Enhancing Aviation Safety Analysis in MROs: A Complex Emergent Model with a Predictive Approach

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Abstract: This study explores the aviation industry's shift from reactive and proactive safety strategies towards predictive safety management, focusing on Maintenance, Repair and Overhaul (MRO) operations. It introduces a novel complex emergent safety model designed to integrate predictive analytics into existing Safety Management Systems (SM) via occurrence reporting data. Moving beyond traditional linear causation models, the proposed framework leverages machine learning and data mining techniques to identify hazards and assess risks, thereby reducing the frequency and severity of incidents and minimising maintenance disruptions. Using the DMADOV methodology, the study aims to extract actionable insights from unexploited safety data, despite challenges such as data quality variations and the stochastic nature of safety. Ultimately, this research advocates for a unified, AI-driven approach to enhance safety capabilities across the aviation industry.

1 INTRODUCTION

Highly technological and risk systems in high reliability industries such as aviation are becoming increasingly complex, raising the potential for catastrophic consequences when failures occur. (Qureshi, 2008) Accidents in aviation, as per ICAO Doc 9156 (ICAO, 1987), are defined as events leading to serious injuries, significant aircraft damage, or the aircraft being missing or inaccessible, during passenger embarkment and disembarkment. Incidents, on the other hand, are occurrences that could impact flight safety, ranging from aircraft operations, technical issues, to interactions with air navigation services and environmental factors. The distinction between accidents and incidents primarily lies in their severity and impact. (ICAO, 1987), (European Parliament and Council, 2015) Understanding both accidents and incidents is crucial, leading to the development of various safety causation models, approaches and methodologies. This evolving safety thinking underlines the industry's commitment towards safety reassurance, especially when considering how relatively young the aviation industry is. (J. J. a Stoop & Kahan, 2005).

Safety causation models are theoretical conceptual frameworks that generate a reasoning of occurrences. They try to explain how and why accidents occur. Accident modelling can be traced to as early as the 1920s. Upon such safety causation models, accident investigations are used to describe and explain the occurrences. (HaSPA (Health and Safety Professionals Alliance), 2012; Reason, 1990) This reactive method did not assist in identifying the problem and subsequently could not prevent a similar incident. In the 1950s, aviation safety investigations shifted from identifying technical factors, to human factors and then moved towards organisational factors to try to understand and solve accidents. Initially, as the aircraft was considered as a complex technological marvel, the main factor for failure was equipment. Then, as technology became more reliable, the focus shifted towards human factors. This Era brought about the concept of Crew Resource Management and was solely focused on the individual. Towards the 1990s, this progressed into considering the operational context of a complex environment within an

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organisation. This systemic perspective led into providing the basis for the development of a **Safety Management System**, SMS. (Reason, 1990)

SMS emerged as a central pillar of modern aviation safety strategy, placing greater emphasis on regulations, organisations and real-time decision-making for safety improvements. Defined by ICAO, SMS encompasses managing organisational structures, responsibilities, and procedures to enhance safety through occurrence reporting. (Gerede, 2015; Yeun et al., 2014) Moving beyond traditional prescriptive approaches, SMS adopts a realistic view of the world, encouraging a paradigm shift towards proactive and predictive safety measures. (Gerede, 2015) EU Regulation 376/2014 reflects this evolution by advocating for the integration of proactive methods with reactive systems for more effective safety improvements. (European Commission, 2014) SMS fosters a safety culture by merging reactive, proactive, and predictive strategies across organisational levels, showing early benefits and driving continuous safety advancements. Reactive methods focus on immediate incident response and mitigation, while proactive and predictive strategies aim to prevent future incidents by identifying and anticipating risks, creating a comprehensive approach to organisational safety management. These are illustrated as per Figure 1. (*Safety Management System | Federal Aviation Administration*, n.d.)

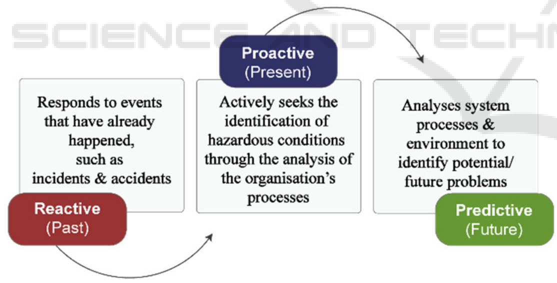

Figure 1: Reactive-Proactive-Predictive methodologies.

Regulations and traditional safety management practices aim to incorporate corrective, preventive, and predictive methodologies into SMS, with a focus on corrective measures and an encouragement of preventive actions. Following EU Regulation 376/2014 (European Commission, 2014), one of the key tools for SMS is occurrence reporting or safety investigations (Elkhweldi & Elmabrouk, 2017), which involve fault analysis for corrective actions and cause analysis for preventive measures. Stoop and Dekker (J. Stoop & Dekker, 2012) question the proactiveness of safety investigations, highlighting the importance of feedback from real-world data for insights into complex systems. This knowledge is crucial for future designs and strategies, making safety investigations a proactive element that complements other safety improvement strategies. However, even though the predictive phase of SMS is recognised it is yet to be defined, clarified, encouraged and enforced by regulations and authorities to organisations.

The predictability of incidents, applied in a maintenance, repair and overhaul (MRO), which makes up just one aspect of the aviation industry, presents a complex and critical challenge. This is due to the multifaceted nature of aviation systems, the variability in operational environments, and the stringent safety standards required. The primary challenge lies in the development and limitations of current safety causation models that are reductionist, linear and resultant. The illusion of containment or preventing 'losses' gives the impression that incidents and accidents alike can be controlled. Many models have a Newtonian Cartesian ideology, that the incident or accident can always be broken down. This leads to a hunt for a broken component. Currently, with no universally accepted model (Grant et al., 2018), the pessimistic conclusion would be that the models are not scientific enough, practical enough, not specific enough nor holistic enough to fully understand how incidents occur. (Hovden et al., 2010) In light of the (r)evolution of many safety causation models,(HaSPA (Health and Safety Professionals Alliance), 2012) unfortunately, their outlook in the current predictive approaches remains limited. The continuous growth and advancements in all aspects of the aviation industry necessitate further developments, which include the way accidents are viewed and their methodologies applied (Amankwah-amoah, 2021).

A complex emergent model that integrates all three rationales – reactive, proactive and predictive is required. This research aims to lay the foundation for complex, non-linear safety thinking in both incident and accident investigations. By integrating a predictive-probabilistic analysis approach into the existing SMS this approach will enhance the capacity to foresee and mitigate safety risks. It aims to statistically reduce the frequency and severity, while minimising disruptions to maintenance operations. (Bartulović & Steiner, 2023).

2 LITERATURE REVIEW

The evolution of safety causation models, from Heinrich's 1931 Domino theory to Hollnagel's 2012 Functional Resonance Analysis Method (FRAM), reflects a shift through three generations of human error modelling (Katsakiori et al., 2009), incorporating human factors and systemic approaches like Reason's Swiss cheese model. Despite challenges in application and interpretation, these models have progressively addressed the complexity of safety management, culminating in the adoption of complex non-linear models in the early 2000s, such as Leveson's STAMP and FRAM, to tackle the dynamic aspects of safety. (Hovden et al., 2010) This literature review critically assesses these models for their principles, strengths, and weaknesses, aiming to promote a shared understanding of accidents and support the development of preventative strategies. (Hovden et al., 2010) By analysing the interaction among various factors within these models and highlighting their unique features, the review advocates for a comprehensive model that addresses the complexity and emergence of incidents, streamlining the evolution and critical examination of safety causation models and their application in enhancing system resilience and safety management.

The Swiss Cheese model was introduced by James Reason and conceptualizes the idea of multiple layers of defence against accidents in complex systems. Each layer of defence has potential flaws, represented as holes in slices of Swiss cheese. The alignment of these holes can lead to a trajectory of accident opportunity, allowing hazards to materialize into losses. The model's strength lies in its visual simplicity and its emphasis on systemic flaws rather than individual error. However, its limitation is the linear and static representation of accident causation, overlooking the dynamic interactions within systems and the non-linear nature of complex failures.(Reason, 1990) While some authors (Dekker, 2002; Maurino, 2001; Shappell & Wiegmann, 2000), considered the model to be too generic and underspecified pinning the model as a representation which lacks the tools to implement the metaphor of cheese's slices and holes. This leaves practitioners making their own interpretation and adaptation. While Luxhøj and Kauffeld (Kauffeld, 2003), think that this is a risk which makes the model impractical, this interpretive flexibility suits particularly well the SCM. (Larouzee & Le Coze, 2020) In fact, in 2000, a simplified version of the SCM was published in the British Medical Journal (BMJ)(Reason, 2000) making an impact in another high-risk industry.

Charles Perrow's Normal Accident Theory (NAT) suggests that accidents are a natural outcome in complex, tightly coupled systems due to the unpredictable and unmanageable nature of their interactions. It highlights the intrinsic risks within high-tech environments, suggesting that the complexity of these systems renders accidents inevitable, hence 'normal'. As this theory recognizes accidents as such, it risks diminishing the emphasis on proactive risk management (Charles, 1999). FRAM, developed by Erik Hollnagel, focuses on how variability in normal system performance can lead to accidents through unexpected interactions. Unlike linear models, FRAM addresses the complexity and non-linear interactions within systems, offering a more dynamic approach to understanding accident causation. This is possible because through the concept of resonance, a small change in one part could amplify and cascade into larger ones. Later, it was also mentioned and explained as the butterfly effect by Dekker. (Dekker, 2017) Moreover, the FRAM's strength lies in its ability to model complex processes and their variabilities. It provides an analysis method by defining a system in terms of functions, which represent activities that people perform, whereas each function can be defined by six aspects; the time allocated, input items that are processed, preconditions that trigger the task, the way the function is controlled, the resources that are consumed to process items and the output as a result of the function. However, its application can be challenging due to the need for in-depth understanding of system variabilities and interactions. It requires many resources which would require time to retrieve. In addition, the complex connectivity of web could lead to an infinite number of possibilities making it difficult to predict how variabilities across different functions may couple and resonate. (Erik, 2012)

The Systems-Theoretic Accident Model and Processes (STAMP), Proposed by Nancy Leveson, shifts from event-based to constraint-based approaches in accident analysis. It views accidents as a result of inadequate control or enforcement of safety constraints within a socio-technical system. STAMP's strength lies in its comprehensive approach, incorporating technical, human, and organizational factors. However, its broad scope can make it complex to implement and require significant effort to identify and model relevant constraints.(Leveson, 2004) This model faces challenges that limit its widespread adoption when compared to other models because it requires a deep understanding of system theory which is not synonymous with systems engineering and hence, requires specific education or training. It is also challenging to apply real world application of STAMP to complex systems, hence, make it challenging for practitioners to apply it to their specific contexts. Its emphasis on enforcing constraints on system behaviour offers a novel approach to safety, which, with increased training and awareness, could see broader adoption across various industries. (Leveson, 2004, 2012; Underwood & Waterson, 2012) However, Roelen, Lin and hale (Roelen et al., 2011) suggest that this model is neither embraced by the safety community nor broadly recognised as a significant influencing accident model in the overall field of safety management because Leveson's model does not integrate well with the dominating methods of collecting and analysing safety data. Hence, making event chain models such as the SCM more favourable.

Dekker's Drift into Failure theory proposes that accidents result from systemic drifts into failure, where everyday decisions and actions, although seemingly rational at the time, cumulatively lead to a system's degradation and eventual failure. This model emphasizes the complexity of socio-technical systems and the non-linear, emergent properties of system failures. Its strength lies in its focus on the systemic and emergent nature of failures, challenging the blame culture by highlighting the role of system design and decision-making processes. (Dekker, 2017) While Dekker provides a theory and tries to progress towards a complex and emergent kind of rationale, this theory does not provide a safety causation model that fully explains how an incident, or an accident occurs. Therefore, a limitation of this theory could be in the identification and measurement of drift, which is subtle and evolves over time.

The reviewed models contribute valuable insights into accident causation, highlighting the roles of system complexity, human factors, and organizational processes. However, there exists a gap in integrating these perspectives into a unified model that can accommodate the emergent, unpredictable nature of complex system failures. Current models either focus on linear causation, system components in isolation, or fail to fully address the dynamic interactions and adaptability of complex socio-technical systems. There is a need for a model that not only incorporates the strengths of existing models, such as the graphical visualisation, systemic nature and flexible interpretation of the SCM, the dynamic understanding of FRAM, the normalisation of unstable systems of NAT, and the drift concept with an understanding of non-linear, complex emergent properties from Dekker; but also offers practical tools for identifying and mitigating emergent risks in real-time to keep up with the ever growing technologies.

For the enhancement of safety investigation analysis, this research aims at developing an integrated safety causation model (Grant et al., 2018) that embraces complexity, emergence, and the non-linear dynamics of socio-technical systems. Such a model would provide a more holistic and adaptable framework for understanding and preventing accidents in an increasingly complex and interconnected world. Alongside this integrated model, an analysis will also be developed. This would reflect the novel's notion of non-linearity, complexity and emergence in contrast to previously mentioned models with their own analysis methods or rationale.

3 METHODOLOGY

The DMADOV (Define, Measure, Analyse, Design, Optimise, Verify) methodology (Pyzdek, 2017) will be applied with the goal of designing and developing a predictive-probabilistic, integrated data-based analysis approach. This approach will complement the non-linear, complex, and emergent safety causation model, serving as a practical tool. Specifically, it aims to identify potential areas of emergent risks in maintenance environments by conducting a thorough analysis of already existing unexploited safety data.

In the ***define phase***, the MRO organisation's current SMS will be examined, focusing on the safety investigation process and occurrence report inputting. This involves a thorough review of the existing process for investigating safety incidents, identifying its strengths and limitations. Written occurrence reports, generated from incident investigations, will be looked into to grasp their significance into aviation safety. This will support in formulating problem statements considering the inputting fields and data available. By defining these reports' qualitative and quantitative nature of data, a deeper understanding of the involved processes and the significance of report fields will be gained. This understanding would potentially indicate the specific relationships that need to be measured and subsequently analysed.

Once the investigative process as well as the occurrence reports' fields and criteria would be understood, the data available will be explored into setting attributes from the defined problem statement. This would be the ***measure phase***. Identifying relationships from the investigative process and occurrence reports' criteria and fields will give an indication of specific attributes and categories to extract. Following the identification of such attributes and categories, which must also be inline with the defined problem, the type of data must be studied further. This will lead into extracting the data, cleaning it and refining its quality. The selection of attributes and categories of data, together with its filtration and refinement process are of crucial importance to provide a clear as-is assessment of the reporting data. (Huan & Hiroshi, 2007)

In the ***analysis phase***, techniques and tools for data extraction are chosen based on predefined criteria, often requiring data transformation to meet analysis needs. Artificial Intelligence (AI), Data Mining (DM), and Machine Learning (ML) are key areas in this process. (Huan & Hiroshi, 2007) AI is about creating systems that perform tasks requiring human intelligence, like speech recognition and decision-making. ML, a subset of AI, focuses on developing algorithms that enable computers to learn from data and improve over time without being explicitly programmed. This is crucial for AI systems to adapt and perform complex tasks accurately. DM discovers patterns in large data sets using ML, statistics, and database techniques, converting data into a usable structure. (Han et al., 2011) While DM aims at exploratory analysis to uncover new insights, ML focuses on using these insights for predictions or classifications. Current studies employ DM to uncover patterns and knowledge in data, and ML to learn and make predictions, illustrating ML's versatility across various industries such as healthcare and technology. (*Revolutionizing Healthcare Industry with Machine Learning.*, n.d.) DM supports ML by providing algorithms for systematic data analysis, crucial for understanding customer behaviour, optimising efficiency, and identifying risks or opportunities (A. B.Arockia & S. Appavu, 2013). Together, ML and DM enable organisations to automate data analysis, enhance prediction accuracy, and make informed decisions, essential in data-intensive fields like aviation where safety and data volume are critical. Data mining plays a pivotal role in predictive analysis by employing a range of techniques and tools to extract actionable insights from datasets. Key tools such as WEKA, RapidMiner, KNIME, and Python Libraries support various DM techniques including classification, clustering, regression, association rules, and anomaly detection. Prominent classification methods like decision trees (ID3, C4.5, CART), support vector machines (SVM), naive Bayes (NB), and K-nearest neighbours (KNN) have been extensively utilized. For instance, decision tree induction is celebrated for its efficacy in pattern classification by Han and Kamber (Han et al., 2011), while NB classifiers and SVM have been applied for their probabilistic and discriminative capabilities in aviation safety analysis respectively. (Narasimha & Devi, 2011), (Han et al., 2011) KNN, known for its simplicity and effectiveness, along with decision trees, has contributed to understanding complex data structures in aviation incidents and forecasting models (A. B.Arockia & S. Appavu, 2013), (Gürbüz et al., 2009), (Bineid & Fielding, 2003).

In this analysis phase, the key tools and DM classification techniques will be selected based on the previous phases, highlighting the significance of choosing the right combination of techniques and tools based on specific analysis objectives, essential for deriving meaningful insights and enhancing aviation safety.

In the following phase, machine learning methods and algorithms will be applied through data mining tools and techniques to study relationships and recognise existing trends. This will lead towards evoking strategies to compare criteria, fields and records in the ***design phase***. Utilising a machine learning platform together with the deployment of functions, algorithms and selected methods, a design procedure will be established. The selection of different functions to assess performance levels and their impacts will necessitate redesigns. These redesigns will make part of the ***optimize phase***. Through the iteration of the design and optimise phases, the previously defined data and relationships will undergo verification for reliability purposes. This methodology will enable the validation of the predictive-probabilistic approach, in the final ***verify phase***.

After the literature review of the safety causation models aimed at paving the way for the development of a complex emergent model, the DMADOV methodology and its phases were discussed for the development of a predictive-probabilistic analysis approach, which is defined further in Figure 2. Ultimately, through this analysis approach, applied on specified criteria and attributes of safety occurrence reporting data, it would also support the complex emergent safety causation model in understanding the occurrence of incidents.

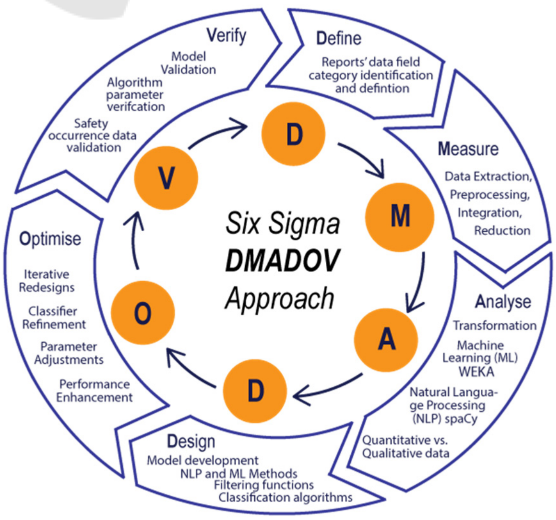

Figure 2: DMADOV phases.

4 POTENTIAL IMPACT

The study embarks on an innovative journey to develop a complex emergent safety causation model, leveraging the power of machine learning algorithms and methods to foster a predictive-probabilistic approach. Utilising data from MRO operations, this research underlines the importance of advancing safety thinking in high-risk industries, notably aviation. This progressive exploration aims to unravel and navigate through the intricacies and emergent properties of safety data, promoting a more profound understanding of underlying risks.

Based upon the results of Mathur et al (Mathur et al., 2017), it was analysed that maintenance of the aircraft would significantly reduce the risk of accidents. Therefore, by integrating innovative data mining applications and employing pragmatic predictive-probabilistic strategies through advanced tools, techniques, and methodologies, the study seeks to indicate potential risk incidents before they manifest in an MRO environment. This proactive detection, rooted in the meticulous analysis of safety occurrence reporting data, would substantiate positive impacts. Beyond the mere avoidance of adverse outcomes, this approach signifies a leap towards ensuring safer working environments and enhancing operational efficiency. The anticipated reduction in downtime and interruptions from incidents paves the way for heightened productivity, as resources dedicated to managing or responding to incidents are optimised. Furthermore, this efficiency translates into cost savings, encompassing not only operational costs but also expenses related to repairs, legal fees, and more. (Jardine & Tsang, 2013) The ripple effects of diminished incidents extend to encouraging trust among employees and customers, fortifying a reputation for reliability and safety. Such a reputation could serve as a formidable competitive edge, drawing more business and elevating customer satisfaction. (Doorley & Garcia, 2007) The insights derived from this study are expected to shed light on risk areas and vulnerabilities, guiding strategic decisions and preventive actions. This knowledge empowers organisations to learn from incidents that occur, nurturing a culture of learning and adaptation. It also encourages the adoption of best practices, steering continuous improvement across the board.

5 LIMITATIONS

In developing a predictive, machine learning-driven models, this study faces numerous challenges inherent to the domain of safety performance. The stochastic nature of safety, characterized by complex interactions and unpredictable events, complicates precise quantification and modelling. (J. Stoop & Dekker, 2012) Transitioning from reactive to proactive safety strategies in MRO operations further adds to the complexity, highlighting the importance of training, awareness, and fostering a just culture. (Gerede, 2015), (Phimster et al., 2004) Notably, on the latter, Gerede (Gerede, 2015), continues by mentioning the challenging barriers of 'just culture' that pose on Safety Management Systems, impeding effective reporting, learning, and predictive tool enhancement. This study employs data mining tools and techniques to model safety occurrences' defined queries facing several data limitations within MRO operations. The inherent complexity and abstract nature of safety models necessitate significant simplification for practical application, challenging due to data quality issues like incompleteness and inconsistency. Moreover, the substantial resources required for processing large datasets introduce technological and computational constraints. (Arockia Christopher & Appavu Alias Balamurugan, 2014) The probabilistic nature of safety incidents adds another layer of uncertainty, affecting model reliability and necessitating extensive validation on extensive high-quality data. (Gao & Mavris, 2022) Integration and standardisation of historical data across reporting systems are hindered by technical and regulatory barriers. Additionally, achieving a balance in predictive models to minimise false positives requires sophisticated algorithms capable of adapting to new aviation technologies and failure patterns. The application of Heinrich's pyramid highlights the significance of unreported incidents in the accuracy of safety models, underscoring the challenge of capturing comprehensive data. (Nazeri et al., 2008), (*IATA - IATA Releases 2022 Airline Safety Performance*, n.d.) Finally, incorporating human factors, including variability in maintenance practices and the potential for human error, introduces further complexity, emphasizing the need for a nuanced approach to modelling safety in aviation maintenance and operations.

To conclude, while this research pioneers a predictive rationale for complex emergent safety causation modelling and strives to apply data mining tools and techniques, it faces various limitations ranging from data quality, availability and technological constraints to the unpredictable human element. Addressing these challenges requires extensive efforts to refine methodologies, enhance data management practices, and foster a culture that supports proactive safety management.

6 FUTURE DIRECTION

Given the insights from Nazeri et al. (Nazeri et al., 2008) regarding accident factors and considering the projected growth in air transportation, we stand at a critical juncture. The increasing complexity of air traffic and fleet sizes, alongside the inherent aggravation of conditions affecting accident factors, suggests that accident rates could escalate if proactive measures aren't taken. Current safety investigation methodologies, despite their historical efficacy, face criticism for obsolescence. This highlights the urgent need for a paradigm shift in safety investigations, emphasising data quality, proactive outcomes, and a future-oriented mindset when conducting an investigation (J. Stoop & Dekker, 2012), (A. B.Arockia & S. Appavu, 2013).

A complex emergent safety causation model incorporating effectively all three rationales will be developed and formulated based upon key features and characteristics identified from already existing models and theories. These would include relatability and flexibility while also catering for non-linearity, recognise complex systems and consider emergent properties. Therefore, path the way for complex non-linear emergent safety thinking in incident and accident investigations. An analytical predictive approach will be formulated through the DMADOV methodology whereas the qualitative and quantitative data will be processed through the methodology's phases. Based on previously mentioned case studies, data mining techniques and tools will be applied to study relevant relationships categories and fields. Following through with the analysis, it will continue to fulfil the three rationales by integrating the predictive analysis approach into the existing SMS. The transition towards predictive risk management denotes a promising direction in enhancing aviation safety. Further potential impacts and limitations were then discussed.

In conclusion, the path forward demands a collaborative effort to embrace predictive models of safety management. This paper represents a conceptual first step, introducing a complex-emergent safety causation framework for MROs. While the model is currently theoretical, future work will focus on its empirical validation using real-world occurrence reporting data. This includes testing and refining the framework using machine learning methods to evaluate its practical impact on predicting and mitigating safety risks. By harnessing data and predictive analytics, risks could be anticipated to foster a safer future for aviation. Potentially spreading into other high-risk industries like nuclear power and healthcare. (Nazeri et al., 2008) This transition, while challenging, is essential for advancing safety culture, offering a proactive approach for managing the complexities of modern aviation and beyond.

REFERENCES

A. B.Arockia, C., & S. Appavu, A. B. (2013). Data mining approaches for aircraft accidents prediction: An empirical study on Turkey airline. *2013 IEEE International Conference on Emerging Trends in Computing, Communication and Nanotechnology, ICE-CCN 2013*, *Iceccn*, 739–745. https://doi.org/10.1109/ICE-CCN.2013.6528602

Amankwah-amoah, J. (2021). COVID-19 pandemic and innovation activities in the global airline industry: A review. *Environment International*, *January*.

Arockia Christopher, A. B., & Appavu Alias Balamurugan, S. (2014). Prediction of warning level in aircraft accidents using classification techniques: An empirical study. *The Aeronautical Journal*, *118*(1206), 1217–1223. https://doi.org/10.1007/978-81-322-1665-0_126

Bartulović, D., & Steiner, S. (2023). Conceptual Model of Predictive Safety Management Methodology in Aviation. *Aerospace*, *10*(3). https://doi.org/10.3390/aerospace10030268

Bineid, M., & Fielding, J. P. (2003). Development of a civil aircraft dispatch reliability prediction methodology. *Aircraft Engineering and Aerospace Technology*, *75*(6), 588–594. https://doi.org/10.1108/00022660310503066

Charles, P. (1999). *Normal Accidents: Living with High-risk Technologies*. Princeton University Press.

Dekker, S. W. A. (2002). *The Field Guide to Human Error Investigations*. Ashgate. https://doi.org/10.4324/9781315202778

Dekker, S. W. A. (2017). Drift into Failure: From Hunting Broken Components to understanding complex systems. In *BMC Public Health* (Vol. 5, Issue 1). CRC Press Taylor and Francis Group.

Doorley, J., & Garcia, H. F. (2007). *Reputation Management. The Key to Successful Public Relations and Corporate Communication*. Routledge Taylor & Francis Group.

Elkhweldi, M. A., & Elmabrouk, S. K. (2017). Aviation Risk Management Strategies. *Proceedings of the 2015 International Conference on Industrial Engineering and Operations Management Dubai, United Arab Emirates (UAE), March 3 – 5, 2015*, *March 2014*, 1–7.

Erik, H. (2012). *FRAM: The Functional Resonance Analysis Method: Modelling Complex Socio-Technical Systems*. https://doi.org/10.1201/9781315255071

European Commission. (2014). Regulation (EU) No 376/2014 of the European Parliament and of the Council on the reporting, analysis and follow-up of occurrences in civil aviation, amending Regulation (EU) No 996/2010 of the European Parliament and of the council. *Official Journal of the European Union*, 18.

European Parliament and Council. (2015). Commission Implementing Regulation (EU) No 2015/1018 of 29 June 2015 laying down a list classifying occurrences in civil aviation to be mandatorily reported according to Regulation (EU) No 376/2014 of the European Parliament and of the Council. *Official Journal of the European Union*, *L163*, 1–17.

Gao, Z., & Mavris, D. N. (2022). Statistics and Machine Learning in Aviation Environmental Impact Analysis: A Survey of Recent Progress. *Aerospace*, *9*(12). https://doi.org/10.3390/aerospace9120750

Gerede, E. (2015). A study of challenges to the success of the safety management system in aircraft maintenance organizations in Turkey. *Safety Science*, *73*, 106–116. https://doi.org/10.1016/j.ssci.2014.11.013

Grant, E., Salmon, P. M., Stevens, N. J., Goode, N., & Read, G. J. (2018). Back to the future: What do accident causation models tell us about accident prediction? *Safety Science*, *104*(April 2017), 99–109. https://doi.org/10.1016/j.ssci.2017.12.018

Gürbüz, F., Özbakir, L., & Yapici, H. (2009). Classification rule discovery for the aviation incidents resulted in fatality. *Knowledge-Based Systems*, *22*(8), 622–632. https://doi.org/10.1016/j.knosys.2009.06.013

Han, J., Kamber, M., & Pei, J. (2011). Data Mining: Concepts and Techniques. In *Data Mining: Concepts and Techniques*. Morgan Kaufmann Publishers Inc. https://doi.org/10.1016/C2009-0-61819-5

HaSPA (Health and Safety Professionals Alliance). (2012). *The Core Body of Knowledge for the Generalist OHS Professionals*.

Hovden, J., Albrechtsen, E., & Herrera, I. A. (2010). Is there a need for new theories, models and approaches to occupational accident prevention? *Safety Science*, *48*(8), 950–956. https://doi.org/10.1016/j.ssci.2009.06.002

Huan, L., & Hiroshi, M. (2007). *Computational Methods of Feature Selection*. Chapman and Hall/CRC Press. https://doi.org/10.1016/j.ipm.2009.03.003

IATA - IATA Releases 2022 Airline Safety Performance. (n.d.). Retrieved October 9, 2023, from https://www.iata.org/en/pressroom/2023-releases/2023-03-07-01/

ICAO. (1987). *Doc 9156-AN/900 Accident / Incident Reporting Manual*.

Jardine, A. K. S., & Tsang, A. H. C. (2013). Maintenance, Replacement, and Reliability: Theory and Applications. In *Maintenance, Replacement, and Reliability: Theory and Applications* (2nd ed.). CRC Press Taylor and Francis Group. https://doi.org/10.1201/b14937

Katsakiori, P., Sakellaropoulos, G., & Manatakis, E. (2009). Towards an evaluation of accident investigation methods in terms of their alignment with accident causation models. *Safety Science*, *47*(7), 1007–1015. https://doi.org/10.1016/j.ssci.2008.11.002

Kauffeld, J. T. L. and K. (2003). Evaluating the Effect of Technology Insertion into the National Airspace System.pdf. *The Rutgers Scholar*, *5*.

Larouzee, J., & Le Coze, J. C. (2020). Good and bad reasons: The Swiss cheese model and its critics. *Safety Science*, *126*(February), 104660. https://doi.org/10.1016/j.ssci.2020.104660

Leveson, N. (2004). *A new accident model for engineering safer systems*. *42*, 237–270. https://doi.org/10.1016/S0925-7535(03)00047-X

Leveson, N. (2012). *Engineering a Safer World: System Thinking Applied to Safety*. The MIT Press.

Mathur, P., Khatri, S. K., & Sharma, M. (2017). Prediction of aviation accidents using logistic regression model. *International Conference on Infocom Technologies and Unmanned Systems ICTUS: Trends and Future Directions,* 725–728. https://doi.org/10.1109/ ICTUS.2017.8286102

Maurino, J. T. L. and M. (2001). An aviation system risk model (ASRM) case study: Air Ontario 1363. *Department of Industrial Engineering, Rutgers University, Rutgers Scholar*, *3*, 7. http://rutgersscholar.rutgers.edu/volume03/maurluxh/maurluxh.htm

Narasimha, M., & Devi, V. . (2011). Pattern recognition: An Algorithmic Approach. In *Undergraduate topics in computer science*. Springer.

Nazeri, Z., Donohue, G., & Sherry, L. (2008). Analysing Relationships Between Aircraft Accidents and Incidents. *Research in Air Transportation*, 1–5. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.659.111&rep=rep1&type=pdf%5Cnhttp://catsr.ite.gmu.edu/pubs/NazeriICRAT08_formatted.pdf

Phimster, J. R., Bier, V. M., & Kunreuther, H. C. (2004). *Accident precursor analysis and management: Reducing technological risk through diligence*. THE NATIONAL ACADEMIES PRESS. https://doi.org/10.17226/11061

Pyzdek, T. (2017). *Six Sigma Handbook A complete guide for green belts, black belts and managers at all levels* (Fourth Edi). McGraw-Hill.

Qureshi, Z. (2008). A Review of Accident Modelling Approaches for Complex Critical Sociotechnical Systems. *12th Australian Workshop on Safety Related Programmable Systems (SCS'07), Adelaide*, 47–59.

Reason, J. (1990). *Reason J. - Human Error-Cambridge University Press (1990) .pdf*. Cambridge University Press 1990.

Reason, J. (2000). Human Error: Models and Management. *BMJ*, *320*, 768–770.

Revolutionizing Healthcare Industry with Machine Learning. (n.d.). Retrieved February 28, 2024, from https://www.datasciencecentral.com/how-machine-learning-is-revolutionizing-the-healthcare-industry/

Roelen, A. L. C., Lin, P. H., & Hale, A. R. (2011). Accident models and organisational factors in air transport: The need for multi-method models. *Safety Science*, *49*(1), 5–10. https://doi.org/10.1016/j.ssci.2010.01.022

Safety Management System | Federal Aviation Administration. (n.d.). Retrieved April 10, 2023, from https://www.faa.gov/about/initiatives/sms/explained/basis

Shappell, S. A., & Wiegmann, D. A. (2000). *The human factors analysis and classification system (HFACS)*.

Stoop, J., & Dekker, S. W. A. (2012). Are safety investigations pro-active? *Safety Science*, *50*(6), 1422–1430. https://doi.org/10.1016/j.ssci.2011.03.004

Stoop, J. J. a, & Kahan, J. P. J. (2005). Flying is the safest way to travel: How aviation was a pioneer in independent accident investigation. *Technology*, *1944*(June), 1–37. https://doi.org/10.18757/ejtir.2005.5.2.4392

Underwood, P., & Waterson, P. (2012). A critical review of the stamp, fram and accimap systemic accident analysis models. *Advances in Human Aspects of Road and Rail Transportation*, *January 2016*, 385–394. https://doi.org/10.1201/b12320

Yeun, R., Bates, P., & Murray, P. (2014). Aviation safety management systems. *World Review of Intermodal Transportation Research*, *5*(2), 168–196. https://doi.org/10.1504/WRITR.2014.067234.