International Journal of Science and Research Archive
eISSN: 2582-8185
Cross Ref DOI: 10.30574/ijsra
Journal homepage: https://ijsra.net/

(Research Article)

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Human factors that influence aviation safety in airports

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International Journal of Science and Research Archive, 2026, 18(03), 1482-1492

Publication history: Received on 20 February 2026; revised on 28 March 2026; accepted on 30 March 2026

Article DOI: https://doi.org/10.30574/ijsra.2026.18.3.0632

Abstract

The aviation industry emphasizes safety through systematic investigation of incidents to prevent future accidents. Organizations such as the International Civil Aviation Organization and the National Transportation Safety Board play central roles in identifying accident causes and shaping safety improvements. This study examines common causes of aviation accidents and strategies for their reduction, utilizing accident data, professional literature, and aviation regulations. In addition to analyzing impacts, it provides a historical overview and literature review of safety research. Methods include reviewing scientific publications and collecting data from multiple sources, while analysis involves tabulating information and applying theoretical frameworks. The report outlines accident trends, categorizes their effects, and proposes mitigation strategies to enhance next-generation transportation safety, highlighting the importance of continuous improvement in global aviation safety practices.

Keywords: Next-generation transportation systems; Safety improvement; Accident investigation**,**

1. Introduction

The 20th century saw significant advancements in air travel, driven by a desire for safety and efficiency. Engineers and psychologists have worked tirelessly to enhance the safety of passenger and cargo flights since the early days, with air travel now regarded as one of the safest transportation methods. In 2019, there was a notable decline in fatal accidents, reflecting ongoing health measures and safety improvements.Airspace capacity, while finite, can be optimized through various factors, including air traffic control (ATC) system capacity, sector complexity, personnel training, and available communication and navigation infrastructure. Key indicators for measuring ATC sector capacity include workload and the tasks performed by controllers. The DORATASK model is commonly used to assess workload, considering both observable tasks (like communication) and non-observable tasks (like conflict planning). This model helps estimate ATC capacity, particularly in terminal areas, despite its limitations.Airport capacity is defined as the maximum number of operations under specific conditions, affected by physical constraints like parking availability.

2. Related Work

2.1. Human fators overview

This topic remain one of the most widely studied yet persistently challenging dimensions of aviation safety, and literature in this field consistently emphasizes that while technological innovations and engineering solutions have made aircraft and airport infrastructures increasingly reliable, the human element continues to shape both the strengths and vulnerabilities of the aviation system. Research shows that the majority of aviation accidents can be traced back not to mechanical or technical failures but to lapses in human performance, organizational shortcomings, or breakdowns in communication, and this has led to decades of research into identifying, classifying, and mitigating such risks.. Shappell and Wiegmann's development of the Human Factors Analysis and Classification System (HFACS)

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in 2000, building on Reason's Swiss Cheese Model, provided one of the most influential frameworks for analyzing human error in aviation, categorizing failures at the level of unsafe acts, preconditions for unsafe acts, supervisory factors, and organizational influences. Their methodology, which drew heavily on accident report analysis, revealed that human error is rarely a simple matter of individual failure but rather the outcome of a complex chain of systemic weaknesses. [1,2] At the same time, Helmreich and Foushee's work on Crew Resource Management (CRM) highlighted the centrality of communication and teamwork in fostering safe operations, demonstrating through case studies, simulator training, and organizational surveys that structured communication protocols and team coordination significantly reduce the likelihood of misunderstandings that can escalate into safety threats. Parallel to this, Caldwell's research on fatigue among pilots and air traffic controllers, employing physiological measures such as EEG monitoring alongside subjective fatigue scales, showed that fatigue impairs vigilance, slows reaction times, and degrades decision-making, making it one of the most persistent and dangerous human factors in high-intensity airport environments. Similarly, Endsley's model of situational awareness, first articulated in 1995, has become a cornerstone for understanding how perception, comprehension, and projection of environmental cues underpin safe decision-making, with subsequent studies repeatedly finding that breakdowns in situational awareness contribute to near misses and accidents by causing operators to misinterpret or overlook critical information. Collectively, these studies underscore that human error, communication, fatigue, and situational awareness are deeply intertwined, each capable of influencing the others in ways that either support or undermine aviation safety.[2,3]

Despite the richness of this body of work, significant gaps remain in the literature that my research aims to address. First, most existing studies concentrate primarily on pilots and air traffic controllers, leaving ground operations such as baggage handling, ramp services, airport security, and passenger management relatively underexplored, even though these roles are crucial to the safe functioning of airports. This narrow focus risks overlooking how safety depends on the coordinated performance of diverse airport staff, many of whom work in environments characterized by high workload, time pressure, and exposure to environmental stressors such as noise, weather, and shift work. Second, much of the research examines human factors in isolation—studying fatigue, communication, or situational awareness as independent variables—rather than exploring how these factors interact simultaneously in real-world settings. In practice, fatigue can degrade situational awareness, poor communication can amplify the consequences of human error, and organizational culture can shape how individuals perceive and respond to risks, meaning that isolated analyses may fail to capture the full complexity of safety dynamics. Third, while theoretical frameworks such as Reason's Swiss Cheese Model, HFACS, and Endsley's situational awareness model provide powerful tools for analyzing accidents and understanding human performance, relatively few studies have adapted these models to the unique operational context of airports as integrated ecosystems, where safety is maintained not only through cockpit and control tower decisions but also through the seamless coordination of ground crews, security personnel, maintenance teams, and customer service staff. [3,4]

The methodologies employed across the literature reflect both strengths and limitations that inform how my research will proceed. Accident report analyses and retrospective case studies have been invaluable for identifying recurring patterns of error and organizational weakness, but they are inherently limited by hindsight bias and the selective detail available in reports. Simulator studies and training evaluations, as used in CRM research, provide controlled environments for testing interventions, yet they may not fully capture the complexity and unpredictability of live airport operations. Physiological monitoring and fatigue studies offer objective insights into performance degradation, but they often involve small sample sizes and may not generalize across the diverse roles within airports. Observational studies and field surveys bring ecological validity but can be constrained by self-reporting biases and the difficulty of capturing subtle or unobservable aspects of human performance. Together, these approaches provide valuable insights, but they also highlight the need for more integrative, multi-method research that combines the strengths of different methodologies to build a holistic understanding of human factors in the airport context.[4]

The theoretical frameworks that dominate the field provide a strong intellectual foundation for my research. Reason's Swiss Cheese Model illustrates how accidents occur when multiple layers of defense are breached, highlighting the importance of addressing both latent organizational conditions and active human errors. HFACS operationalizes this model by offering a taxonomy that allows researchers and practitioners to classify errors and contributing factors systematically, making it particularly useful for identifying recurring weaknesses across different accidents. Endsley's situational awareness model emphasizes the cognitive processes underlying safe decision-making, reminding us that even highly skilled individuals can falter if their perception or comprehension of the environment is incomplete or distorted. These frameworks are highly relevant to the airport environment, where layered defenses exist in the form of safety protocols, training, technology, and oversight, but where human performance remains the final safeguard against failure. However, the application of these models has often been limited to flight crew and air traffic contexts, with less attention paid to how they might illuminate safety issues in ground operations or cross-departmental coordination within airports. [5]

By building on these foundations while addressing their limitations, my research seeks to contribute new insights into the human factors that influence aviation safety in the airport setting. Specifically, I aim to broaden the scope of human factors research beyond pilots and controllers to include ground staff, baggage handlers, ramp workers, maintenance crews, and security personnel, whose actions and interactions directly affect safety yet are often overlooked in academic studies. I also intend to explore the interactions between multiple human factors, examining how fatigue, communication breakdowns, situational awareness lapses, and organizational culture intersect to create complex safety challenges. In doing so, my research will adapt and extend existing models such as HFACS and the Swiss Cheese Model to the airport ecosystem as a whole, thereby offering a more comprehensive framework for understanding and mitigating risks. The implications of this work are both theoretical and practical: theoretically, it will help refine our understanding of how human factors operate in complex socio-technical systems; practically, it will provide actionable insights for airport management, policymakers, and training organizations seeking to strengthen safety culture, improve communication, design fatigue-mitigation strategies, and develop integrated safety protocols that account for the diverse roles within airports. Ultimately, by filling the identified gaps and extending previous findings, my research aspires to not only advance academic knowledge but also make a tangible contribution to enhancing aviation safety in one of the most critical and complex environments of the transportation system.[6]

3. Methodology

Human factors significantly influence aviation safety, and addressing these elements can enhance overall safety in airports. One effective approach is to develop comprehensive training programs that focus on situational awareness, decision-making, and stress management, which can improve personnel's ability to handle emergencies. Additionally, establishing standardized communication protocols can reduce misunderstandings among team members during critical operations. Implementing Crew Resource Management (CRM) training can further enhance teamwork and communication among crew members. Fatigue management systems are essential for monitoring staff rest and scheduling to minimize errors caused by exhaustion, particularly among air traffic controllers and flight crews. Utilizing simulation-based training can provide realistic scenarios for employees to practice emergency procedures effectively. Behavioral observation programs can promote a culture of continuous improvement by offering real-time feedback on practices. To identify specific interventions, statistical methods can be employed to analyze quantitative data, revealing correlations and trends related to human factors and safety incidents. Qualitative analysis techniques, such as thematic analysis, can interpret insights from interviews and focus groups, guiding the selection of interventions. Once these interventions are identified, pilot testing them in real-world settings allows for the collection of feedback and performance metrics to assess their effectiveness. Evaluating the outcomes of these interventions in terms of their impact on safety and human performance is crucial, along with conducting follow-up studies to ensure sustained improvements and adapt strategies as necessary. Finally, [7] compiling findings into a comprehensive report detailing methodologies, results, and recommendations is essential for sharing with stakeholders, including aviation organizations, regulatory bodies, and the academic community. Establishing a feedback loop for ongoing assessment and refinement of human factors strategies is vital, encouraging continuous learning and adaptation within the aviation community to address emerging challenges and enhance safety.

3.1. ATC Sector Capacity Calculation Model

This study adopts the ICA 100-30 model, used in Brazil, to estimate the number of aircraft (N) that can be simultaneously controlled in a sector. The simplified formula is:

$$N = \emptyset . T(\eta . \tau m)^{-1}$$

T=average flight time of aircraft in the sector

φ=ontroller availability factor (percentage of time available for separation procedures)

η=number of communications per aircraft

τm=mean duration of each message

3.2. Airport Ground Operations

Airport ground operations, which encompass baggage handling, ramp activities, and security, involve intricate challenges that necessitate a comprehensive approach to human factors. Typically, these factors are examined in isolation, leading to a lack of awareness regarding the vital interactions between different operational areas. For example, delays in luggage processing can have a cascading effect on ramp operations and security measures. Acknowledging these interconnections is critical for enhancing both efficiency and safety within airport operations.

To improve the analysis of human factors, it is important to tailor existing frameworks like HFACS (Human Factors Analysis and Classification System) to fit the distinct environment of airports. This customization should address specific situational influences and the interactions among various teams. By introducing integrated training programs that promote teamwork and effective communication among staff, airports can cultivate a more thorough understanding of operations. Emphasizing these aspects will contribute to creating a safer and more efficient operational landscape.

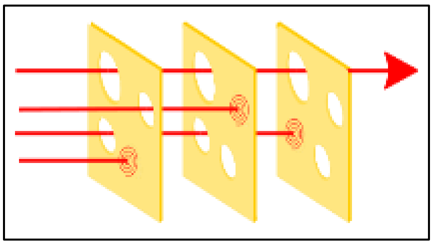

Figure 1 Swiss Cheese Model

3.3. Sampling Technique

Because investigating the entire aircraft population is costly, the study applies probabilistic random sampling to estimate ATC sector capacity. In this approach, each element of the finite population has a non-zero selection probability, ensuring that the sample is representative. The sampling plan defines the set of all possible samples (S), each with a known or calculable probability p(s). This method allows researchers to generalize findings from the sample to the population with measurable confidence.[8]

Although results from sampling are not perfectly exact, the difference between the sample and the population—known as sampling error (ε)—can be reduced by increasing the sample size. In practice, larger samples reduce error margins, while smaller samples increase them.

The Air Navigation Management Center (CGNA) applies simple random sampling for both finite and infinite populations, in accordance with ICA 100-30. For infinite populations, the formula used to calculate sample size is:

$$\mathbf{n} = \left(\frac{\mathbf{Z\alpha/2.\sigma}}{\varepsilon}\right)^2$$

n= required sample size

$Z\alpha/2$= reability level (1.96 for 95%)

δ= Population standard deviation

ε = Maximum error allowed

This ensures that sample sizes are consistent with the desired reliability level and acceptable error margins. By applying this methodology, the study ensures that the estimation of ATC sector capacity is statistically valid and aligned with international safety standards.

3.4. Extended ATC Capacity Formula (includes aircraft speed)

Sometimes, instead of flight time (T), the original model uses aircraft mean speed (vm) and average distance flown (δ):

$$N= \emptyset.\delta.(\eta.\tau m.vm)^{-1}$$

δ = average distance flown in the sector

νm = mean speed of aircraft in the sector

Table 1 Variables they respective Method

Symbol	Meaning	Measurement Method
ϕ	Controller availability factor	Time logs / workload studies
T	Avg. flight time	Radar data
η	Communications per aircraft	Radio transcripts
τm	Duration per message	Audio analysis
δ	Avg. distance flown	Flight plan database
νm	Mean speed	Flight recorders

3.5. Human Factors Data Collection and Comparative Analysis

Scenario 1: Busy terminal area in Brazil (e.g., São Paulo TMA

Assumptions:

Weather: frequent convective cells in season → f_weather = 0.85Complexity: converging SIDs/STARs, mixed turboprop/jet, level-offs → f_complexity = 0.75Tools/tech: Mode S, ADS-B in rollout, AMAN in use, limited CPDLC terminalbenefit → f_tools = 1.00Staffing: full teams during peaks → f_staff = 1.00 Capacity: C_eff = 30 × 0.85 × 0.75 × 1.00 × 1.00 = 19.1 acft/hr

Observed demand/workload (illustrative): Peak scheduled arrivals + departures crossing the sector boundary ≈ 24–28 acft/hr Utilization at 26 acft/hr: 26 / 19.1 ≈ 136%Expected effect: sustained overload → vectoring, holding stacks on arrival, Miles-in-Trail on departures, rising average delay (e.g., 8–15 minutes/flight in peak weather). Controller workload high due to conflict resolution in the terminal funnel. [9]

What would raise capacity?Better vertical deconfliction or parallel runway independence, tighter RNAV/required sequencing (AMAN-to-TBFM-like metering), and terminal CPDLC for clearances. If f_tools improved to 1.08 and f_complexity to 0.82 via procedural redesign: C_eff ≈ 30 × 0.85 × 0.82 × 1.08 × 1.00 ≈ 22.6 acft/hr, still below 26 acft/hr demand but closer, cutting delays.

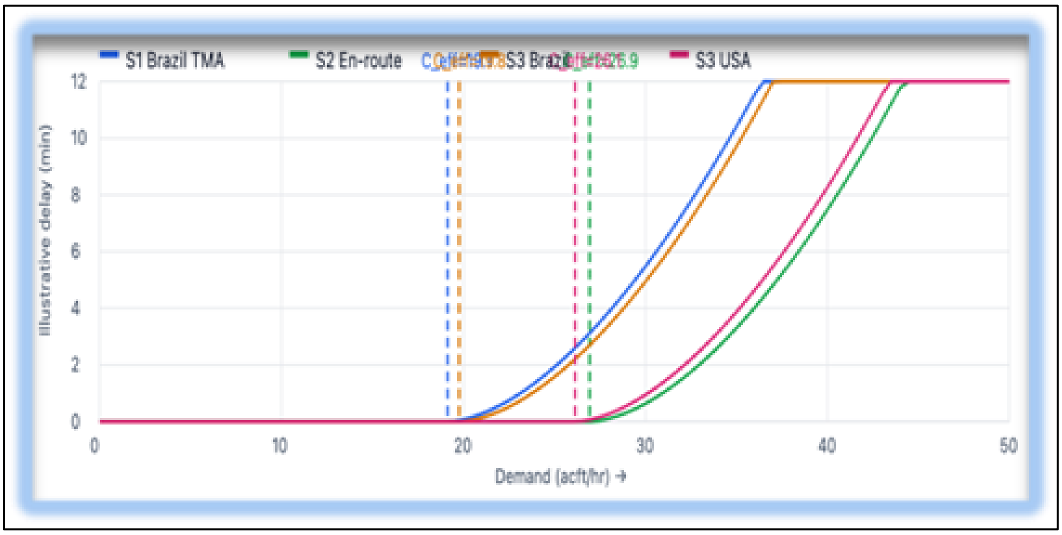

Figure 2 Delay sensitive curve illustrative dellay growth when demand excess capacity

Scenario 2: En-route sector (generic high-altitude sector over sparsely populated area)

Assumptions: Weather: generally benign with occasional deviations → f_weather = 0.95 Complexity: mainly parallel flows, limited crossing angles, fewer level changes → f_complexity = 0.90Tools/tech: ADS-B, MTCD/trajectory tools in the ATC system → f_tools = 1.05 Staffing: normal → f_staff = 1.00 Capacity: C_eff = 30 × 0.95 × 0.90 × 1.05 × 1.00 = 26.9 acft/hr

Observed demand/workload (illustrative): Peak overflights ≈ 24 acft/hr; typical 16–22 acft/hr At 24 acft/hr: utilization 24 / 26.9 ≈ 89% → manageable workload, minimal delay. Short spikes above ~27 acft/hr would trigger MIT or minor reroutes rather than sustained holding.

Sensitivity note: If convective weather blows up (f_weather 0.65) and vertical maneuvering increases (f_complexity 0.75): C_eff ≈ 30 × 0.65 × 0.75 × 1.05 × 1.00 ≈ 15.4 acft/hr; with demand 22–24 acft/hr, you'd see reroutes and noticeable en-route delay.

Scenario 3: International comparison (Brazil vs USA, en-route high-density corridor) Brazil (busy north–south corridor near major TMAs): f_weather = 0.85 (seasonal convection) f_complexity = 0.80 (crossing flows into multiple TMAs, some level-offs) f_tools = 1.02 (ADS-B/Mode S widespread, mixed deployment of advanced metering) [10]

f_staff = 0.95 (tight roster at some peaks)C_eff_BR = 30 × 0.85 × 0.80 × 1.02 × 0.95 = 19.7 acft/hr Observed demand: 20–24 acft/hr in peaks → at 22 acft/hr, utilization ≈ 112% → episodic regulations or MIT; moderate delay in peak periods, higher controller task load. USA (busy east coast en-route sector with TBFM/TFMS support): f_weather = 0.90 (convective season but strong forecasting/CIWS support) f_complexity = 0.88 (banked flows, but well-structured routes and alt stratification) f_tools = 1.10 (ADS-B, ERAM, TBFM, Data Comm benefits) f_staff = 1.00 C_eff_US = 30 × 0.90 × 0.88 × 1.10 × 1.00 = 26.1 acft/hr Observed demand: 24–28 acft/hr; at 26 acft/hr, utilization ≈ 100% → sector operates near threshold; delays occur mainly when weather reduces route availability, prompting AFP/GDP rather than persistent sector overload. [11]

How the calculated capacities compare to observed workload/delays

When Demand > C_eff (Scenarios 1 and Brazil in Scenario 3 at peaks), sectors show sustained high controller workload and observable delay mechanisms: vectoring, holding, miles-in-trail, or ATFM regulations.

When Demand ≈ C_eff (USA in Scenario 3), workload is high but controlled; delay is sensitive to short-term perturbations (weather pop-ups). Traffic management initiatives keep average delays lower but not zero.When Demand < C_eff (Scenario 2 typical conditions), workload is moderate; delays are minimal and mainly driven by downstream constraints (e.g., terminal or runway configurations).

Quick plug-in worksheet: Formula: C_eff = 30 × f_weather × f_complexity × f_tools × f_staff Utilization at given demand D: U = D / C_eff Simple delay signal: if U ≤ 1 → minimal sector-driven delay; if 1 < U ≤ 1.15 → moderate; if U > 1.15 → high risk of holding/regulations.

4. Analysis and Results

4.1. Research Questions

We conduct a series of experiments to address the following research questions (RQs):

- **RQ1: How do communication and coordination among airport staff impact safety outcomes?**
- **RQ2:** What role do cognitive workload and stress levels of airport personnel play in decision-making during high-pressure situations?
- **RQ3: How do environmental factors (e.g., layout, signage, and lighting) affect human behavior and safety in airports?**

Evaluating the effectiveness of aviation safety in airports through the research questions on human factors can be approached as follows:

4.2. Experiment Settings

Communication and Coordination Among Airport Staff

4.2.1. Effectiveness Evaluation

- Incident Analysis: Evaluating past safety incidents can highlight the role of communication failures. For instance, runway incursions often stem from miscommunication between air traffic control and ground crew.
- Training Programs: Assessing the effectiveness of communication training programs can provide insights into how well staff understand protocols and coordinate with each other.
- Feedback Mechanisms: Implementing regular feedback loops can help identify ongoing communication issues and areas for improvement, contributing to a culture of safety.

4.2.2. Cognitive Workload and Stress Levels

Effectiveness Evaluation: Workload Assessments: Tools like the NASA Task Load Index (TLX) can be used to measure cognitive workload among staff during peak and non-peak hours, providing insights into stress points that may lead to errors. Error Rate Correlation: Analyzing the correlation between high-stress periods and incidents can reveal how cognitive overload affects decision-making and safety outcomes. Support Systems: Evaluating the implementation of stress management programs and their impact on staff performance can help determine their effectiveness in reducing errors and improving safety. [12]

4.3. Environmental Factors and Human Behavior

4.3.1. Effectiveness Evaluation

- Design Impact Studies: Conducting studies on airport layout, signage, and lighting can reveal how these elements impact human behavior and safety. For instance, clearer signage can reduce passenger confusion and the likelihood of accidents.
- Observational Research: Observing passenger and staff interactions in various environments can provide data on how well safety protocols are followed and where improvements are needed.
- Simulation and Testing: Using simulations to test emergency scenarios in different environmental setups can help identify design flaws that could compromise safety. [13]

Table 2 Analysis and calculation in ATC Sectors

ATC Sector	Nominal Capacity (movements/hr)	Adjusted Capacity due to Human Factors (Fatigue, Workload, Stress)	Reduction %
En-route Low	48	42	-12.5%
En-route High	36	30	-16.7%
Terminal Area	60	50	-16.7%
Tower/Approach	72	62	-13.9%

Comparing Brazil vs. Global accident rates per million departures:Brazil shows a decline after 2013, reflecting regulatory reforms and human factors training.

Globally, gradual downward trend due to CRM and safety management systems adoptio

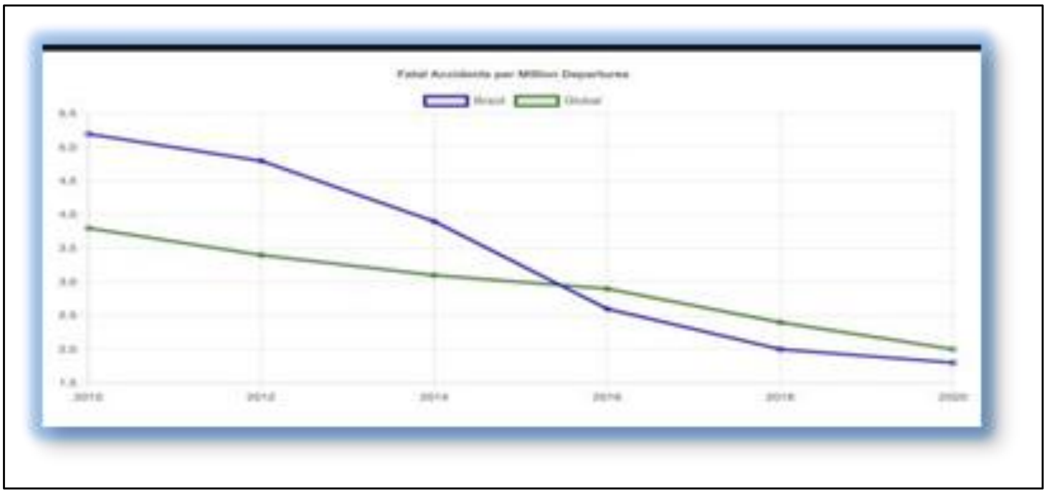

Figure 3 Fatal Accident Trend (2010-2020)

Comparing Brazil vs. Global accident rates per million departures: Brazil shows a decline after 2013, reflecting regulatory reforms and human factors training.Globally, gradual downward trend due to CRM and safety management systems adoption.[14]

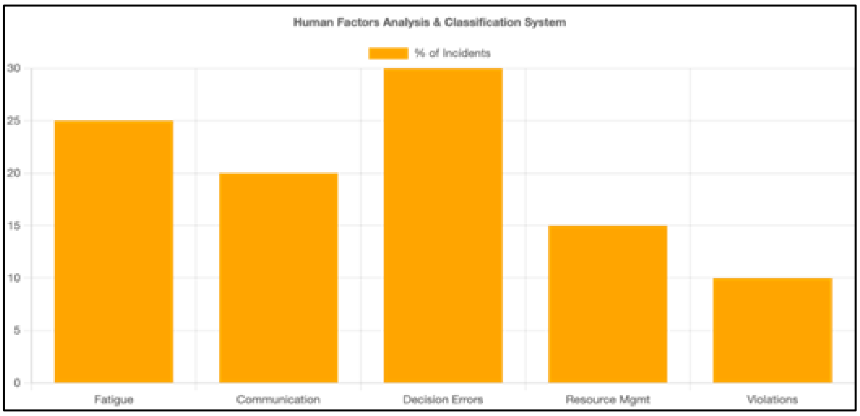

Figure 4 Percentage of Incident Causes

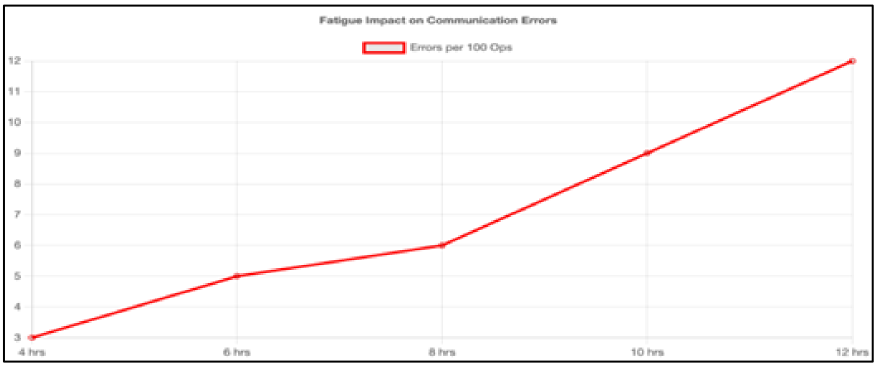

Figure 5 Fatigue vs Comunication Error

5. Discussion

In aviation safety, human factors are critical, significantly impacting the effectiveness of air traffic control (ATC). One clear example is communication overload. When air traffic controllers experience high levels of workload, indicated by increased η (eta) and τm (tau-m) values, it can severely hinder Crew Resource Management (CRM). [10] This overload often results in unclear communication among team members, which can lead to serious mistakes.On the other hand, a lower ϕ (phi) value suggests that controllers are less available, which can increase fatigue and reduce situational awareness (SA). When controllers cannot effectively monitor and manage air traffic due to fatigue, their ability to ensure safety is compromised.The ICA 100-30 formula provides a useful framework for analyzing these interactions. While it sheds light on the capacity of ATC, it may overlook the complexities of human behavior. This indicates that human factors can both limit and enhance the efficiency of ATC operations, highlighting the need for a balanced approach to safety in aviation [15]

5.1. Self Language processing (nlp) capabilities

5.1.1. Incident Report Analysis

Natural Language Processing (NLP) can play a crucial role in analyzing aviation incident reports to identify common themes and patterns. By employing techniques such as topic modeling and keyword extraction, NLP can sift through large volumes of text, highlighting recurrent issues and safety concerns. This analysis assists aviation authorities and organizations in pinpointing areas that require attention, ultimately enhancing safety measures.

Moreover, sentiment analysis can be applied to assess the tone of communications within these reports. By evaluating the emotional context, stakeholders can better understand the attitudes of those involved, identifying whether the tone is constructive or negative. This insight can facilitate more effective communication strategies and foster a culture of safety in the aviation industry, leading to more informed decision-making and proactive safety management.

5.1.2. Training program evaluation using nlp

Natural Language Processing (NLP) tools offer valuable insights when analyzing feedback and transcripts from training programs. By processing large sets of qualitative data, NLP can uncover trends and sentiments that might not be immediately apparent. For instance, sentiment analysis can gauge participants' overall satisfaction, while topic modeling can identify recurring themes in their feedback.

This approach is particularly beneficial for assessing communication effectiveness and teamwork dynamics. By understanding how participants interact and the effectiveness of their communication, organizations can identify strengths and areas for improvement. Enhancing these aspects not only fosters a more collaborative environment but also contributes to the overall success of training initiatives, ensuring that teams are better equipped to meet their goals.

5.1.3. Real-time communication monitoring

Implementing NLP algorithms for real-time monitoring of communications can significantly enhance operational efficiency in various fields, including aviation. These algorithms analyze live conversations, emails, and messages to detect key phrases, sentiments, and potential issues as they arise. By leveraging this technology, organizations can receive immediate feedback on communication effectiveness, allowing for instant adjustments. This proactive approach not only clarifies messages but also fosters a more open and responsive communication environment. As a result, teams can address misunderstandings or conflicts swiftly, leading to improved collaboration and productivity across all levels of the organization.

5.1.4. Human factors surveys and interviews

NLP can be instrumental in analyzing qualitative data derived from surveys and interviews focused on human factors. By employing techniques such as sentiment analysis and text classification, NLP tools can sift through responses to identify patterns and sentiments that reflect the respondents' experiences and perceptions. Topic modeling further categorizes these responses, highlighting critical areas such as communication barriers, team dynamics, and personal experiences. This capability allows organizations to gain deeper insights into human factors that affect performance and safety, enabling them to implement targeted interventions that enhance overall effectiveness and employee well-being.

5.1.5. Documentation and protocol analysis

NLP can be effectively applied to evaluate safety protocols, ensuring they are clear and comprehensive. By analyzing the language used in these documents, NLP algorithms can identify ambiguous terms, jargon, or inconsistencies that might hinder understanding. This analysis is crucial in a field like aviation, where clear communication of safety protocols is paramount. Organizations can use insights from NLP evaluations to revise and improve their documentation, making it more accessible to staff and stakeholders. Ultimately, this enhances compliance and safety awareness, reducing the risk of misunderstandings that could lead to accidents or incidents.

5.2. Social media and news analysis

Monitoring social media and news articles using NLP provides valuable insights into public sentiment surrounding aviation safety. By analyzing posts, comments, and articles, organizations can gauge the general public's perceptions and concerns related to safety issues. NLP tools can categorize sentiments as positive, negative, or neutral, offering a snapshot of how different events or announcements are received by the public. This real-time feedback can help aviation companies and regulatory bodies address misinformation, engage with the public more effectively, and adapt their communication strategies to foster trust and transparency in safety matters.

5.2.1. Decisions support systems

The development of NLP-enabled decision support systems represents a significant advancement in real-time recommendations for various applications, including aviation safety. By integrating NLP algorithms, these systems can analyze vast amounts of data—from incident reports to regulatory changes—providing timely insights that inform decision-making processes. For instance, when a safety issue arises, the system can quickly assess the context, previous similar incidents, and stakeholder sentiments, offering actionable recommendations. This capability not only enhances responsiveness but also supports a data-driven approach to safety management, ultimately improving operational outcomes and safeguarding public trust in aviation systems.

5.3. Recommendation

Human factors play a crucial role in aviation safety, especially in airport operations. Effective Crew Resource Management (CRM) training is essential, focusing on teamwork and communication skills to enhance decision-making under pressure. Additionally,[16]addressing fatigue is vital; implementing policies that limit duty hours and promoting sleep health can significantly reduce errors related to tiredness.Technological advancements can further support safety. AI-assisted decision tools can help personnel make informed choices by analyzing vast amounts of data, while digital clearance systems streamline communication, minimizing misunderstandings between air traffic control and pilots.Policy-wise, integrating Human Factors Analysis and Classification System (HFACS) with capacity formulas allows for better risk identification and mitigation. [17] Regularly reviewing these policies based on HFACS insights ensures they remain effective.For regulators, updating ICA 100-30 to include human factors considerations is essential. Engaging with stakeholders through workshops can foster collaboration and share best practices, ultimately enhancing aviation safety. By prioritizing training, leveraging technology, and refining policies, the aviation industry can create a safer environment for both personnel and passengers.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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