPCR2	UAED3	4	P-UA
4	PUSCAM4	UAED3	2	P-UA
5	OOPO1	UAV3	1	O-UA
6	USIS3	UAV3	1	US-UA
7	OOPOV1	USFCKP4	3	O-US
8	OOPOV1	USFCKP3	4	O-US
9	USPIO3	PUSPCR2	4	US-P
10	PUSCAM3	UAV3	1	P-UA

Figure 3.5: Snippet of edges.csv

3.6 Complex Network

A complex network serves as an effective tool for the quantitative representation of intricate systems and has been extensively applied in the analysis of risk propagation across domains such as information systems, power networks, and financial systems. More recently, it has also been adopted in the field of safety risk analysis. Aircraft accidents are often the result of interactions among multiple influencing factors or other multi-causal mechanisms. Through the examination of network characteristics, it becomes possible to uncover the underlying mechanisms and inherent patterns governing such complex systems. Gephi is an open-source, lightweight software platform designed for social network analysis and graph visualization. Compared to alternative tools, Gephi provides superior graphical representations for complex network structures. In this study, Gephi was utilized both to visualize the complex network of accident causation and to compute the associated topological feature parameters.

3.6.1 Establishment of the accident cause network model

After identifying the accident-cause nodes, constructing the chain and creating the csv files, it was essential to employ specialized complex network visualization software to determine an appropriate layout and properly scale the graphical representation for modeling purposes. The causal factors and their relationships were imported into Gephi. Furthermore, key network characteristic parameters were computed using algorithms implemented in Gephi. The way nodes are connected in the network plays an important role in how risk spreads between different factors. To better understand this, it was necessary to examine how these factors group together and interact. Since the idea of "closely connected" or "loosely connected" nodes is not clearly defined, a quantitative approach was used to identify these groupings.

3.7 Network Metrics and Structural Analysis

Following the construction and visualization of the network in Gephi, a set of quantitative network metrics namely degree centrality, betweenness centrality, clustering coefficient, and modularity are computed to analyze the structural properties of the network and to identify critical elements within the system. These metrics provide insight into the relative importance of nodes, the strength of interactions, and the overall organization of the network.

Centrality measures are employed to evaluate the significance of individual nodes within the network. In particular, degree centrality quantifies the number of direct connections associated with each node, thereby indicating its level of influence within the system. Betweenness centrality is computed to identify nodes that act as critical intermediaries in the propagation of risk, highlighting factors that serve as bridges between different parts of the network and facilitate the transmission of causal influences.

In addition to these measures, the clustering coefficient is calculated to evaluate the degree to which nodes in the network tend to form tightly connected groups. This metric reflects the tendency of neighboring nodes to be interconnected, thereby providing insight into the local cohesiveness of the network and the presence of closely interacting clusters of causal factors.

Furthermore, modularity is calculated to assess the presence of community structures within the network. Modularity analysis partitions the network into clusters (communities) of densely connected nodes, which may represent groups of interrelated causal factors. This facilitates the identification of underlying patterns and substructures within the accident causation network.

The community size is also analyzed to evaluate the distribution and relative importance of these clusters. Larger communities may indicate dominant groupings of interacting factors, while smaller communities can highlight more localized or specific interaction patterns.

CHAPTER 4 RESULTS AND DISCUSSION

4.1 Dataset Description

A total of 90 Loss of Control–Inflight (LOC-I) occurrence reports were analyzed in this study. Nodes and edges were extracted and established for each report. The occurrence reports were sourced from the Aviation Safety Network database and selected to ensure broad geographical representation across continents. Temporal constraints were not applied, as the objective of the study was to identify human factors contributing to LOC-I accidents rather than time-based trends.

4.2 Complex Network Analysis of LOC-I Aviation Accidents

After studying 90 LOC-I accident reports and recording the associated human factors as nodes and the causal relationships between them as edges, a complex network was formed.

4.2.1 Accident Causation Model Formation

The stochastic network model of LOC-I accidents was visualized using the Fruchterman Reingold algorithm to map the complex interdependencies between 85 causal nodes and 316 edges. To enhance the interpretability of the systemic hierarchy, nodes were color-coded according to their respective HFACS levels: Organizational Influences (Green), Unsafe Supervision (Light Blue), Preconditions for Unsafe Acts (Orange), and Unsafe Acts (Pink). The relative weight of each element which is represented by node diameter and edge thickness quantifies the frequency of these factors within the accident dataset. This spatial arrangement reveals how latent organizational failures propagate through the supervisory chain to create the preconditions that ultimately manifest as active errors in the cockpit.

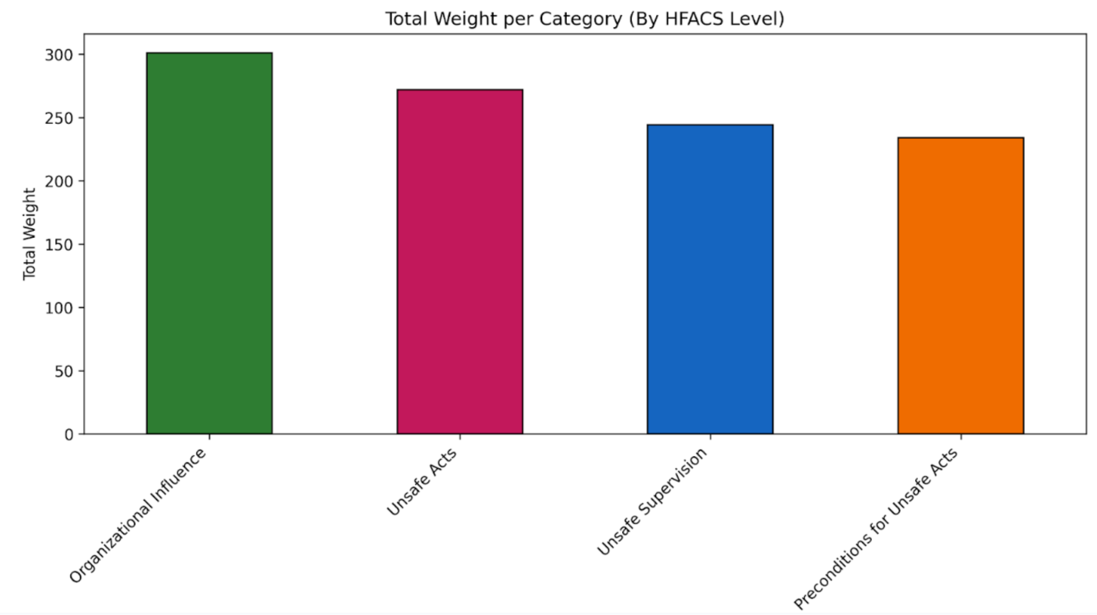

Figure 4.1: Total Weight per Category

Nodes

Table 4.1: Key Human Factors and Their Weights

Level	Factor	Weight	Code
Organizational Influence	Training	49	ORMHR3
	Risk Management	46	OOPOV1
Unsafe Acts	Poor Decision	48	UAED6
	Improper Procedure	32	UAED1
Preconditions for Unsafe Acts	Failed to Communicate/Coordinate	48	PUSPCR2
	Loss of Situational Awareness	44	PUSCAM6
Unsafe Supervision	Failed to Provide Training	45	USIS4
	Failed to Provide Oversight	43	USIS3
Organizational Influence	Standards	32	OOPP3

Edges

Table 4.2: Key Edges and their Weights

Source	Target	Weight	Remarks
ORMHR3	USIS4	24	Training $\rightarrow$ Failed to Provide Training
USIS4	PUSCAM6	16	Failed to Provide Training $\rightarrow$ Loss of Situational Awareness
OOPOV1	USIS3	12	Risk Management $\rightarrow$ Failed to Provide Oversight
PUSPCR2	UAED6	12	Failed to Communicate/Coordinate $\rightarrow$ Poor Decision
PUSCAM6	UAED6	10	Loss of Situational Awareness $\rightarrow$ Poor Decision
USIS3	PUSPCR2	10	Failed to Provide Oversight $\rightarrow$ Failed to Communicate/Coordinate

The resulting network model illustrates a clear cascading effect where the highest-weighted path originates in the Organizational Influence (Green) layer and terminates in the Unsafe Acts (Pink) layer. The prominence of Training (ORMHR3) as the most influential node (Weight = 49) suggests that LOC-I accidents are rooted in high-level administrative deficiencies rather than isolated pilot error. This organizational gap directly fuels the strongest edge in the model: the link between Training and Failed to Provide Training (USIS4) (Weight = 24). This pathway highlights a critical vulnerability in the safety chain. When the organization fails to prioritize training resources, it effectively handicaps the supervisory level, leading to a cascade of risk. For example, in the case of Iran Aseman Airlines Flight 3704, the airline did not have a simulator training program to demonstrate the effects of mountain waves and was unable to properly assess the effectiveness of the crew's training, which represents an organizational level failure (ORMHR3). This weakness at the organizational level led to a supervisory failure Failure to Provide Training (USIS4). As a result of these shortcomings at both the organizational and supervisory levels, the flight crew were not adequately prepared to operate in mountain wave conditions.

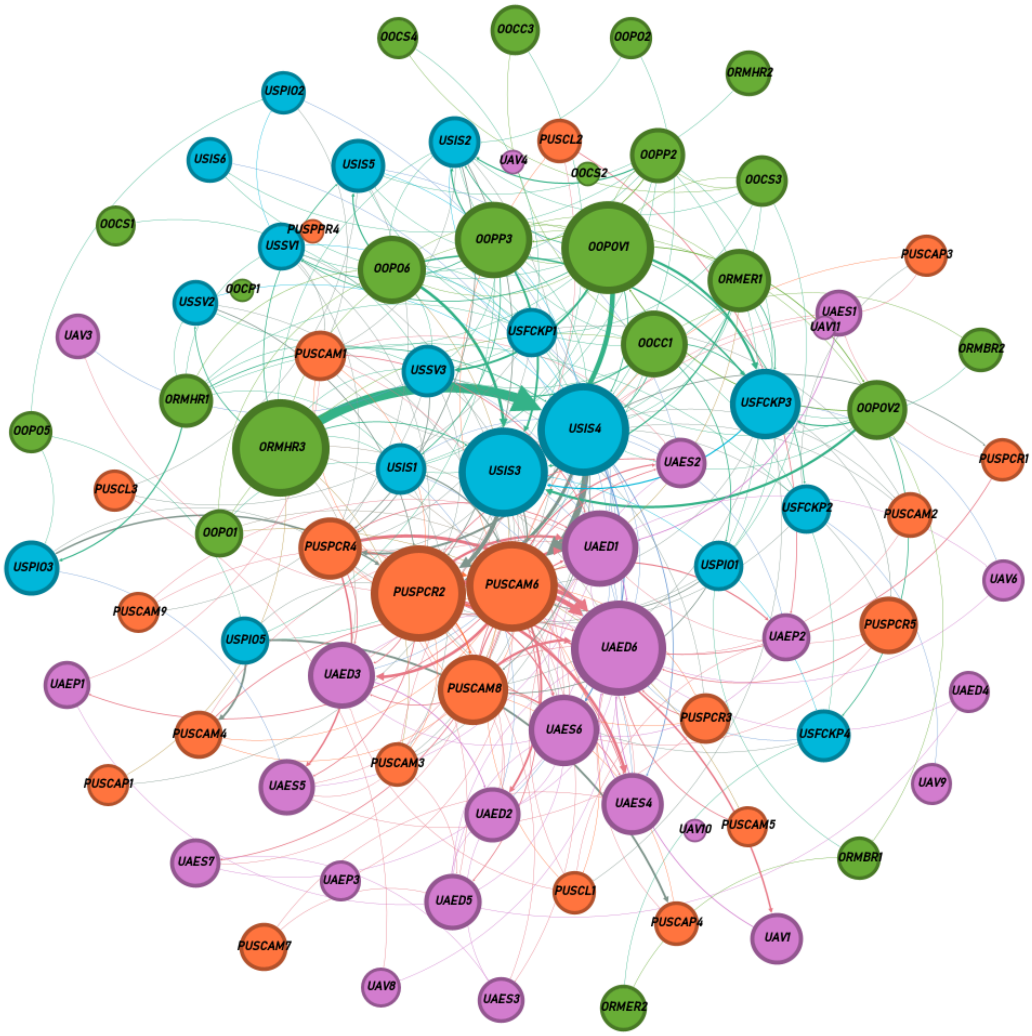

Figure 4.2: Complex Network of LOC-I Accidents

4.2.2 Network Model Based on Modularity

To uncover the underlying architecture of the LOC-I causal network, the Louvain community detection algorithm by Blondel et al.[26] was applied (Modularity = 0.329). This analysis successfully partitioned the network into 11 distinct modularity classes, demonstrating a non-random, structured consolidation of risk factors. Quantitative filtering of these results identified five primary communities that consist of multiple interconnected nodes. These communities represent the dominant recurring patterns where specific human factors cluster to produce an accident. Conversely, the remaining six communities were found to be single-node isolates. These represent outlier risk factors that, while present in the data, do not participate in the standard propagation pathways identified in the broader dataset. The figure shows the five dominant communities in the network:

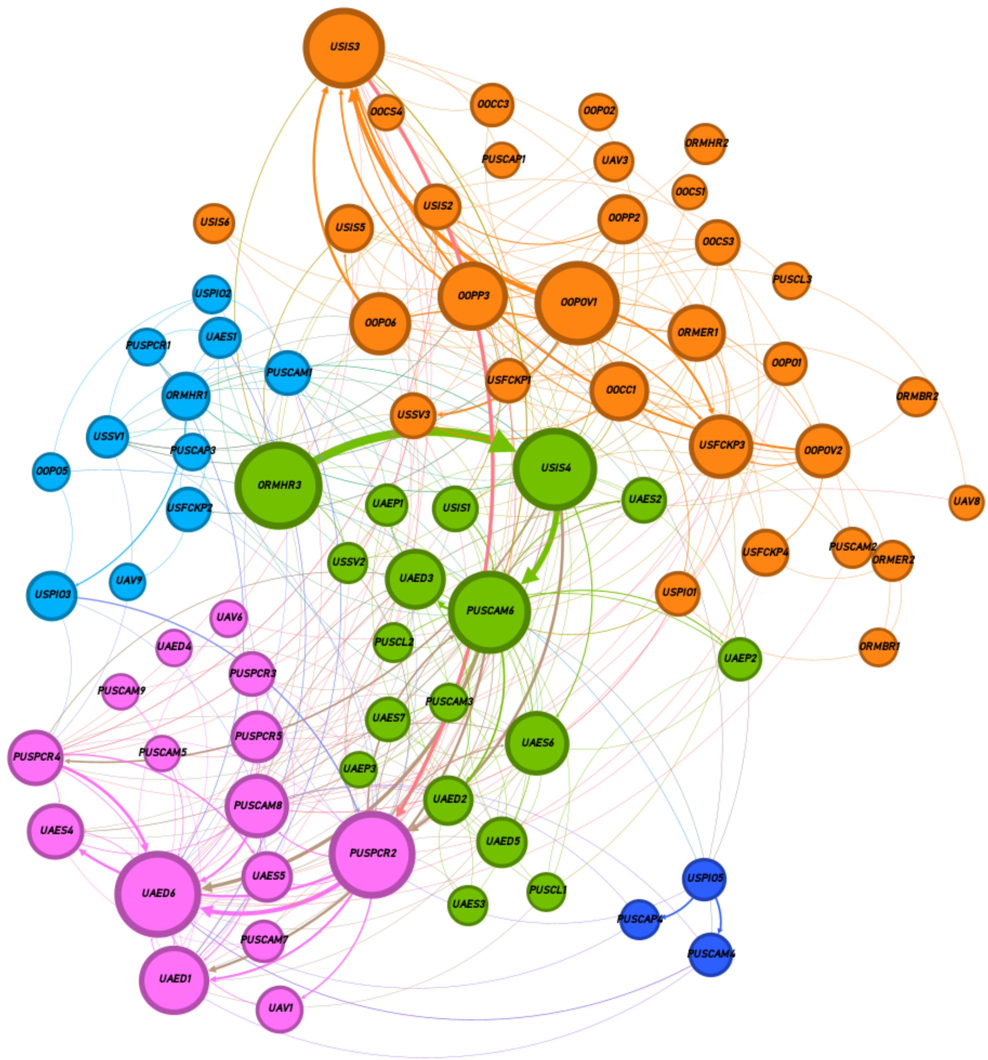

Figure 4.3: LOC-I accident community complex network

Setup:

Gephi Parameters

- Randomize : 10
- Use edge weights: On
- Resolution: 1.0

Results:

- Modularity: 0.318
- Modularity with resolution: 0.298
- Number of communities: 11

A modularity score of 0.318 indicates a significant degree of clustering. This suggests that safety interventions should not be applied broadly across all 85 nodes, but should instead target the core patterns identified in the five multi-node communities. Certain HFACS factors have a high affinity for one another. Thus, clustering allows for a shift from reactive safety management to a structural approach. By objecting the connectivity within one of the five primary failure patterns, the entire propagation chain for that specific accident type can be disrupted.

4.2.3 Network Topology Analysis

4.2.3.1 Network Scale and Density

- Number of Nodes: 85
- Number of Edges: 316
- Diameter: 5
- Average path length : 2.285 $\rightarrow$ On average, it only took about three steps for one factor in the network to influence another.
- Density: 0.044 $\rightarrow$ mathematically low/sparse, but in real life network this is a tight network as suggested by the average path length.

Algorithm for average diameter and average path length :

Ulrik Brandes, A Faster Algorithm for Betweenness Centrality, in Journal of Mathematical Sociology 25(2):163-177, (2001)

The LOC-I causal network is defined by a high degree of connectivity relative to its scale, consisting of 85 nodes and 316 edges. While the network density is mathematically sparse at 0.044, the average path length of 2.285 indicates that, on average, it requires fewer than three steps for an organizational or supervisory failure to propagate through the system and manifest as a terminal event. Furthermore, a network diameter of 5 confirms that even the most distant causal factors in this 90-project dataset are separated by a very short chain of influence, suggesting a compact and highly reactive causal structure. Thus the buffer between a latent organizational flaw and a catastrophic accident is thin. In practical terms, this means that a single failure in Organizational Level does not have to navigate a long, complex chain of safeguards before it impacts pilot performance.

The Loss of Control In-Flight (LOC-I) complex network will be analyzed using several network metrics, including degree centrality, betweenness centrality, clustering coefficient, modularity, and PageRank, in order to understand the structural roles of different causal factors within the accident system. Using multiple metrics is necessary because LOC-I accidents emerge from complex interactions among organizational, supervisory, environmental, and human factors rather than from a single point of failure. Degree centrality identifies factors that frequently co-occur with many other causes, highlighting commonly involved elements in accident chains. Betweenness centrality reveals bridging factors that connect different parts of the network and enable the propagation of failures across HFACS levels. The clustering coefficient helps identify groups of closely interacting factors that tend to appear together in accident scenarios, while modularity detects larger communities of related causes within the network structure. PageRank further identifies influential factors that gain importance through their connections with other significant nodes. Together, these metrics capture different structural characteristics of the LOC-I network, providing a more comprehensive understanding of how interacting failures collectively contribute to the development of loss of control accidents.

4.2.3.2 Node degree

1. **Node Degree Analysis**

Figure below shows all the nodes with total degree greater than or equal to 10.

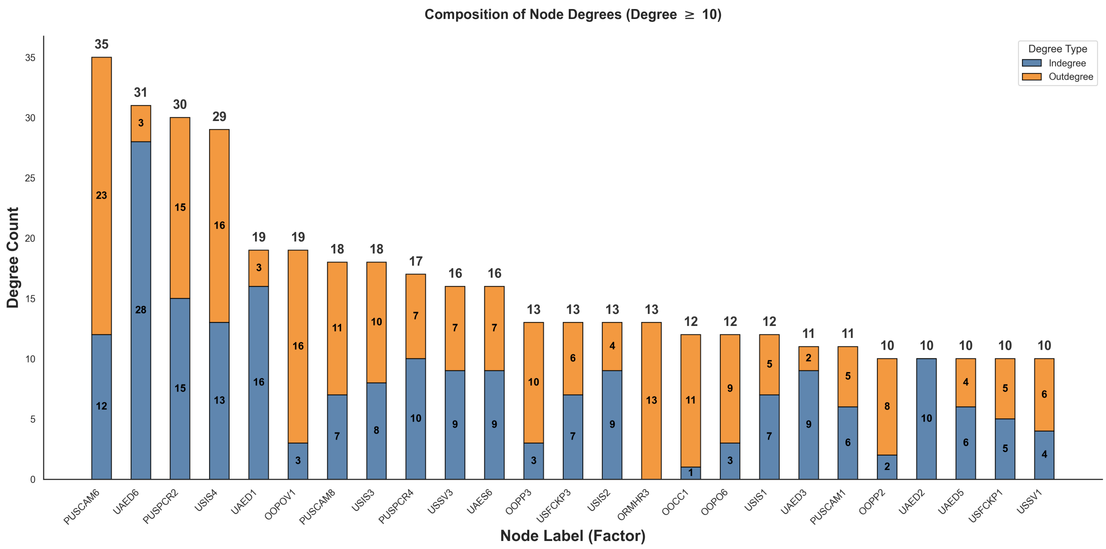

Figure 4.4: Composition of Node Degrees(Degree ≥ 10)

Table 4.3: Nodes with highest degree

Node	**Factor**	**In**	**Out**	**Total**
PUSCAM6	Loss of Situational Awareness	12	23	35
UAED6	Poor Decision	28	3	31
PUSPCR2	Failed to communicate/coordinate	15	15	30
UAED1	Improper Procedure	13	16	29
OOPOV1	Risk Management	3	16	19

To evaluate the specific role of individual causal factors, the network's degree distribution was analyzed, distinguishing between In-degree (influences received) and Out-degree (influence exerted). The analysis identified Loss of Situational Awareness (PUSCAM6) as the most connected hub in the network with a total degree of 35, driven primarily by a high Out-degree of 23. In contrast, Poor Decision (UAED6) functioned as a primary "sink" node, possessing the highest In-degree in the dataset (28) but a negligible Out-degree (3). Other critical connectors included Failed to Communicate/Coordinate (PUSPCR2) and Improper Procedure (UAED1), both of which maintained a balanced ratio of inward and outward influences, serving as major conduits for risk propagation across the HFACS levels.

Table 4.4: Nodes with highest in-degree

Node	**Factor**	**Level**	**In Degree**
UAED6	Poor Decision	Unsafe Acts	28
UAED1	Improper Procedure	Unsafe Acts	16
PUSPCR2	Failed to communicate/coordinate	Preconditions for Unsafe Acts	15
USIS4	Failed to Provide Training	Unsafe Supervision	13
PUSCAM6	Loss of Situational Awareness	Preconditions for Unsafe Acts	12
PUSPCR4	Failed to use all available resources	Preconditions for Unsafe Acts	10

The In-Degree analysis identifies the nodes that act as primary convergence points within the LOC-I causal network. Poor Decision (UAED6) emerged as the most significant ”sink” in the system, receiving 28 inward edges. This was followed by Improper Procedure (UAED1) with an In-Degree of 16 and Failed to Communicate/Coordinate (PUSPCR2) with 15. The data indicates that the highest concentration of inward-flowing risk occurs at the Unsafe Acts and Preconditions for Unsafe Acts levels. For example, in the Lion Air Flight 610 accident, heavy workload (task saturation) contributed to the crew setting the stabilizer trim cut-out switch to “Normal”, representing poor decision-making, which subsequently allowed the MCAS to activate and push the aircraft nose further downward. Similarly, in Colgan Air Flight 3407, pilot fatigue degraded decision-making ability. These cases illustrate how adverse preconditions can impair crew judgment and lead to poor operational decisions.

Table 4.5: Nodes with highest out-degree

Node	**Factor**	**Level**	**Out-Degree**
PUSCAM6	Loss of Situational Awareness	Preconditions for Unsafe Acts	23
USIS4	Failed to Provide Training	Unsafe Supervision	16
OOPOV1	Risk Management	Organizational Influence	16
PUSPCR2	Failed to communicate/coordinate	Preconditions for Unsafe Acts	15
ORMHR3	Training	Organizational Influence	13
PUSCAM8	Task Saturation	Preconditions for Unsafe Acts	11

The Out-Degree analysis highlights the nodes with the greatest potential to influence other factors within the LOC-I causal network. Loss of Situational Awareness (PUS-CAM6) emerged as the most potent transmitter of risk, exerting influence over 23 other nodes. This is followed by Failed to Provide Training (USIS4) and Risk Management (OOPOV1), both of which possess an Out-Degree of 16. The data demonstrates that risk is primarily sourced from two areas: high-level Organizational Influences and cognitive Preconditions for Unsafe Acts. For example in case of Ethiopian Airlines Flight 302, crews's lack of awareness(Loss of Situational Awareness) on loads on stabilizer at high speed lead to crew struggling with manual trim procedure(Omitted Step in Procedure).

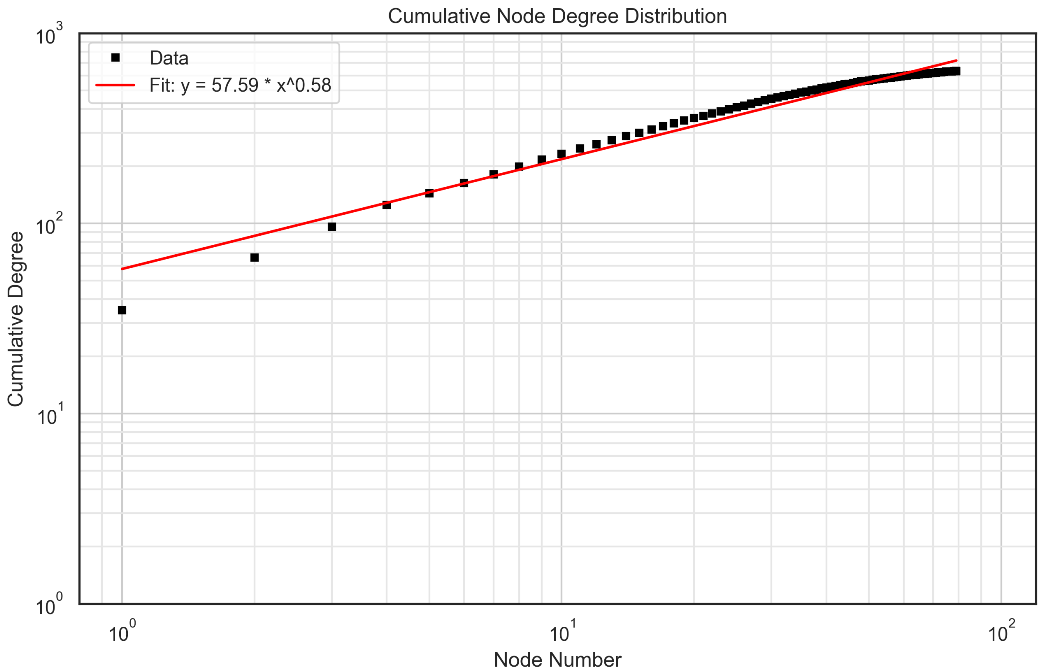

Figure 4.5: Cumulative Node Degree Distribution

The cumulative distribution follows the following power law:

$$\log_{10}(D) = 0.58 \log_{10}(i) + \log_{10}(57.59)$$

An exponent of 0.58 confirms a scale-free architecture, a structural pattern where the distribution of connections follows a power law rather than a normal bell curve. In such a system, most nodes have very few connections, while a small number of hubs are extraordinarily well-connected, effectively lacking a single ”characteristic scale” or average degree. This mathematical signature reveals a robust-yet-fragile system. While the network is resilient to random, isolated failures represented by the long tail of the distribution it is dangerously vulnerable to the alignment of its primary hubs.

The 0.58 exponent suggests an ultra-small world property where the distance to disaster is remarkably short; because these hubs act as massive shortcuts across the network, a latent organizational failure can reach a terminal unsafe act in fewer than three steps by leveraging high-degree nodes like Loss of Situational Awareness (PUSCAM6). Consequently, effective intervention requires a surgical disruption of these hubs rather than a broad-spectrum safety mandate. By targeting the top 10% of nodes, the structural mechanism for accident propagation is degraded, preventing the systemic escalation that leads to a loss of control.

2. Node Weighted Degree Analysis

Degree analysis identifies the structural variety of a network by counting how many unique types of factors a single node can trigger. This method reveals which risks are most versatile in their ability to spread across different categories of failure. In contrast weighted degree analysis measures the actual volume of causal pressure by accounting for how frequently these connections occur across all accident reports. While a high degree shows that a node has many possible paths to an accident, a high weighted degree identifies the specific high intensity hubs that represent the most persistent threats to aviation safety.

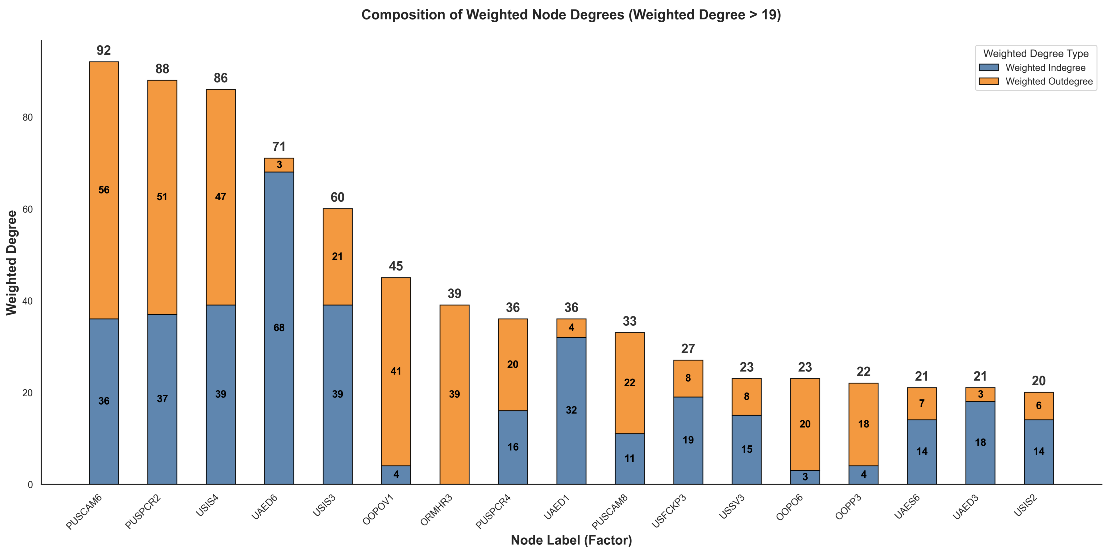

Figure 4.6: Composition of Weighted Node Degree Distribution(Weighted Degree ≥ 19)

Table 4.6: Nodes with highest weighted degree

Node	**Factor**	**Level**	**Weighted Degree**
PUSCAM6	Loss of situational awareness	Preconditions for Unsafe Acts	92
PUSPCR2	Failed to communicate/coordinate	Preconditions for Unsafe Acts	88
USIS4	Failed to provide training	Unsafe Supervision	86
UAED6	Poor decision	Unsafe Acts	71
USIS3	Failed to provide oversight	Unsafe Supervision	60

The Weighted Degree analysis identifies the most critical nodes based on their total causal volume (Sum of In-Degree and Out-Degree). Loss of Situational Awareness (PUSCAM6) emerged as the most significant hub with a total weight of 92, followed closely by Failed to Communicate (88) and Failed to Provide Training (86). These three nodes act as the primary junctions where organizational, supervisory, and operational risks intersect.

Table 4.7: Nodes with highest weighted in-degree

Node	**Factor**	**Level**	**Weighted In-Degree**
UAED6	Poor decision	Unsafe Acts	68
USIS4	Failed to provide training	Unsafe Supervision	39
USIS3	Failed to provide oversight	Unsafe Supervision	39
PUSPCR2	Failed to communicate/coordinate	Preconditions for Unsafe Acts	37
PUSCAM6	Loss of situational awareness	Preconditions for Unsafe Acts	36

The analysis of Weighted In-Degree identifies the most influenced nodes accumulated from the other nodes. Poor Decision (UAED6) is the most significantly influenced node with a weight of 68, indicating it is the most frequent terminal outcome of upward failures. Failed to Provide Training (USIS4) and Failed to Provide Oversight (USIS3), both with a weight of 39. The data shows that the Unsafe Acts level serves as the ultimate of active failure, while Unsafe Supervision acts as a critical factor induced by latent organizational deficiencies.

Table 4.8: Nodes with highest weighted out-degree

Node	**Factor**	**Level**	**Weighted Out-Degree**
PUSCAM6	Loss of situational awareness	Preconditions for Unsafe Acts	56
PUSPCR2	Failed to communicate/coordinate	Preconditions for Unsafe Acts	51
USIS4	Failed to provide training	Unsafe Supervision	47
OOPOV1	Failed to provide oversight	Organizational Influence	41
ORMHR3	Training	Organizational Influence	39

The weighted out-degree analysis identifies the factors that are most influential to affect others over the rest of the network. Loss of situational awareness (PUSCAM6) is the highest-intensity driver with a weight of 56, followed by Failed to communicate (51). Notably, the organizational level appears as a significant source of risk through Failed to provide oversight (41) and Training (39). This data indicates that while the preconditions level has the highest immediate impact, the organizational level provides the sustained pressure that feeds the entire causal chain.

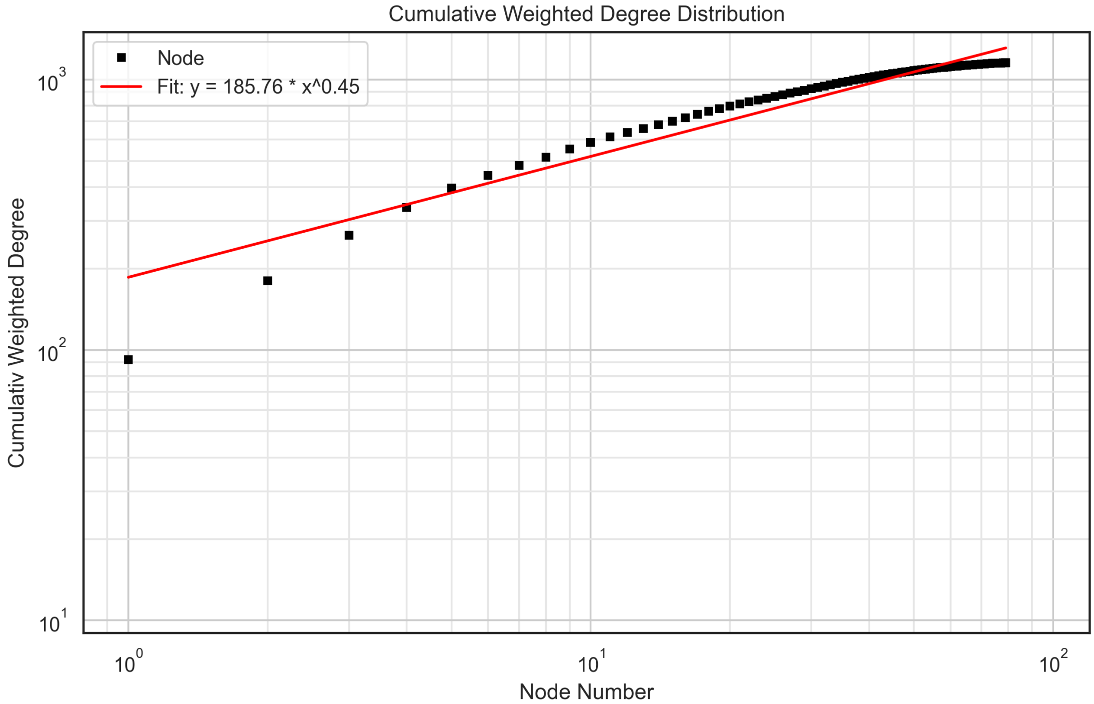

Figure 4.7: Cumulative Weighted Degree Distribution

The cumulative distribution follows the following power law:

$$\log_{10}(wd) = 0.45 \log_{10}(i) + \log_{10}(185.76)$$

The value of exponent (0.45) indicates a high degree of causal concentration. In practical terms, it means that for every step we move toward the top-tier hubs, the weighted risk increases exponentially rather than linearly. This proves that LOC-I accidents are not caused by a diverse range of problems, but by the repeated, high-intensity activation of the same core failures. This high intercept suggests that even in a ”stable” aviation environment, there is a massive underlying reservoir of latent connectivity waiting to be triggered by a hub failure. Since the distribution follows a known power law, the behavior of the network becomes predictable. This justifies shifting resources away from broad safety mandates and toward high-intensity hub mitigation.

4.2.3.3 Cluster Analysis

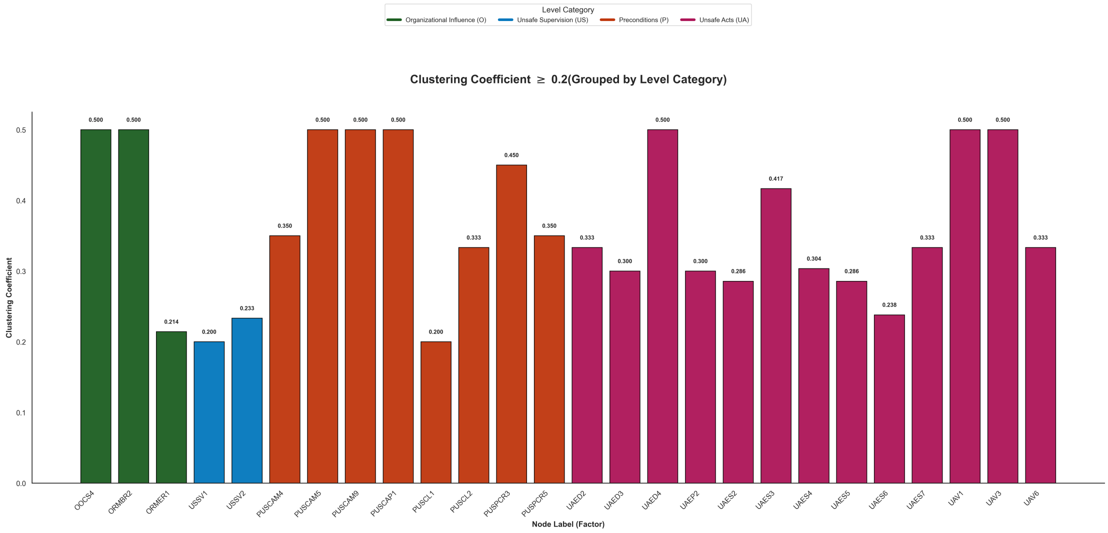

Figure 4.8: Clustering coefficient grouped by level category

Average clustering coefficient: 0.168

Algorithm: Simple and slow brute force

The nodes with high coefficients also exhibit a strong correlation with their neighbors. The risk to a neighboring node increases if these nodes/factors take place in the accident.

4.2.3.4 Betweenness Centrality

Table 4.9: Nodes with Highest Betweenness Centrality

Node	Factor	Level	Betweenness Centrality
PUSCAM6	Loss of situational awareness	Preconditions for Unsafe Acts	443.049264
PUSPCR2	Failed to communicate/coordinate	Preconditions for Unsafe Acts	366.925825
USIS4	Failed to provide training	Unsafe Supervision	203.56854
UAED6	Poor decision	Unsafe Acts	118.416667
UAED1	Improper procedure	Unsafe Acts	94.066175
USIS3	Failed to provide training	Unsafe Supervision	91.329869
PUSCAM8	Task saturation	Preconditions for Unsafe Acts	88.417454
OOPOV1	Risk management	Organizational Influence	87.662179
USSV3	Failed to enforce rules and regulations	Unsafe Supervision	82.853753

Betweenness centrality is an important metric in complex network theory that measures how frequently a node appears on the shortest paths connecting other nodes in the network. In the context of an HFACS (Human Factors Analysis and Classification System) network, it identifies factors that act as critical intermediaries in the propagation of failures across different system levels. A higher value indicates that the node has greater control over failure flow within the network.

From the results, PUSCAM6 (Loss of situational awareness) and PUSPCR2 (Failed to communicate/coordinate) have the highest betweenness centrality values (443.05 and 366.93), indicating that they are the most critical intermediary factors in the network. These nodes also have high weighted degree and lie on a large number of shortest paths, meaning many causal chains pass through them. For example, loss of situational awareness frequently acts as an intermediary between environmental conditions, system malfunctions, and unsafe pilot actions in LOC-I accidents. In the case of Air France Flight 447 crash, unreliable airspeed indications led to confusion about the aircraft's flight condition, causing the crew to lose awareness that the aircraft had entered a stall. This loss of situational awareness linked upstream factors such as instrument malfunction and high workload with downstream unsafe control inputs that ultimately resulted in loss of control..

The betweenness centrality analysis reveals that accident causation is not driven solely by isolated failures but by key intermediary factors that connect different layers of the HFACS framework. Interventions targeting these high-centrality nodes particularly situational awareness, communication, and training would be the most effective for disrupting failure propagation and improving system safety.

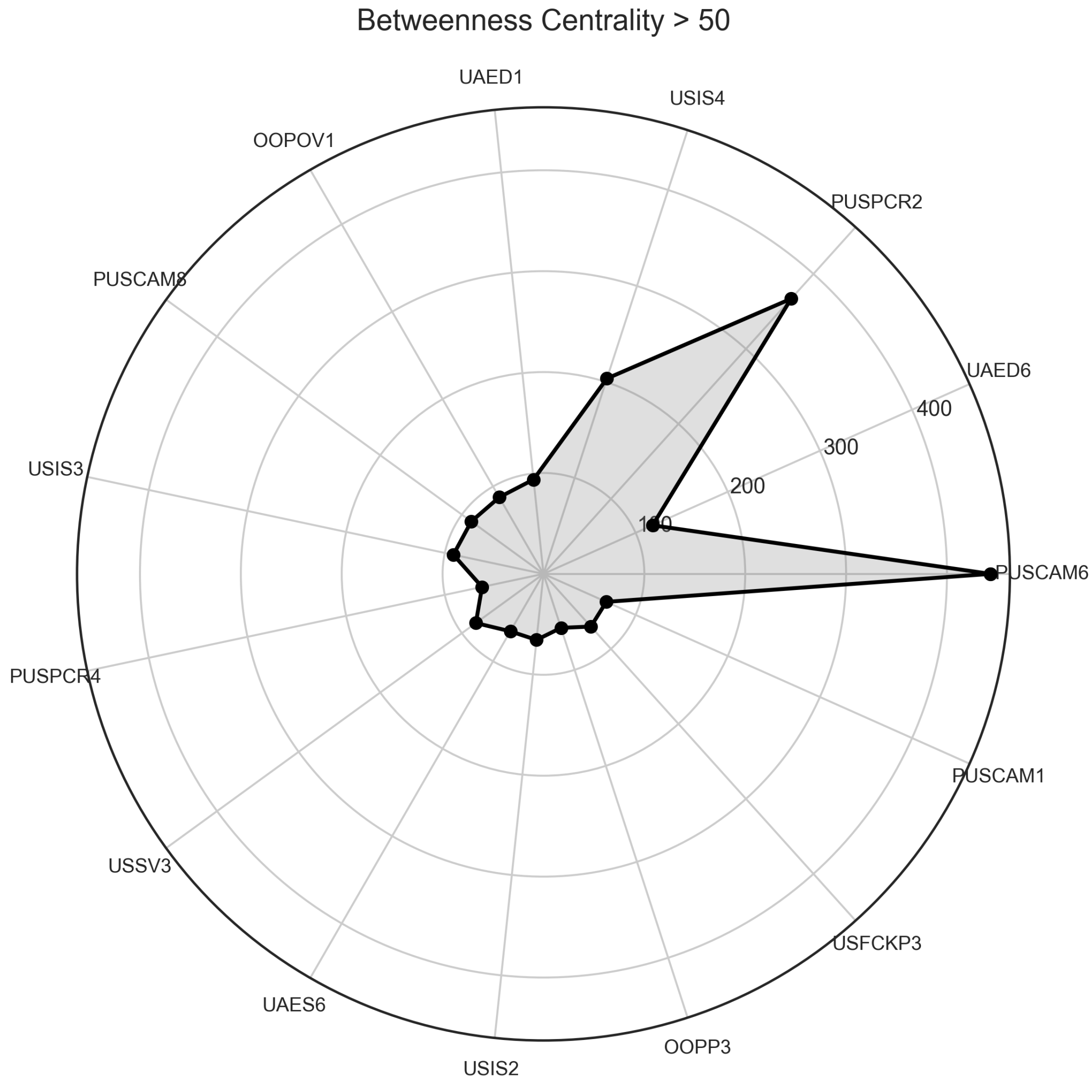

Figure 4.9: Radar chart of Betweenness Centrality (Betweenness Centrality ≥ 50)

4.2.3.5 PageRank

PageRank measures the relative importance of nodes based on both the number and quality of their connections. A node is considered important if it is influenced by or connected to other important nodes. Higher PageRank values indicate nodes that are more central and influential in the overall network structure. From the table, UAED6 (Poor decision) has the highest PageRank value (0.126), indicating it is the most influential node in the network and is strongly connected to other significant factors. This is followed by UAED1 (Improper procedure) and UAED2 (Misdiagnosed emergency), showing that multiple unsafe acts dominate the top rankings. Other unsafe act nodes such as not current/qualified for the mission, omitted checklist item, and violated training rules also have relatively high values, reinforcing that unsafe acts are the most prominent and influential outcomes in the network. In contrast, nodes like PUSPCR2 (Failed to communicate/coordinate) and PUSCAM6 (Loss of situational awareness) have lower PageRank values, suggesting that while they are important (as seen in betweenness centrality), they are less dominant in terms of overall influence compared to unsafe acts. Overall, the PageRank values indicate that the network is strongly centered around unsafe acts, these nodes represent the most significant and influential points in the system. This suggests that failures tend to accumulate and manifest at the unsafe act level, making them critical targets for safety interventions.

The nodes with highest PageRank are given below:

Table 4.10: Nodes with highest PageRank

Node	**Factor**	**Level**	**Page Rank**
UAED6	Poor decision	Unsafe Acts	0.126038
UAED1	Improper procedure	Unsafe Acts	0.079907
UAED2	Misdiagnosed emergency	Unsafe Acts	0.069904
UAV8	Not current/ qualified for the mission	Unsafe Acts	0.046178
UAES5	Omitted checklist item	Unsafe Acts	0.036476
UAV6	Violated training rules	Unsafe Acts	0.02815
PUSPCR2	Failed to communicate/coordinate	Preconditions for Unsafe Acts	0.027498
UAES6	Poor technique	Unsafe Acts	0.02325
PUSCAM6	Loss of situational awareness	Preconditions for Unsafe Acts	0.020946

4.2.4 Modularity Analysis

Modularity analysis was performed using the Louvian community detection algorithm to better understand the underlying structure of the LOC-I causal network.The results showed a modularity value of 0.318, indicating a meaningful level of clustering within the network. Based on this analysis, the network was divided into 11 distinct communities, where 6 were single-node isolates, suggesting that the relationships between risk factors are not random but instead form structured groups. These communities reflect how different causal factors tend to interact more closely with certain groups of factors, providing insight into the interconnected nature of LOC-I accident causation.

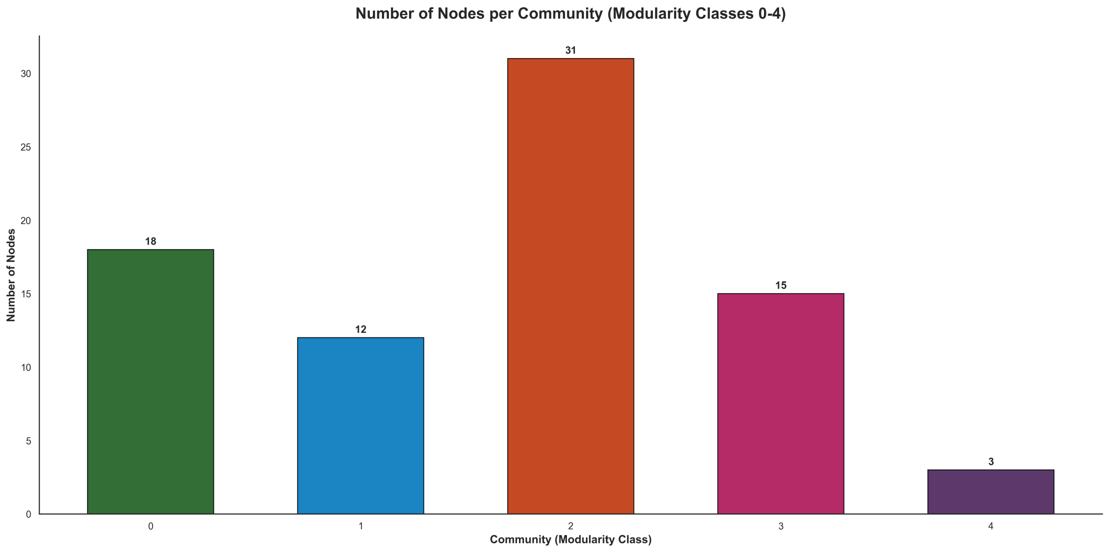

Figure 4.10: Composition of communities by HFACS levels

Table 4.11: Distribution of HFACS Levels across Communities

Community	**0**	**1**	**2**	**3**	**4**
Organizational Influence	5.5%	17%	55%	0%	0%
Unsafe Supervision	16%	33%	30%	0%	33%
Preconditions for Unsafe Acts	22.2%	25%	10%	55%	66%
Unsafe Acts	55%	25%	5%	45%	0%

The modularity results prove that LOC-I accidents are not monolithic; they follow five distinct structural patterns:

1. **Community 0**

   55% Unsafe Acts, this community represents the point of impact. The lack of organizational nodes here suggests these are ”active” failures where the crew is forced to deal with immediate tactical errors that have become disconnected from high-level policy. The data reveals that this cluster is dominated by cognitive and skill-based failures, specifically Loss of Situational Awareness (PUSCAM6) and Spatial Disorientation (UAEP2). Interestingly, the only organizational influence present is Training (ORMHR3), which links directly to a suite of supervisory failures regarding guidance and qualification. This community represents a pathway where inadequate preparation (Training/Supervision) leaves a crew vulnerable to high-stress, rapid-onset emergencies.

Table 4.12: HFACS Factors for Community Class 0 (Part 1)

Class	HFACS Level 1	HFACS Level 2	HFACS Level 3	Code	Full Form
0	Organizational Influence	Resource Management	Human Resources	ORMHR3	Training
0	Unsafe Supervision	Inadequate Supervision	Failed to provide guidance	USIS1	Failed to provide guidance
0	Unsafe Supervision	Inadequate Supervision	Failed to provide training	USIS4	Failed to provide training
0	Unsafe Supervision	Supervisory Violations	Authorized unqualified crew for flight	USSV2	Authorized unqualified crew for flight
0	Preconditions for Unsafe Acts	Substandard Conditions of Operators	Adverse Mental States	PUSCAM6	Loss of situational awareness
0	Preconditions for Unsafe Acts	Substandard Conditions of Operators	Adverse Mental States	PUSCAM3	Distraction
0	Preconditions for Unsafe Acts	Substandard Conditions of Operators	Physical/Mental Limitation	PUSCL1	Insufficient reaction time
0	Preconditions for Unsafe Acts	Substandard Conditions of Operators	Physical/Mental Limitation	PUSCL2	Visual limitation
0	Unsafe Acts of Pilot Operators	Errors	Decision Errors	UAED2	Misdiagnosed emergency
0	Unsafe Acts of Pilot Operators	Errors	Decision Errors	UAED3	Wrong response to emergency
0	Unsafe Acts of Pilot Operators	Errors	Decision Errors	UAED5	Inappropriate maneuver

Class	HFACS Level 1	HFACS Level 2	HFACS Level 3	Code	Full Form
0	Unsafe Acts of Pilot Operators	Errors	Perceptual Errors	UAEP1	Misjudged distance/altitude/airspeed
0			Perceptual Errors	UAEP2	Spatial disorientation
0			Perceptual Errors	UAEP3	Visual illusion
0	Unsafe Acts of Pilot Operators	Errors	Skill-Based Errors	UAES6	Poor technique
0			Skill-Based Errors	UAES2	Failed to prioritize attention
0			Skill-Based Errors	UAES3	Inadvertent use of flight controls
0			Skill-Based Errors	UAES7	Over-controlled the aircraft

Table 4.13: HFACS Factors for Community Class 0: Perceptual and Skill-Based Errors

2. **Community 1**:

   This community involves every layer of the HFACS model. It demonstrates perfect alignment between organizational neglect, supervisory failure, and pilot error. This community is the mathematical representation of a total system breakdown. Unlike the reactive nature of Community 0, this cluster is rooted in administrative decisions, such as Schedules (OOPO5) and Selection (ORMHR1). These latent factors propagate through supervisory failures such as Improper Manning (USPIO3) and Failed to Identify At-Risk Aviator (USFCKP2) eventually manifesting as cognitive lapses like Channelized Attention (PUSCAM1) and violations such as Intentionally Exceeding Aircraft Limits (UAV9).

Table 4.14: HFACS Factors for Community Class 1

Class	HFACS Level 1	HFACS Level 2	Node	Factor
1	Organizational Influence	Organizational Process	OOPO5	Schedules
1	Organizational Influence	Resource Management	ORMHR1	Selection
1	Unsafe Supervision	Failed to Correct a Known Problem	USFCKP2	Failed to identify at-risk aviator
1	Unsafe Supervision	Planned Inappropriate Operations	USPIO2	Failed to provide adequate brief time
1	Unsafe Supervision	Planned Inappropriate Operations	USPIO3	Improper manning
1	Unsafe Supervision	Supervisory Violations	USSV1	Authorized unnecessary hazard
1	Preconditions for Unsafe Acts	Substandard Conditions of Operators	PUSCAM1	Channelized attention
1	Preconditions for Unsafe Acts	Substandard Conditions of Operators	PUSCAP3	Physiological incapacitation
1	Preconditions for Unsafe Acts	Substandard Practice of Operators	PUSPCR1	Failed to back-up
1	Unsafe Acts of Pilot Operators	Errors	UAES1	Breakdown in visual scan
1	Unsafe Acts of Pilot Operators	Violations	UAV9	Intentionally exceeded the limits of the aircraft

3. **Community 2**:

   Since over half of this community is composed of Organizational Influence, it functions as a reservoir of systemic risk. These failures may stay dormant for long periods. Intervening here is the most effective way to provide long-term stability to the system. The presence of Lack of Funding (ORMBR1) and Excessive Cost Cutting (ORMBR2) alongside Risk Management (OOPOV1) proves that financial pressure directly degrades safety oversight. In this module, the organization is structurally incentivized to bypass safety protocols to maintain Operational Tempo (OOPO2). The clustering of Norms and Rules (OOCC1), Values and Beliefs (OOCC3), and Failed to Enforce Rules (USSV3) indicates a cultural breakdown. This suggests that in Community 2 accidents, violating standards is almost an organizational expectation. The ”unpreparedness” seen in UAV3 is a logical output of a culture that devalues formal accountability. This community is the only one where all four categories of Failed to Correct a Known Problem appear. This indicates a closed-loop of patterns where unsafe tendencies and document errors are ignored by supervisors, likely due to the organizational pressure from above.

Table 4.15: HFACS Factors for Community Class 2

Class	**HFACS Level 1**	**HFACS Level 2**	**HFACS Level 3**	**Node**	**Factor**
2	Organizational Influence	Organizational Climate	Culture	OOCC1	Norms and rules
2			Culture	OOCC3	Values and beliefs
2	Organizational Influence	Organizational Climate	Structure	OOCS4	Formal accountability for actions
2			Structure	OOCS3	Communication
2			Structure	OOCS1	Chain-of-command
2	Organizational Influence	Organizational Process	Operations	OOPO6	Deficient planning
2			Operations	OOPO1	Time pressure
2			Operations	OOPO2	Operational tempo
2	Organizational Influence	Organizational Process	Oversight	OOPOV1	Risk management
2			Oversight	OOPOV2	Safety programs
2	Organizational Influence	Organizational Process	Procedures	OOPP3	Standards
2			Procedures	OOPP2	Instructions
2	Organizational Influence	Resource Management	Equipment/facility Resources	ORMER1	Poor Design

Table 4.16: HFACS Factors for Community Class 2 (Part 2)

Class	HFACS Level 1	HFACS Level 2	HFACS Level 3	Code	Factor
2	Organizational Influence	Resource Management	Equipment/facility Resources	ORMER2	Purchasing of Unsuitable Equipment
2	Organizational Influence	Resource Management	Human Resources	ORMHR2	Staffing/manning
2	Organizational Influence	Resource Management	Monetary/Budget Resources	ORMBR1	Lack of funding
2			Monetary/Budget Resources	ORMBR2	Excessive cost cutting
2	Unsafe Supervision	Failed to Correct a Known Problem	Failed to correct document in error	USFCKP1	Failed to correct document in error
2			Failed to initiate corrective action	USFCKP3	Failed to initiate corrective action
2			Failed to report unsafe tendencies	USFCKP4	Failed to report unsafe tendencies
2	Unsafe Supervision	Inadequate Supervision	Failed to provide operational doctrine	USIS2	Failed to provide operational doctrine
2			Failed to provide oversight	USIS3	Failed to provide oversight
2			Failed to provide performance	USIS6	Failed to provide performance
2			Failed to provide qualifications	USIS5	Failed to provide qualifications
2	Unsafe Supervision	Planned Inappropriate Operations	Failed to provide correct data	USPIO1	Failed to provide correct data
2	Unsafe Supervision	Supervisory Violations	Failed to enforce rules and regulations	USSV3	Failed to enforce rules and regulations
2	Preconditions	Substandard Conditions	Adverse Mental States	PUSCAM2	Complacency

Table 4.17: HFACS Factors for Community Class 2 (Part 3)

Class	HFACS Level 1	HFACS Level 2	HFACS Level 3	Code	Factor
2	Preconditions for Unsafe Acts	Substandard Conditions of Operators	Adverse Physiological States	PUSCAP1	Impaired physiological state
2	Preconditions for Unsafe Acts	Substandard Conditions of Operators	Physical/Mental Limitation	PUSCL3	Incompatible intelligence/aptitude
2	Unsafe Acts of Pilot Operators	Violations	Failed to properly prepare for the flight	UAV3	Failed to properly prepare for the flight
2	Unsafe Acts of Pilot Operators	Violations	Not current/qualified for the mission	UAV8	Not current/qualified for the mission

4. **Community 3**:

   This module is characterized by a heavy concentration of Preconditions (55%) and Unsafe Acts (45%). It is uniquely defined by "Substandard Practice of Operators," specifically a total collapse of Crew Resource Management (CRM) and professional discipline. Key factors include Get-home-itis (PUSCAM9), Haste (PUSCAM5), and Task Saturation (PUSCAM8). These mental states manifest in terminal errors like Poor Decision (UAED6), Improper Procedure (UAED1), and explicit violations such as Violated Training Rules (UAV6).

Table 4.18: HFACS Factors for Community Class 3

Class	HFACS Level 1	HFACS Level 2	HFACS Level 3	Code	Factor
3	Preconditions for Unsafe Acts	Substandard Conditions of Operators	Adverse Mental States	PUSCAM8	Task saturation
3			Adverse Mental States	PUSCAM9	Get-home-itis
3			Adverse Mental States	PUSCAM5	Haste
3			Adverse Mental States	PUSCAM7	Misplaced attention

Table 4.19: HFACS Factors for Community Class 3 (Part 2)

Class	HFACS Level 1	HFACS Level 2	HFACS Level 3	Code	Factor
3	Preconditions for Unsafe Acts	Substandard Practice of Operators	Crew Resource Management	PUSPCR2	Failed to communicate/coordinate
3			Crew Resource Management	PUSPCR4	Failed to use all available resources
3			Crew Resource Management	PUSPCR5	Failed of leadership
3			Crew Resource Management	PUSPCR3	Failed to conduct adequate brief
3	Unsafe Acts of Pilot Operators	Errors	Decision Errors	UAED6	Poor decision
3			Decision Errors	UAED1	Improper procedure
3			Decision Errors	UAED4	Exceeded ability
3			Skill-Based Errors	UAES5	Omitted checklist item
3			Skill-Based Errors	UAES4	Omitted step in procedure
3		Violations	Failed to adhere to brief	UAV1	Failed to adhere to brief
3			Violated training rules	UAV6	Violated training rules

5. **Community 4**:

   This community is uniquely narrow, consisting entirely of Unsafe Supervision (33%) and Preconditions (66%). Unlike the broader systemic clusters, this community focuses exclusively on the degradation of the human element through exhaustion. The pathway is exceptionally direct: Inadequate Opportunity for Crew Rest (USPIO5) leads immediately to Mental Fatigue (PUSCAM4) and Physical Fatigue (PUSCAP4). Notably, this cluster lacks Unsafe Acts , suggesting that fatigue in this dataset acts as a universal ”background radiation” that primes the crew for failure rather than being the terminal error itself.

Table 4.20: HFACS Factors for Community Class 4

Class	HFACS Level 1	HFACS Level 2	HFACS Level 3	Node	Factor
4	Unsafe Supervision	Planned Inappropriate Operations	Provided inadequate opportunity for crew rest	USPIO5	Provided inadequate opportunity for crew rest
4	Preconditions for Unsafe Acts	Substandard Conditions of Operators	Adverse Mental States	PUSCAM4	Mental fatigue
4	Preconditions for Unsafe Acts	Substandard Conditions of Operators	Adverse Physiological States	PUSCAP4	Physical fatigue

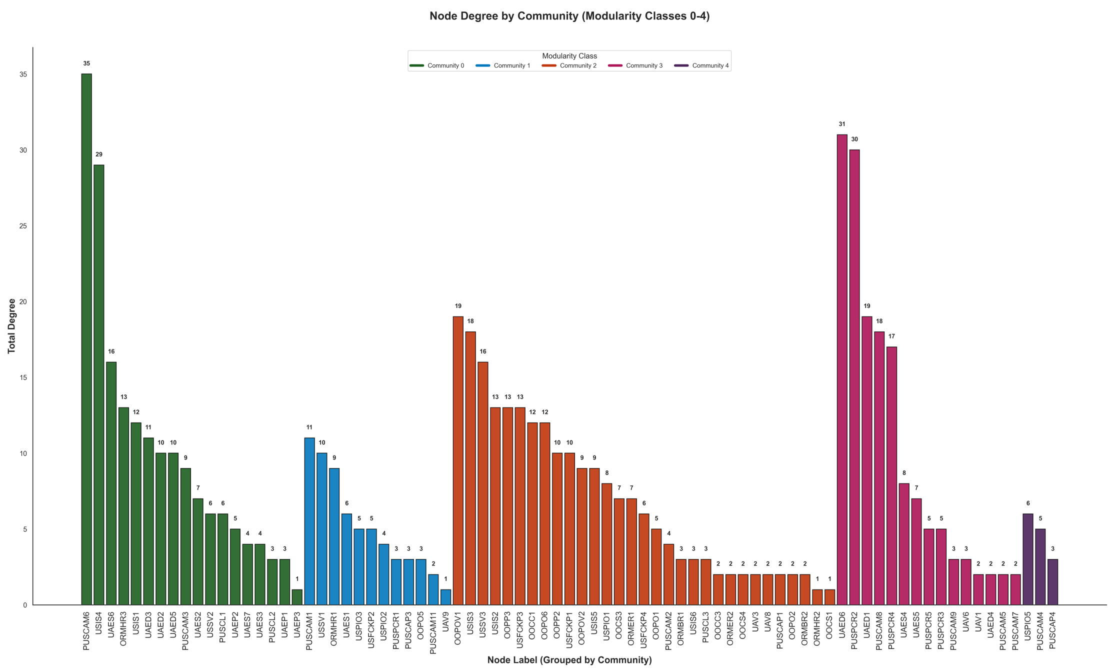

Figure 4.11: Node Degree by Community

4.3 Limitations

1. HFACS coding involves expert judgement, introducing a degree of subjectivity.
2. Accident report vary in:
   - Level of detail
   - Terminology

- Investigation depth

3. Some causal relationships are implicit than explicitly stated, requiring interpretative assumptions

4. Network results are sensitive to:

    - Coding consistency
    - Edge definition criteria

4.4 Challenges Faced

1. Difficulty in:

    - Interpreting amigious statements in accident reports
    - Mapping narrative text to specific HFACS categories

2. Time-consuming nature of manual HFACS coding

3. Inconsistencies between different accident investigation authorities's reporting styles

4. Challenges in:

    - Defining directionality of causal links
    - Avoiding over-connection in the network

5. Learning curve associated with Gephi and complex network analysis

4.5 Budget Analysis

Table 4.21: Budget Analysis

SN	Category	Description	Estimated Cost (NPR)	Justification
1	Data Collection	Accident reports (ASN database)	0	Open-Source data used
2	Software Tools	Python, Gephi, LaTeX, MongoDB	0	Open-source tools
3	Computing Resources	Personal computer/laptop usage	5000	Electricity cost
4	Internet and Data Access	Online journal access, downloads, cloud usage	5000	Required for research
5	Documentation and Writing	MS Word/LaTeX, report formatting, Canva	0	Free/Student License
6	Visualization and Analysis	Graph plotting, Modularity analysis tools	0	Included in open-source tools
		Total	**10000**	

CHAPTER 5 CONCLUSION AND FUTURE ENHANCEMENT

5.1 Conclusion

This study combined the HFACS framework with Complex Network Theory to explore the causal structure of Loss of Control In-Flight (LOC-I) accidents. The analysis revealed that these accidents are rarely the result of a single pilot error; rather, they arise from interacting clusters of human factors. Loss of Situational Awareness often initiates a chain of poor decisions and control actions, while communication failures can further amplify risk, especially in multi-crew operations. Organizational factors, such as insufficient training and oversight, also contribute significantly to these unsafe conditions. Overall, LOC-I accidents reflect a systemic progression of failures rather than isolated events, emphasizing the need for multi-level safety interventions. Based on the specific objectives, the following conclusions are drawn:

- Causal Extraction and Categorization: Through a systematic review of 90 LOC-I reports, a total of 85 unique causal factors were identified and categorized within the HFACS hierarchy. This process transitioned qualitative accident narratives into a structured dataset suitable for mathematical modeling.
- Network Construction and Validation: A directed, weighted network consisting of 316 edges was established. The validation of these causal relations with a Subject Matter Expert (SME) ensured that the model accurately reflects the operational realities of aviation safety while providing a statistically significant sample size for topological analysis.
- System Connectivity and Stability: The network achieved an average degree of 3.718, placing the system firmly in the supercritical regime. This confirms the formation of a percolating cluster (giant component), proving that LOC-I accidents are not isolated events but are governed by a unified, interconnected system of failures.
- Identification of Critical Hubs: Topological metrics successfully pinpointed the dominant drivers of accident sequences. Loss of Situational Awareness was identified as the primary super-hub with a weighted degree of 92, indicating its role as the most critical bridge for risk propagation across the network levels.

- Structural Organization and Modularity: The discovery of a scale-free property, evidenced by the power-law distribution $\log_{10}(wd) = 0.45\log_{10}(i)+\log_{10}(185.76)$, proves that the network is robust against random errors but highly vulnerable to failures in central hubs. Furthermore, the identification of five distinct community structures through modularity algorithms allows for the segmentation of complex accidents into manageable, specialized failure clusters for targeted safety interventions.

The identification of specific super-hubs provides a high-fidelity look at where this causal pressure is most concentrated. The application of a modularity algorithm segmented the interactions between human factors into five distinct failure communities. These clusters represent recurring failure modules that range from immediate tactical crises in the cockpit to deeper, long-term organizational reservoirs.

By analyzing the network through these modular segments, it becomes evident that while the specific path of an accident may appear unique, the structural vulnerabilities remain consistent across the dataset. The high weighted degrees of the identified hubs suggest that the network is mathematically fragile. It is robust against random variations but highly vulnerable to the failure of its central nodes.

Consequently, aviation safety efforts should shift from broad, resource-intensive mandates toward surgical interventions targeting these high-traffic junctions. By dismantling the connections within these critical communities, organizations can achieve a disproportionate reduction in accident probability, moving the industry toward a more proactive and predictive safety management paradigm.

5.2 Scope for Future Enhancement

1. Automation of HFACS classification using Artifical Intelligence
    - Machine learning classification of Human factors can be implemented to accelerate the classification process
    - Large Language Models can be used for semantic accident interpretations

2. Dynamic Failure Chain Modeling instead of Static Network Visualization in Gephi

   Instead of static network visualization, future work can develop temporal network models to capture the sequence and timing of failures. This approach would highlight how organizational and supervisory deficiencies propagate through operations, identify critical escalation points, and support proactive safety interventions.

3. Visualization and Decision-Support Tool Development

   The Gephi network model can be further developed into an interactive dashboard, enabling investigators and safety managers to explore human factor interdependencies, identify critical nodes, and make data-driven safety decisions.

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Appendix A: HFACS Risk Factor Encoding

Table A.1: HFACS Classification and Encoding Scheme(Organizational Influence and Unsafe Supervision

HFACS Level 1	HFACS Level 2	HFACS Level 3	Risk Factor Description	Code
Organizational Influence	Resource Management	Human Resources	Selection	ORMHR1
			Staffing/manning	ORMHR2
			Training	ORMHR3
		Monetary/Budget Resources	Lack of funding	ORMBR1
			Excessive cost cutting	ORMBR2
		Equipment/Facility Resources	Poor design	ORMER1
			Purchasing of unsuitable equipment	ORMER2
	Organizational Climate	Structure	Chain-of-command	OOCS1
			Delegation of authority	OOCS2
			Communication	OOCS3
			Formal accountability for actions	OOCS4
		Policies	Hiring and firing	OOCP1
			Drugs and alcohol	OOCP2
			Promotion	OOCP3
		Culture	Norms and rules	OOCC1
			Organizational justice	OOCC2
			Values and beliefs	OOCC3
	Organizational Process	Operations	Time pressure	OOPO1
			Operational tempo	OOPO2
			Incentives	OOPO4
			Schedules	OOPO5
			Deficient planning	OOPO6
		Procedures	Clearly defined objectives	OOPP1
			Instructions	OOPP2
			Standards	OOPP3
		Oversight	Risk management	OOPOV1
			Safety programs	OOPOV2
Unsafe Supervision	Inadequate Supervision	—	Failed to provide guidance	USIS1
		—	Failed to provide operational doctrine	USIS2
		—	Failed to provide oversight	USIS3
		—	Failed to provide training	USIS4
		—	Failed to track qualifications	USIS5
		—	Failed to track performance	USIS6
	Planned Inappropriate Operations	—	Failed to provide correct data	USPIO1
		—	Failed to provide adequate brief time	USPIO2
		—	Improper manning	USPIO3
		—	Mission not in accordance with rules/regulations	USPIO4
		—	Inadequate opportunity for crew rest	USPIO5
	Failed to Correct a Known Problem	—	Failed to correct document in error	USFCKP1
		—	Failed to identify at-risk aviator	USFCKP2
		—	Failed to initiate corrective action	USFCKP3
		—	Failed to report unsafe tendencies	USFCKP4
	Supervisory Violations	—	Authorized unnecessary hazard	USSV1
		—	Authorized unqualified crew for flight	USSV2
		—	Failed to enforce rules and regulations	USSV3

Table A.2: HFACS Classification and Encoding Scheme (Preconditions for Unsafe Acts and Unsafe Acts)

HFACS Level 1	HFACS Level 2	HFACS Level 3	Risk Factor Description	Code
Preconditions for Unsafe Acts	Substandard Conditions of Operators	Adverse Mental States	Channelized attention	PUSCAM1
			Complacency	PUSCAM2
			Distraction	PUSCAM3
			Mental fatigue	PUSCAM4
			Haste	PUSCAM5
			Loss of situational awareness	PUSCAM6
			Misplaced attention	PUSCAM7
			Task saturation	PUSCAM8
			Get-home-itis	PUSCAM9
		Adverse Physiological States	Impaired physiological state	PUSCAP1
			Medical illness	PUSCAP2
			Physiological incapacitation	PUSCAP3
			Physical fatigue	PUSCAP4
		Physical/Mental Limitation	Insufficient reaction time	PUSCL1
			Visual limitation	PUSCL2
			Incompatible intelligence/aptitude	PUSCL3
			Incompatible physical capability	PUSCL4
	Substandard Practice of Operators	Crew Resource Management	Failed to back-up	PUSPCR1
			Failed to communicate/coordinate	PUSPCR2
			Failed to conduct adequate brief	PUSPCR3
			Failed to use all available resources	PUSPCR4
			Failure of leadership	PUSPCR5
			Misinterpretation of traffic calls	PUSPCR6
		Personal Readiness	Excessive physical training	PUSPPR1
			Self-medicating	PUSPPR2
			Violation of bottle-to-throttle requirement	PUSPPR3
			Violation of crew test requirement	PUSPPR4
Unsafe Acts of Pilot Operators	Errors	Skill-Based Errors	Breakdown in visual scan	UAES1
			Failed to prioritize attention	UAES2
			Inadvertent use of flight controls	UAES3
			Omitted step in procedure	UAES4
			Omitted checklist item	UAES5
			Poor technique	UAES6
			Over-controlled the aircraft	UAES7
		Decision Errors	Improper procedure	UAED1
			Misdiagnosed emergency	UAED2
			Wrong response to emergency	UAED3
			Exceeded ability	UAED4
			Inappropriate maneuver	UAED5
			Poor decision	UAED6
		Perceptual Errors	Misjudged distance/altitude/airspeed	UAEP1
			Spatial disorientation	UAEP2
			Visual illusion	UAEP3
	Violations	—	Failed to adhere to brief	UAV1
		—	Failed to use the radar altimeter	UAV2
		—	Failed to properly prepare for the flight	UAV3
		—	Flew an unauthorized approach	UAV4
		—	Flew an overaggressive maneuver	UAV5
		—	Violated training rules	UAV6
		—	Briefed unauthorized flight	UAV7
		—	Not current/qualified for the mission	UAV8
		—	Intentionally exceeded aircraft limits	UAV9
		—	Continued low-altitude flight in VMC	UAV10
		—	Unauthorized low-altitude canyon running	UAV11

Appendix B: Example of extracting association relationships among occurrence cause nodes

Table B.1: Establishment of Causal chains among causal factors

Occurrence	Direct and indirect causes of the occurrence	Stratified identification of occurrence cause factors	Node relations
Investigation report on Sol Líneas Aéreas flight 5428, a Saab 340 that crashed near Prahuaniyeu, Argentina, following a loss of control in icing conditions, killing all 22 occupants.	**Direct causes:** While climbing at night in instrument meteorological conditions, the Saab 340A encountered severe icing at around 17,800 ft and later at 14,000 ft. Ice accumulated on the wings faster than the de-icing systems could remove it, significantly reducing lift and increasing drag. As a result, airspeed decayed, compounded by the engines not being set to full power. The aircraft subsequently entered an aerodynamic stall, leading to a loss of control and impact with the ground. **Indirect causes:** The crew entered icing conditions without adequately monitoring environmental cues such as temperature, cloud cover, precipitation, and ice accumulation. Although only slight icing was forecast, the aircraft encountered severe icing, and the associated risks were not properly evaluated or mitigated through adequate briefing. Increasing stress due to ineffective corrective actions led to loss of situational awareness. Icing conditions exceeded the aircraft's certified ice protection capability, while airspeed was maintained close to stall speed. Flight and Operations Manual procedures were only partially followed, and the onset of stall was recognized late. Stall warnings activated at lower-than-expected speeds due to icing, and an inappropriate stall recovery technique—prioritizing angle-of-attack reduction at the expense of altitude—was applied. Organizational factors included outdated operating specifications, incomplete compliance with RAAC requirements, failure to update aircraft and training manuals, lack of manufacturer-recommended stall recovery guidance, insufficient Line Oriented Simulation training, external crew scheduling, and non-compliance with airworthiness directives related to propeller maintenance.	**(1) Organizational influences:** Training(ORMHR3), Poor Design(ORMER1), Delegation of authority(OOCS2), Instructions(OOPP2), Standards(OOPP3), Risk management(OOPOV1), Safety Programs(OOPOV2) **(2) Unsafe supervision:** Failed to provide correct data(USPIO1), Failed to correct document in error(USFCKP1), Failed to enforce rules and regulations(USSV3) **(3) Preconditions for unsafe acts:** Loss of situational awareness(PUSCAM6), Failed to use all available resources(PUSPCR4) **(4) Unsafe acts:** Omitted checklist item(UAES5), Misdiagnosed emergency(UAED2), Inappropriate maneuver(UAED5)	OOPP2→USPIO1 ORMER1→USFCKP1 OOPP3→USSV3 OOPOV1→USPIO2 USPIO1→PUSCAM6 USFCKP1→PUSPCR4 PUSCAM6→UAED5 UAED2→UAED5

Appendix C: Python Code fot Nodes and Edge csv files

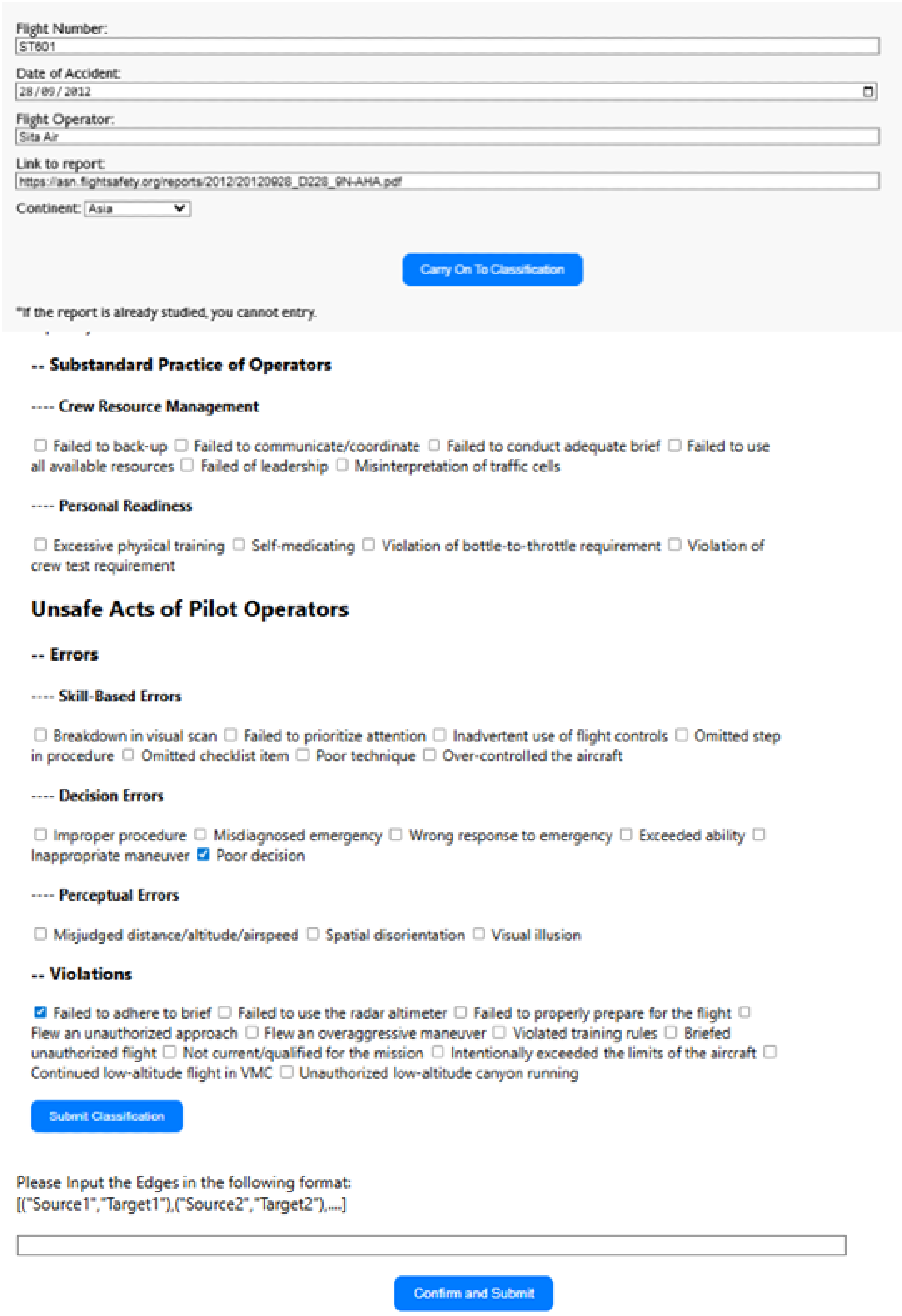
Listing 1: Python Script for HFACS Node and Edge Extraction from MongoDB

```python
from pymongo import MongoClient
import pandas as pd
from collections import Counter

# -------------------- MongoDB Connection --------------------
MONGO_URI = ""
client = MongoClient(MONGO_URI)

db = client["HFACS_App"]
report_collection = db["Report_Records"]

# -------------------- HFACS Definitions --------------------
HFACS_ORDER = ["O", "US", "P", "UA"]

HFACS_PREFIXES = {
    "US": "Unsafe Supervision",
    "UA": "Unsafe Acts",
    "P": "Preconditions for Unsafe Acts",
    "O": "Organizational Influence"
}

def get_hfacs_level(node):
    # longest-prefix-first (CRITICAL)
    for prefix in ["US", "UA", "P", "O"]:
        if node.startswith(prefix):
            return prefix
    return "UNK"

def get_hfacs_category(node):
    for prefix, name in HFACS_PREFIXES.items():
        if node.startswith(prefix):
            return name
    return "Unknown"

# -------------------- NODES --------------------
node_counter = Counter()

for doc in report_collection.find({}, {"Code Vector": 1, "_id": 0}):
    codes = doc.get("Code Vector", [])
    node_counter.update(codes)

nodes_df = pd.DataFrame(node_counter.items(), columns=["id", "weight"
    ])
```

```python
nodes_df["label"] = nodes_df["id"]                          # Gephi label
nodes_df["category"] = nodes_df["id"].apply(get_hfacs_category)
nodes_df["level"] = nodes_df["id"].apply(get_hfacs_level)

nodes_df.to_csv("nodes.csv", index=False)

# -------------------- EDGES (STRICT SWISS CHEESE) --------------------
edge_counter = Counter()
edge_categories = {}

for doc in report_collection.find({}, {"Edges": 1, "_id": 0}):
    edges = doc.get("Edges", [])

    for edge in edges:
        a, b = edge

        level_a = get_hfacs_level(a)
        level_b = get_hfacs_level(b)

        # Reject unknown levels
        if level_a == "UNK" or level_b == "UNK":
            continue

        # Enforce Swiss Cheese direction
        if HFACS_ORDER.index(level_a) < HFACS_ORDER.index(level_b):
            source, target = a, b
        else:
            source, target = b, a

        src_level = get_hfacs_level(source)
        tgt_level = get_hfacs_level(target)

        edge_counter[(source, target)] += 1
        edge_categories[(source, target)] = f"{src_level}-{tgt_level}"

edges_df = pd.DataFrame(
    [
        (src, tgt, weight, edge_categories[(src, tgt)])
        for (src, tgt), weight in edge_counter.items()
    ],
    columns=["source", "target", "weight", "category"]
)

# -------------------- Write to CSV -----------------------
edges_df.to_csv("edges.csv", index=False)
```

```

print("nodes.csv and edges.csv created")
```

Appendix D: Website for Data logging



Flight Number:
ST601
Date of Accident:
28/09/2012
Flight Operator:
Sita Air
Link to report:
https://asn.flightsafety.org/reports/2012/20120928_D228_9N-AHA.pdf
Continent: Asia

Carry On To Classification

*If the report is already studied, you cannot entry.

-- Substandard Practice of Operators

---- Crew Resource Management

☐ Failed to back-up ☐ Failed to communicate/coordinate ☐ Failed to conduct adequate brief ☐ Failed to use all available resources ☐ Failed of leadership ☐ Misinterpretation of traffic cells

---- Personal Readiness

☐ Excessive physical training ☐ Self-medicating ☐ Violation of bottle-to-throttle requirement ☐ Violation of crew test requirement

Unsafe Acts of Pilot Operators

-- Errors

---- Skill-Based Errors

☐ Breakdown in visual scan ☐ Failed to prioritize attention ☐ Inadvertent use of flight controls ☐ Omitted step in procedure ☐ Omitted checklist item ☐ Poor technique ☐ Over-controlled the aircraft

---- Decision Errors

☐ Improper procedure ☐ Misdiagnosed emergency ☐ Wrong response to emergency ☐ Exceeded ability ☐ Inappropriate maneuver ☑ Poor decision

---- Perceptual Errors

☐ Misjudged distance/altitude/airspeed ☐ Spatial disorientation ☐ Visual illusion

-- Violations

☑ Failed to adhere to brief ☐ Failed to use the radar altimeter ☐ Failed to properly prepare for the flight ☐ Flew an unauthorized approach ☐ Flew an overaggressive maneuver ☐ Violated training rules ☐ Briefed unauthorized flight ☐ Not current/qualified for the mission ☐ Intentionally exceeded the limits of the aircraft ☐ Continued low-altitude flight in VMC ☐ Unauthorized low-altitude canyon running

Submit Classification

Please Input the Edges in the following format:
[("Source1","Target1"),("Source2","Target2"),....]

Confirm and Submit

Figure D.1: Website for data logging

Appendix E: Snippet of accident nodes and edges in JSON

Listing E.1: Example Accident Record Stored in JSON format


```json
{
  "_id": {
    "$oid": "69abe0a00a64a73a9a907105"
  },
  "Flight Details": {
    "Flight Number": "IRC3704",
    "Operator": "Iran Aseman Airlines",
    "Date": "2018-02-18",
    "Continent": "Asia",
    "Link": "https://asn.flightsafety.org/reports/2018/20180218_AT72_EP-ATS.pdf"
  },
  "Report Studied by": "saurya",
  "Code Vector": [
    "ORMHR3",
    "ORMER1",
    "OOCS3",
    "OOPP2",
    "OOPP3",
    "USIS3",
    "USIS4",
    "USPIO1",
    "USPIO2",
    "USPIO3",
    "USFCKP3",
    "PUSCAM2",
    "PUSCAM6",
    "PUSCAM8",
    "PUSPCR2",
    "PUSPCR4",
    "PUSPCR5",
    "UAES4",
    "UAES5",
    "UAES6",
    "UAED6",
    "UAV4"
  ],
  "Edges": [
    ["ORMHR3","USIS4"],
    ["OOCS3","USPIO1"],
    ["USIS3","PUSPCR2"],
    ["PUSPCR4","UAES5"],
    ["USPIO1","PUSCAM6"],
```

```
    ["PUSPCR2","UAES4"]
  ],
  "Nodes": [
    "Training",
    "Poor Design",
    "Communication",
    "Instructions",
    "Standards",
    "Failed to provide oversight",
    "Failed to provide training",
    "Failed to provide correct data",
    "Failed to provide adequate brief time",
    "Improper manning",
    "Failed to initiate corrective action",
    "Complacency",
    "Loss of situational awareness",
    "Task saturation",
    "Failed to communicate/coordinate",
    "Failed to use all available resources",
    "Failed of leadership",
    "Omitted step in procedure",
    "Omitted checklist item",
    "Poor technique",
    "Poor decision",
    "Flew an unauthorized approach"
  ]
}
```