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From the reconceptualisation of the safety event to an innovative systemic risk management approach

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DECLARATION

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SUMMARY

Literature

“An event is something that happens, especially when it is unusual or important” (Collins, 2024) in an unpredictable and unplannable way. Events are characterised by their potential consequences, and a safety event is specifically identified when there is a likelihood of causing harm to individuals or damage to objects.

The literature on the analysis of safety and management systems has a common theme: safety events are complex, potentially involving many interrelated factors. The relationships between these factors are non-linear and involve “a particularly dynamic and complex combination of planned and unplanned factors”, including those that are normal and non-normal within that operational environment.

Research objectives

This mixed-methods research study addressed the following research objectives:

1. Reconceptualising the definition of safety events.
2. Building a data model solution.
3. Exploring the implications for Risk Management.
4. Assessing organisational impact implications.

Defining safety events

Safety events are conceptualised as dynamic and complex combinations of co-occurring factors, both related and unrelated, within a specific space-time context. The empirical demonstration is that a deviation from an intended process is “a particularly dynamic and complex combination of planned and unplanned factors” that enables a probabilistic prediction of a safety event, advancing the evolving field of safety thinking.

Research has shown that Artificial Intelligence can potentially support the identification of these combinations. However, extracting interpretable and reader-friendly machine-learning models is necessary to effectively support operational feedback as part of the process of interactions between humans and machine-learning algorithms to assess whether the decision rules are "useful" to satisfy target users' needs in the valid usage scenario and are easy to understand and interpret (i.e., "usable") (Xu, 2019).

Case Study 1 (Detecting precursors to Unstabilised Approach)

A rapid review provided a comprehensive overview of the research on using Artificial Intelligence based on machine learning algorithms to investigate the unstabilised approach focused on identifying the data-in-data-out approach used to generate safety-relevant knowledge from existing data. Specifically, the study aimed to explore the aspects of data integration and the level of explainability of the machine learning model. According to the work of Arrieta (2020), these were only considered interpretable Decision Trees and Rule-Based Learner models. The results evidenced that most research applied data mining on a single database, specifically collecting flight data from routine monitoring and generating uninterpretable patterns (Oehling & Barry, 2019).

The machine learning model deployed a series of rules based on the available data. The model shows the role of the Flight Data Monitoring events, their severity class, the recovery of delay in departure, some specific routes, and crew composition. For example, an unstabilised approach is indicated True with a probability of 1.0 if the flight is recovering from a delay in departure with a sequence of operational exceedances leading from high speed between 5000 ft-3000 ft and concluding with a delayed flap configuration for landing below 1000 ft. and if one or more of these operational exceedances have a high severity value.

A single flight can generate multiple Flight Data Monitoring events or exceedances if various parameters or conditions deviate from established safety criteria or Standard Operating Procedures at different times during the flight. As a future initiative, analysing Flight Data Monitoring events as multivariate time series data rather than separately can help identify and leverage temporal dependencies to enhance the predictive capabilities of unstabilised approaches.

Case Study 2 (Detecting precursors to safety events during Aircraft Turnaround)

A rapid review of the research on using Artificial Intelligence based on machine learning (ML) algorithms was conducted to investigate safety events during an aircraft turnaround. The aircraft turnaround is a complex process that comprises several tasks that need to be completed from when it arrives at the assigned gate until it is ready for departure. No literature on safety using Artificial Intelligence based on machine learning algorithms existed. Rather, the research focused on business goals in AI-Operations to improve operational efficiency and profitability, for example, to predict turnaround times (Halmesaari, 2020; Asadi et al., 2020; Luo et al., 2023) or specific sub-activities like passenger boarding (Schultz & Reitmann, 2018; 2019).

While these studies share a common business goal and objectives and use the same type of operational data, their analytical approaches differ significantly, suggesting that addressing a complex problem requires exploring various solutions. The validity of the approaches is measured only in terms of predictive accuracy and operational efficiency, without generating operational feedback by an expert as part of the process of interactions between humans and machine learning algorithms to augment the capacity to build data-efficient predictive models and increase the level of trust afforded by a given mode.

The machine learning model deployed a series of rules based on the available data. The model indicates the precursor role of on-time performance in departure as a predictive factor of safety events during aircraft turnaround activities combined with particular departure/arrival airports and flight types (e.g., domestic). For example, a rule describes the configuration of an aircraft departing on time and arriving at airports like Catania ("CTA"), Palermo ("PMO") or Cagliari ("CAG"). Its confidence value of 0.614 means the model is 60% confident that a safety event could occur during the aircraft turnaround.

Implications for risk management

The data analysis of two case studies generated clear and simple patterns. However, the predictive potentiality of the data model indicates that more extensive and diverse data sources could reveal more intricate patterns, better capturing the configuration of a safety event with their planned and unplanned factors. Given the complexity of both case studies, gathering additional data sources would have been necessary to fully map a wide range of potential conditions in everyday performance.

The positive feedback from experts indicated that the identified sets of precursors were valuable for meeting the needs of target users in valid usage scenarios. These rules were considered usable because they were easy to understand and interpret, potentially changing the game for risk management in practice. The experts involved in the operational feedback indicated that the identified sets of precursors were valuable for meeting the needs of target users in valid usage scenarios, suggesting that the data model solution enabled the extraction of interpretable and reader-friendly machine learning models in both case studies.

Organisational Impact

Writing a cross-case report summarised and consolidated the findings and lessons from the case studies focused on the challenges encountered while implementing the data model solution. These studies revealed two primary themes. Firstly, they highlighted the sensitivity of the required data, which posed challenges in data collection due to data protection and legal compliance issues. Secondly, the studies emphasised the necessity of manual efforts to handle various data formats stored across different business systems, each using distinct tools and technologies. This diversity in data handling methods posed potential risks to data quality, integrity, and overall manageability, imposing constraints on the research project.

A series of semi-structured interviews were conducted involving aviation professionals with different backgrounds and expertise based on the basic principles of the CUBE methodology (McDonald, 2017) as part of a socio-technical systems analysis to deploy an AI-based solutions system change. The primary objective of the CUBE was to support organisational change efforts by providing a structured and systematic analysis approach. It facilitated transitioning from the current 'as-is' condition to the desired 'to-be' state. The last part of the interview was designed to capture the knowledge or awareness of participants on AI implementation in their operational environment and pinpoint potential areas of improvement.

The analysis of evidence gathered during case studies and interviews highlights the inherent complexity in implementing AI-based applications (i.e., Big Data Analytics), necessitating significant organisational changes involving people and technology. Within the aviation industry, the adoption of such technologies remains relatively undeveloped. In this highly regulated and complex environment, initiatives tend to be started in response to prescriptive norms, industry standards or standardisation efforts, mainly when driven by influential institutions or large organisations.

Thematic Analysis facilitated a comprehensive and well-structured approach to identifying patterns or themes within the qualitative data of the interviews. During the discussions, participants identified potential barriers hindering successful implementation and emphasised the need for specific initiatives to overcome these challenges. As a relatively new technology, one major obstacle is the lack of knowledge about the technology itself and its potential benefits. To address this, participants recommended developing an information and training program to reach all organisational levels, bridging the gap between technology and humans.

The CUBE methodology (McDonald, 2017), a comprehensive and evidence-driven assessment methodology for social-technical modelling, was used to consolidate the evidence gathered from data, insights derived from interviews, and findings obtained from the conduction of the case studies. This methodology provided valuable insights into assessing risks at a specific time and determining the necessary steps to transition from the current state ('as-is') to the complexities of implementing AI-based applications in organisations ('to-be').

The analysis of the current state ('as-is') revealed that regulations govern both processes. Operators need to establish, implement, and maintain a management system to ensure alignment in systems and processes. The difference between one operator and another lies in the dimensions of sensemaking and culture, where variations emerge among operators regarding the maturity of that operator's system, or in other words, the level of development, implementation, and effectiveness of the organisation's SMS.

The analysis of what could change ('to-be') confirms that implementing AI-based applications requires profound change management. While awaiting industry regulations to align with the adoption of new technology in the field of action, particularly in the field of AI governance (Stix, 2022), initiatives must be identified across all dimensions of the CUBE. Although new technology presents opportunities and benefits, the fear of AI replacing individuals and making them obsolete can generate resistance to change (Fountaine et al., 2019).

The CUBE methodology, introduced in this study to consolidate the interview results, established a set of prerequisites for an effective system, supporting identifying potential solutions. Active engagement from management is essential for a successful implementation, particularly from the CEO or Accountable Manager. Without their support and commitment, the likelihood of success in the implementation process would be significantly compromised. The importance of managerial roles is underscored in maintaining ongoing commitment and support, facilitating effective communication and coordination, and fostering expertise in big data (Tabesh et al., 2019).

In terms of the potential of this new technology, there is a shared awareness of its strategic importance in implementation. The majority of the participants emphasised its potential benefits for enhancing operations. The optimisation of processes with cost-saving advantages, along with a more structured and objective decision-making process, were the most frequently cited benefits. It is worth noting that one participant also highlighted the potential for this technology to impact safety knowledge to enhance risk management.

Conclusion

The research, in its complexity and multidisciplinarity, has demonstrated its ability to address the research questions, from the reconceptualisation of the safety event to the design of a data model and data analytics process for extracting interpretable patterns

and how these patterns can provide information that can be applied to an innovative systemic approach in risk management. Finally, it highlights the inherent difficulties in the system for effective implementation of AI-based applications. The research concludes its work, opening the door to further new initiatives that can drive the change management process where organisations, people and technology are simultaneously involved.

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To my beloved son Andrea, I hope to have inspired you to pursue your dreams and always believe that it is possible to achieve them, even when there are obstacles to overcome. Everyone can be overcome with determination and confidence in their abilities.

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I want to express my heartfelt gratitude to my mother and father for shaping the person I have become today and for the invaluable life lessons you have imparted to me. I would also like to acknowledge my dear sister, Silvia, who holds a significant place in my life.

My role as an insider-action researcher has produced positive and negative outcomes. On the positive side, my deep familiarity with the aviation domain has proven invaluable in identifying practical solutions, particularly during case studies. However, this has also required a delicate balance with the academic aspects to prevent the risk of 'reverse engineering' and ensure alignment with the relevant professional context. One of my notable achievements at the outset of this research project was proposing solutions with universal applicability across diverse risk management contexts.

This thesis represents the culmination of years of hard work, collaboration, and support from many individuals and institutions. I am profoundly grateful for the opportunities I

have been given, and I look forward to contributing to the field of risk management in the years to come.

Thank you all for being a part of this remarkable journey.

The best is yet to come.

Fabio Toti, September, 2023

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CHAPTER 1. INTRODUCTION AND OVERVIEW

1.1. Rationale

An essential element in thinking about the future is managing uncertainty and risks with the strategic importance of anticipating them and identifying the measures for containing them. Organisations that manage risks always look for ways to be resilient and have a sustainable business, dealing daily with the management dilemma to balance production and protection by controlling the safety risks.

Risk management has evolved over the years along with socio-technological changes. Methods and techniques for analysing adverse outcomes, identifying the proper corrective actions, evaluating the continued effectiveness of the implemented risk controls, and supporting the ongoing identification of new hazards have become more sophisticated for the desired outcome to reduce the residual risk to As Low As Reasonably Achievable (ALARA) (Lakey & Lewins, 1987) or Practicable (ALARP) (Great Britain. Health and Safety Executive, 1992).

Among the initiatives promoted to improve safety and health in organisations that deal with risks, Safety Management Systems (SMS) provide a strict framework for analysing hazards and controlling risks**.** Implementing a structured and systemic approach to control safety risks in operations has contributed to more proactive organisational behaviours and standards by looking at adverse events and producing even more safety performances accordingly.

However, despite many industry sectors recording excellent safety numbers, everyone commonly agrees that the systems must remain aware of and constantly search for weaknesses to mitigate the risk of undesirable outcomes. Today, accidents and severe or significant incidents are rare in ultra-safe systems, and even if they still provide insights and a clear understanding of the complex factors involved, it is necessary to create innovative and proper response models. When things go well, complacency grows, and there might be a reluctance to change (Amalberti, 2001; 2017). Paradoxically, is safety excellence a paramount or a hazard?

Statistical data from the last ten years on the European Union's public health and safety confirm this positive trend. The following tables show that at a different set of EU Member states and periods, both all NACE activities (Table 1-1) and selected activities co-related with Industry (Table 1-2) accounted for a continuous incidence rate reduction for fatal accidents (Eurostat, 2023). Incidence rates have been calculated as the ratio between

(i) the number of accidents (non-fatal or fatal for a given year, country, sector, sex, age group, or other breakdowns) and (ii) the corresponding number of employed persons (reference population) multiplied by 100,000. The term NACE derives from the French *Nomenclature statistique des Activités économiques dans la Communauté Européenne*.

Table 1-1 Fatal Accidents at Work by Incidence Rate per 100,000 persons employed - All NACE activities (Eurostat, 2023)

GEO/TIME	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
EU - 27 countries (from 2020)	2,30	2,14	1,92	2,00	2,01	1,84	1,79	1,77	1,74	1,77
EU - 28 countries (2013-2020)	2,02	1,91	1,78	1,83	1,83	1,69	1,65	1,63		
EU - 27 countries (2007-2013)	2,04	1,94	1,78	1,83	1,83	1,68	1,65	1,62		
EU - 15 countries (1995-2004)	1,79	1,71	1,58	1,63	1,62	1,52	1,48	1,46		

Table 1-2 Fatal Accidents at Work by Incidence Rate per 100,000 persons employed - Agriculture; Industry and Construction (except Mining); Services of the business economy (Eurostat, 2023)

GEO/TIME	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
EU - 27 countries (from 2020)	2,78	2,67	2,41	2,52	2,58	2,31	2,26	2,23	2,17	2,11
EU - 28 countries (2013-2020)	2,49	2,42	2,26	2,33	2,39	2,15	2,12	2,08		
EU - 27 countries (2007-2013)	2,53	2,40	2,25	2,34	2,38	2,14	2,11	2,07		
EU - 15 countries (1995-2004)	2,23	2,13	2,05	2,11	2,13	1,97	1,91	1,89		

An ultra-safe system such as commercial air transport has also recorded the same positive trends. The graph Figure 1-1 confirms the continuous downward trend for the industry over the past ten years, IATA airline companies, and those associated with the IOSA programme, underlining the importance of standardisation (IATA, 2023). The International Air Transport Association (IATA) is a trade association of the world's airlines that supports airline activity and helps to set industry policy and standards. Its audit programme, called IOSA (IATA Operational Safety Audit), is an internationally recognised and accepted evaluation system designed to assess an airline's operational management and control systems.

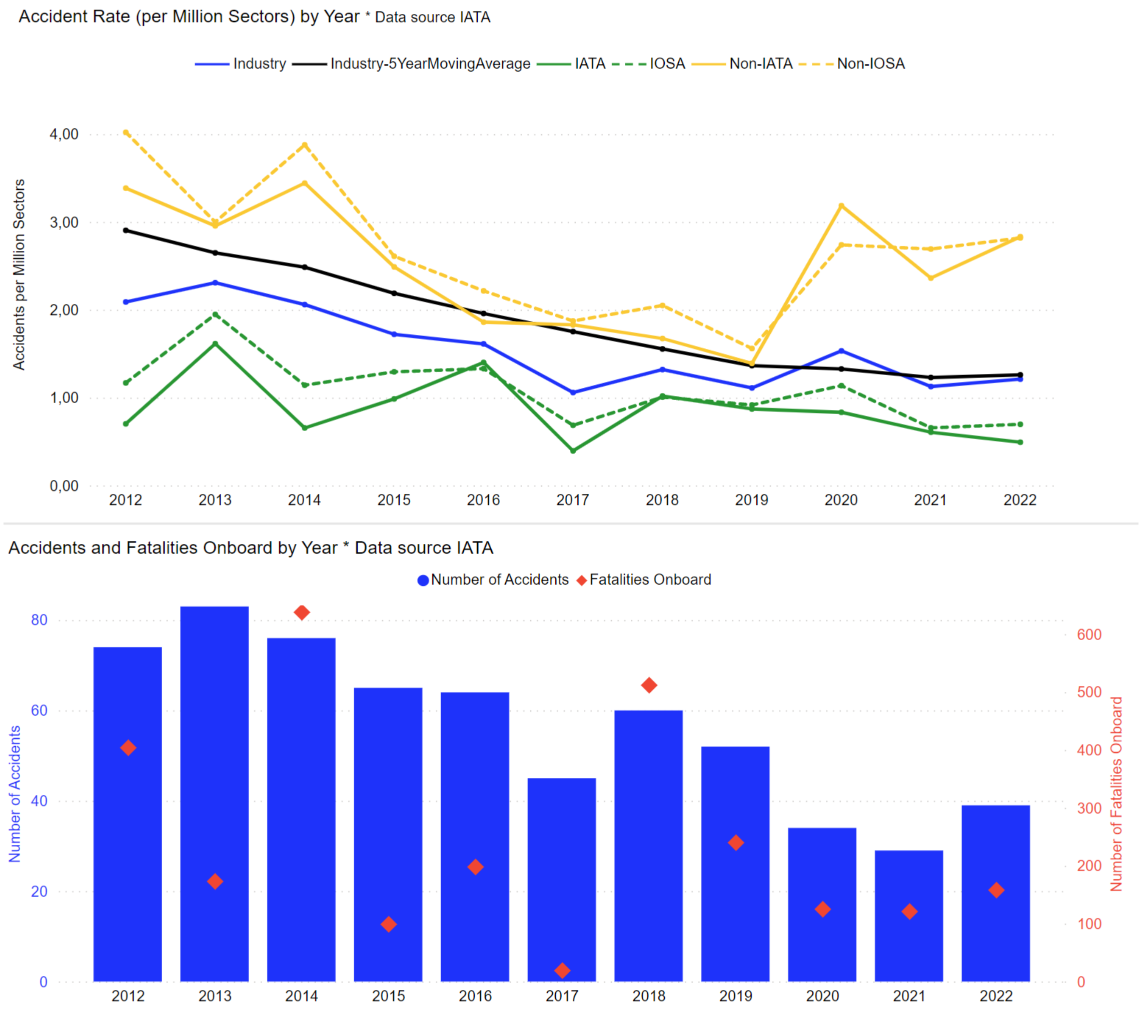
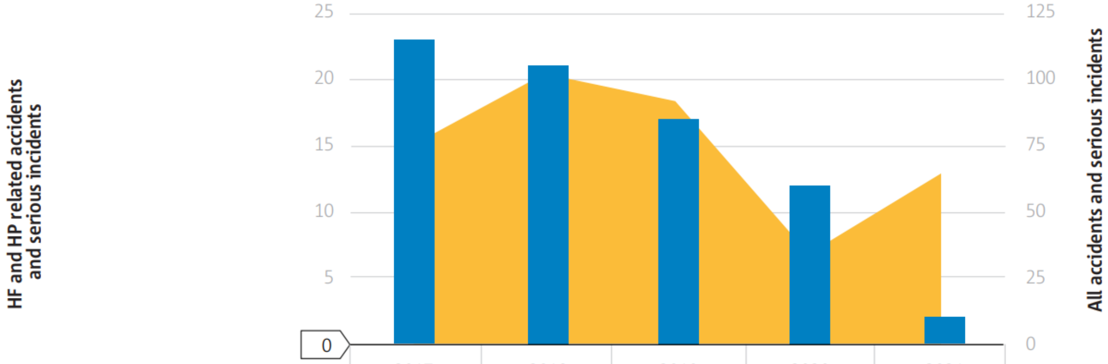


Figure 1-1 Accident Rate and Accident and Fatalities Onboard by Year (IATA, 2023)

The traditional safety approach, called Safety-I, addresses investigating adverse events and their unwanted consequences by identifying the system's failures or malfunctions to reduce the number of accidents or incidents as low as possible. In this approach, purely reactive, human error is primarily seen as the leading cause of accidents or incidents.

In Europe, in a summary of 5 years of performances in commercial air transport large aeroplanes, human factors (HF) and human performance (HP) have been identified as the primary safety issues that negatively contribute to accidents and serious incidents (Figure 1-2) (EASA, 2022).



	2017	2018	2019	2020	2021
Accidents and serious incidents	76	102	92	34	64
HF/HP accidents and serious incidents	23	21	17	12	2

Figure 1-2 Human factors and human performance accidents and serious incidents involving commercial air transport airline and air-taxi aeroplanes (EASA, 2022)

The reduction in the overall number of accidents and serious incidents for 2020 has not positively impacted the number of HF/HP-related issues for the same year. The data reported for 2021 is preliminary and is likely to increase since HF or HP issues will be recorded within the accident and serious incident investigations once the final report is published.

Things go right because the system functions as it should, and things go wrong when something has malfunctioned or failed. Hollnagel (2013; 2015) opposes the just mentioned Safety-I perspective to his Safety-II. He argues that safety processes should move from ensuring that "as few things as possible go wrong" to ensuring that "as many things as possible go right", with the system's ability to succeed under varying conditions. This approach, purely proactive, places the role of humans as a resource necessary for system flexibility and resilience.

The COVID-19 pandemic has frozen out the safety and risk implementation process and changed the world of work. In its Strategic Framework on Health and Safety at Work 2021-2027, the EU has outlined the leading actions to improve workers' health and safety over the forthcoming years. The strategy focuses on three cross-cutting objectives: managing change brought by green, demographics, and especially digital transitions. In the era of Big Data, digital transformation opens up many opportunities in many industrial sectors. EU-funded research projects like PROSPERO (PROactive Safety PERformance for Operations) ran between 2012 and 2015 (European Commission, 2017), first exploring the importance of having the capacity to anticipate and prevent socio-technological complex system incidents through a process of extracting and discovering patterns in large data sets. To a reasonable extent, the research project demonstrated the utility of integrating operational databases from different stakeholders (e.g., airlines and airports) to study multiple features and variables. The data collection and integration from multiple heterogeneous sources provide ample measurement space for more accurate risk predictions reflecting causality models (Baranzini & Zanin, Risk Prediction & Risk Intelligence in Aviation – the next generation of aviation risk concepts from PROSPERO FP7 Project, 2015).

Today, data volume, variety and velocity are so much greater that intelligent computers can only manage them. The deployment and development of Artificial Intelligence (AI) technologies have significantly grown in recent years, creating opportunities for innovation and initiatives and affecting our work and everyday lives. The power of machine learning (ML) algorithms enables uncovering insights into data and identifying scenarios, what-if, or fertile-conditions factors to anticipate adverse situations in probabilistic terms.

The research conducted for the Master's thesis (Toti, 2017) further explored the feasibility of assembling different and multiple sources in an extensive database. The study of casual paths across multiple arrays of predictor variables intended to demonstrate the assumption that safety events are not unforeseen and unpredictable but likely occur when specific pattern configurations or sets of pre-conditions are physically or temporarily present within an operational scenario. The combination of risk and pattern returns an integrated definition in a statistical metric related to deviation from expected earnings or outcomes.

1.2. Research aims and objectives

A safety event is recognised when there is a likelihood of causing harm to individuals or damage to objects. Similarly, a security event is explicitly recognised when there is a likelihood of posing a threat to people, property, the environment, or, in the context of a financial event, disrupting the regular functioning of a system, process, or operation. Regardless of the consequences and specific types, an event is defined as a change of state (Cacciabue, 2010) or performance variability (Hollnagel, 2012; 2017). This highlights how deviations from normal operations or planned scenarios can introduce various risks.

The research aims to propose and validate a novel definition of a safety event, extending its applicability to other event types, clarifying its dynamic nature and particular configuration, and then making it predictable and, furthermore, exploring implications in contributing to an evolving risk management process, leading to a distinct strategy and approach in predictive terms.

The research objectives encompass the following:

1. A reconceptualisation of the safety event definition and its validation, clarifying its dynamic nature and particular configuration, and implications on the safety thinking striving to improve the safety processes and risk management in quantitative and probabilistic terms.
2. Building a data model solution grounded in the novel definition of safety event, enabling the extraction of interpretable patterns from merged and extensive datasets.
3. Foster an innovative and evolving risk management approach and strategy in predictive terms, spanning from hazard identification to risk monitoring, driven by insights derived from patterns.
4. Identify the potential barriers to implementing AI-based applications like predictive analytics in a complex organisational context and propose solutions for managing an organisational change.

The theoretical concept is validated through two case studies exploring safety concerns within an ultra-safe system, specifically the commercial air transport domain. These studies aim to extract interpretable patterns and accumulate knowledge through in-depth analysis. Furthermore, an expanded application of the case studies seeks to drive the future direction of the research, pioneer an innovative approach, and enhance the capability to predict safety events.

1.3. Thesis structure

The structure of the thesis comprises seven chapters.

Chapter 1: Introduction and Overview

The introductory chapter lays the foundation by providing contextual information about the research project and thesis structure.

Chapter 2: Literature Review

This chapter provides a comprehensive academic review of safety thinking's evolution spanning a century. It traces the development of safety concepts from the Industrial Revolution to the contemporary era. A selection of a sample of studies relevant to the research goals for examining state-of-the-art AI-based solutions like predictive analytics in the industry and aviation domains, with a particular focus on the AI approach used to extract patterns from merged and extensive databases to demonstrate a distinctive perspective within the current body of evidence. Due to the multidisciplinary nature of this research, careful source selection and rapid reviews were conducted to avoid redundancy.

Chapter 3: Research hypothesis and Overview of the methodological approach

This chapter combines a description of the process used to drive the research study and a concise, high-level summary of the methods and techniques used. The exploration of theories, concepts, and empirical discoveries identified during the comprehensive literature review concerning the evolution of safety thinking facilitates the establishment of a targeted and purposeful research framework. This process enhances the study's integrity and positions it to contribute substantially to advancing safety thinking and the risk management field of study. This chapter also outlines the chosen methodologies that ensure robust and credible outcomes. It establishes links between proposed theories, hypotheses, research questions, and the analytical techniques and data employed.

Chapters 4-5 Application through Case Studies

These chapters delve into the practical application of the research methodology to real operational scenarios, specifically within the ultra-safe domain of commercial aviation. The primary objective of these case studies is to validate the advanced concepts. The chapters explore risk pattern detection and the identification of latent combinations of unstable approaches and safety events during the aircraft turnaround process, addressing safety concerns across two operational areas: flight and ground operations.

Chapter 6: Organisational Impact

This chapter examines the feasibility of implementing AI-based applications like predictive analytics in a complex organisational context. Semi-structured interviews were conducted to evaluate barriers impeding the change management. Specifically, descriptive data will be gathered and analysed to understand the systematic approach to dealing with organisational change in the execution of two specific risk management tasks: risk assessment and safety performance monitoring. This chapter proposes solutions for a successful implementation.

Chapter 7: Discussion and Conclusion

This chapter serves the following purposes: summarising the key findings and addressing them concerning the research questions, interpreting the results obtained from the case studies and key themes related to organisational impact, acknowledging the study's limitations, providing recommendations for implementation and future research, and concluding with a summary that briefly recaps the key findings and their implications.

CHAPTER 2. LITERATURE REVIEW

2.1. Introduction

History has taught us that safety thinking is a dynamic concept. It needs continuous revision and development to match the context of a changing society. The evolution of theories and methods has allowed us to move further and further back in time to the point of detection of potential accidents and incidents.

The research aims to be part of this development process, advancing its proposal by looking at the timeline of safety progress and its effects on today's world and the world of tomorrow. Dr. Carl Sagan (1980) said: "You have to know the past to understand the present and shape the future", advancing the concept that we live along a string of cause and effect.

This chapter brought different strategies to situate the research within existing knowledge, providing a historical overview of improving safety thinking. The search process of academic journals, books, and other sources allowed the identification of the relevant theories, methods, and gaps in the past and present research to create a theoretical foundation to explain the issues that drive the theory advanced in this research.

It reviewed the evolution of safety and risk research frameworks over the last century worldwide, combining different approaches and surveying academic sources about safety risk theories, methods, and gaps across existing and past research. The objective was to give a clear picture of the state of knowledge on the topic and how the theoretical framework relevant to the research study gave a basis for the research theory, an advanced approach to safety risk grounded on more evidence-based and innovative Artificial Intelligence (AI) methods.

The three main themes of the literature review attempted to provide a structured approach to exploring the evolution of safety thinking:

1. History Review of Accident Causal Models and Management Systems. This theme likely delved into the various models and frameworks used to analyse and

manage historical accidents and incidents. This review included the development of Safety Management Systems, root cause analysis methods, and other approaches to understand the causes of accidents and improve safety outcomes.

2. History Review of Models on Human Factors Risks**.** Human factors play a crucial role in safety, and this theme would explore how different models and theories have evolved to understand better and address human-related risks. This section covered ergonomics, cognitive factors, human error analysis, and integrating human factors principles into safety practices.

3. The third part explored state-of-the-art AI-based applications, specifically predictive analytics in various industrial and aviation domains. The achievement was ensured by selecting a relevant sample of studies aligned with the research objectives. The review highlighted the approach used to extract valuable insights from data and make informed decisions on how big data and machine learning algorithms analysed historical data and made predictions, emphasising three key aspects of the process: data integration, algorithmic methodologies, and interpretability.

2.2. History Review of Accident Causal Models in Industry

Safety has several similar definitions, for example, a state or condition of being safe or freedom from the risk of injury, danger, or loss.

In the early twentieth century, severe accidents at work were frequent during the Industrial Revolution era. In response, several national, international, and governmental bodies gave birth to safety campaigns in the industry to reduce workplace hazards. As a result, researchers began to study why and how accidents occur and how to prevent them, giving origin to the first models that could explain the dynamics of an accident. Their development and complexity emerged from a socio-technical industry improvement and safety thinking progress.

The year 2019 marked 100 years from the first human history accident causation model proposed by Greenwood and Woods (1919) with their basic concept of accident proneness. Many others have followed that model throughout the years. Figure 2-1 below shows the evolution of significant accident causation models introduced over the last century and their comparison based on theoretical and methodological elements (Fu et al., 2020).

Initially, safety practitioners applied statistical methods to understand and explain accidents. The first investigation was conducted at the UK ammunition factories to assess the incidence of industrial accidents on individuals. The main causal factor identified was that people with specific characteristics were most prone to accidents (Greenwood & Woods, 1919). This theory was the basis for further studies on industrial accidents (Farmer, 1927). Afterwards, Farmer and Chambers (1929), as a conclusion of their work, coined the concept of 'Accident prone tendency', referring to those who have a natural tendency to incur an accident with their personal qualities.

Accident causation model	Proposed year	Factors definition	Object factors	Human factors	Organisational factors	Modularity	Simple chain	Complex chain	Systematic mesh
APT	1919	×	×	○	×	×	○	×	×
Domino theory	1931	×	○	○	×	○	○	×	×
Accident liability	1949	×	○	○	×	×	○	×	×
Accident epidemiology	1949	×	○	○	×	×	○	×	×
Bird's model	1966	×	○	○	○	○	○	×	×
ETT/ EARM	1968	×	○	○	○	○	×	○	×
Surry's model	1969	×	×	○	×	○	○	×	×
Hale's model	1970	×	×	○	×	×	○	×	×
Wigglesworth's model	1972	×	×	○	×	×	○	×	×
Lawrence's model	1974	×	×	○	×	×	○	×	×
Kitagawa's model	——	×	○	○	○	○	○	×	×
OIT	1980s	×	○	○	○	○	○	×	×
Tripod Beta model	1980s	×	○	×	×	×	×	○	×
Swiss cheese model	1990	×	○	○	○	○	○	×	×
3 M/5 M model	——	×	○	○	○	×	×	○	×
Bow-Tie model	1990s	×	○	×	×	×	×	○	×
AcciMap	1997	×	○	○	○	○	×	×	○
CREAM	1998	×	○	○	○	×	×	×	○
Stewart's model	2001	×	○	○	○	○	×	○	×
HFACS	2001	○	○	○	○	○	×	○	×
STAMP	2004	×	○	○	○	○	×	×	○
OAC	2006	×	○	○	○	○	×	×	○
OOGM	2010	×	○	○	○	○	×	×	○
SHIPP	2011	×	○	○	○	○	×	×	○
IPICA	2011	×	○	○	○	○	×	×	○
FRAM	2012	×	○	○	○	×	×	×	○
TeCSMART framework	2016	×	○	○	○	○	×	×	○
24Model (V4.0)	2016	○	○	○	○	○	×	×	○

APT: Accident Prone Tendency; OIT: Orbit Intersecting Theory; ETT: Energy Transfer Theory; EARM: Energy Accidental Release Model; OAC: Occupational Accident Model; OOGM: Offshore Oil and Gas Model.

Figure 2-1 Comparison of the factors and accident path of accident causation models (Fu et al., 2020)

Mintz and Blum (1949) critically reviewed the principle of 'Accident proneness', advancing the concept of 'Accident liability' because the conditions related to the environment also have to be considered, especially in the legal and insurance aspects of accidents, which required the allocation of blame. Moreover, adopting the idea of proneness limited the hypothesis about the causality of an accident on a single cause or a small group of factors without considering other reasonable aspects. Later studies clarified the term conditions in relation to the mechanical nature of the workplace and the presence of dangerous materials. Kune (1985) depicted the theory in a graphical model to represent the relationship between 'Accident liability' and its leading factors (Figure 2-2).

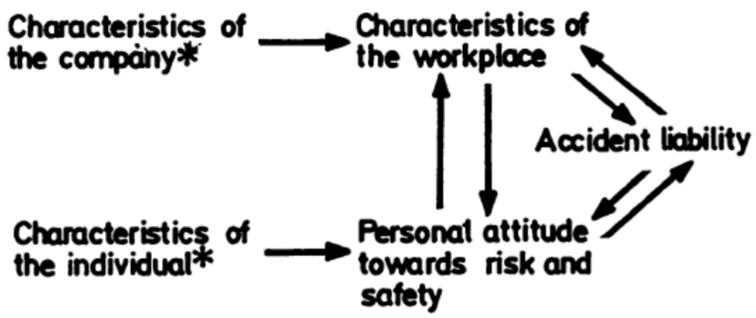


Figure 2-2 Accident Liability model (Kune, 1985)

In the '70s, Jean Surry paved the way for human-based decision tree models. Based upon the theory that an accident is a deviation from an intended process, Surry's model (1969) purposed to assess the potential or actual dangerousness of a situation by analysing the cognitive stages of the process of information processing starting from the human perception of a hazard (Figure 2-3).

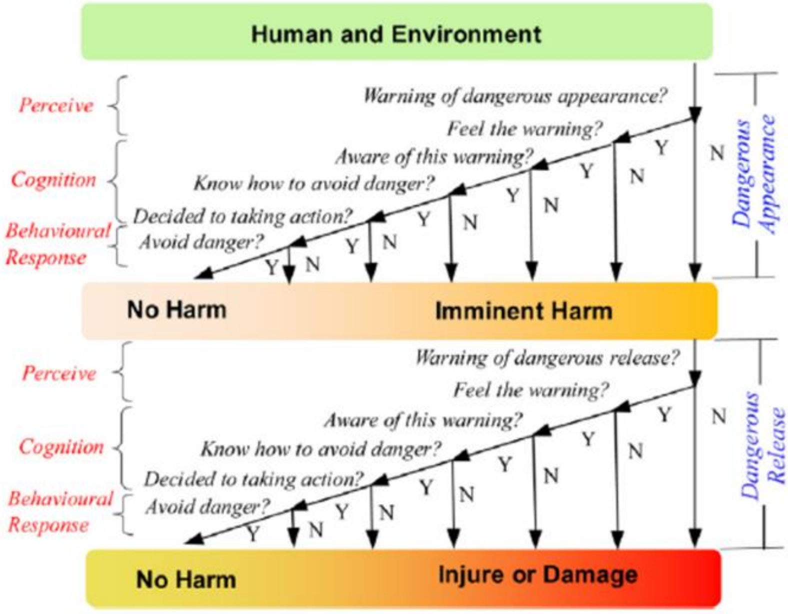


Figure 2-3 Surry's model (Fu et al., 2020)

The role of information processing in the causality of an accident promoted the development of other similar models to Surry's model, like Hale's model (1970), Wigglesworth's model (1972) and Lawrence's model (1974). Hale and Hale designed their model based on the definition of the accident: “the failure of a person to cope with the true situation presented to him" (Hale & Hale, 1970, p. 3). The model aimed at mapping every factor that influences or could influence information handling at every stage of the decisional process until the binary condition of action or non-action results (Figure 2-4).

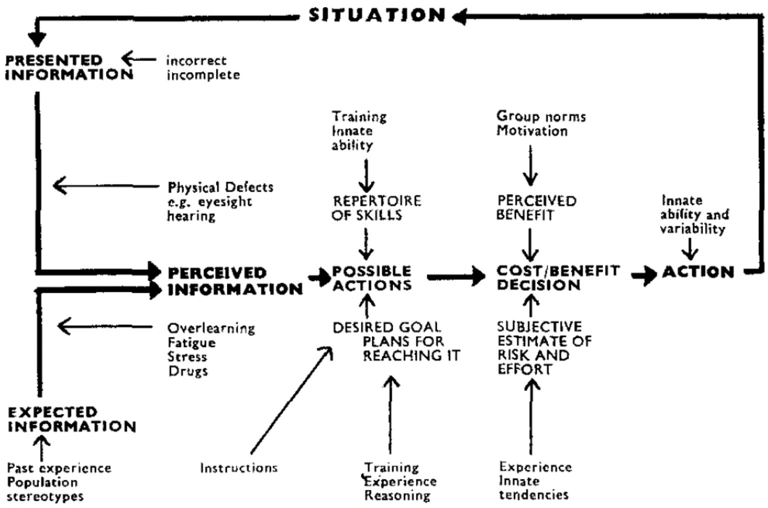


Figure 2-4 Model of accident causation (Hale & Hale, 1970)

Instead, Wigglesworth (1972) proposed his accident model, observing the correlations between stimulus and response. He argued that the answer is a function of a stimulus, specifically that a human error occurs when a person incorrectly or inappropriately responds to an external stimulus. The relation between the two may depend on various cognitive variables, the random factors of which play a role in the consequences of an accident in terms of injury or no injury (Figure 2-5).

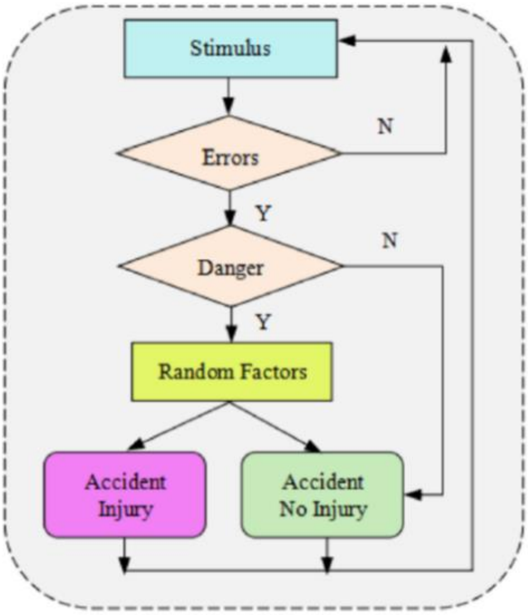


Figure 2-5 Wigglesworth's accident model (Fu et al., 2020)

The analysis of 405 accidents involving 424 fatalities in South African gold mines brought Lawrence (1974) to develop his model 'Lawrence's accident model' (Figure 2-6). The classification of 794 errors evidenced the cognitive map of human response to detecting warnings during production activities. Lawrence argued that an accident resulted from a mistake or incorrect answer to an initial alert. Nevertheless, in case of the lack of an initial warning, the liability had to be allocated to poor management or ineffective monitoring systems. As with Wigglesworth's accident model, random factors can trigger accidents with or without harm.

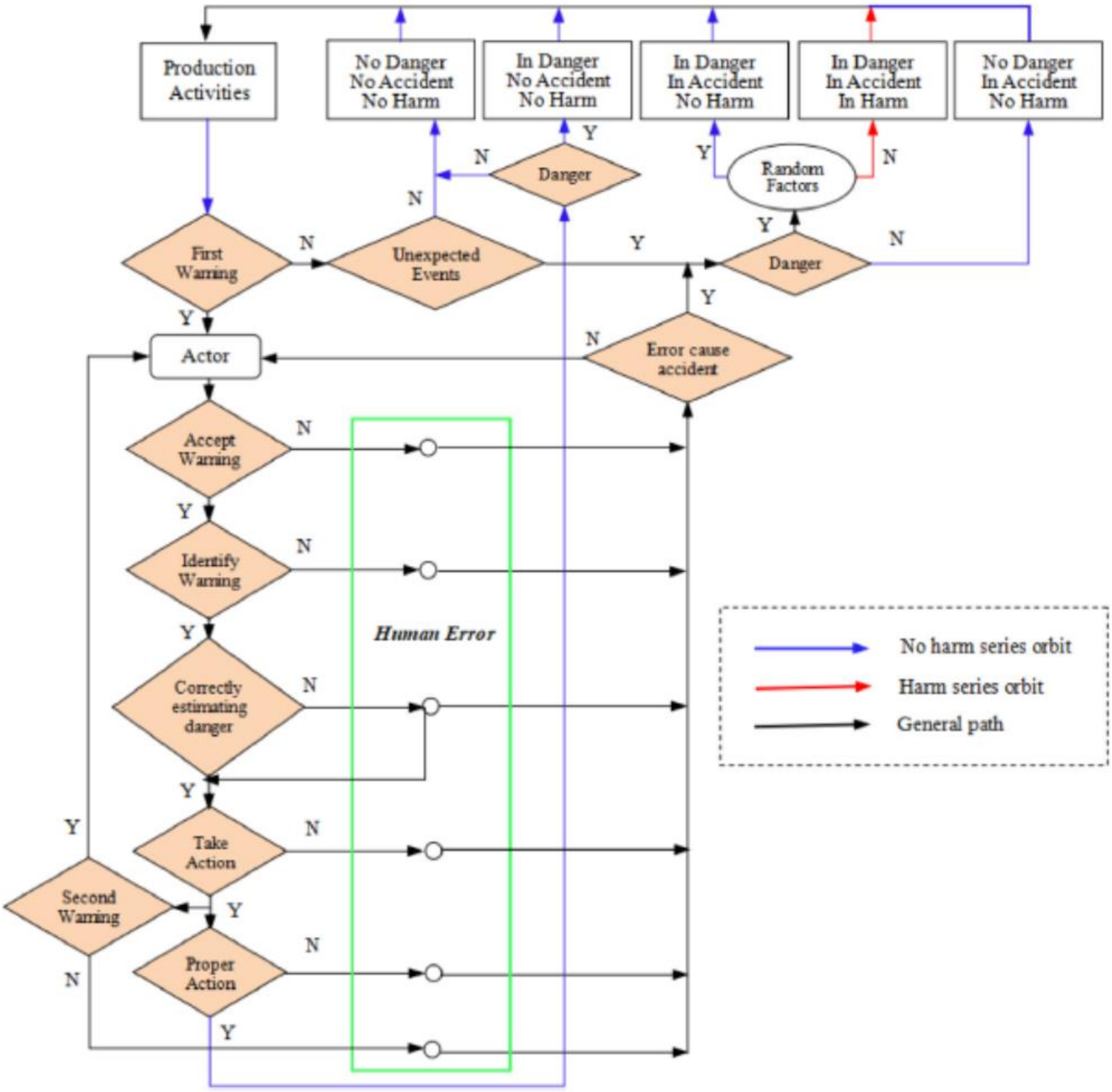


Figure 2-6 Lawrence's accident model (Fu et al., 2020)

Together with such individual-oriented model developments, the history of more system-wide and industrial accident modelling can be indeed traced back to the original works by Heinrich.

His study on understanding accidents continued for over thirty years and was the foundation of many modern safety management teachings. The theories of the 'Safety Pyramid' and the 'Five Domino Model' (Heinrich, 1931), further updated in later book editions, influenced the safety thinking of later generations. The accident triangle, also called 'Heinrich's Triangle' or 'Heinrich's Pyramid' (Figure 2-7), was founded on collecting and analysing a massive amount of accident data reported by a large insurance company's employer. The distribution per injury level evidenced a numeric relationship among the accidents, supporting the theory that "in a workplace, for every accident that caused a major injury, there were 29 accidents that caused minor injuries and 300 accidents that caused no injuries". Therefore, industrial companies would see a correlating fall in major accidents by reducing minor accidents.

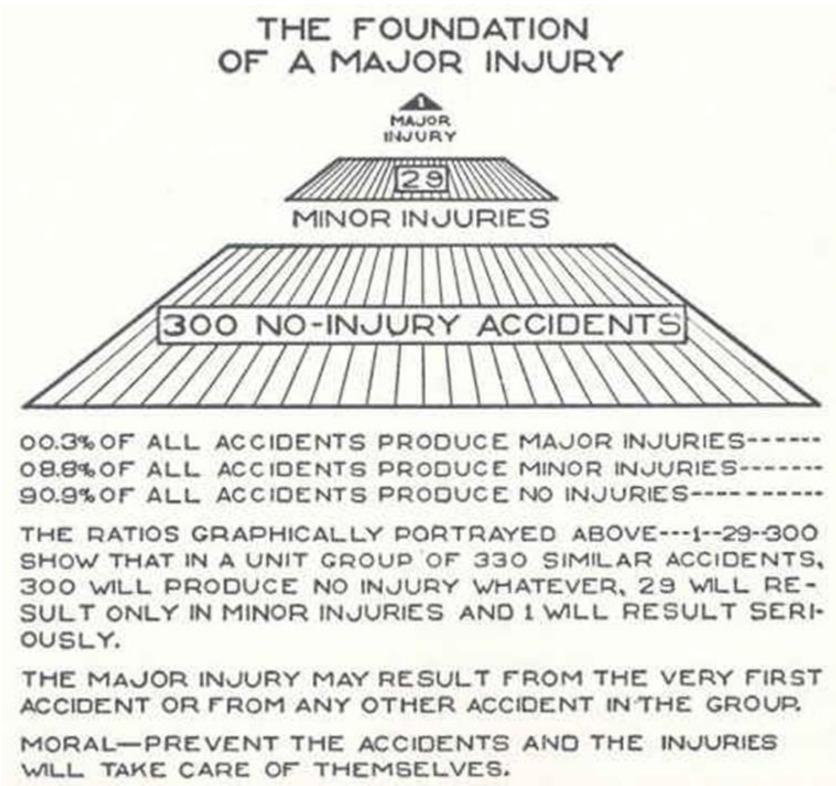


Figure 2-7 Heinrich's Pyramid (Heinrich, 1931)

Further studies reviewed the ratio 300-29-1. Bird's work in 1966 updated the relationship based on the analysis of 1.7 million accident reports from almost 300 companies in ten minor injuries (first aid only) for one serious injury accident, 30 damage-causing accidents, and 600 near misses (Bird & Germain, 1966). The numbers used by Bird were confirmed by a 1974 study by A. D. Swain, entitled *The Human Element in Systems Safety*; *a guide for modern management* (Swain, 1974).

Over the years, the effectiveness of the accident prevention strategy in large industry sectors opened a discussion about the current validity of the Heinrich ratio. Seward and Castle, relying on the collection and analysis of the 9-year data history (2006-2014) of the Bureau of Labor Statistics, identified that the ratio of 20-5-1 appeared to be more adherent to the current occupational safety issues and unique industries or work environments (Dunlop et al., 2019).

The other famous work developed by Heinrich was the domino theory or domino effect (Heinrich, 1931). The model assumed that an injury culminated from a chain of sequential events or circumstances in a fixed or logical order. Metaphorically, it is shown as a falling row of dominoes; the first fall caused the second, followed by the third, and so on (Figure 2-8).

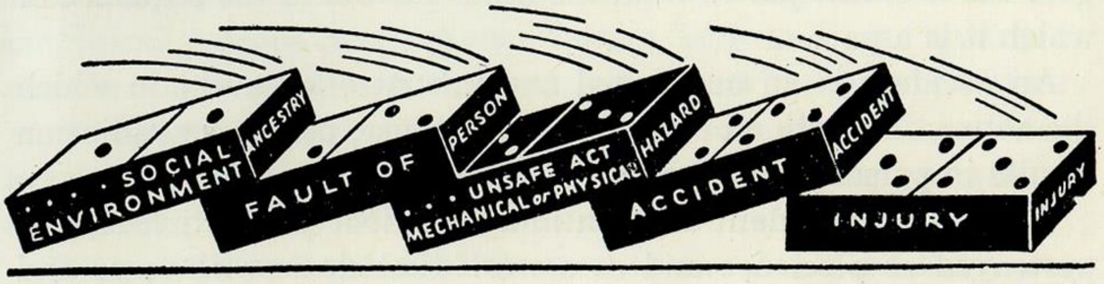


FIG. 3. The injury is caused by the action of preceding factors.

Figure 2-8 Heinrich's Domino theory – Domino's falling (Heinrich, 1931)

Accident prevention relied on stopping the domino effect. Since the study attributed 88% of all injuries to workers' unsafe acts and mechanical hazards, Heinrich argued that removing this central factor from the sequence made the preceding factors ineffective (Figure 2-9).

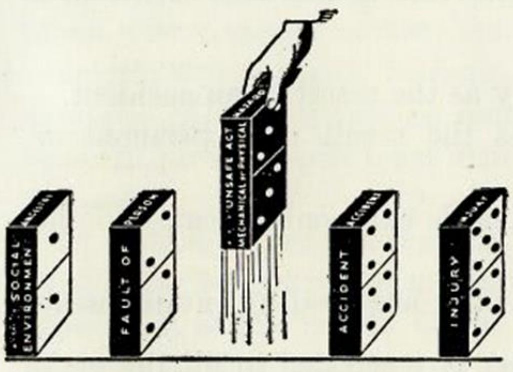


FIG. 4. The unsafe act and mechanical hazard constitute the central factor in the accident sequence.

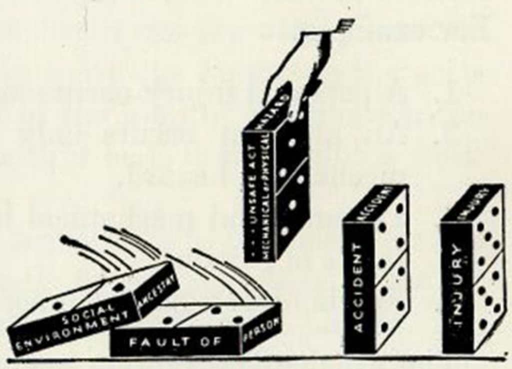


FIG. 5. The removal of the central factor makes the action of preceding factors ineffective.

Figure 2-9 Heinrich's Domino theory – Domino's barrier (Heinrich, 1931)

These studies provided much valuable information and proposed some new analysis methods that are still valid today, even if the founding principles are too simplistic because they focus solely on emphasising the fault of individuals.

The proposal by Heinrich to address prevention activities at supervisors' or forepersons' levels (1959) opened a discussion within the researchers' community about the role of management in accidents. The term management was firstly and explicitly indicated in the accident model developed by Bird and Germain (1966) based on the belief that the root cause of an accident is a 'lack of control' considered a management defect. The concept, subsequently taken up by Weaver (1971) and Bird and Loftus (1974), emphasised the importance of supervision as part of the management function (Figure 2-10) (Othman et al., 2018). Adams (1976) further updated the domino scheme, breaking down the 'organisational errors' factor into three separate tiles: 'management structure', 'operational errors' and 'tactical errors' and their combination (Figure 2-11).

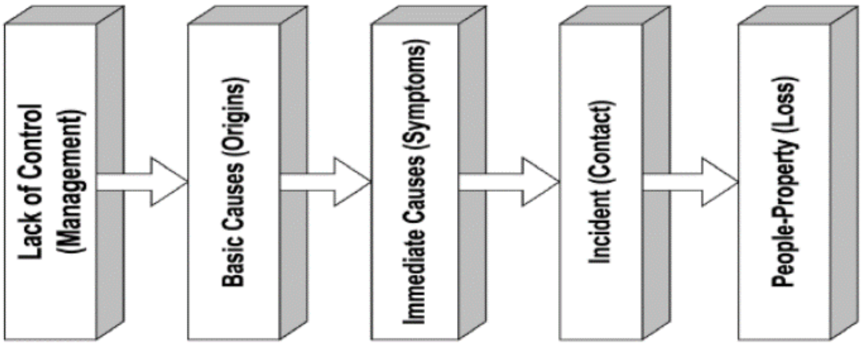


Figure 2-10 Bird and Loftus, domino model (Othman et al., 2018)

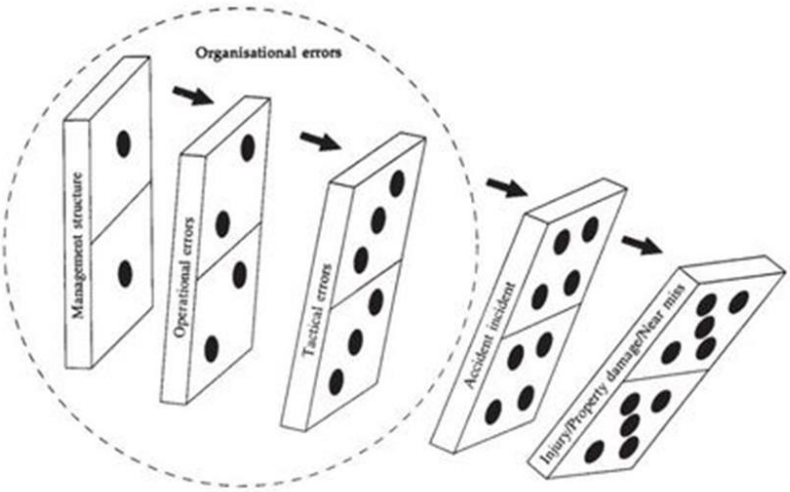


Figure 2-11 Adams domino model (Adams, 1976)

James Reason released another causal model that took inspiration from the principles of the Domino theory in the early 90s. Reason's accident model, later renamed 'Swiss cheese', is the most widely known accident model among safety researchers and practitioners. It represents the paradigm that constitutes a way of viewing accidents or incident dynamics in many industry sectors. Its evolution over the years, shown in Table 2-1, gave origin to a set of crucial safety concepts: the 'resident pathogens' metaphor developed by Reason, the concept of 'defence-in-depth' brought in by Wreathall and the 'Swiss cheese' metaphor proposed by Lee (Laurozee & Le Coze, 2020).

Table 2-1 Different representations of Reason's model (Laurozee & Le Coze, 2020)

Version (year)	**Representation**	**Reading direction**
Mark I (1990)	Perspective	Left to right
Mark II (1990)	Flat	Left to right
Mark X (1995)[1]	Flat	Top to bottom
Mark III (1997)	Flat	Left to right & Top to bottom
Swiss cheese model	Perspective	Right to left

The following industrial accidents marked the 1980s: Three Mile Island, 1979; Bhopal, 1984; Chernobyl and Challenger, 1986; Herald of Free Enterprise and King's Cross Station, 1987; and Piper Alpha, 1988. A thorough review of these accidents provided clues to understanding failures, leading to Reason's hypothesis (2000) that human beings are involved in two different ways in accidents or incidents occurring in complex work contexts. He advanced the distinction between active and latent failure. Active failures are unsafe acts with immediate adverse effects committed by people in direct contact with the system. Latent failures occur in "upstream" systemic factors: organisational, supervisory or preconditions levels. These failures are referred to as "latent" because they often go undetected when they occur.

The latent conditions are the inevitable "resident pathogens". The "resident pathogens" may lie dormant within the system for many years until the combination with certain factors creates the conditions for an accident or incident opportunity. Similarly, this happens for the human body, where an illness combines the "resident pathogens" with external factors such as stress and toxic agencies.

'Defense in-depth' is an ancient military strategy that relies on defending with different defensive lines instead of a strong one. This strategy aims to delay and buy time during

[1] As this model (Maurino et al., 1995) was not named, the authors of the table refer to it as Mark X.

the advancement of an attacker to mitigate the advantage of surprise. It allows time to reconstruct the defences and prepare a counterattack (Stitching Tripod Foundation, 2015; Luttwak, 2016). Based upon this concept, Wreathall provided Reason with a standard-setting model adopted in nuclear culture that is applicable to any productive organisation. Five elements are designed as overlapping planes showing the defensive layers present in any system: decision-makers, line management, preconditions, production activities and defences. Reason named these components 'healthy' against the pathology of any complex system.

The holes in any plane graphically show the fallibility of any defensive layer because every component of the system is vulnerable. The alignment of the holes is intended to show the 'trajectory of accident opportunity' Given the characteristics of the system involved, multiple failures that interact with each other will occur despite efforts to avoid them (Perrow, 1984). Lee proposed replacing the planes with cheese slices in the early 90s, giving origin to the final model.

The figures below show the first published version of the model drawn with the collaboration of Wreathall with the first explicit mention of 'defence in depth' and the alignment of the holes (Figure 2-12) and the ultimate version of the model (Figure 2-13).

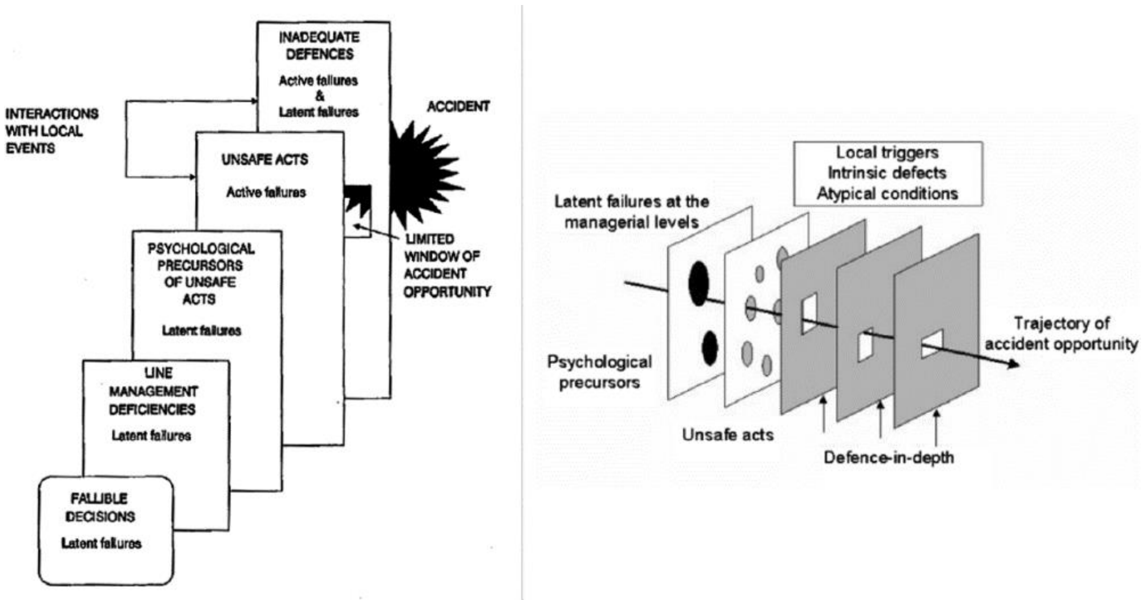


Figure 2-12 First published version of the Reasons accident model (Laurozee & Le Coze, 2020)

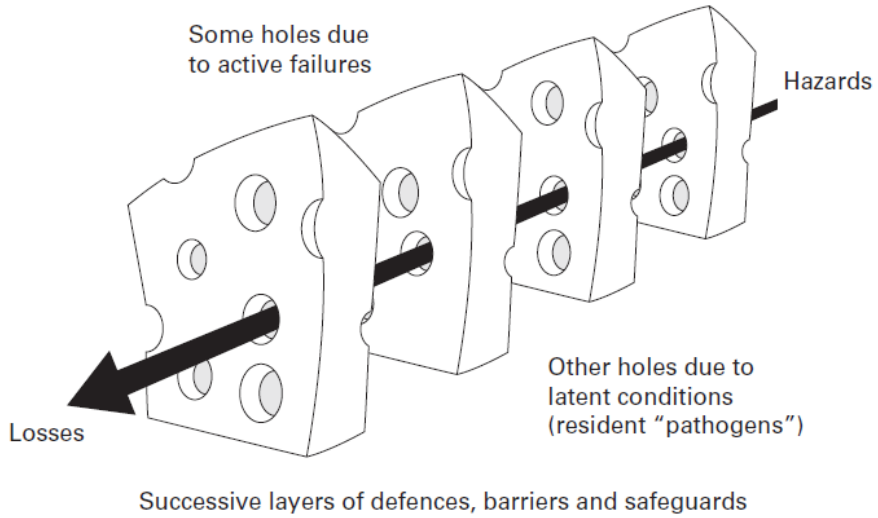


Figure 2-13 The "Swiss cheese" accident causation model (Reason, 2000)

Reason's work inspired the development of 'Tripod Beta' (Stitching Tripod Foundation, 2015) and 'Bowtie' (de Ruijter & Guldenmund, 2016). Shell International Exploration and Production BV developed the 'Tripod Beta' model as the result of Shell-funded academic research with the involvement of three universities: Universiteit Leiden, Victoria University and the University of Manchester. The technique, widely used today in the industry for incident analysis and investigation, has been thought to support the investigation team in finding answers to what happened, how it happened, and why. The process comprises three steps:

1. The first step aims to find the logical sequence of events, according to the Tripod theory, where an incident is an "event or a chain of events which cause or could have caused injury, illness, harm or damage (loss)" (Stitching Tripod Foundation, 2015, p. 17).
2. The second step aims to seek which barriers did not stop the incident sequence.
3. The third and last step aims to identify the causes of that failure by placing the causation path.

The 'Tripod causation path' is a sequence of three elements: (i) 'Underlying causes' that identify the 'latent failures'; (ii) 'Preconditions', namely the organisational and environmental factors influencing the human behaviour in the incident; and (iii) 'Immediate causes' that identify the 'active failures'.

Similar to the 'Tripod beta' is the 'Bowtie'. The origin of the model is unclear. The first appearance occurred at the University of Queensland in Australia in the course lecture on Hazard Analysis of Imperial Chemical Industry, and it was later applied by Shell Group as an accident analysis method after the Piper Alpha accident that happened in 1988 at the oil platform in the North Sea (Fu et al., 2020). The 'Bowtie' model combines multiple events leading to an undesirable state or hazard condition, termed 'Top event', which could evolve into a possible range of combined failure modes with relative consequences. Like a bowtie form, the graphical shape has multiple potential risk scenarios. The model depicts the connection between a hazard as a central event, its threats, and its consequences, creating a conceptual separation between a proactive and reactive part of a risk scenario. The left-hand side describes the events potentially leading toward the central event or hazard condition. The right-hand side of the model represents the combination of the consequences after triggering the central event or the hazard condition. Between these elements are set out barriers acting as layers of defence either on the left or the right-hand side. The left barriers function to prevent and control the hazardous conditions triggering when a threat occurs, while the right-side barriers function to recover from consequences when the hazardous situation occurs. The model is widely used in many industry sectors to evaluate and support risk assessment more than investigation analysis.

After World War II, nationalising the industry in Britain and technological innovation prompted the UK government to research new approaches, leading to increased productivity. The Tavistock Institute of Human Relations was engaged in a large project to disseminate new social techniques developed in the industry. Trist and Bamforth investigated this matter in the coal mining industry as part of this project. Their study assessed that combining production technology with a social work system was necessary to achieve optimum productivity. Their experiments showed that adopting a more effective production method did not improve production if social relations were affected. This theory originated from 'Socio-Technical Systems', also named the 'Tavistock approach' (Trist & Bamforth, 1951).

Based on this concept, some models were developed to support the analysis of organisational accidents, defined by Reason as "events that occur within complex modern technologies…. have multiple causes involving many people operating at different levels of their respective companies" (Reason, 1997, p. 1).

As part of his research to study a new risk management strategy in STS organisations, Rasmussen proposed the 'AcciMap model' (1997). He argued that an accident resulted from a sequence of events in which individuals' acts, decisions, and errors triggered the "loss of control of a physical process capable of injuring people or damaging property"

(Rasmussen, 1997, p. 184). Rasmussen designed the causal model mirroring his socio-technical system framework involved in risk management through six hierarchical levels ranging from legislators at the top, organisations and operations management, to system operators at the bottom. The analysis process starts from the bottom level and goes up by identifying the behavioural flow among the systems depicted by the same groups (Figure 2-14).

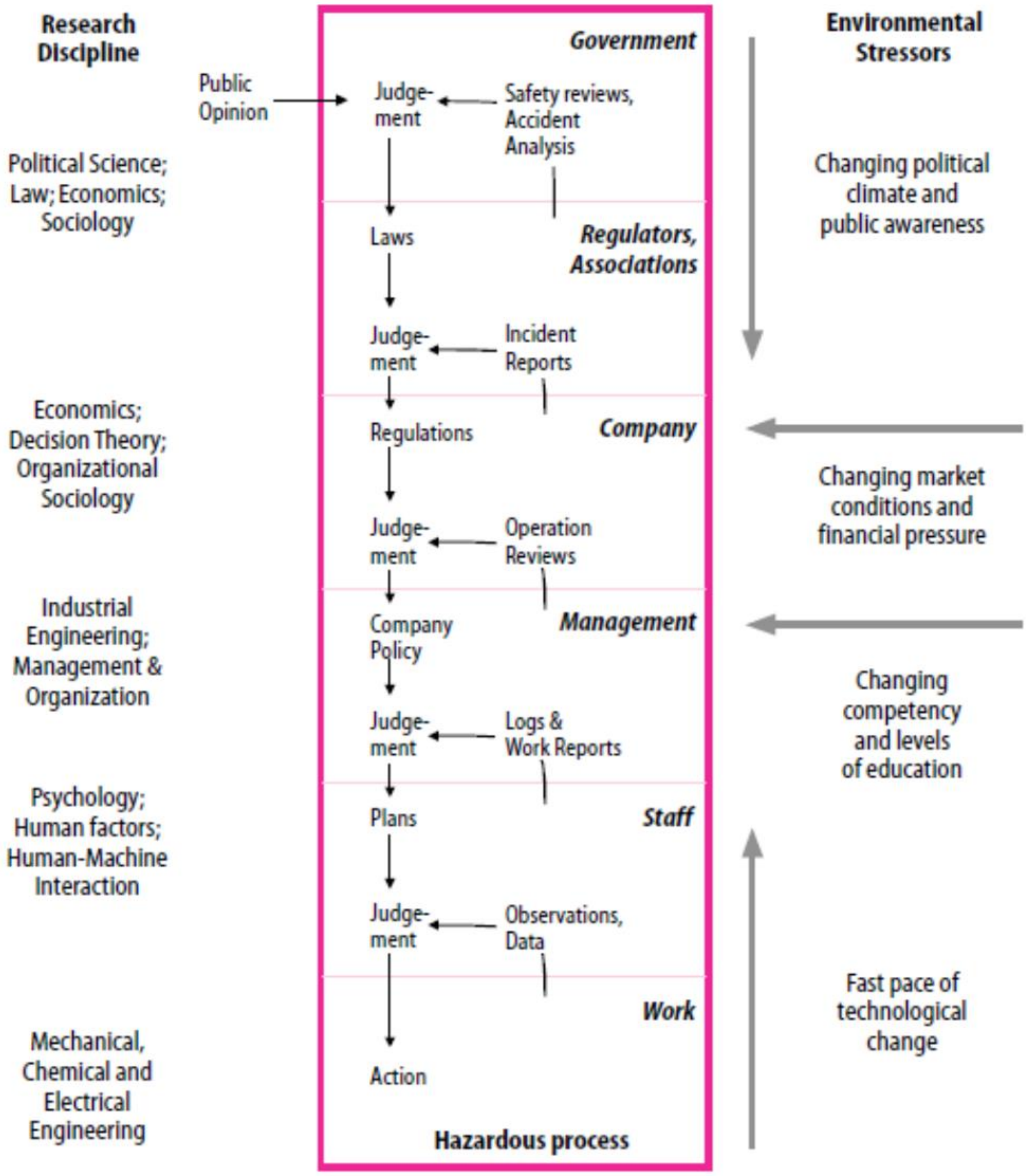


Figure 2-14 The 'AcciMap model' (Rasmussen, 1997)

The lack of guidelines did not allow a standardised approach to the model and its utilisation among the users. However, the model was adopted to analyse several accidents (Branford, 2011). Figure 2-15 shows the accident analysis carried out through AcciMap of Esso's Gas Plant Explosion at Longford in Australia in 1998 (Hopkins, 2001) when the release of about ten metric tons of hydrocarbon vapours caused an explosion with the loss of two people and eight injured. The investigation ascertained that the accident originated from a fracture of one heat exchanger due to a thermal shock. The inoperativeness of a pump supplying heated lean oil for four hours cooled down the heat exchanger, favouring ice formation. When the standard operations restarted, the pumping of heat oil led to a stress condition due to the temperature difference until the temperature difference broke.

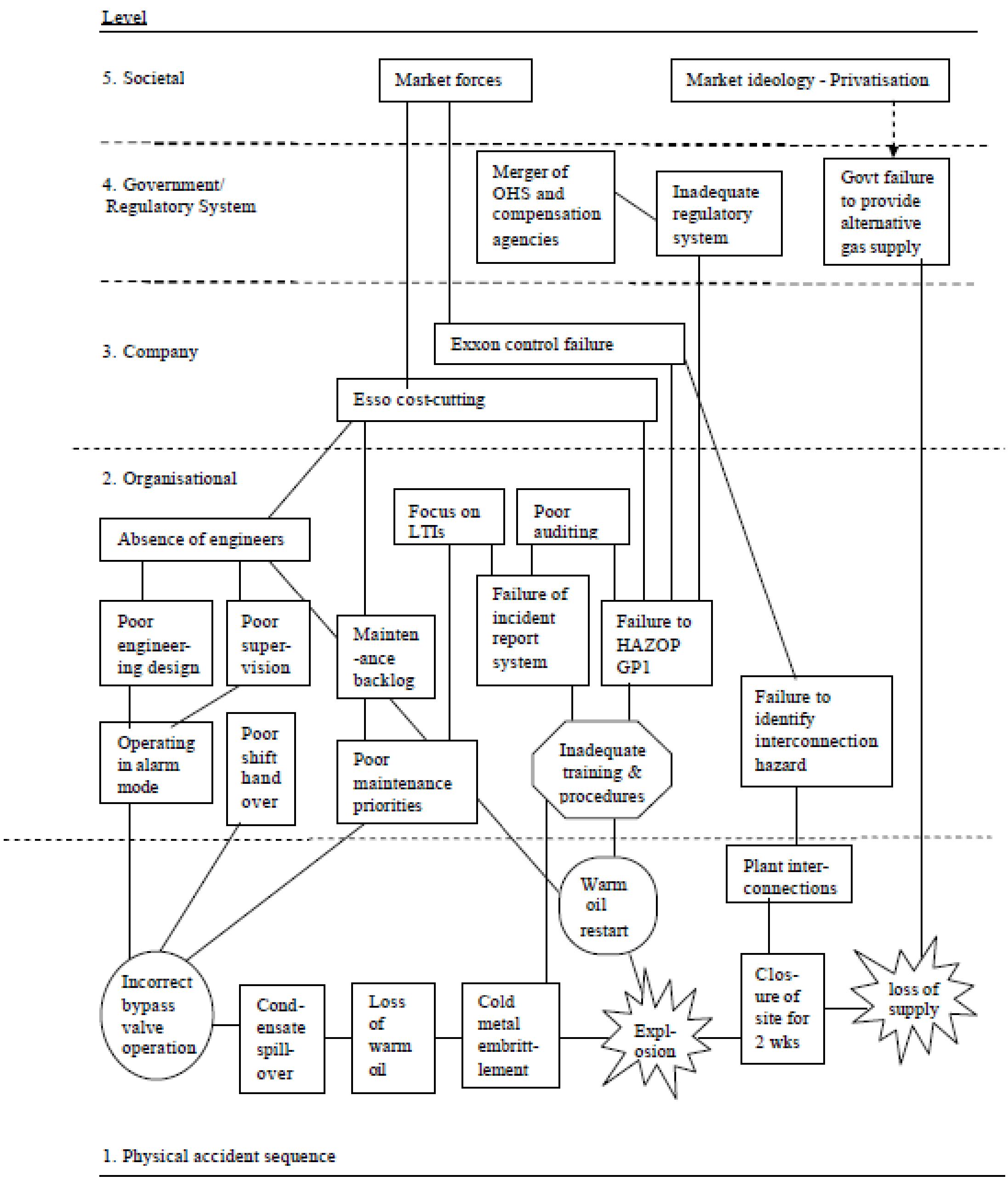


Figure 2-15 AcciMap of Esso Gas Plant Accident (Hopkins, 2001)

Rasmussen's work (1997) represents the STS framework in hierarchical levels, and the triggering analysis among the levels as a critical system part gave origin to subsequent models. For example, in the STAMP model (Leveson, 2004), Levenson assumed that loss events result from component failures, external disturbances, interactions among system components, and individual system components' behaviour. Moreover, when controls and constraints among the parts fail to avoid safety events, accident prevention activity should reinforce those controls and conditions on the system's development, design, and operation.

Levenson designed her model, splitting it into two hierarchical systems: development and operations. Each level imposes constraints on the activity of the level below. At the same time, control processes operate between levels to control the functions at lower levels in the hierarchy. The 'communication channels' allow the delivery of information about safety constraints on the level below (downward arrow) and receive feedback from the level down about the effectiveness of the limitations (upward arrow). An example of a typical socio-technical hierarchical safety control structure standard in a regulated, safety-critical industry in the United States, such as air transportation, is shown in Figure 2-16.

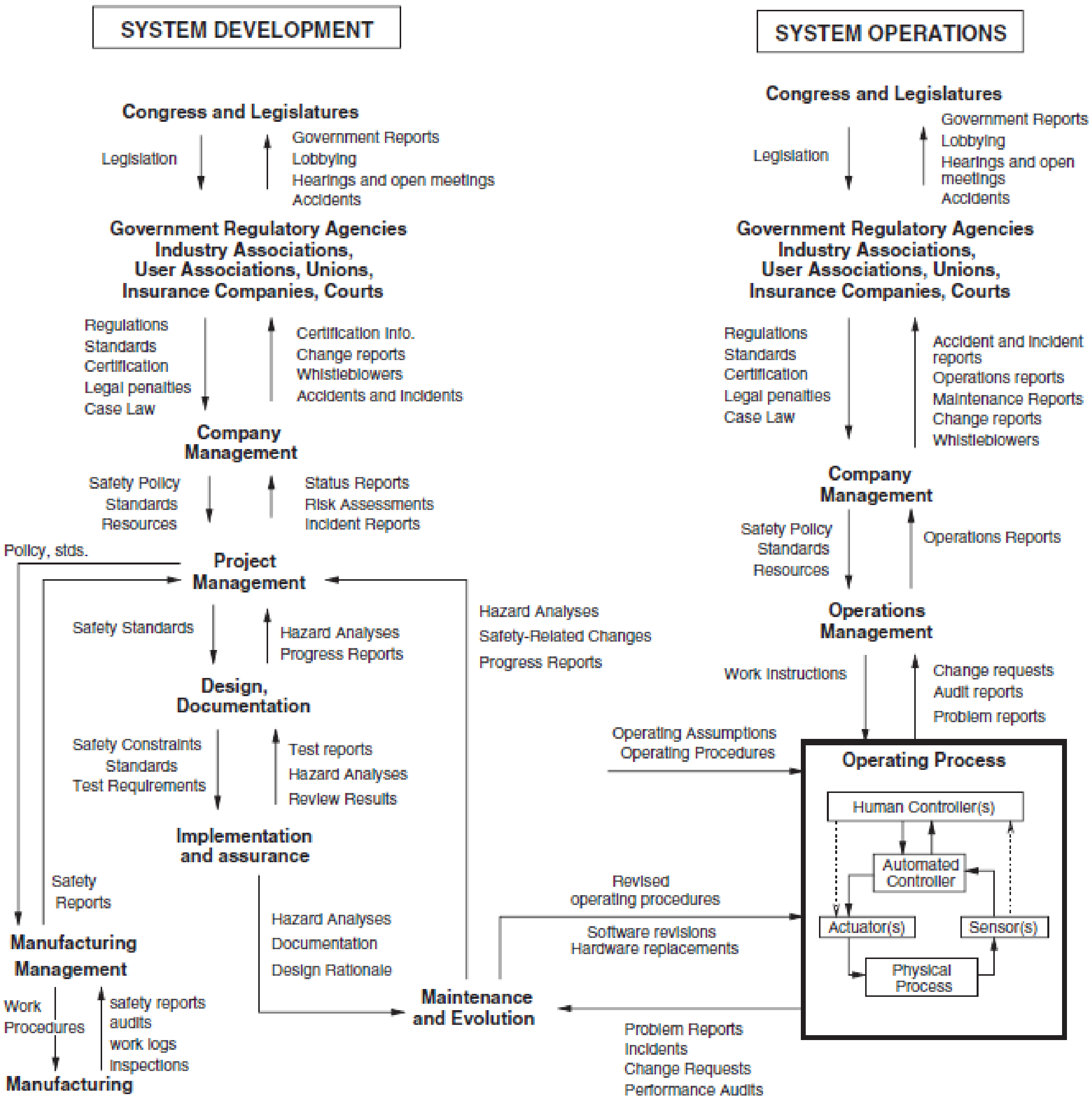


Figure 2-16 General form of a model of socio-technical control (Leveson, 2004)

The dynamic process of modelling and achieving goals across a complex socio-technical system, as a factor influencing the occurrence of an accident, was the theory advanced by Venkatasubramanian and Zhang in their model called TeCSMART ('Teleo-Centric System Model for Analysing Risk and Threats' (2016).

The name turns around the term 'Teleo' originating from the Greek word Telos (Ţέλος), meaning goal or purpose. Venkatasubramanian and Zhang argued that actions and decisions, taken up by different agents as individuals and groups at every level of a hierarchical socio-technical system, are influenced by achieving these goals.

In a complex framework made by interconnectedness and interactions with humans and the environment, the tolerance for taking more risks and keeping unethical behaviour amplifies the consequences. Hazardous situations like violations and market manipulations made these system-of-systems potentially fragile and susceptible to systemic failures (Figure 2-17).

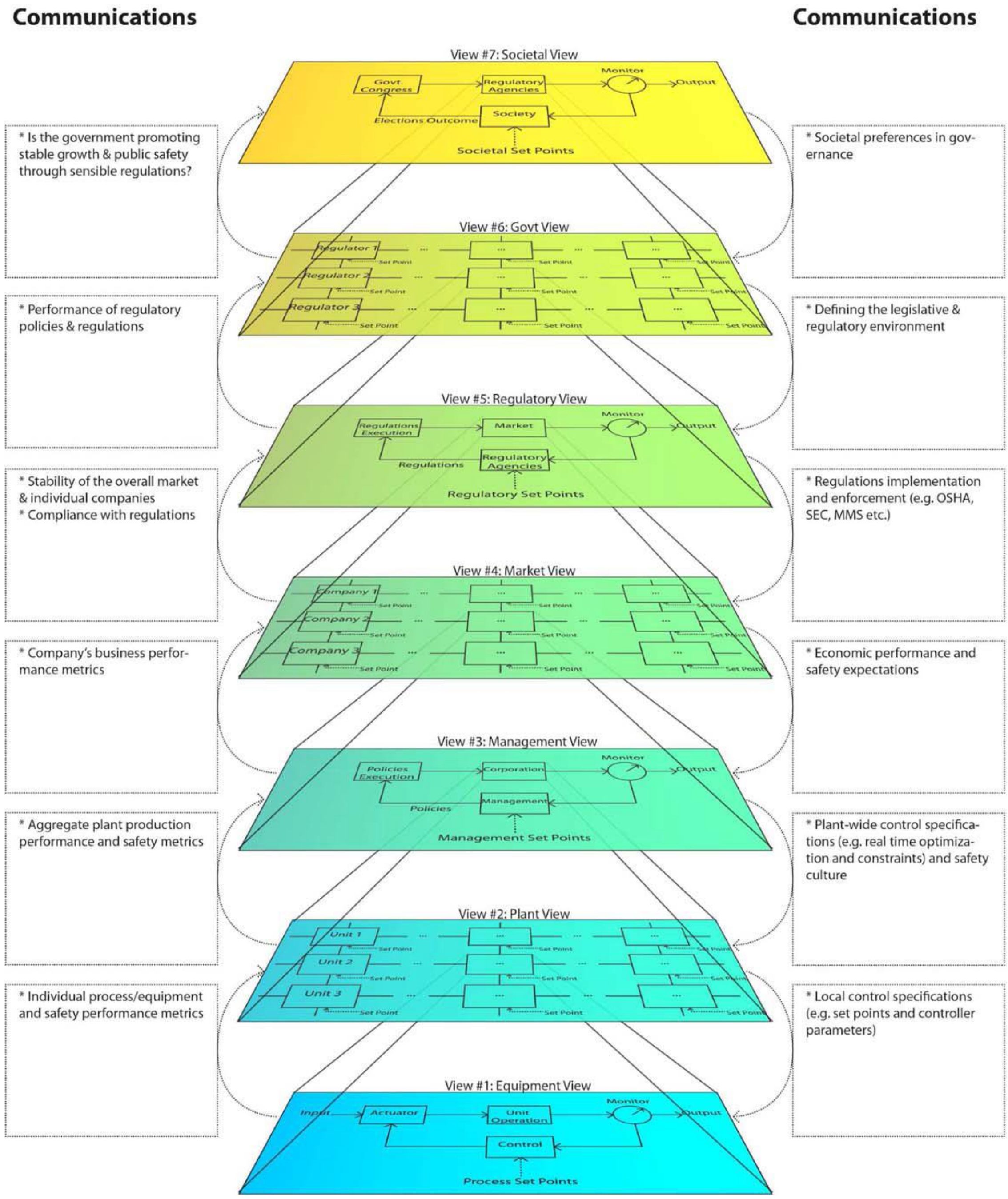


Figure 2-17 TeCSMART framework (Venkatasubramanian & Zhang, 2016)

A real example of those assumptions is represented by the findings from the analysis of two fatal crashes between October 2018 and March 2019 at Lion Air Flight 610 and Ethiopian Airlines Flight 302, involving two Boeing 737 MAX series aircraft, a total of 346 people died. The House Committee on Transportation and Infrastructure's final report, apart from findings linked to the Maneuvering Characteristics Augmentation System (MCAS) software, detailed how "tremendous financial pressure" was on Boeing and the 737 MAX program to compete with its European counterpart, Airbus. The production pressure undermined the entire system from design to certification.

"Boeing's design and development of the 737 MAX was marred by technical design failures, lack of transparency with both regulators and customers and efforts to downplay or disregard concerns about the operation of the aircraft" (The House Committee on Transportation & Infrastructure, 2020, p. 32).

In the middle of the last century, despite the development of technology, the effects on the control of systemic risks were negligible. Human actions remained a significant source of vulnerability to the integrity of interactive systems in any field, so much so that the studies moved to reduce the human component to risk. The goal to identify, predict, and mitigate human error led to the design of many models for assessing human reliability. A literature search by Bell and Holroyd (2009) classified the methods as first-generation, second-generation, and third-generation.

The first generation of HRA is primarily based on evaluating the human error probability (HEP), considering the potential impact of modifying factors such as time pressure, equipment design, and stress. The second generation of HRA developed in response to the first generation's criticism for failing to consider other elements, such as the impact of context, organisational factors, and errors in commission. The third generation includes the latest human reliability analysis approach to emphasise quantification and prediction.

Before the 2000s, Hollnagel proposed CREAM (Cognitive Reliability and Error Analysis Method) (1998), which is recognised as one of the unique second-generation tools. Hollnagel describes CREAM as fully bidirectional because the principles can be applied for retrospective analysis and performance prediction. The model is based on a fundamental distinction between competence and control. A classification scheme separates genotypes (causes) and phenotypes (manifestations) and proposes a non-hierarchical organisation of categories linked using the sub-categories called antecedents and consequents.

After realising that the inspiring principles needed review, Hollnagel proposed a new method called FRAM (Functional Resonance Analysis Method) (2012; 2017). The change originated from the assumption that, in a socio-technical context, it did not make sense anymore to understand error problems focusing only on the human component. It was necessary to extend the study to the conditions affecting the performance variability where performance means to be a sequence of actions.

The model is a qualitative method conceived to work either retrospectively or prospectively. It supports the accident or incident investigation or assesses potential risks. The design was created around four basic principles to describe the process of doing something: (i) the 'Equivalence of successes and failures; (ii) the 'Approximate adjustments'; (iii) 'Emergence'; and (iv) 'Functional resonance'. The analysis process clearly distinguishes the difference between 'function' or 'activity' and 'task'. While in literature, they are considered synonyms and interchangeable, 'function' or 'activity' refer to the means necessary to achieve a goal or produce a specific outcome, differently from 'task', which refers to the actions as designed. In other words, 'functions' or 'activity' are related to the condition Work-As-Done (WAD) and 'task' to the Work-As-Imaged (WAI).

Hollnagel argues that the difference between success and failure relies only on the type of outcome. Things go right or wrong in the same way, even if the general view considers them differently. If the consequences can be different, it does not mean that the underlying process must be different. In many socio-technical systems, work conditions never wholly match what is specified or prescribed. The Work-As-Done (WAD) always differs from the Work-As-Imagined (WAI). Therefore, individuals, groups, or organisations apply 'approximate adjustments' to adapt their performance to present conditions.

The variability of a standard performance rarely explains the cause of an accident. Unexpected and severe outcomes may result from combining the variability of multiple functions. Its prediction does not happen by analysing the individual part but by understanding the whole system and relationships. Hence, the term 'emergence', also known as 'emergent behaviour', identifies a system that depends not on its part but on its relationship.

The principle of 'Functional resonance explains the amplification of the severity level when this combination occurs'. 'Functional resonance' is the last step of a conceptual evolution that starts from knowing the physical phenomenon of resonance and passes through the concept of stochastic resonance applied to systems. Hollnagel defines 'Functional resonance' as "the detectable signal that emerges from the unintended interaction of the everyday variability of multiple signals" (Hollnagel, 2012; 2017).

The literature review uncovered that causal models serve as valuable tools for aiding experts in pinpointing the underlying causes and comprehending the interconnections among various system components that may have contributed to an undesirable event, whether an accident or an incident. The ultimate objective is to understand what happened, how it happened, and why it happened to identify suitable measures to prevent a recurrence of the same accident or incident. A review of the literature reveals that the development and intricacy of these models are closely intertwined with the complexity of the system and the evolution of safety thinking.

Accidents were defined as deviations from intended processes (Surry, 1969), a concept later elaborated upon by Hale and Hale (1970) and Wigglesworth (1972), who first introduced the role of random factors as contributing to deviations, later taken up by Lawrence (1974). This deviation, the gap between the designed and intended process for achieving an outcome and its actual execution, forms the foundation of the principle articulated by Hollnagel in his FRAM (Functional Resonance Analysis Method) (2012; 2017), which distinguishes between 'Work-as-Imaged' and 'Work-as-Done'. However, it is essential to note that a single factor alone is usually insufficient to justify an accident. Perrow (1984) and, later, Reason (1990) emphasised that accidents rarely stem from a single factor but result from a complex interplay of various elements. These elements may encompass human error, organisational influences, inadequate supervision, preconditions for unsafe actions, and the unsafe actions themselves, suggesting the complexity and diverse nature of the factors involved.

Any causal model's utilisation relies on individuals' expertise and subjective capability to apply the model correctly and in line with its fundamental principles. Consequently, all models inherently possess qualitative and reactive qualities, recognising that accidents are generally unpredictable. The research aims to demonstrate that an event becomes quantitatively predictable when the configuration of factors that converge at a specific space-time moment is understood. The intersection of the concepts of deviation from the intended process and the combination of these factors form the core elements of reconceptualising safety events.

2.3. History Review of Accident Causal Models in Aviation

In the early days of aviation, the approach was purely reactive. Safety concerns were mostly related to technical factors. Aviation pioneers had little safety regulation, practical experience, or engineering knowledge to drive them. The 'fly-fix-fly' methodology of Orville and Wilbur Wright worked to identify and remove unsafe mechanical or physical conditions to prevent a recurrence, generally addressed in mechanical development and state-of-the-art technology. The investigations focused on ascertaining the failure(s) that caused the accidents instead of identifying the system deficiencies that remained undetected or free to become the source of future accidents (Earnest, 1997).

The 20th IATA Technical Conference held in Istanbul in 1975 concluded its weekly work with the message on the importance of generating awareness of human factors in the aviation industry, "the wider nature of Human Factors and its application to aviation seem still to be relatively little appreciated. This neglect may cause inefficiency in operation or discomfort to the persons concerned; at worst, it may bring about a major disaster". The statement unlikely anticipated the Tenerife runway collision in 1977, where 583 people died. It gave back a lesson on how human factors played a crucial role in the accident and precisely how the interactions between humans and their environment were critical to safety.

The SHELL model was the first conceptual model of human factors designed for the aviation system to identify critical issues in the interaction between human beings and other components. The model was first developed by Elwyn Edwards in 1972 and later modified into a 'building block' structure by Frank Hawkins in 1984 (Kiss, 2005). Edward's version, SHEL, takes its name from the initial letters of its components: Software, Hardware, Environment and Liveware, referring to humans. Hawkins added one more L to emphasise the relationship between humans working with other humans (Figure 2-18).

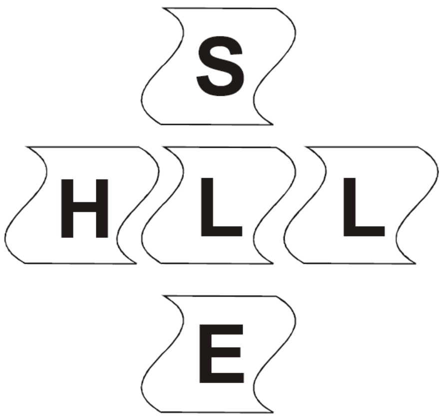


Figure 2-18 SHELL Model (ICAO, 2018)

In the 1990s, introducing organisational accidents changed aviation safety into a systemic perspective. The Swiss Cheese Model (Reason, 1990) and its evolution over 20 years contributed to developing causal models and aviation accident prevention. Starting from the theory that an accident is a sequence of organisational and human failures, improving the defensive layers through the investment of resources in error mitigation, either active or latent, is still a part of the principles underpinning proactive safety. The model is still widely cited today and is considered a paradigm in the aviation industry.

Wiegmann and Shappell developed their HFACS (Human Factors Analysis and Classification System) framework (Shappell & Wiegmann, 2000), drawing upon James Reason's work to identify a tool to assist in the Navy's aviation accident investigation process. The Human Factors Analysis and Classification System (HFACS) uses the same levels presented by Reason in his model. They added a taxonomy using over 300 Naval aviation accidents to release objective, standardised, data-driven analysis and intervention strategies. The investigation process suggested by the authors is to work backwards, in time, from the accident, beginning with the unsafe acts and going back to the organisational influences (Figure 2-19).

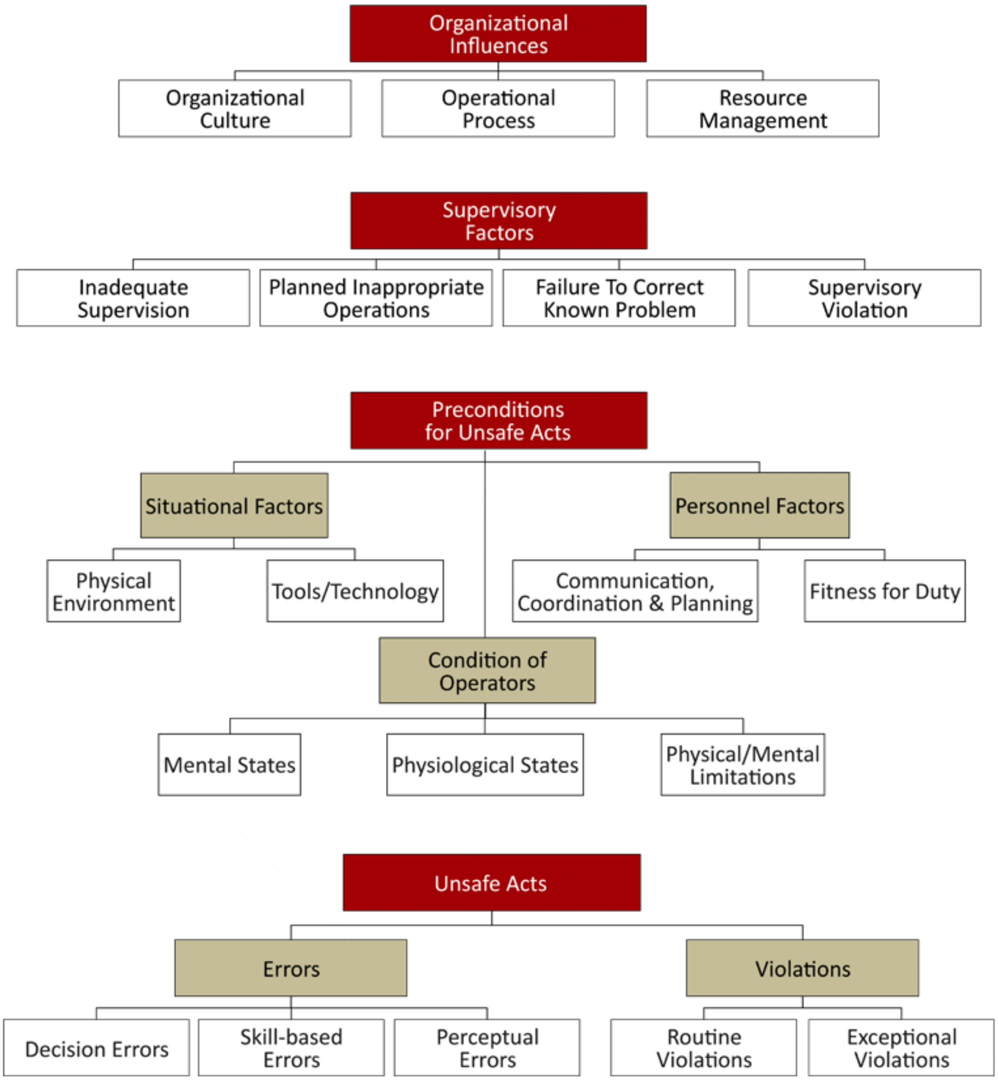


Figure 2-19 HFACS framework (HFACS Inc., 2014)

One of the most popular and well-known methods used in aviation is the same strategy adopted by HFACS in the investigation process. Root Cause Analysis (RCA) is a systematic process for identifying the root causes of faults or problems. It comprises four steps:

1. the identification and description of the problem,
2. the drawing of a timeline from the usual situation up to the time the problem occurred,
3. the distinction between the root cause and other causal factors (e.g., using event correlation), and
4. establish a causal graph between the root cause and the problem.

RCA generally serves as input to identify critical issues and corrective measures to avoid reoccurring problems. The name of this method varies from one application domain to another. According to ISO/IEC 31010 (Risk management – Risk assessment techniques), RCA may include the following techniques: Five whys, Failure Mode and Effects Analysis (FMEA), Fault Tree Analysis (FTA), Ishikawa diagram and Pareto analysis.

The principles advanced in RCA are part of the occurrence classification in aviation. Today, Regulation (EU.) No 376/2014 (EASA, 2014) regulates the reporting, analysis, and follow-up of occurrences in civil aviation. It methodologically begins with the identification of the events within an occurrence.

Occurrence and event seem to have a similar meaning, but they are distinct concepts. The Regulation (EU) 376/2014 defines occurrence as "any safety-related event which endangers or, if not corrected or addressed, could endanger an aircraft, its occupants or any other person and includes, in particular, an accident or serious accident incident".

The definition of an event is still discussed today. Cacciabue defines it as a "change of state of the system", whereas a human event is "the execution of an action leading to the change of state of the system" (2010, p. 123). Therefore, the occurrence reports the fact in its entirety with cause and effect(s) and event(s) part of this logical structure.

The decomposition of an occurrence is graphically depicted with a timeline from the root cause until the last event occurred. This temporal sequence is called Event Time Line (ETL). Cacciabue distinguishes the events as negative and positive. A 'negative event' represents the system's failure, whereas a 'positive event' is the barrier that stops the accident trajectory. In other words, this difference brings back to the concepts 'things go wrong' and 'things go right', later reflected in the views of Safety-I and Safety-II (Hollnagel et al., 2015).

Occurrence reports are classified using the ADREP taxonomy to facilitate information exchange across the EU Member States. The Accident/Incident Data Reporting (ADREP) taxonomy, operated and maintained by ICAO, is a compilation of attributes and the corresponding values that allow data standardisation across Europe to enhance the detection of actual or potential hazards.

The literature review reveals the role of the development of causal models as a measure of system complexity growth in the aviation industry. However, current regulations regarding the management of safety occurrences, especially the database containing them, require a linear approach to their classification. The approach is purely conventional because, in the history of aviation, not all incidents have followed a linear trajectory where the chain of events could be applied. It is cited, for example, the incident involving a Beechcraft 1900D in 2003. The Final Report concluded its investigation that "the probable cause of this accident was the airplane’s loss of pitch control during takeoff. The loss of pitch control resulted from the incorrect rigging of the elevator control system compounded by the airplane’s aft center of gravity, which was substantially aft of the certified aft limit" (NTSB, 2004, p. 131). The term ‘compounded’ was used to ensure linearity. Upon a more thorough examination of the report, it becomes evident that the accident resulted from two separate and unrelated events, each of which, on its own, might not have caused the accident.

The definition of an event is still discussed today. Cacciabue defines it as a "change of state of the system", where a human event is "the execution of an action leading to the change of state of the system" (2010, p. 123), highlighting the role of deviation from the planned process. The distinction between positive and negative events defines the scenario by differentiating between what caused the deviation from the effective barrier, enabling the interruption of the chain of events leading to a potential accident. This concept can be applied to Safety I and II's philosophical contrast. In Safety-I, accidents are perceived as deviations from the norm, and the objective is to minimize these deviations as much as possible. In Safety II, systems continuously adjust and adapt to changing conditions, acknowledging that humans are not only sources of error but also of adaptation and resilience (Hollnagel et al., 2015).

2.4. History Review of Management Systems

The pandemic has slowed the growth of management systems in many industrial sectors, impacting sustainable production and operations management. Therefore, today, more than before, it is crucial to keep working to improve safety performances and lessen the incident and accident rates to mitigate the risk of fatal accidents with a consequent increase in fatalities.

History teaches us that an accident or catastrophic event, in some way, causes not only financial loss but also reputation damage. The costs arising from those events, both direct and indirect, are often unsustainable and, in some cases, have irreversible effects. Therefore, organisations need to improve their SMS and especially their risk management in an integrated management approach that encompasses all business risks, including safety, commercial, quality of service, and environmental impact, to implement sustainability strategies. The aviation system comprises many functional systems such as operations, finance, environment, safety, and security, and it involves many personnel in other functions. In an operational scenario, all the functional systems produce some risk that must be appropriately managed to reduce the probability of any unsafe event. Then, one of the strategy points is to build up integrated risk-based management that encompasses all business risks, including safety, commercial, quality of service, and environmental impact, to implement and develop sustainable business strategies (ICAO, 2018).

Even if sustainability is commonly linked with economics, when an organisation becomes unsustainable, the primary symptom is the finances; a sustainable organisation creates profit for its shareholders while protecting the environment and improving the lives of those with whom it interacts. An organisation must maintain profitability to stay in business by balancing output with acceptable or practicable safety risks, including the costs involved in implementing safeguards or risk controls. The need to balance profitability and safety, also called production and protection, is a requirement by any organisation that delivers services, even if their relationship is complex and has not been adequately addressed by current theories regarding organisational accidents (Goh et al., 2012).

The Safety Management System (SMS) was conceived by combining risk concepts and safety defences to contrast organisational incidents or accidents. It progressed over the years based on developing the thinking process of its elements, safety, management and system. The SMS split out into two distinct evolutions: accident-related and organisational models. The first, illustrated previously, was explicitly founded on accident understanding and prevention with the insertion of barriers; the second drove the organisational aspects of controlling risks by implementing barriers (Li & Guldenmund, 2018).

The term barrier initially came from Haddon's ten strategies (Haddon Jr, 1995), later retrieved by Reason in his 'Defence in-depth' concept. Haddon extended the energy-based accident models by inserting countermeasures to reduce human and economic losses, focusing on eliminating, controlling, modifying and mitigating energy and its effects. The goal of the barriers aims to reduce the likelihood of escalation from a hazard, prevent accidents or incidents, and protect against unwanted threats. They are broadly categorised as hardware, physical, and behavioural or soft when they involve human action.

While the semantic meaning of the term safety is clear, the semantic issues of management and systems have broad and complex objectives that deal with several topics in various fields. Apart from the numerous definitions from the literature and discussions on the subject, the management principles are described around the four primary functions using POLC, which stands for planning, organising, leading, and controlling (Gordon et al., 2009). Meanwhile, a system refers to collecting processes to transform input into output.

Over the years, the definitions have followed each other and are tailored to the industrial fields they referred to describe its application best. Table 2-2 summarises the historical sequence of SMS definitions, linking definitions to industry fields (Li & Guldenmund, 2018).

Table 2-2 SMS definitions (Li & Guldenmund, 2018)

Author(s)	Industry	Definition
Kysor, 1973		A Safety Management System (SMS) can be defined as a planned, documented safety program that incorporates certain basic management concepts and activating elements into a well-organised safety system. The safety activity areas and supporting details that comprise this system act and interact with one another to help achieve the desired safety level or risk level. A total safety management system consists of objects: parameters such as input, process, output, and feedback control; attributes: properties of parameters such as the external manifestation of how an object is known, observed, or introduced in a process; relationships: bonds that link objects and attributes in the system process.
Carrier, 1993	Offshore	ADCQ's Safety Management System (SMS) covers a broad band of safety activities and provides positive management control.

Waring, 1996	General	Functionalist/engineering world view: a set of documented procedures or people using such a set of guidelines.
		Interpretive world view: a human activity system including control monitoring communication, operational and other elements, and complex human factors.
IAEA, 1999	Nuclear	The safety management system comprises those arrangements made by the organisation to promote a strong safety culture and achieve good safety performance.
Mitchison and Papadakis, 1999	Legislation (directive)	A Safety Management System (SMS) is defined in the Directive (Seveso II) as including 'the organisational structure, responsibilities, practices, procedures, processes and resources for determining and implementing the major-accident prevention policy', in other words, the system for implementing safety management.
Edwards, 1999; Hsu et al., 2010	Aviation	A safety management system is no more than a systematic and explicit approach to managing safety – just as a quality management system is a systematic and detailed approach to improving the quality of a product to meet the customer's requirement.
DOE	Energy	Safety Management Systems provide a formal, organised process whereby people plan, perform, assess, and improve the safe conduct of work. The Safety Management System is institutionalised through Department of Energy (DOE) directives and contracts to establish the Department-wide safety management objective, guiding principles, and functions.
Ivan et al., 2003	Transport	A highway Safety Management System (SMS) is a systematic process designed to assist decision-makers in selecting effective strategies to improve the efficiency and safety of the transportation system.

The primary purpose of the SMS is to manage and control risks and, by doing this, to prevent accidents and injuries. Hence, the core element of any SMS is the risk management process. The process, with activities and how they are linked and structured, is depicted in several ways. The steps can be from four to six, but in any case, the process starts with hazard identification and is followed by risk assessment. Hazard and risk are often confused. A hazard refers to a fact or situation leading to damage or loss. At the same time, risk is a measure assessing the likelihood that a hazard condition can lead to an undesired outcome. The strategy to reduce the risk value as low as reasonably or practicably achievable depends on implementing preventive or recovery barriers. In any case, a residual risk must be taken into account. Accepting residual risks is a prerogative task at the organisation's executive management level within the decision-making process. These steps into a circular workflow ensure continuous improvement, making the process more mature at the end of each lap.

In ISO 31000, "the risk management process involves the systematic application of policies, procedures and practices to communicating and consulting, establishing the context and assessing, treating, monitoring, reviewing, recording and reporting risk". The process is illustrated in Figures 2-20 (ISO, 2018).

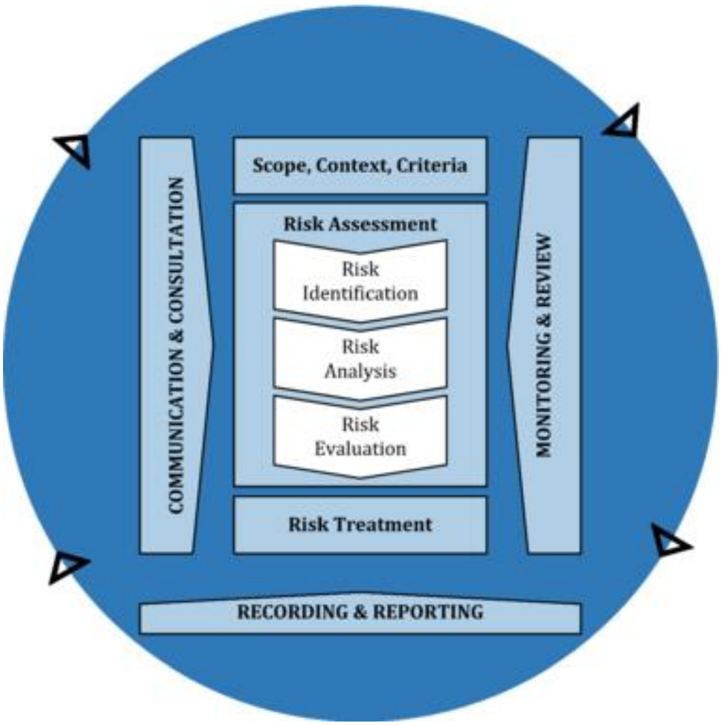


Figure 2-20 Risk management process of ISO 31000 (ISO, 2018)

Events, barriers, and management are the elements that a complete safety management model should contain (Li & Guldenmund, 2018). Accident models and theories aim to create a risk inventory based on identifying hazards or threats, accident prevention comes from implementing barriers based on the risk analysis of events, and safety performance assesses the Management efforts and barrier effectiveness (Figure 2-21).

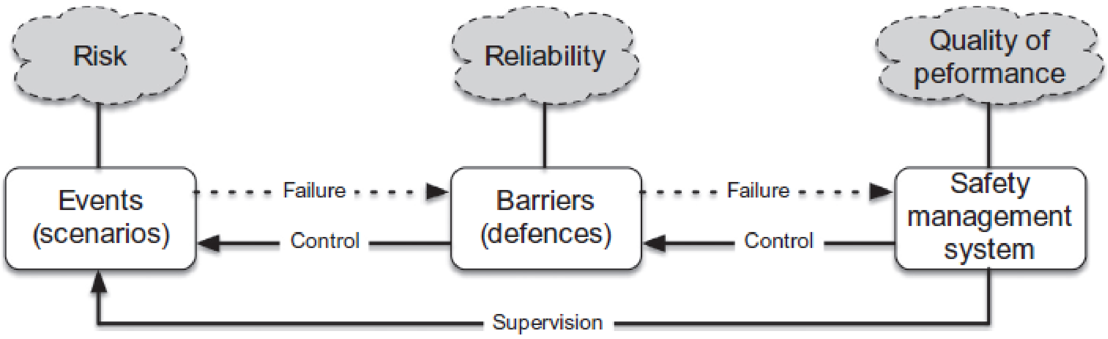


Figure 2-20 The relation between Scenarios, Barriers and SMS (Li & Guldenmund, 2018)

Safety performance monitoring and measurement is a branch of the SMS framework consisting of processes and activities undertaken by organisations to determine whether the SMS is operating according to expectations and requirements. The performance management process involves identifying one or more indicators that measure the assessment of the continued effectiveness of implemented control strategies and support the identification of new hazards. Kaplan and Norton introduced the Balanced Scorecard in the early 1990s as a strategic management tool (Kaplan & Norton, 1992). The Balanced Scorecard emphasises the use of both financial and non-financial measures to evaluate organisational performance. In this framework, leading indicators are used to predict future performance, while lagging indicators provide feedback on past performance. The British Petroleum (BP) US Refineries Independent Safety Review Panel report, also called Baker's report in 2007, linked the concept of leading and lagging indicators to measuring Active and Reactive Monitoring (Hopkins, 2009). Today, the relationship between leading and lagging refers to giving a metric to those situations, predicting a future event differently by measuring what has already happened. In other words, the distinction between precursors and their outcomes.

The legislation developed last decade aimed to publish specific standards and guidelines across the different industrial sectors. Although the criteria could be applied to other industries, an SMS still involves compliance with particular industry safety laws and regulations. Figure 2-21 shows a partial summary of the standard for general SMS.

Organisation	Industrial sector	Name/year	Aim for
ISO	General	ISO 45001/Under development	Occupational health and safety management systems
	General	ISO 9000 serise/1987, 2008, 2015	Quality management systems
	General	ISO 14001/1992, 1995, 1996, 2004, 2015	Environmental management systems
	General	ISO 31000/2009	Risk management
EU (European union)	Chemical industry (also other industries)	Seveso Directive (Directive 82/501/EEC)/1982 Seveso II (Directive 96/82/EC)/1996 Seveso III (Directive 2012/18/EU)/2012	Control of major-accident hazards involving dangerous substances
	General	(Directive 89/391/EEC)/1996	Guidance on risk assessment at work
BS (BSI Group, British Standard)	General	BS 5750/1979	Quality management systems
	General	BS 7750/1994	Specification for environmental management systems
	General	BS 8800/1996, 2004	Occupational health and safety management systems
	General	BS OHSAS 18001/2007	Occupational safety and health management systems
OHSA (United States)	General	PART 1910 (Standards–29CFR)/since 2001	Occupational safety and health standards

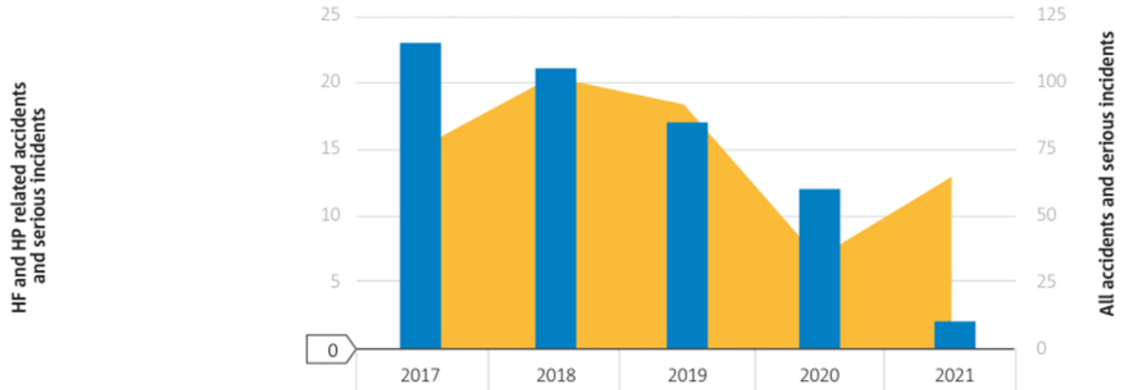
Figure 2-21 Standards for general SMS (Li & Guldenmund, 2018)

The Safety Management System has defined a systematic and proactive approach to safety management in aviation, including necessary organisational structures, accountability, responsibilities, policies, and procedures (ICAO, 2016). The management system is depicted as an ancient temple supported by four pillars representing the main components: (i) safety policy and objectives, (ii) safety risk management, (iii) safety assurance, and (iv) safety promotion.

The SMS implementation is a gradual process that takes time to mature fully, requiring constant updating to adapt it to changes and collaboration among the entire system. For example, in aviation, deploying the various elements of SMS took a decade and fostered collaboration among legislators, authorities and stakeholders. The entry of force of regulations made the SMS application mandatory, and today, most certified organisations have them adequately in place.

However, the system is looking for new solutions to enhance safety and operational efficiency. Amalberti (2001; 2017) argued that when a system reaches safety excellence, the risk is to release awareness and search for weaknesses before leading to safety breakdowns. The safer the system, the smaller the window of opportunity to change, making safety excellence a threat instead of a paramount issue. This vision could suggest that the present means for safety risk analysis and assessment might be inadequate or "limited" to tackle such a limited window of safety opportunities in ultra-safe systems (Amalberti, 2001; 2017). New modern and advanced methods could enhance the situation. The Regulatory Bodies are also asking how to improve their SMS and, consequently, their risk management. The worldwide implementation of an SMS by aviation stakeholders shows a change from the traditional reactive and compliance-based oversight to new evidence-based and data-based models, including more proactive and performance-based tools and methods. Therefore, in the context of distributed authority, a parallel need for National Aviation Authorities (NAAs) is introduced to perform their safety oversight functions similarly, accepting a performance-based approach as the upcoming challenge in implementing advanced safety oversight systems (ICAO, 2016). Such directions fit in with new AI developments based on predictive and prescriptive models of risk analysis.

Although, and fortunately, accidents are increasingly rare, they seem not to represent a source of learning anymore. However, Figure 2-22 for the 5-years (2017-2021) on Commercial Air Transport large aeroplane accident and serious incident reports identify human factors (HF) or human performance (HP) as a significant component of the causes of accidents and serious incidents (EASA, 2022).



	2017	2018	2019	2020	2021
Accidents and serious incidents	76	102	92	34	64
HF/HP accidents and serious incidents	23	21	17	12	2

Figure 2-22 Human Factors and Human Performance accidents and serious incidents involving Commercial Air Transport airline and air-taxi aeroplanes (EASA, 2022)

Consequently, reducing operational risks requires a new approach, shifting the focus to predictive and data-driven assessments and analysis. The goal is to have the capacity to capture those early and weak signals that represent the precursors to predict organisational and operational safety issues, supporting the decision-making process to improve personnel training and awareness rather than technology and regulatory harmonisation. A well-projected, resilient, or robust system resists catastrophic events but remains the same until we cannot reduce the system's fragile conditions. It is more efficient to predict the occurrence of an event that may harm it (Aven, 2016).

Organisations have included the implementation of effective Safety Management Systems (SMS) as the latest initiative in the realm of safety and risk management. In the aviation industry, SMS implementation is not considered a best practice; it is a mandatory requirement by regulation with the primary objective to comprehensively address all aspects necessary to meet these prescribed regulatory obligations and assess its effectiveness concerning the desired outcome.

The Safety Management System is an organisational model for managing hazards and associated risks. It is also defined as a systematic and proactive approach to risk management in safety. It consists of four pillars representing the fundamental elements of the system, ranging from organisational structures, policies, processes, and procedures to risk management activities involving verifying the effectiveness of mitigation actions and identifying new hazards. Lastly, it encompasses activities necessary to ensure the maintenance of personnel skills and the sharing of safety-related information both within the organisation and with stakeholders.

In this context, processes play a pivotal role as they ensure the standardisation of activities at the organisational level, thereby enhancing the effectiveness and efficiency of process-related activities. The conceptual map, drawn and developed with the use of the IBM® SPSS® Modeler Text Analytics tool to study the relationships between the SMS concept and ideas embedded in the historical sequence of SMS definitions (Table 2-2), empirically suggests the importance of this aspect in maintaining an effective system towards to the best practice (Appendix 1).

2.5. State-of-the-Art of AI-based Applications in Industry

2.5.1. Introduction

The rapid advancement of Artificial Intelligence (AI) and Machine Learning (ML) in the last decade sparked concerns about the potential impact on several areas. These concerns include the university research on the role of AI and ML as enablers of new methods, processes, management, and evaluation in research (Chubb et al., 2022).

AI is a technology set that enables innovative and intelligent machines to perform various advanced functions and approaches to solve data-in-data-out problems. An interdisciplinary science that Stanford University computer scientist John McCarthy defines as "the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable" (2007, p. 2).

The concept of ‘waves’ or ‘generations’ in the evolution of AI is a framework proposed by various scholars and researchers in the field, and no single person or entity can be credited with setting the wave model. According to McCarthy, the first wave of AI involved rule-based systems and symbolic reasoning. The second wave focused on statistical methods and machine learning, and the third wave should involve the development of systems that can reason and learn more like humans, using approaches such as deep learning and natural language processing.

However, other researchers have proposed different wave models, and there is ongoing debate and discussion about the validity and usefulness of such models (The BIM Engineers, 2023). Some argue that the wave model oversimplifies the complexity of AI research and development and that AI progress is more gradual and incremental than characterised by discrete waves. Overall, the wave model is one of several frameworks that have been proposed to help understand the evolution of AI and its potential future directions.

Today, we are in the second wave and entering the third. The second wave of AI, also known as ‘Machine Learning’ or ‘Statistical Learning’, is characterised by development algorithms and techniques that enable machines to learn from data and improve their performance over time without being explicitly programmed. Key characteristics of second-wave AI include:

1. Data-driven: Machine learning algorithms rely on large amounts of data to learn and improve their performance.
2. Empirical: Machine learning is based on learning from examples and patterns in data rather than explicitly programmed rules.
3. General purpose: Machine learning algorithms can be applied to several tasks and domains, from image recognition to natural language processing.
4. Black box: Some machine learning algorithms are difficult to interpret, meaning it can be challenging to understand how they arrived at a particular decision or prediction.

The continuous growth of data creation and access to large amounts of data has speeded up this technological progress with the development of cheaper and faster computers and the design of many data mining models that attempt to refine further the process of deriving quality data and optimise operations. The latest statistics reported that the total amount of data captured, managed, and processed has globally increased in the last decade, reaching 64.2 zettabytes in 2020 (Holste, 2021). The estimates for the coming years are growing strongly.

Data analytics has made sense of all this data. Extracting relevant and valuable information from collecting, cleaning, sorting and analysing raw data assists organisations in identifying patterns and generating insights using computer algorithms to make decisions, advance actions, and provide predictions with an accurate level of reliability. Moreover, these conditions allow the investigation of many problems throughout any economic, medical, industrial and primarily academic research field.

The third wave of AI, also known as 'Cognitive AI' or 'Deep Learning', builds upon the second wave but aims to develop machines that can reason, learn, and understand the world more like humans. Key characteristics of third-wave AI include:

1. Human-like reasoning: Cognitive AI aims to develop systems that simulate human thought, can reason, and make decisions more like humans, using neural networks and deep learning methods.
2. Multimodal: Cognitive AI aims to integrate multiple modes of perception, such as vision, hearing, and touch, to create an exhaustive understanding of the world.
3. Explainable: Cognitive AI aims to develop models and algorithms that humans can more easily interpret and understand, helping build trust and accountability.
4. Context-aware: Cognitive AI aims to develop machines that can understand and adapt to the context in which they operate, considering factors such as time, location, and user preferences.

The third wave of AI represents a shift towards more sophisticated and human-like forms of artificial intelligence, potentially enabling new applications and services in healthcare, education, and transportation.

2.5.2. Artificial Intelligence Approach in Industry

Artificial intelligence (AI) adoption in various industrial sectors has been characterised by growing interest and investment in AI technologies and competencies with different times, applications and objectives. AI is primarily used to automate tasks, improve decision-making, and develop new products and services. On the other hand, there are challenges associated with adopting AI in organisations, such as AI competency and readiness, data privacy and ethical concerns, liability and regulatory aspects. Most organisations lack processes to support AI management, a system of procedures and operations, and AI in management controls to support and favour an effective AI-implementing system.

As of 2023, AI adoption has reached 35% among companies, with notable implementation in industries such as financial services, healthcare, manufacturing and retail (Hostinger, 2024). These sectors leverage AI platforms and tools to streamline operations, enhance productivity, and innovate service and product offerings. Below are examples illustrating the diverse applications of AI across various industries:

1. Healthcare: AI is being used to improve the accuracy and efficiency of medical diagnoses, drug discovery, and patient care.
2. Manufacturing: AI is being used to optimise production processes, improve quality control, and reduce downtime.

3. Retail: AI is being used to personalise customer experiences, optimise supply chain management, and improve fraud detection.

The strategy employed to document the current state of Artificial Intelligence utilisation within identified industrial sectors primarily centred on the 'data-in-data-out' approach. The approach used by the researchers to extract risk patterns for analysing particular events, specifically on two elements: merging data into a unified database and generating risk patterns that could be readily interpreted. Explainable AI (XAI) represents a form of Artificial Intelligence with a core focus on developing methods and techniques that enhance the transparency and comprehensibility of AI models and solutions. Unlike the 'black box' approach or type of ‘not readable’, where the underlying rationales behind results may remain unclear (Molnar, 2022), XAI strives to make these processes more accessible to human understanding.

The following Table 2-3, extracted from the work of Arrieta et al. (2020), provides an overall picture of the classification of Machine Learning models attending to their level of explainability. Transparent models convey some degree of interpretability by themselves. Models belonging to this category can also be approached in terms of the domain in which they are interpretable: simulatability, decomposability and algorithmic transparency. Simulatability denotes the ability of a model to be simulated or thought about strictly by a human. Hence, complexity takes a dominant place in this class. Decomposability is the ability to explain each of the parts of a model (input, parameter and calculation). It can be considered intelligible. Algorithmic transparency can be seen in different ways. It deals with the ability of the user to understand the process followed by the model to produce any given output from its input data. Finally, post-hoc explainability targets models that are not readily interpretable by design by resorting to diverse means to enhance their interpretability.

Table 2-3 Overall picture of the classification of ML models attending to their level of explainability (Arrieta et al., 2020)

Model	**Transparent ML Models**			**Post-hoc analysis**
	Simulatability	**Decomposability**	**Algorithmic Transparency**	
Linear/Logistic Regression	Predictors are human readable and interactions among them are kept to a minimum	Variables are still readable, but the number of interactions and predictors involved in them have grown to force decomposition	Variables and interactions are too complex to be analyzed without mathematical tools	Not needed

Decision Trees	A human can simulate and obtain the prediction of a decision tree on his/her own, without requiring any mathematical background	The model comprises rules that do not alter data whatsoever, and preserves their readability	Human-readable rules that explain the knowledge learned from data and allow for a direct understanding of the prediction process	Not needed
K-Nearest Neighbors	The complexity of the model (number of variables, their understandability and the similarity measure under use) matches human naive capabilities for simulation	The amount of variables is too high and/or the similarity measure is too complex to be able to simulate the model completely, but the similarity measure and the set of variables can be decomposed and analyzed separately	The similarity measure cannot be decomposed and/or the number of variables is so high that the user has to rely on mathematical and statistical tools to analyze the model	Not needed
Rule Based Learners	Variables included in rules are readable, and the size of the rule set is manageable by a human user without external help	The size of the rule set becomes too large to be analyzed without decomposing it into small rule chunks	Rules have become so complicated (and the rule set size has grown so much) that mathematical tools are needed for inspecting the model behaviour	Not needed
General Additive Models	Variables and the interaction among them as per the smooth functions involved in the model must be constrained within human capabilities for understanding	Interactions become too complex to be simulated, so decomposition techniques are required for analyzing the model	Due to their complexity, variables and interactions cannot be analyzed without the application of mathematical and statistical tools	Not needed
Bayesian Models	Statistical relationships modeled among variables and the variables themselves should be directly understandable by the target audience	Statistical relationships involve so many variables that they must be decomposed in marginals so as to ease their analysis	Statistical relationships cannot be interpreted even if already decomposed, and predictors are so complex that model can be only analyzed with mathematical tools	Not needed
Tree Ensembles	✗	✗	✗	Needed: Usually *Model simplification* or *Feature relevance* techniques

Support Vector Machines	✗	✗	✗	Needed: Usually *Model simplification* or *Local explanations* techniques
Multi-layer Neural Network	✗	✗	✗	Needed: Usually *Model simplification, Feature relevance* or *Visualization* techniques
Convolutional Neural Network	✗	✗	✗	Needed: Usually *Feature relevance* or *Visualization* techniques
Recurrent Neural Network	✗	✗	✗	Needed: Usually *Feature relevance* techniques

With the aim of addressing the research objectives, three specific research questions were employed to examine the data-in-data-out approach in analysing pertinent studies. This exploration aimed to uncover patterns within extensive datasets and extract pertinent safety insights related to specific target events.:

- RQ1: Has data been collected and integrated from multiple sources?
- RQ2: Which of the relevant machine learning models have been used?
- RQ3: Is the machine learning model interpretable?

Concerning the RQ3 and according to Table 2-3 (Arrieta et al., 2020), the machine learning model interpretable only considered Decision Trees and Rule-Based Learners models.

2.5.2.1. Healthcare

Machine learning algorithms in healthcare are commonly applied to analyse medical images and identify patterns that can help diagnose diseases and treatments. The literature search was carried out to identify relevant studies using machine learning algorithms to predict COVID-19.

The identification of relevant literature was conducted by accessing the electronic database Pubmed. The search string used to query this database based on keywords within the Title/Abstract is shown below:

```
("COVID 19" OR “COVID-19” OR “SARS-CoV-2”)
AND
("machine learning")
AND
("risk pattern" OR "risk patterns")
```

The initial search returned around 700 studies. The following screening process led to the identification, as shown in Table 2-4, of five examples of relevant papers related to this specific issue.

Table 2-4 Sample of studies in the Healthcare Machine Learning Approach

Reference	Year	RQ1	RQ2	RQ3
Yu, X. (2020). Risk Interactions of Coronavirus Infection across Age Groups after the Peak of COVID-19 Epidemic. *17*(14), 5246-5259.	2020	No	Vector Autoregressive Models for Multivariate Time Series	No
Andersen, L. M., Harden, S. R., Sugg, P. D. M. M., Runkle, P. D. J. D., & Lundquist, T. E. (2021). Analysing the spatial determinants of local Covid-19 transmission in the United States. *754*.	2021	Yes	Logistic regression	No
Yue, H., & Hu, T. (2021). Geographical Detector-Based Spatial Modeling of the COVID-19 Mortality Rate in the Continental United States. *18*(13), 6832-6847.	2021	Yes	Geographical detector	No
Cordas dos Santos, D. M., Liu, L., Gerisch, M., Hellmuth, J. C., von Bergwelt-Baildon, M., Kunz, W. G., & Theurich, S. (2022). Risk Stratification Based on a Pattern of Immunometabolic Host Factors Is Superior to Body Mass Index? Based Prediction of COVID-19-Associated Respiratory Failure. *14*(20), 4280-4295.	2022	No	Logistic regression	No
Nazia, N., Law, J., & Butt, Z. A. (2022). Identifying spatiotemporal patterns of COVID-19 transmissions and the drivers of the patterns in Toronto: a Bayesian hierarchical spatiotemporal modelling. *12*(1), 1-13.	2022	Yes	Bayesian spatial regression model	No

The history taught that COVID-19 transmission and mortality was determined by diverse and complex factors such as physiological, socioeconomic, demographic, geographic and timing. Overall, the selected studies were carried out to explore the distribution and the impact factors of the morbidity and mortality of the COVID-19 disease per cluster and geographical distribution. The list of explanatory variables used in individual studies dealt with the research choice of accessing one or more sources. Applying the regression models provided to estimate, in terms of risk factors, the relationship between one or more independent variables and a response, dependent, or target variable, ensuring explainable and not-interpretable results.

2.5.2.2. Manufacturing

Enhancing efficiency, improving quality, reducing costs, and increasing overall productivity are examples of how machine learning is used in manufacturing. The literature search was provided to identify relevant studies using machine learning algorithms to predict equipment failures before they occur. So, manufacturers can reduce downtime, improve equipment reliability, and increase efficiency.

The relevant literature was identified by accessing the electronic database Academic Search Complete. The search string used to query this database based on keywords within the Title/Abstract is shown below:

```
("equipment failure")
AND
("machine learning")
AND
("risk pattern" OR "risk patterns")
```

The initial search returned around 9,297 studies. Since the area of study is extensive, a two-step screening strategy was applied to search relevant papers related to the same area of investigation, identify a specific issue, and extract similar studies to compare the approaches.

Condition monitoring of wind turbines is critical to ensure their long-term stable operation. Predictive troubleshooting tools are essential in enhancing efficient diagnosis and monitoring processes, especially for wind turbines, which consist of several components. The benefits rely on increasing the equipment efficacy, lowering the downtimes and reducing costs.

The end of the screening strategy, as shown in Table 2-5, led to the selection of five examples of relevant papers related to the same issue.

Table 2-5 Sample of studies in Manufacturing Machine Learning Approach

Reference	Year	RQ1	RQ2	RQ3
Yang, C., Qian, Z., Pei, Y., & Wei, L. (2018). A Data-Driven Approach for Condition Monitoring of Wind Turbine Pitch Systems [Article]. *Energies (19961073)*, *11*(8), 2142.	2018	No	Support Vector Regression	No
Renström, N., Bangalore, P., & Highcock, E. (2020). System-wide anomaly detection in wind turbines using deep autoencoders [Article]. *Renewable Energy: An International Journal*, *157*, 647-659.	2020	No	Artificial Neural Network	No
Amini, A., Kanfoud, J., & Tat-Hean, G. (2022). An Artificial Intelligence Neural Network Predictive Model for Anomaly Detection and Monitoring of Wind Turbines Using SCADA Data [Article]. *Applied Artificial Intelligence*, *36*(1), 1-14.	2022	No	Artificial Neural Network	No
Attallah, O., Ibrahim, R. A., & Zakzouk, N. E. (2023). CAD system for inter-turn fault diagnosis of offshore wind turbines	2023	No	Linear Discriminant Analysis	No

via multi-CNNs & feature selection [Article]. *Renewable Energy: An International Journal*, *203*, 870-880.				
Liu, J., Wang, X., Xie, F., Wu, S., & Li, D. (2023). Condition monitoring of wind turbines with the implementation of spatio-temporal graph neural network [Article]. *Engineering Applications of Artificial Intelligence*, *121*	2023	No	Graph Neural Networks	No

The selected studies evidenced that the predictive approach to condition monitoring of wind turbines involved the only use of internal data provided by sensors, images (e.g., thermographic infrared images) or control systems (i.e., SCADA stands for Supervisory Control And Data Acquisition) without integrating external data to evaluate environmental conditions. The used classifiers deployed explainable and not-interpretable results.

2.5.2.3. Retail

Machine learning has a wide range of retail applications to improve operational efficiency, enhance customer experience, and drive revenue growth.

Some examples include:

1. Demand forecasting: Machine learning algorithms can be used to forecast demand for different products based on factors such as historical sales data, promotional activities, weather, and events.
2. Customer segmentation: Retailers can use machine learning algorithms to segment their customers based on purchase behaviour, demographics, and preferences, helping retailers to personalise their marketing and offer more targeted promotions.
3. Price optimisation: Machine learning algorithms can help retailers optimise their prices based on factors such as competitor prices, customer demand, and inventory levels.
4. Fraud detection: Machine learning algorithms can detect real-time fraudulent transactions, reducing retailers' risk of financial loss.
5. Inventory management: Machine learning algorithms can be used to optimise inventory levels by predicting demand and identifying which products are likely to sell out.
6. Supply chain management: Machine learning algorithms can be used to optimise supply chain operations, such as predicting delivery times and identifying potential disruptions.

Diverse and complex factors determine every single area of the application. The literature search was provided to identify relevant studies using machine learning algorithms for fraud detection, one of the most common sensitive topics for any industry. Of its pervasive impact, fraud detection and prevention are integral to every business today. It is a process that detects scams and prevents fraudsters from obtaining money or property through fraudulent means. It is a serious business risk that needs to be identified and mitigated in time.

The relevant literature was identified by accessing the electronic database Google Scholar. The search string used to query this database based on keywords within the Title/Abstract is shown below:

```
("fraud detection")
AND
("machine learning")
AND
("risk pattern" OR "risk patterns")
```

The initial search returned around 116 studies. The following screening process led to the identification, as shown in Table 2-6, of five examples of relevant papers related to this specific issue.

Table 2-6 Sample of studies in Retail Machine Learning Approach

Reference	Year	RQ1	RQ2	RQ3
Shimin, L., Ke, X., Huang, Y., & Xinye, S. (2020). An Xgboost based system for financial fraud detection. E3S Web of Conferences.	2020	No	XGBoost (Extreme Gradient Boosting)	No
Kumar, A. (2021). Ensemble Technique on Predictive Analysis and Fraud Orders Detection using Supervised Machine Learning Algorithms in Supply Chain Management. *Turkish Online Journal of Qualitative Inquiry*, *12*(7).	2021	No	Random Forest	Yes
Min, W., Liang, W., Yin, H., Wang, Z., Li, M., & Lal, A. (2021). Explainable deep behavioral sequence clustering for transaction fraud detection. *arXiv preprint arXiv:2101.04285*.	2021	No	DBSCAN (Density-Based Spatial Clustering of Applications with Noise)	No
Westerski, A., Kanagasabai, R., Shaham, E., Narayanan, A., Wong, J., & Singh, M. (2021). Explainable anomaly detection for procurement fraud identification—lessons from practical deployments. *International Transactions in Operational Research*, *28*(6), 3276-3302.	2021	No	Multivariate outlier detection	No
Knuth, T., & Ahrholdt, D. C. (2022). Consumer fraud in online shopping: Detecting risk indicators through	2022	No	Decision Tree	Yes

data mining. *International Journal of Electronic Commerce*, *26*(3), 388-411.				

The selected studies evidenced that managing the predictor target as binary (e.g., fraudulent transaction, not fraudulent transaction) led to deploying interpretable patterns differently by managing the predictor target as risk scoring in which other classifiers fit better. The variables were included in one database (e.g., financial database) in all selected cases.

2.5.3. Artificial Intelligence Approach in Aviation

The process of discovering valuable safety-relevant knowledge from data collection with the support of Artificial Intelligence based on Machine Learning is also progressing in aviation. Being aware of the constant evolution of aviation safety and the continuous improvement of Safety Risk Management to anticipate threats and associated risks (EASA, 2017), the adoption of this technology represents a further strategic initiative that the industry is setting out to ensure safety improvement.

To introduce new perspectives and methods for managing safety, ICAO has recommended in its Global Aviation Safety Plan (GASP) the implementation of Predictive Risk Management as a broad objective with a long-term target to be reached by 2028 (ICAO, 2016). Recently, and in line with the first significant milestone of the industry, the European Aviation Safety Agency (EASA) has published a roadmap to approach Artificial Intelligence in aviation (EASA, 2020; 2023), followed by a concept paper as a guide for machine learning applications still opened for consultation.

The EASA Research Agenda 2022-2024 has set Machine Learning as a topic to implement (2022, p. 7) within the main objectives associated with the research requests to prepare for the evolution of aviation standards, support the development of new safety and security management concepts/methods/tools, investigate the safety, security and environmental threats, support both proactive and reactive safety management, and obtain knowledge and data on novel products, technologies or types of operation.

Today, many initiatives in aviation have the same objective: to take advantage of data science applications. Programs, partnerships, EU-funded projects and academic research are still in progress to foster a paradigm shift in safety analysis by moving on a data-driven approach. EASA has set up a project team to establish the Agency's initial vision of AI development. In parallel, some voluntary partnership programmes have been initiated to collect massive amounts of data.

For example, EASA Data4Safety (D4S) (EASA, 2023) is a partnership based on data fusion, including safety reports, flight data, surveillance data, and weather data, as a single entity. IATA (International Air Transport Association) is following a similar approach. Voluntary participation in the Global Aviation Data Management (GADM) programme allows worldwide aviation stakeholders to access a data management platform at a global level. All sources of operational data from the incidents (IDX), flight data (FDX) and accidents (ADX) feed into a standard, interlinked database structure (IATA, 2024). Airbus manages a third extensive programme called Skywise, an industry data platform to address aircraft operations challenges (Airbus, 2024). However, no studies have been still published concerning outcomes and results.

Reminding of the strategy previously applied to explore the current state of Artificial Intelligence in the Industry, three specific research questions were applied to a selection of relevant studies in the aviation domain to investigate the data-in-data-out approach to discover patterns in large datasets to get relevant safety knowledge on specific target events:

- RQ1: Has data been collected and integrated from multiple sources?
- RQ2: Which of the relevant machine learning models have been used?
- RQ3: Is the machine learning model interpretable?

As previously discussed, concerning the RQ3 and according to Table 2-3 (Arrieta et al., 2020), the machine learning model interpretable was only considered Decision Trees and Rule-Based Learners models.

Table 2-7 Sample of studies in Aviation Machine Learning Approach

Reference	Year	RQ1	RQ2	RQ3
Wagner, D. C., & Barker, K. (2014). Statistical methods for modeling the risk of runway excursions. *Journal of Risk Research*, *17*(7), 885-901.	2014	No	Logistic regression and Bayesian logistic regression	No
Lukáčová, A., Babič, F., & Paralič, J. (2014, January). Building the prediction model from the aviation incident data. In *2014 IEEE 12th International Symposium on Applied Machine Intelligence and Informatics (SAMI)* (pp. 365-369). IEEE.	2014	No	Decision trees	Yes
Mathur, P., Khatri, S. K., & Sharma, M. (2017, December). Prediction of aviation accidents using logistic regression model. In *2017 International Conference on Infocom Technologies and Unmanned Systems (Trends and Future Directions)(ICTUS)* (pp. 725-728). IEEE.	2017	No	Logistic regression	No
Lališ, A., Socha, V., Kraus, J., Nagy, I., & Licu, A. (2018, March). In *2018 IEEE aerospace conference* (pp. 1-8). IEEE.	2018	No	Linear regression	No
Zhang, X., & Mahadevan, S. (2019). *Decision Support Systems*, *116*, 48-63.	2019	No	Support Vector Machine and an	No

			ensemble of deep neural networks	
Barry, D. J. (2021). Estimating runway veer-off risk using a Bayesian network with flight data. *Transportation Research Part C: Emerging Technologies*, *128*, 103180.	2021	Yes	Bayesian networks	No

In aviation, data collection primarily relies on two primary sources: incident or accident reports through access to available and public databases and flight data monitoring (FDM). Accident or incident reports represent only a small fraction of safety occurrences in aviation (Lališ et al., 2018), even if they represent a very important source for data mining experiments (Lukáčová et al., 2014), while flight data involves the automatic recording of various flight parameters, allowing for the collection of a substantial number of variables (Barry, 2021).

The data model is almost always based on a single database relative to a data source. Barry (2021), in his analysis on estimating runway veer-off risk, combined flight data with meteorological data to derive additional features. It is worth noting that the algorithms used do not tend to provide information on the dynamic nature of events. Instead, their primary purpose is to guarantee a probability value that can be used in a preventive manner.

The transformation of the numerical attribute 'Number of Fatalities' into a binary 'Fatalities' allowed the extraction of interpretable results from the FAA Accident/Incident Data System (AIDS) database containing incident data records for all categories of civil aviation to predict accidents without fatal injuries (0) or with fatal injures (1). The application of selected Decision Tree algorithms like C5.0, CART and CHAID to the data model generated decision rules resulted in the combination of a set of attributes (Lukáčová et al., 2014).

2.6. Summary

The literature review uncovered that the definition of 'event' is still discussed today (Cacciabue, 2010). However, all reviewed definitions underlined the role of deviation from the intended process (Surry, 1969). Cacciabue defines it as a "change of state of the system", where a human event is "the execution of an action leading to the change of state of the system" (2010, p. 123), Hollnagel a performance variability (2012; 2017) and in the healthcare domain, it is "a deviation from generally accepted practice or process that reaches the patient and causes severe harm or death" (Hoppes & Mitchelle, 2014, p. 3) or "a situation where best or expected practice does not occur" (Nationwide Children's Hospital, 2021).

It is a general understanding and not necessarily attributed to a specific individual or source that a safety event is typically an unplanned situation specifically identified when there is a likelihood of causing harm to individuals or damage to objects. The research objective aims to redefine this concept by including new empirical data, insights, and evolving paradigms. The research goal also seeks to emphasise its dynamic characteristics and uncover the particular dynamic and complex configuration contributing to deviations from normal operations.

Reason's original model first advanced that disasters in socio-technical systems typically arise from multiple causal factors, underscoring the critical importance of combinations, as each element, though necessary, remains insufficient to lead to a catastrophic outcome. The significance of the combinations was previously argued by Wigglesworth (1972), who first introduced the role of random factors as contributing to deviations, which Lawrence later took up in his causal models (1974).

The diverse nature of the factors as elements of explaining the change of state, variability of the performance or deviation from the expected process was first advanced by Leplat (1989), who advocated that performance and activity are closely influenced by the dichotomy condition of the task as prescribed by designers or managers and as conceived by individuals. Later, Hollnagel, in his FRAM (2012; 2017), indicated that work conditions often deviate from what is strictly specified or prescribed within many socio-technical systems, underscoring the difference between Work-As-Done (WAD) and Work-As-Imagined (WAI), and suggesting the different nature of the factors involved in an event: planned linked to the Work-As-imaged (WAI) and unplanned associated to Work-As-Done (WAD).

The current generation of AI systems offers tremendous benefits. However, their effectiveness could be limited by the machine's inability to explain its decisions and actions to a user (Gunning, 2017), so there is a demand for more transparent and interpretable models, the ability to explain the model for building trust and deployment of artificial intelligence systems in critical domains (Dwivedi et al., 2023).

The strategy to employ the current state of artificial intelligence utilisation within identified industrial sectors primarily centred on the 'data-in-data-out' approach to extract risk patterns for the analysis of particular events uncovered that the majority of the selected studies relevant to the research objective deployed algorithms not easily interpretable or understandable by humans, where the underlying reasons behind the results may not be immediately apparent.

In contrast, Kumar (2021) employed a different approach to predict sales and orders in the binary category of fraud or not. This approach produced interpretable results, utilising Decision Tree Classifiers and achieving high accuracy. Similarly, transforming the target event into a binary condition indicated that it is possible to build prediction models containing interpretable decision rules in the form of sets of 'if-then' statements (Lukáčová et al., 2014) instead of 'black box' algorithms.

The development of causal models in the last 100 years since the 'accident proneness' proposed in 1919 (Greenwood & Woods, 1919) shows the evolution of safety science in supporting the investigation of accidents or incidents with their contributing factors. Waterson et al. (Robertson et al., 2015) traced the development of the scientific study of safety through three separate ‘ages’: the 'Age of Technology', the' Age of human factors', and the 'Age of Complex Socio-Technical Systems' by describing the increasing complexity of the models themselves that had to adapt to the increasing complexity of systems depending on the application area.

Accident causation models can help us understand how accidents occur and identify their underlying causes to prevent future incidents. However, they primarily operate reactively. The rapid advancement of Artificial Intelligence (AI) and Machine Learning (ML) in the last decade sparked concerns about their potential impact on several areas and the development of numerous unexplored applications. These concerns include reshaping the field of safety science and academic research on the role of AI and ML as enablers of new methods, processes, management, and evaluation in research (Chubb et al., 2022).

The strategy employed to document the utilisation of Artificial Intelligence within identified industrial domains generated three main insights: the lack of production of interpretable patterns, the validation of the model solely based on statistical parameters and the need for more organisational knowledge and expertise. Simple possession of data and a model is insufficient; the ability to interpret the patterns to identify appropriate control measures is essential. Model validation cannot rely solely on statistical parameters analysis. Expert validation is necessary to evaluate the results concerning usability in operational contexts and improve the model's predictive capacity. These tasks require human factors, socio-technical systems and operational knowledge, which may not always be available in current organisational settings. Therefore, there must be organisational readiness to implement and interpret AI models to devise suitable countermeasures to mitigate the risk. This is a novel challenge for the predictive approach.

Integrating AI implementation with organisational requirements presents a challenge that needs to be addressed. It encompasses not only the adoption of new technology but also understanding the profound complexity of safety events and their management to identify appropriate actions for reducing the risk level. This necessitates human and organisational factors together with a socio-technical systems framework to support the analysis of these factors, thus advocating for a methodology like CUBE (McDonald, 2017) to drive organisational change and provide for a structured and systematic approach to analysis and aid in the transition from the current 'as-is' condition to the desired 'to-be' state.

CHAPTER 3. RESEARCH HYPOTHESIS AND OVERVIEW OF THE METHODOLOGY APPROACH

This chapter introduces the research hypothesis, which aims to propose and validate a reconceptualisation of the definition of a safety event. It outlines the research methodology employed to investigate this hypothesis. It highlights its dynamic nature and far-reaching implications for the evolution of risk management processes, paving the way for developing a distinctive predictive strategy and approach. Furthermore, this chapter comprehensively overviews the study's data collection methods, sources, and analytical techniques. Ethical considerations related to the research process are also discussed.

3.1. Master's Thesis

The Master's thesis titled 'Model of Predictive Analysis in an Ultra-safe System' (Toti, 2017) inspired and prepared an investigation laying the groundwork for the current research. The findings and evidence in this study contributed to developing a knowledge base and set the stage for subsequent exploration in the field.

The Master's thesis encompassed the following research questions:

1. Is it possible to predict an unsafe event?
2. Are incidents random situations, or do they occur in certain conditions?
3. Is making errors a constant feature of human behaviour, or are humans forced to make errors due to the operating scenario?

The evolutionary step forward of the Bowtie method, a widely employed risk assessment model, served as a framework for accomplishing the research objectives outlined in the Master's thesis. The Bowtie, depicted graphically in a diagram illustrating the risk scenario in a comprehensible bowtie-shaped image, underwent revision to address an improved risk overview. The diagram was extended to incorporate the predictive area alongside the existing reactive and preventive aspects, fostering new relationships among its elements: hazards, threats, and consequences (Figure 3-1).

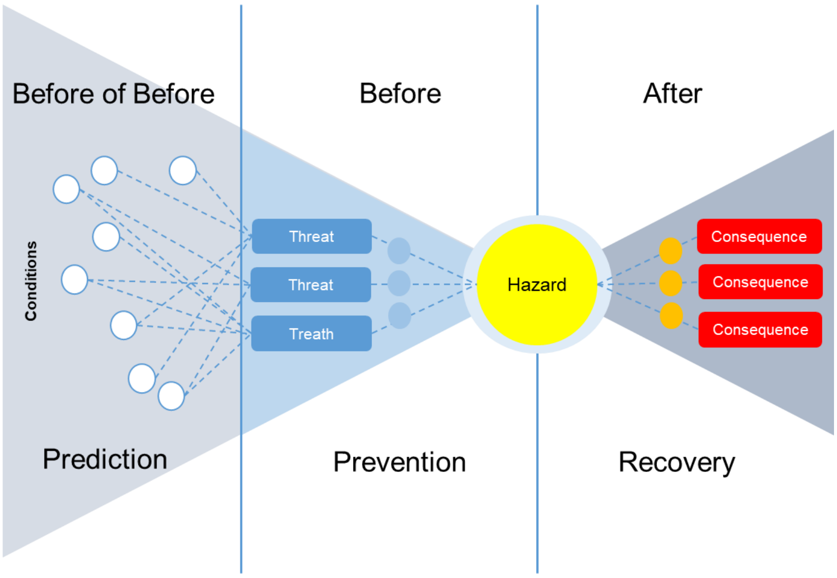


Figure 3-1 Example of Bowtie diagram revised (Toti, 2017)

Logistic regression, a statistical method widely used for binary classification problems where the outcome variable is binary (e.g., success/failure, yes/no, 1/0), was applied to an integrated and large dataset to explain pertinent relationships. The empirical demonstration was performed by designing and conducting a case study within an ultra-safe system like commercial aviation. The study investigated a safety event, such as the Unstabilised Approach.

The output analysis generated diverse findings, revealing the complexity of the safety event and the need for a comprehensive understanding of the involved variables. Parameter estimation in two distinct models demonstrated face validity and a certain level of correspondence, indicating that specific conditions during a flight can substantially elevate the odds of unstable approaches. The flap late extension events during the approach, detected at three different times over the flight, were more than 30 times more likely to occur for flights with unstable approaches.

Notably, factors such as seasonality, planned destination, and departure delays were also identified as significant. Any fight recovering an inherited delay at departure increases the odds of being in flap late extension during approach by more than 30%. A seasonality effect is present with increased likelihoods in Spring and Summer by a multiplicative factor of 2,51 and 3,41 times, respectively. In winter, the odds of being in a flap late extension during approach are reduced by more than 90%. These results suggested the feasibility of estimating the probability of an unstable approach based on the configuration and combination of predictor values.

3.2. Research Hypothesis

The literature review uncovered that safety thinking has evolved over the years due to factors that reflect changing societal, technological, and organisational contexts from early and elementary rule-based approaches to more complex, interdisciplinary, and proactive strategies encompassing human factors, systems thinking, culture, and technology.

The evolution of causal models has followed a similar trend of moving from simple to complex, linear to dynamic, and individual-focused to systemic. The common thread, however, is the recognition of the multifaceted, interrelated, and adaptive nature of accidents or incidents and the need for more comprehensive approaches to understanding the causes and providing insights into how systems function and why they occur.

Technological advances, including data analytics, artificial intelligence, and automation, are revolutionising safety thinking, moving it towards a data-driven approach. Organisations can now gather and analyse vast amounts of data to identify patterns, predict potential hazards, and potentially enable new applications and services in several industrial sectors. These technological advancements also impact academic research to explore complex questions and challenges across disciplines.

The summary of the previous chapter established that an event is recognised as a deviation from the intended process (Surry, 1969) and has declined successively as a change of state (Cacciabue, 2010) or performance variability (Hollnagel, 2012; 2017). Events are characterised by their potential consequences. A safety event is recognised when there is a likelihood of causing harm to individuals or damage to objects. Similarly, a security event is explicitly recognised when there is a likelihood of posing a threat to people, property, the environment, or, in the context of a financial event, disrupting the regular functioning of a system, process, or operation.

The research objective seeks to contribute to the development process of safety thinking by proposing and validating a novel definition of a safety event aimed at clarifying its dynamic nature and implications in contributing to an evolving risk management process, leading to a distinct strategy and approach in predictive terms. The assumption that a safety event is "a particularly dynamic and complex combination of planned and unplanned factors" enables a probabilistic prediction and aims to describe the relationship of the elements involved in the dynamic process leading to a variance or deviation from the normal process rather than identifying it and assessing its outcomes. The definition is based on two key aspects: firstly, the composition and relationship of factors, and secondly, the distinct natures of these factors involved in the dynamic process.

Reminding of the concepts discussed in the previous chapter, James Reason originally proposed that disasters in socio-technical systems often arise due to the combination of numerous causal factors. This concept highlights the significance of the combination, as every single element is essential yet insufficient on its own to trigger the catastrophic outcome: "These accidents arose from the adverse conjunction of several diverse causal sequences, each necessary but none sufficient to breach the system's defences by itself." (Reason, 1990, p. 475). The significance of the combinations was previously argued by Wigglesworth (1972), who first introduced the role of random factors as contributing to deviations.

The diverse nature of the factors as elements of explaining the change of state, variability of the performance or deviation from the expected process was first advanced by Leplat (1989), who advocated that performance and activity are closely influenced by the dichotomy condition of the task as prescribed by designers or managers and as conceived by individuals. Later, Hollnagel, in his FRAM (2012; 2017), indicated that work conditions often deviate from what is strictly specified or prescribed within many socio-technical systems, underscoring the difference between Work-As-Done (WAD) and Work-As-Imagined (WAI) and suggesting the different nature of the factors involved in an event: planned linked to the Work-As-imaged (WAI) and unplanned associated to Work-As-Done (WAD).

The conclusions from the Master's thesis (Toti, 2017) highlighted a notable potential in data analysis. Specifically, the research underscored the effectiveness of employing predictive analysis techniques on data integrated from diverse sources into a unique dataset. This data-driven approach facilitates the retrospective identification of correlations between factors and the specific contextual conditions in which they emerge, differentiating between planned and unplanned. The underlying premise of this approach challenges the assumption that safety events are inherently unforeseen or unpredictable, suggesting instead that they occur in combination with specific conditions in a given space-time window.

Moreover, it underscored the potential of identifying these combinations by employing predictive analysis techniques to merge data from various sources into a unified dataset. These techniques enable the retrospective identification of correlations between safety events and the specific contextual conditions under which they occur. This approach was founded on the premise that safety events are not inherently unforeseen or unpredictable but manifest in combination with certain conditions.

The literature review uncovered that the current generation of AI systems offers tremendous benefits. However, their effectiveness could be limited by the machine's inability to explain its decisions and actions to a user (Gunning, 2017), so there is a demand for more transparent and interpretable models; the ability to explain the model for building trust and deployment of artificial intelligence systems in critical domains (Dwivedi et al., 2023). The 'if-then' statement in decision rules from identifying and analysing patterns offered interpretable machine learning models that are readily comprehensible and explainable for domain experts. It also provided predictability regarding the occurrence and reasoning behind outcomes, notably when input variables or algorithmic parameters are altered.

Hence, the validity of the theory is achieved by implementing this innovative predictive analysis methodology that leverages artificial intelligence capabilities and is grounded in machine learning principles. The primary aim is to benefit through these new technologies, thereby enabling the deployment of interpretable risk patterns as potential 'what-if scenarios' or instances characterised by conditions favourable to target events. These events hold the potential to culminate in safety-related incidents, all of which are subjected to careful validation by domain experts to ensure a worthy degree of reliability, comprehensibility, and especially applicability.

The process of systematically creating a structured representation of data and its interrelationships to perform this innovative predictive analysis methodology aims at comprehending and analysing the potential combination of factors contributing to a safety event is outlined through two fundamental principles presented by Hollnagel in his FRAM (2012; 2017):

1. Distinguishing Work-As-Imagined (WAI) from Work-As-Done (WAD): The method underscores the contrast between the idealised conceptualisation of the tasks (WAI) and their actual executions (WAD). Since it is impossible to predict exactly how things will happen in real work situations ahead of time, every task encompasses envisioned scenarios during planning (WAI) and the potential deviations that might arise during execution (WAD). This approach necessitates collecting relevant data surrounding anticipated and unforeseen conditions, when present, for each task, contributing to a comprehensive and precise picture of the socio-technical framework, including its technical, human, organisational, and environmental dimensions.

2. Equivalence of Successes and Failures: The method acknowledges that things go right and wrong similarly. Successes and failures often share the same underlying processes despite different outcomes. Variances in outcomes do not inherently signify differences in the processes. Consequently, for each task or activity, the intended target event can be dichotomised into a binary condition characterised by two potential outcomes: occurrence (1) or non-occurrence (0). This classification approach, termed binary classification, aims to predict the presence or absence of the target event within each task or activity based on the available data.

In theory, the analysis of risk patterns derived from implementing this predictive analysis methodology within a so-organised database can effectively depict the dynamic nature of a safety event. Exploring the hypothesis of likening a safety event to a risk pattern can pave the way for new and innovative applications in the risk management process in every sector, domain or situation.

Presently, safety risks are typically managed by deploying suitable safety barriers. In scenarios where a safety event is unforeseeable and unpredictable, risk reduction is achieved by applying preventive or recovery measures to lower the associated risk level. The concept of 'breaking the risk pattern' (Baranzini et al., 2013; Baranzini & Zanin, 2015) could offer an innovative, novel and further risk mitigation strategy, moving the mitigation measures directly on the combination of the factors configuring a safety event breaking its conditions-fertile, as shown in Figure 3-2.

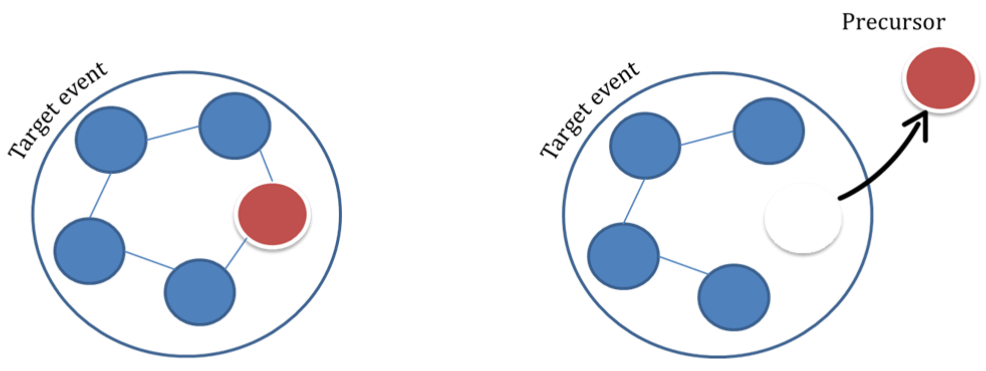


Figure 3-2 The concept of 'breaking the risk pattern'.

Heinrich previously advanced a similar approach to the Domino Model or Domino Theory (Heinrich, Industrial Accident Prevention: a Scientific Approach, 1931) and later taken up by Weaver (1971), Bird and Loftus (1974) (Othman et al., 2018) and Adams (1976). The linear sequence toward an accident can be stopped by breaking the chain at any point. The Domino Model or Domino Theory explains accidents as the linear propagation of a chain of causes and effects like a row of dominoes, where the fall of one initiates the next, and this chain reaction continues until the entire row falls. If this sequence is interrupted by removing even one of its components, the injury will not occur.

As part of the efforts to prevent accidents or incidents and improve safety, both concepts highlight the importance of identifying and addressing the root causes or the strong predictors and contributing factors before they can lead to an accident or incident. The linear or non-linear sequence toward an accident or incident can be stopped by breaking the chain or combination at any point.

Integrating data analytics into risk management aims to transform the conventional subjective and individually perceived approach, even when overseen by experts, into a more comprehensive framework driven by data-driven insights. Many organisations currently assess operational effectiveness by tracking lagging indicators, often related to safety incidents. However, it becomes possible to uncover the dynamic nature of a safety event through a complex pattern of precursors and then identify the potential leading indicators. These leading indicators can then be quantified as predictive factors for anticipating and preventing future safety events.

As previously discussed, the Master's thesis (Toti, 2017) data analysis discovered that the late flap configurations increased the likelihood of an unstable approach by 30 times. A subsequent analysis of three years' performance data from two airline companies confirmed a significant correlation between the 'Late Flap extension below 1000 ft' event in Flight Data Monitoring and unstable approaches. The results suggested that by addressing the identified precursor as a leading indicator, organisations can identify trends or issues early and take preventive measures to improve future outcomes (i.e., lagging indicators) positively or negatively. Refer to Tables 3-1 and 3-2 for a summary of the performance results.

Table 3-1 Unstabilised approach Performance Company 1

Company 1	**2018**	**2019**	**2020**
Flight cycles	140,343	139,286	54,978
UA events rate per 1,000 flights	2,47	1,99	1,60
Late Flap events rate per 1,000 flights	2,30	1,66	1,27

Table 3-2 Unstabilised approach Performance Company 2

Company 2	**2018**	**2019**	**2020**
Flight cycles	40,087	40,424	14,385
UA events rate per 1,000 flights	1,37	0,64	1,25
Late Flap events rate per 1,000 flights	1,30	0,54	0,90

These findings strongly suggest that managing the identified precursor, when maintained within specific parameters, employs a noticeable influence on the subsequent outcomes – either positively or negatively. This correlation highlights the significance of monitoring the precursor to enhance or mitigate the overall performance regarding a safety event, in this case, the approach stability.

3.3. Overview of the methodological approach

This chapter also provides an overview of the methodologies and techniques employed throughout the research study. It delves into the strategies, approaches, and methodologies, focusing on ethical considerations and inherent limitations.

The research study adopted a mixed-methods research design strategically to encompass the following research objectives:

1. Reconceptualising safety events definition: This research objective aims to advance a novel definition of safety events, clarifying their dynamic nature and the comprehensive implications they entail.
2. Building a data model solution: A comprehensive data model solution is developed firmly to validate the novel definition of safety events. This solution facilitates the extraction of meaningful risk patterns from combined data sets, enhancing their interpretability to understand data-driven insights.
3. Risk Management approach implications: The hypothesis of comparing a safety event to a risk pattern explores the feasibility of a new and innovative risk management approach in predictive terms across the entire process, from hazard identification to continuous risk monitoring.
4. Organisational impact implications: This research objective explores the implications of implementing Big Data Analytics in a complex organisational context and proposing solutions for managing an organisational change.

Reconceptualising safety events definition

Starting from the conclusions of the Master's thesis (Toti, 2017), this research goal was accomplished by thoroughly examining academic journals, books, and other sources, allowing the identification of the relevant theories, methods, and gaps impacting the development of safety thinking over the past century from the time of the industrial revolution to today and how artificial intelligence and machine learning algorithms are providing valuable insights into the potential for innovation and improvement in safety practices of various industrial sectors.

Building a Data Model Solution

Yin's methodology (2009) was a guiding framework for implementing a recognised and established procedural approach to validate the reconceptualisation of the definition of the safety event, as illustrated in Figure 3-3. His Case Study Research provided comprehensive coverage of the design and use of the case study method as a valid research tool.

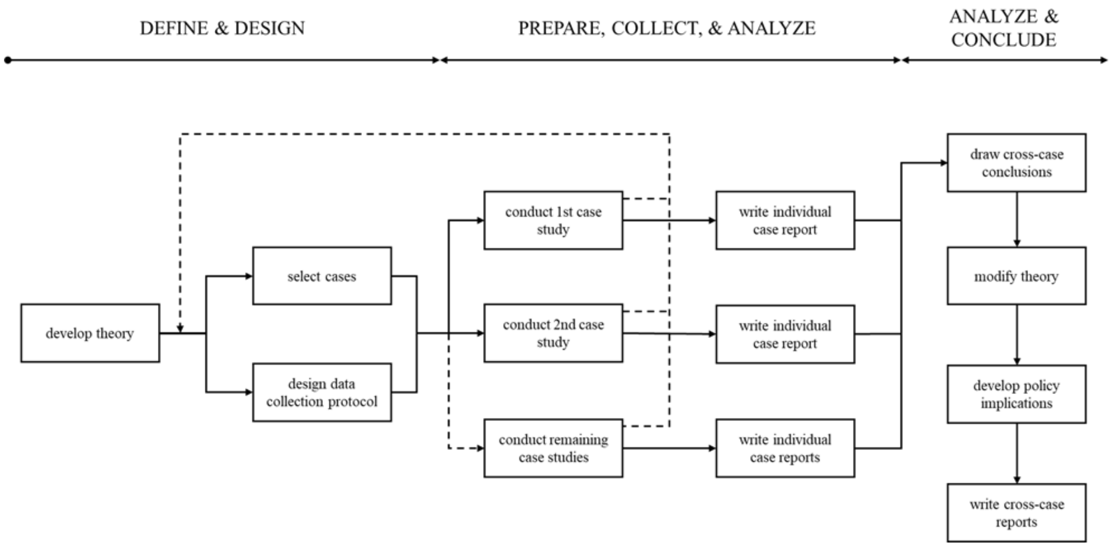


Figure 3-3 Case studies strategy (Yin, 2009)

The Data Model Solution developed to validate the research theory was applied to two case studies for an in-depth investigation of real-world safety issues, facilitating the validation of the theory across different contexts and enhancing their generalisability. Each case study was managed as a data mining and analytics project. The CRISP-DM (Cross-Industry Standard Process for Data Mining) methodology (Shearer, 2000) provided a structured and iterative approach to managing the various stages of a data-driven project.

The CRISP-DM methodology (Shearer, 2000) encompasses the following phases:

1. Business Understanding: Explain the initial phase of CRISP-DM to identify the business problem or goal the project aims to address.
2. Data Understanding: Detail how to collect and explore the relevant data for the analysis. Describe the data sources, data quality assessment, and any preprocessing steps to ensure the data's suitability for analysis. Discuss how to gain insights into the data, identify patterns, and address any initial data-related challenges.
3. Data Preparation: Outline the steps to clean, transform, and preprocess the data. Describe how to handle missing values, outliers, and inconsistencies. Explain any feature engineering techniques to create new variables or modify existing ones. Highlight the importance of preparing the data for modelling while maintaining data integrity.
4. Modelling: Discuss the selection of appropriate modelling techniques based on the research objectives and the nature of the data. Describe the algorithms or methods used and explain the rationale behind the choices. Detail the process of building, training, and evaluating models. Mention any parameter tuning or model selection strategies employed.
5. Evaluation: Explain how the performance of the models is assessed using relevant evaluation metrics. Discuss how the models are validated using cross-validation or holdout validation techniques.
6. Deployment: Describe the process of deploying the chosen model or solution in a real-world context. Discuss any challenges or considerations related to implementation, integration, and user acceptance. Highlight how deploying the solution contributes to solving the initial business problem.

In addition, the operational feedback provided by an expert is part of this process of interactions between humans and machine learning algorithms, which integrates the results of the Evaluation phase of the CRISP-DM model (Shearer, 2000) with the involvement of an expert on the topic investigated. The purpose is to augment the capacity to build data-efficient predictive models and increase the level of trust afforded by a given mode.

Risk Management Approach Implications

The application of Yin's (2009) methodology to the analysis and conclusion, as illustrated in Figure 3-3, extended beyond the theory validation, compelling support between the empirical data and the theoretical hypothesis concerning the implications for a new and innovative risk management approach in predictive terms across the entire process, from hazard identification to continuous risk monitoring.

Organisational Impact Implications

This part employed a qualitative research method (semi-structured interviews) to identify design issues and evaluate the feasibility, practicality, resources, and time required to implement the proposed data model solution in organisations. A cross-case report anticipated and informed the process for conducting the interviews, allowing the identification of the common themes, patterns, or areas of interest gathered during the execution of the case studies. It enabled the identification of the commonalities, differences, and overarching themes to be incorporated into the interview questions.

The semi-structured interview strategy relies on its goal of exploring a predetermined thematic framework. Its structure allows for investigating different facets of the research questions, and the flexible protocol promotes two-way communication between the researcher and the participants with the possible benefit of highlighting additional and unevaluated topics. It provides a framework for the interview while allowing for open-ended discussion.

A preliminary test or pilot study of the interview questions and topic guide was conducted with a small sample of participants. The pilot study aimed to evaluate the interview questions' clarity, appropriateness, and effectiveness and identify potential issues or challenges before conducting the other interviews. The participants involved in the pilot study were selected based on their similarity to the intended interviewees regarding characteristics, expertise, or experiences related to the research topic. Aim for a diverse sample that represents different perspectives and backgrounds.

This study followed all TCD ethical guidelines and was approved by the School of Psychology Research Ethics Committee. Informed consent was obtained from all interview participants, and steps were taken to ensure participant confidentiality and privacy.

Some adjustments were made in the second case study to detect safety events in the aircraft turnaround process due to incomplete data collection. It was impossible to get the data according to the original data modelling due to technical problems in data extraction.

CHAPTER 4. CASE STUDY 1 (Detecting precursors to unstabilised approach)

4.1. Introduction

According to the statistics (Figure 4-1), almost all worldwide aircraft accidents, either fatal or non-fatal, occur during landing (‘LND’) (IATA, 2022).

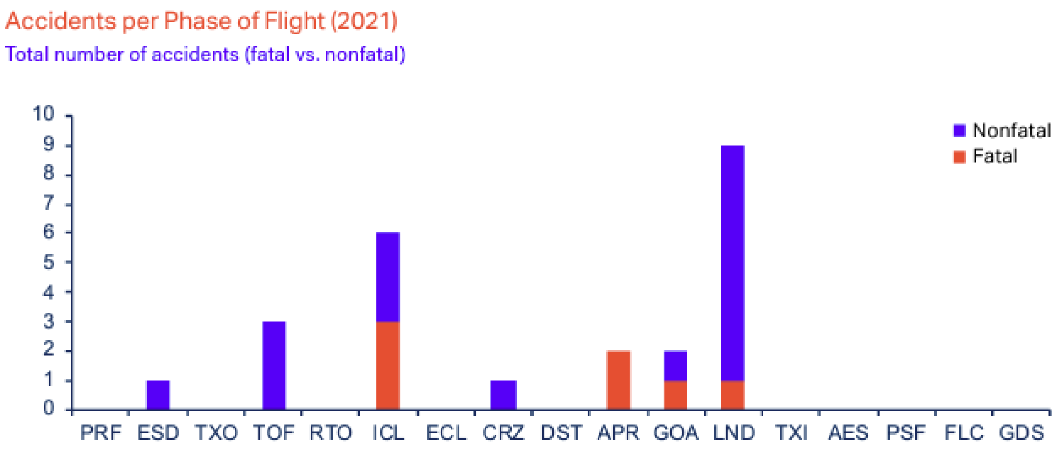


Figure 4-1 Accidents per Phase of Flight (IATA, 2022)

Unstable Approach (UA) and Continued Landing after Unstable Approach continue to be an undesired aircraft state in aviation, increasing the risk of an approach and landing incident and or accident estimated to be respectively a contributory factor in 17% and 15% of 2017-2021 aircraft accidents (IATA, 2022). The Flight Safety Foundation (FSF) published older statistics establishing UA as a causal factor in 66% of 76 approach and landing accidents and incidents worldwide between 1984 and 1997 (FSF, 2000). A study conducted by Embry-Riddle Aeronautical University reported that anywhere from 3% to 5% of all air carrier approaches are unstable. Of those, only 3% to 4% result in a go-around or missed approach. Despite extensive training programs and guidance from professional aviation organisations, the rate of unstable approaches has remained the same (Joslin & Odisho, 2020).

Monitoring and addressing an unstabilised approach in aviation is of the highest importance to ensure the safe landing of aircraft, thereby reducing the potential for accidents and their associated consequences, such as runway excursions, landing short, controlled flight into terrain (i.e., CFIT), hard landings, or tail strikes (IATA, 2022). IATA data regarding the distribution of incidents by category and flight phases for 2017-2021 confirm that this phenomenon is a critical component of aviation safety and operational efficiency.

For a quick and clear understanding, the graph depicting category distribution highlights those categories that represent potential consequences resulting from an unstable approach (Figure 4-2), confirming its role as a high-risk, undesired aircraft state.

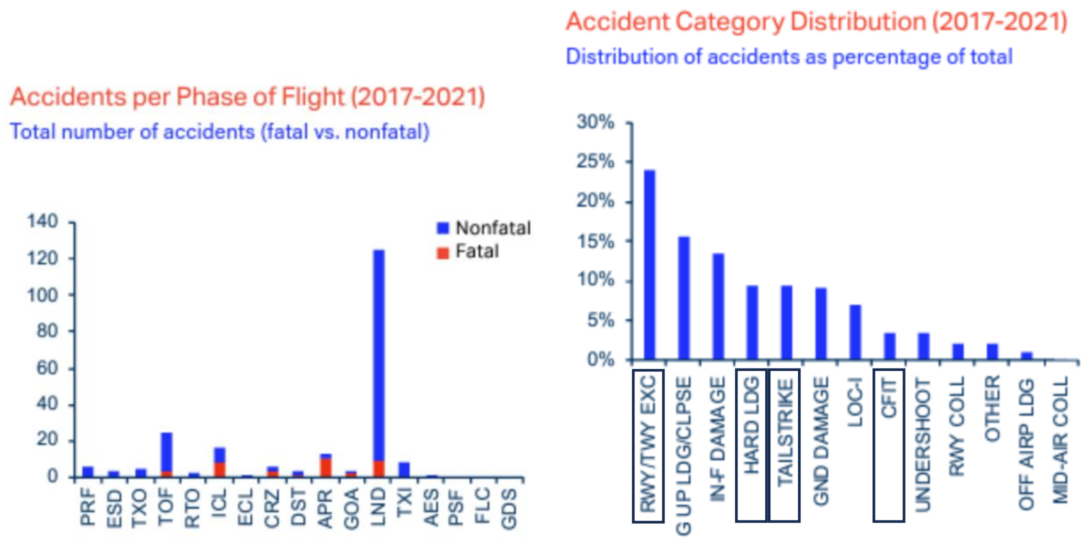


Figure 4-2 Accidents per Phase of Flights and Category Distribution (2017-2021) (IATA, 2022)

EASA adopts a reporting platform called ECCAIRS 2.0 for mandatory event reporting. This platform incorporates the ICAO ADREP taxonomy and sets out the suggested parameters for a stabilized approach (ECCAIRS 2020, 2020).

Stabilised approach: These recommended parameters define a stabilised approach and should be met by 1,000 feet above airport elevation in IMC or 500 feet in VMC:

1. The aircraft is on the correct flight path;
2. Only small changes in heading/pitch are required to maintain the correct flight path;
3. The aircraft speed is not more than VREF + 20 knots indicated airspeed and not less than VREF;
4. The aircraft is in the correct landing configuration;
5. Sink rate is no greater than 1,000 feet per minute; if an approach requires a sink rate greater than 1,000 feet per minute, a special briefing should be conducted;
6. Power setting is appropriate for the aircraft configuration and is not below the minimum power for approach as defined by the aircraft operating manual;

7. All briefings and checklists have been conducted;
8. Specific types of approaches are stabilised if they also fulfil the following: instrument landing system (ILS) approaches must be flown within one dot of the glide slope and localizer; a Category II or Category III ILS approach must be flown within the expanded localiser band; during a circling approach, wings should be level on final when the aircraft reaches 300 feet above airport elevation; and
9. Unique approach procedures or abnormal conditions requiring a deviation from the above elements of a stabilised approach require a special briefing. (FSF ALAR tool kit).

Establishing and maintaining a stabilised approach criterion (Figure 4-3) is the most effective safeguard to reduce the likelihood of reaching unwanted consequences. Standardisation is the means to achieve compliance. The publication of Standard Operating Procedures (SOPs) within the Flight Crew Operating Manual (FCOM) and pilot training sessions set in flight simulators provide the practice of those procedures.

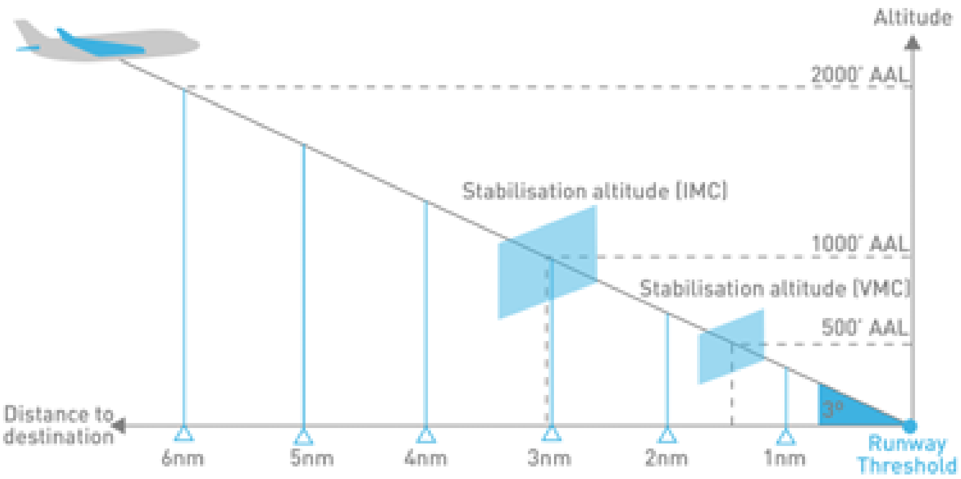


Figure 4-3 Stabilised approach criteria checkpoints (Martinez et al., 2019)

Landing is the last part of a flight, where an aircraft returns to the ground. An effective landing is completed if the airspeed and the rate of descent are adequately reduced to allow the aircraft a safe touchdown. Still, it is also a result of a well-planned and well-executed descent phase from the cruise level. The trajectory or angle of descent is controlled by an automated system (autopilot) or by the pilot by varying engine power, vertical rate, or pitch angle (lowering the nose) to fulfil the requested airspeed.

Because of their task demand load, the approach and landing are the phases of the flight with the highest workload for pilots. Specific charts and information from computers are used for each phase of a flight and can range from a detailed map of an airport with its facilities to covering a vast area (e.g., oceanic routes) and many other types. Using these data, airline pilots can determine their position, the lowest altitude that assures a safe clearance from obstacles, the route to a destination, navigation aids along the way, and other helpful information such as radio frequencies and airspace boundaries.

The FDM system is a proactive and non-punitive safety method that allows airline operators to collect and analyse aircraft flight data. Its goal is to monitor and compare the standard procedures provided for in the operations manual with those put into practice by the crews in daily flight activity to develop and improve standardisation, training programs for flying personnel, and, in general, safety.

Establishing the deviation from a stabilised approach relies on the analysis conducted by an FDM expert that assesses if the undesired aircraft state affects a reduction in safety margins. To accomplish it, the analyst generally considers some factors: approach type (visual or instrumental), the severity of the event or events type, flight envelope and energy, and personal assessment based on personal expertise. However, it is essential to highlight that at least one criterion is necessary but insufficient to evaluate whether an approach is stabilised.

4.2. Previous studies

A rapid review was conducted to provide a comprehensive overview of the research on using artificial intelligence (AI) based on machine learning (ML) algorithms to investigate the unstabilised approach.

The research questions were designed to investigate the data-in-data-out approach to extracting and discovering safety-relevant knowledge in large datasets to predict it:

- RQ1: Has data been integrated from multiple sources?
- RQ2: Which machine learning algorithm has been used?
- RQ3: Is the machine learning algorithm interpretable?

Concerning the RQ3 and according to Table 2-3 (Arrieta et al., 2020), the machine learning model only considered Decision Trees and Rule-Based Learner models.

The research was identified from the Google Scholar electronic database. The search string used to query this database based on metadata (title, abstract, keywords) is shown below. In addition to the papers returned by the above database, some handpicked papers recommended by domain experts but not returned by the search string were also included.

```
("artificial intelligence" OR "AI")
AND
("machine learning" OR "ML")
AND
("unstabilised approach" OR "unstabilised approaches" OR
"destabilised approach" OR "destabilised approach")
AND
("flight operation" OR "flight operations")
```

The initial search returned 16 papers related to the research topic. The papers were then classified as relevant (R), not relevant (NR) or critical (C), whereas critical included papers with some critical information about the research questions. The screening process identified two papers as relevant and six as critical. The rest of the seven papers were considered as not relevant. Only one paper was excluded because it was duplicated and written in the French language.

The objective of the review is to identify the data-in-data-out approach used to generate safety-relevant knowledge from existing data, specifically on data fusion and model explainability. Models are interpretable when a human can understand how the model works without any other aid or technique. In contrast, an explainable model is a function that is too complicated for a human to understand. An additional aid or technique is necessary to understand how the model works. These models are called black-box.

In consideration of a series of elements related to the transparency of the model and the technical activities that must be carried out to make the model readable (Arrieta et al., 2020), as already discussed during the literature review, only the Decision Trees and Rule-Based Learners models were considered interpretable. The results evidenced that most research applied data mining on a single database, specifically collecting flight data from routine monitoring (i.e., Flight Data Monitoring). Only in one case were Automatic Dependent Surveillance-Broadcast (ADS-B) flight data and the airport weather information (METAR) integrated. The weather conditions were used as the influencing factors to carry out the risk index of the flights landing at Taipei Songshan Airport. The majority of the research used uninterpretable models.

In contrast, only one study deployed an interpretable model like the Decision Tree to predict the Unstable Approach Risk Misperception (Odisho II, 2020). The analysis revealed that six variables significantly contributed to its prediction: (i) glideslope deviation, (ii) selected approach speed deviation, (iii) localizer deviation, (iv) flaps not extended, (v) drift angle; and (vi) approach speed deviation. The researcher ranked these variables per importance following the decision tree predictive model analysis results.

Table 4-1 summarises the results of the rapid review process. Only relevant or critical papers are included.

Table 4-1 Research used for the rapid review

Paper reference	**Year**	**Classification**	**RQ1**	**RQ2**	**RQ3**
Oehling, J., & Barry, D. J. (2019). Using machine learning methods in airline flight data monitoring to generate new operational safety knowledge from existing data. *Safety Science*, *114*, 89-104.	2019	Critical	No	Unsupervised learning (Local Outlier Probability)	No
Clachar, S. (2016). *Novelty detection and cluster analysis in time series data using variational autoencoder feature maps*. The University of North Dakota.	2016	Relevant	No	Unsupervised learning (Variational Autoencoder Feature Map)	No
Chrysanthos, N. (2014). *Kernel methods for flight data monitoring*. Troyes.	2014	Critical	No	Kernel	No
Andrzejczak, C. (2010). A Study of Factors Contributing to Self-Reported Anomalies in Civil Aviation.	2010	Critical	No	Unsupervised document classification system	No
Odisho II, E. V. (2020). *Predicting Pilot Misperception of Runway Excursion Risk Through Machine Learning Algorithms of Recorded Flight Data*. Embry-Riddle Aeronautical University.	2020	Relevant	No	Decision Tree	Yes
Tsai, P., & Lai, Y. (2021). Risk Assessment of Final Approach Phase with ADS-B Trajectory Data and Weather Information using Artificial Neural Network. 2021 IEEE International Intelligent Transportation Systems Conference (ITSC).	2021	Critical	Yes	Neural network models	No

Puranik, T. G., Rodriguez, N., & Mavris, D. N. (2020). Towards online prediction of safety-critical landing metrics in aviation using supervised machine learning. *Transportation Research Part C: Emerging Technologies*, *120*, 102819.	2020	Critical	No	Random Forest regression	No
Li, L., Hansman, R. J., Palacios, R., & Welsch, R. (2016). Anomaly detection via a Gaussian Mixture Model for flight operation and safety monitoring. *Transportation Research Part C: Emerging Technologies*, *64*, 45-57.	2016	Critical	No	Gaussian Mixture Model	No

4.3. Aims and Objectives

According to the research theory, the main goal of Case Study 1 was to discover "a particularly dynamic and complex combination of planned and unplanned factors" that enable a probabilistic prediction of UA occurrence, identifying the predictors and patterns potentially occurring for any flight of a selected fleet (Embraer fleets).

The process commenced with preprocessing raw fleet data using computational techniques and statistical screening. Subsequently, machine learning models were trained, validated, and prioritised based on their high interpretability as sequences of 'if-then' rules, aiming to predict the likelihood of a UA occurrence better.

Such decision rules returned accurate and generalisable UA versus non-UA flight classifications. Such predictions ultimately would be proposed to inform decision-making to mitigate the risks of UAs. More interestingly, such trained algorithms might even be run and scored before a flight departure to screen the risk level of a UA event for that flight. Thus, it functions in a fully predictive model: anticipating the risk of a highly probable UA flight before it takes off or, in general, before the landing phase. This later predictive aspect has a clear safety-added value for flight planning, operations and training.

Overall, the objective is first to investigate the phenomenon in-depth and generate evidence-based knowledge to support organisations and pilots in identifying which factors could affect a UA predictably. Second, the prediction outcomes (the identified 'if-then' decision rules) must be validated from an ML modelling performance and operational feedback of an expert on such results. Third and finally, to understand where to alter or break such risk patterns operationally by acting upon and minimising the risk outcome.

4.4. Methodology

Case Study 1 and all other case studies of this work were handled consistently using the same data analysis framework. This methodological framework would keep the analytical and exploratory methodology consistent and reproducible across all cases. Based on the machine learning approach, this framework is called the Cross Industry Standard Process for Data Mining (CRISP-DM) methodology (Shearer, 2000). CRISP-DM helps to plan, organise, and implement data science or machine learning projects consistently and reliably.

The CRISP-DM consist of six phases describing a complete data science life cycle. It covers business understanding and scoping of the data analysis, data preparation, training of ML models, validation and model deployments. CRISP-DM is depicted as an idealised sequence of data and model governance events. Some tasks can be performed in different orders, but the main stages are sequential. Overall, the instantiation of the machine learning project based on the CRISP-DM framework is facilitated by the IBM SPSS® Modeler software platform. This AI-oriented platform was used to build all the predictive models and conduct all the required data analytics. CRISP-DM is shown in Figures 4-4 below.

Figure 4-4 Phases of the CRISP-DM Reference Model (Shearer, 2000)

All CRISP-DM phases are described as follows.

The optimal learning strategy from ML may involve combining the complementary strengths of humans and machines (Gennatas et al., 2020). This process, called Human-in-the-loop machine learning (HITL-ML) (Monarch, 2021), has a double goal to make the machine learning process robust, optimising every step and making humans more efficient and more effective.

The operational feedback provided by an expert is part of this process of interactions between humans and machine learning algorithms, which integrates the results of the Evaluation phase of the CRISP-DM model (i.e., machine) with the involvement of an expert on the topic investigated (i.e., human). The purpose is to augment the capacity to build data-efficient predictive models and increase the level of trust afforded by given models.

4.4.1. Stage One – Business understanding

Business understanding focuses on describing and specifying the objective and purpose of generating predictive models. The critical aspect here is to delimit and define what objectives would drive the investigation with data and the effect of predictive modelling. The argument is not about data types or availability in this process. Nevertheless, it is more about the objective of using data and what business problems are being solved by this approach.

In this first case study, the research question was the identification of predictors and risk patterns of UA events, according to the research theory. The study was conducted on a selected fleet, specifically the Embraer E-Jet family, a narrow-body short- to medium-range twin-engine jet airliner. This objective was carried out by analysing one-year flight operations data of 37,555 flights. The airline's core business objective was straightforward: reduce the UA approach events for volume or frequency for the referred fleet operations. This objective was specified and supported by the following priority on safety issues for UA in this case study.

4.4.2. Stage Two – Data understanding

The second stage, data understanding, focuses on translating business objectives into reliable and generalisable measures or variables. Such variables generally define what, where, when, and how to maximise, minimise, or quantify a quantity, quality, or pattern of evidence of a business objective.

Some essential steps are required to translate a business understanding into a data-based framework called the ‘data understanding’ process. The following ones are paramount to converting a business interest into predictive models based on data:

1. Determine the possible range of variables to consider. In this case study, it was decided to explore the maximum capacity of available features, both planned and unplanned, to discover any possible combination.
2. Evaluate if the variable recorded across databases could fit a search for risk patterns. In this case study, some suggestions came from flight safety experts regarding selecting the proper operational exceedances and discarding those that could interfere with the data analytics process of UA. It was decided, for example, only to consider the operational exceedances that occurred in a flight's descent and approach phases.
3. Evaluate what variables measured might be altered or manipulated operationally. For example, a variable initially measured in months for the analysis's convenience and interpretability is operationally transformed into years. In this case study, it was not immediately clear if an independent variable determined a change in the target variable. The execution of many trials on the same test allowed the researcher to get the most accurate target value.
4. Consider a plan for how the recommendations or solutions from a predictive risk pattern could impact the business objectives. In this case study, the information extracted by the risk pattern analysis of a UA could generate knowledge for business decisions and opportunities, such as identifying leading indicators and countermeasures to mitigate the UA risks or even designing operational scenarios to support evidence-based training.
5. Generate expectations on what solutions are most likely to impact organisationally: In this case study, the main objective is to contribute with a novel predictive strategy and a proactive and reactive approach for UA.

4.4.3. Stage Three – Data Preparation (Data Collection)

The third stage, data preparation, comes after a clear view of data understanding. Data preparation processes all available data to screen it, prepare it to serve the algorithms and make UA predictions accordingly. It comprises several activities, from initial data collection to final data pre-processing, to maximise overall data quality by cross-validation strategy selection. Notably, combining more datasets (across departments and operational data) in a single and larger framework was understood as key to extending the list of variables and technically augmenting the capacity of predictive analysis, consequently contributing to hypothesis validation.

This wide-range integration of cross-departmental variables about the same flight was intended to boost the richness in measurement space and depth of available conditions to control. Finally, the larger and richer variable set was intended to increase the explanatory power of the predictive models to be tested.

4.4.3.1. Initial data collection

Data access was started by the Safety, Flight Operations and Information Technology departments involved, which supported the complete data modelling design. Data requisition was a time-intensive, not trivial, and sometimes sensitive action because of the sensitive nature of some data, such as Crew data requisition. The data acquisition process was not trivial. An organisational process affected by the company's lack of transparent data governance and data policy made the initial data collection time-consuming.

Four Microsoft Excel spreadsheets were imported in IBM SPSS® Statistics ver. 28 for initial pre-screening and combined by keyed Date and Flight Number features. This final extensive dataset was imported into IBM SPSS® Modeler software (ver. 18.3). A total of 37,722 flight samples for 2016 were collected. They contained operational and crew data features and operational exceedance measures recorded during the descent and approach flight phases. A total of 316 cases were identified as unstabilised approaches (UA). This number is equivalent to 0,84% of the total flights with a rate of 8,38 events (UA) per 1,000 flights. Following the quantitative likelihood definition issued by the Federal Aviation Administration (2017) and shown in Figure 4-5 below, such UA volumes suggest that the UA event is a relatively frequent event type, occurring more than ten times yearly.

	Qualitative	Quantitative – Time/Calendar-based Occurrences Domain-wide/System-wide
Frequent A	Expected to occur routinely	Expected to occur more than 10 times per year
Probable B	Expected to occur often	Expected to occur between one and 10 times per year
Remote C	Expected to occur infrequently	Expected to occur one time every 1 to 3 years
Extremely Remote D	Expected to occur rarely	Expected to occur one time every 3 to 10 years
Extremely Improbable E	Unlikely to occur, but not impossible	Expected to occur less than once every 10 years

Figure 4-5 Likelihood Definitions – Commercial Operations/Large Transport Category (Federal Aviation Administration, 2017)

Table 4-2 shows the number of variables (last column) grouped by three primary databases: Operational, Crew and Flight Data Monitoring (FDM) (first, second and third table rows, respectively).

Table 4-2 Data sources

Index	Database	Number of variables
1	Operational	37
2	Crew	18
3	FDM	47

The operational database (Operational) contains planned and unplanned data for each operated flight. The planned data refers to flight plan information such as Flight Number, From, To, and Time of Arrival. In contrast, unplanned data refers to mapping the changes to the scheduled operation, such as Delay Code and Delay Amount in Departure and Arrival. The Crew database contains the de-identified information on pilots for each operated flight, such as Role, Age, Flight Hours Total and Flight hours in the last 30 days at the moment of flying. Finally, the FDM database contains the operational exceedances from the descent to landing phases recorded by the FDM program, such as Type of Event and Severity. The list of the variables and the relative descriptions for each database have been attached in Appendix 2 at the end of the thesis.

Notably, the role or importance of any individual variable or their particular combination to predict a UA is unknown.

4.4.3.2. Data pre-processing

All available data were preliminarily screened for data/feature completeness, values distributions, control of missing data patterns, duplicates, out-of-threshold values, feature engineering, feature selection, and balancing. This time-consuming process is fully described in Table 4-3 below.

Table 4-3 Data screening process

Data/Feature screening criteria	Solutions implemented
Completeness	The initial merged dataset is almost complete after data pre-processing (99,55%). Only 168 cases were removed (0,45%).
Value distributions	Almost all variables were transformed as a categorical feature to optimise tree-like algorithm processing.
Control of missing data	Null values were removed to a sample of 160 complete missing cases across the data frame. Null values were removed to eight cases in the Crew Volume category field.
Duplicates	No duplicates were found.
Out-of-threshold values	None
Feature engineering	The binning technique was applied to reclassify the variables into homogeneous and parsimonious classes.
Feature selection	Filter feature selection methods evaluated the relationship between input and target variables.
Balance (for imbalanced targets)	The Synthetic Minority Oversampling Technique (SMOTE) (Chawla et al., 2002) was used as the standard algorithm to balance the underrepresented class in the target feature (i.e., UA cases)

After completing all pre-processing solutions, the data was ready to learn a set of dedicated baseline ML models.

4.4.4. Stage Four – Modelling (Data Analysis)

A preliminary selection of a set of baseline ML models brings the CRISP-DM process into the fourth phase: Modelling. The critical primary objective was to meet an accurate and generalisable UA prediction. Technically, the goal was to maximise a bias-variance trade-off (Rajnarayan & Wolpert, 2008) of any model to predict UA consistently and proficiently. Implementing and testing very interpretable and glass-box ML models was a clear choice. Namely, a choice was driven towards readable decision tree-type classifiers.

Once the input and output features were defined, the modelling phase started. A preliminary set of ML models was fit on all available data to train and select the best models. The selection process of such baseline ML models was driven towards decision tree-type algorithms. The reason relied on their effortlessness in understanding, interpreting, and fitting well with the available tabular data and a binary classification objective like the one involved in this case study (i.e., the target of prediction UA vs non-UA). Specifically, C5.0 (Pandya & Pandya, 2015), CHAID (Chi-square automatic interaction detection) (Ritschard, 2013), Quest (QUEry generator for STructured sources) (Bergamaschi et al., 2013), and C&R Tree (Classification and Regression Tree) (Loh, 2011) classification types algorithms were selected to run 40 based line decision tree models.

To better determine how well the models work and estimate how they generalise consistently to new data, all data was split into training, validation and test sets using the partition sizes 60%, 30%, and 10%, respectively. No clear evidence shows which method and parameter combination would consistently outperform others (Birba, 2020). The method for data splitting and the parameters to use would vary depending on the data and the dataset size (Muraina, 2022) and cannot be predetermined. The objective was to fit the models on the training set, select the final model on the validation set, and finally cross-validate its performance levels on the test set (Cawley & Talbot, 2010).

The Auto-Classifier Node of the SPSS Modeler fit all baseline models on the training set. The best accurate predictive models were selected based on performance on the validation set. The purpose was to avoid a model selection bias by minimising the selection of over-optimistic models if chosen from the training set. Furthermore, the selected models on the validation set were tested for their Area Under the Curve (AUC) and accuracy levels. Such final best models were saved as the final best models. Overall, the CHAID 4 decision tree was automatically identified as the classifier with the highest performance rate in the test set. The model evaluation results are presented in the subsequent section (i.e., Evaluation).

The CHAID 4 decision tree algorithm is also favourably an explainable glass-box model: the feature predictor's importance to the model prediction is differentiated and exposed. Combining planned and unplanned factors as 'if-else' statements or decision rules can explicitly define a risk pattern in the feature predictors. Thus, the role of all essential features detected in the model is exposed and associated with predicting UA events. The CHAID 4 decision tree algorithm generated 67 rules for the UA class prediction, reaching an overall minimum test set accuracy of 90% for any of the decision rules. As an illustrative example, Figure 4-6 reports one example of a decision rule.

Rule 48 for 1.0 (773; 1.0)

```
if @DeltaDelay > -14.003
and @eventtype.1_cat in [ "OtherEvents" "Speed high between 5000-3000 feet" ]
and @eventtype.2_cat in [ "OtherEvents" ]
and @eventtype.3_cat in [ "Flap late setting above 500 AFE" ]
and @Severity_Max_cat in [ "3.0+" ]
then 1.000
```

Figure 4-6 Example of Rule 1 for UA True (1,000)

The decision rule describes the configuration factors of a UA. The numbers in bold show the number of records the rule applies (Instances) and the proportion of those records for which the rule is True (Confidence).

The rule set combines three types of variables:

1. Recovery delay from departure (@DeltaDelay).
2. Sequence of Flight Data Monitoring events occurred at different times during the descent/approach phases (@eventtype.X_cat).
3. Severity class of the Flight Data Monitoring events (@Severity_Max_cat).

An unstabilised approach is indicated True with a probability of 100% (1.0) if the flight is recovering from a delay in departure with a sequence of operational exceedances (e.g., @eventtype.1, @eventtype.2, @eventtype.3) leading from high speed between 5000 ft-3000 ft and concluding with the delayed flap configuration for landing below 1000 ft. One or more of these operational exceedances have a high value of severity (e.g., 3 or more). Severity is computed automatically by the flight data application, comparing the parameter limits with the degree of deviation from the established standard operating procedures into four event severity categories (e.g., 1 Low, 4 High).

Another example of a decision rule is shown in Figure 4-7.

Rule 15 for 1.0 (2,158; 0.998)

```
if @eventtype.2_cat in [ "Gear Late Extension" ]
and @eventtype.3_cat in [ "Gear Late Extension" "OtherEvents" "no event" ]
and @Severity_Max_cat in [ "3.0+" ]
and @Route_cat in [ "FCOLIN" "NAPLIN" "OtherRoutes" ]
and @Crew Volume_Cat in [ "1-2 crew" ]
and @CPAge_cat in [ "CPAge 43-52" "CPAge +52" ]
then 1.000
```

Figure 4-7 Example of Rule 2 for UA True (1,000)

Again, the numbers in bold red show the number of records the rule applies (Instances) and the proportion of those records for which the rule is True (Confidence).

The rule set combines five types of variables:

1. Sequence of Flight Data Monitoring events occurred at different times during the descent/approach phases (@eventtype.X_cat).
2. Severity class of the Flight Data Monitoring events (@Severity_Max_cat).
3. Flight route (@Route).
4. Flight crew numbers on-board (@Crew Volume_Cat)
5. Age of the Captain (@CPAge_cat)

An unstabilised approach is indicated as True with a probability very close to 100% (0.998) when a sequence of operational exceedances like ‘Gear Late Extension’ (e.g., @eventtype.2, @eventtype.3) when combined with one or more of these operational exceedances recording a high level of severity (e.g., 3 or more), specific flight routes like Roma Fiumicino (“FCO”) o Napoli (“NAP”) to Milano Linate (“LIN”), a standard cockpit configuration with two pilots (“1-2 crew”) excluding, for example, those flights with an additional planned flight crew for line check or training purposes, and Captain's age clustering (e.g., more than 43 years).

The full list of the rules generated with more than 95% confidence has been reported in Appendix 3. For easy reading, it is essential to emphasise that every indent in the rules describes a lower branching in the decision tree.

4.4.5. Stage Five – Evaluation

The CHAID 4 model performance is shown in Table 4-4. For easy reading of the table, the numbers following the model refer to different versions or iterations of the algorithm with varying levels of complexity and pruning strategies. The model estimated an optimal model performance (i.e., Accuracy and AUC criteria) of the unseen data in the test set with an Accuracy value of 99.216 and the AUC (Area Under the Curve) at 0.998.

Table 4-4 Performance Model (Testing Set)

	Model	No. Fields Used	Overall accuracy (%)	Area Under Curve	Accumulated accuracy (%)	Accumulated AUC
1	CHAID 4	19	99.216	0.998	99.216	0.998
2	CHAID 2	11	99.12	0.998	99.12	0.998
3	CHAID 3	19	99.252	0.998	99.252	0.998
4	CHAID 1	11	99.084	0.998	99.084	0.998
5	Quest 2	16	98.882	0.997	98.882	0.997

Figure 4-8 shows the confusion matrix of the model, where it is evident that there is complete control of false positives and negatives. The detailed analysis in the confusion matrix again confirms the model's ability to generate accurate predictions.

Results for output field @UA1000

Individual Models

Comparing $R-@UA1000 with @UA1000

Correct	74,240	99.68%
Wrong	238	0.32%
Total	74,478	

Coincidence Matrix for $R-@UA1000 (rows show actuals)

	0.000000	**1.000000**
0.000000	37,028	211
1.000000	27	37,212

Performance Evaluation

0.000000	0.692
1.000000	0.687

Evaluation Metrics

Model	AUC	Gini
$R-@UA1000	1.0	1.0

Figure 4-8 Confusion matrix

4.4.6. Stage six – Deployment

The data model was not deployed and used in a real-operation context.

4.5. Operational feedback validation

As explained in the methodology section of this case study, operational feedback is a solution to integrate expert knowledge and machine-learned models. The purpose is to assess whether the identified decision rules are "useful" to satisfy target users' needs in the valid usage scenario and are easy to understand and interpret (i.e., "usable") (Xu, 2019).

A selection of the most significant decision rules for many instances and high confidence were shown to a former professional pilot and safety expert. The machine learning model results were discussed around two open-ended questions in an arranged meeting by phone:

- RQ1: Are the decision rules plausible outputs to describe UA events?
- RQ2: Are the decision rules easy to understand and interpret UA events?

The expert gave positive feedback, highlighting the clarity and ease of interpretation of the 'if-then' statements, which offer valuable insights for addressing risk mitigation actions.

4.6. Summary

The data analysis generated clear and simple patterns. However, the predictive potential of the data model indicates that more extensive and diverse data sources could reveal more intricate patterns, better capturing the configuration of a safety event with their planned and unplanned factors.

The results from this case study suggest that using the rule sets makes it possible to understand the dynamic nature of an unstabilised approach with a certain degree of confidence. The combination of planned and unplanned factors in an 'if-else' statement explains the circumstances surrounding UA events with a remarkable degree of the predictive capacity of such AI models. The analysis results, in summary, confirm the model's ability to generate accurate predictions and be cross-generalisable.

The data mining process of deducing 'if-then' rules from a data set, also called rule induction, identifies the inherent relationship between the variables. Based on the available data, the analysis of the rules with the highest number of instances indicates that the combination of the severity class of some Flight Data Monitoring events, such as 'Flap late setting above 500 ft' and 'Gear late extension', can be considered strong UA predictors.

Although the case study aimed to empirically demonstrate the reconceptualisation of the safety event by identifying combinations of planned and unplanned factors, it produced several specific rules linking predictor variables to unstable approaches. These rules were validated by confirming with an expert that they are interpretable and plausible. However, despite the available data not covering all potential threat situations, some consideration can be advanced regarding what the rules tell us about causal patterns and how this information could be translated into effective safety measures.

To be realistic, applying the 'breaking the risk pattern' in the everyday operational realm may not always be possible or, at the very least, challenging. Therefore, if the condition cannot be removed, the strategy is to attempt to manage it. The lack of factual evidence can only suggest that operational exceedances such as 'Flap late setting above 500 ft' and 'Gear late extension', identified as precursors, could have a human factor-related cause. Some recommendations to translate into effective safety measures to mitigate common human factors across various aviation flight categories and prevent safety events could be specific UA awareness and prevention training provision, pilot training, Crew Resource Management (CRM) training and enhancement of organisational knowledge regarding elements contributing to UA (Kelly & Efthymiou, 2019).

The expert gave relevant examples from his professional experience throughout the interview, showing how SMS organisations can effectively turn information into practical risk-reduction strategies in similar situations: from leveraging a risk assessment to evaluate the hazard or hazards, suggesting a mitigation action plan to be approved by the Accountable Manager, assigning responsibilities, and implementing control strategies. In the context of managing Unstable Approaches, the expert emphasised the pivotal role of addressing human factors and enhancing human performance. Specifically, he highlighted the importance of fostering effective communication among flight crew and establishing a safety promotion program to reinforce adherence to Standard Operating Procedures. Additionally, the expert stressed the significance of reviewing flight techniques to bolster safety margins. These actions collectively underscored the proactive approach necessary for mitigating risks and ensuring operational safety within SMS organisations.

To further elaborate on this final recommendation, uncovering the dynamic nature of a safety event and then identifying the potential leading indicators through the complex pattern of precursors can enable organisations to implement the knowledge of the issues that may result in a UA. These leading indicators can then be quantified as predictive factors for anticipating and preventing future safety events. As shown in Tables 3.1 and

3.2, the trends indicate that the capacity to take action to the identified precursors leads to implementing mitigation measures, which in turn impact the safety performance of the safety event either positively or negatively.

4.7. Recommendation

A single flight can generate multiple Flight Data Monitoring events or exceedances if various parameters or conditions deviate from established safety criteria or Standard Operating Procedures at different times during the flight. As a future initiative, analysing Flight Data Monitoring events as multivariate time series data rather than separately can help identify and leverage temporal dependencies to enhance the predictive capabilities of unstabilised approaches.

CHAPTER 5. CASE STUDY 2 (Detecting precursors to safety events during aircraft turnaround process)

5.1. Introduction

The aircraft turnaround process, also called aircraft ground handling, is one of the more complex activities in airport operations and an example of socio-technical system (STS) work design. The turnaround process starts when the aircraft reaches the parking position or assigned stand after landing, and the chocks are set ('on-block time') and ends when the aircraft is ready to leave after removing the chocks ('off-block time'). The parking position can be located at the gate with the aircraft connected at the terminal through a passenger boarding bridge (e.g., stand) or on the apron, known as the remote position (Schmidt, 2017). The complexity relies on the sequence of performing tasks, people, and vehicles involved during a scheduled time frame. Compliance with that time frame is a strategic factor of airline success, specifically for short and medium-haul flights, and an objective for the aviation services companies that provide airport ground and cargo handling services. Delays or operational disruptions can have consequences on customer satisfaction and brand reputation.

The aircraft turnaround process is a compelling example of the necessity of finding the right balance between production and protection. In any organisation engaged in the delivery of services, production and profitability are linked to safety risks. The management dilemma is to keep these elements under control to operate in an area where one of the two elements does not affect the other and vice versa (i.e., safety space). The purpose is to avoid extreme organisational exposure to financial situations or catastrophic events (ICAO, 2018).

Aircraft turnaround defines the servicing process while an aircraft is grounded between the execution of two successive flights. It consists of a tight sequence of activities from arrival to departure, generally carried out by different handling companies and ground vehicle types in a relatively limited space. Standardisation is one of the requirements to ensure safe and efficient ground operations based on these premises. The Airport Handling Manual (AHM), published annually by IATA, provides updated best practices. The Figures below describe the sequence of ground handling operations from the aircraft's arrival to its departure (Figure 5-1) and a vehicle positioning layout around the aircraft while it is undergoing a turnaround process (Figure 5-2) (Fitouri-Trabelsi et al., 2013).

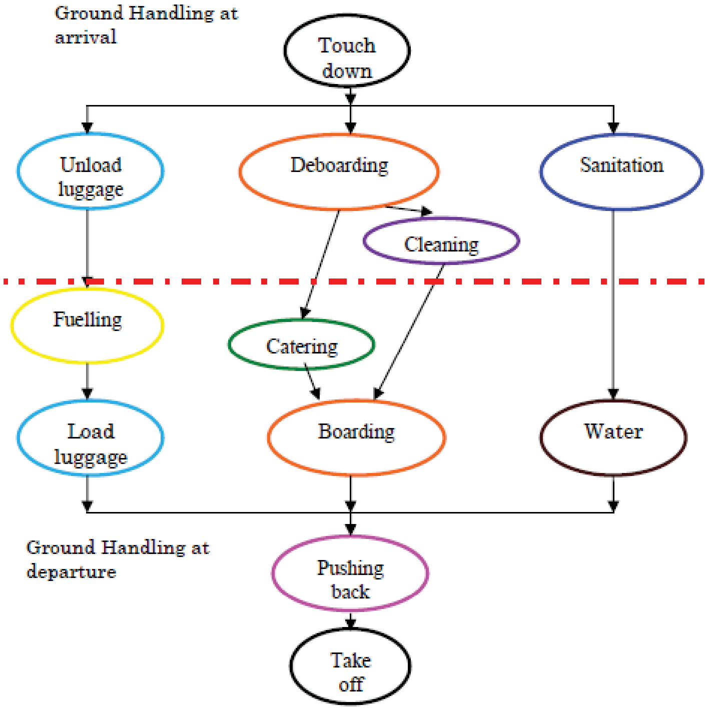


Figure 5-1 Ground handling activities at arrival and departure (Fitouri-Trabelsi et al., 2013)

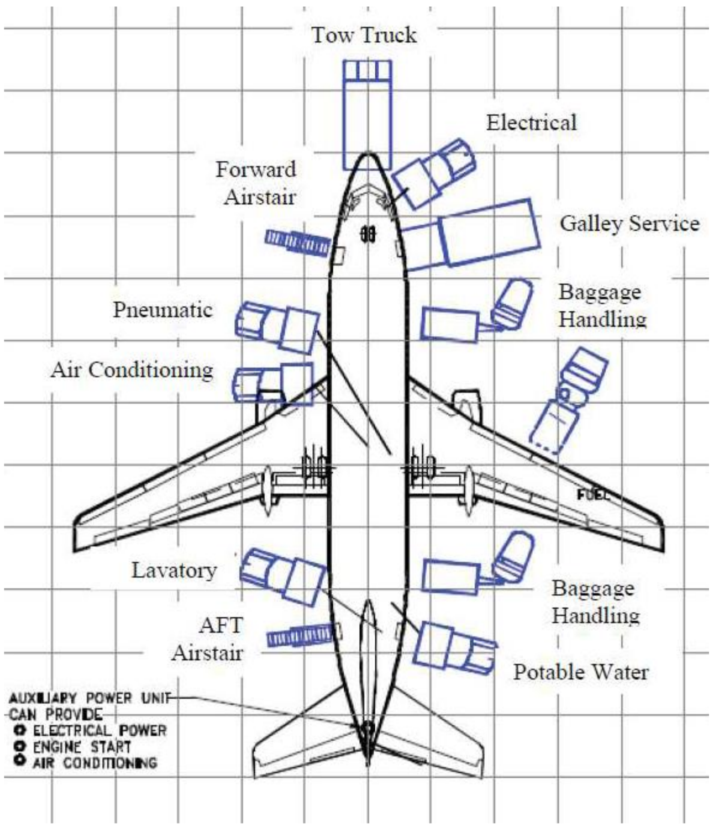


Figure 5-2 Ground handling arrangements (Fitouri-Trabelsi et al., 2013)

It is common knowledge that accidents or incidents are often preceded by safety-related situations and operational deficiencies that reveal safety hazards. Therefore, this information is an essential resource for their detection. The safety reporting system or occurrence reporting is a source of data to identify hazards, allowing pilots, air traffic controllers, cabin crew, dispatchers, maintenance technicians, and ground operations to report events or near misses that pose a risk to safety in the interest of feeding the operational risk management and improving the accident or incident prevention.

In the context of safety data collection and analysis, any organisation should establish a voluntary reporting system that complements a mandatory reporting system. The mandatory reporting system is regulated by Regulation (EU) No 376/2014 on the reporting, analysis, and follow-up of occurrences in civil aviation and following implemented by the Implementing Regulation (EU) 2015/1018 laying down a list of classifying occurrences to be mandatorily reported. In contrast, a voluntary reporting system aims to facilitate the collection of occurrences that may not be captured by the mandatory reporting system or other safety-related information which the reporters perceive as an actual or potential hazard to aviation safety.

The list of mandatory occurrence reports (MOR) has been structured so that the pertinent occurrences are linked with categories of activities to facilitate reporting those occurrences. Moreover, the regulation specifies that the list is not exhaustive. Following that list, the occurrences related to ground handling that potentially could be generated during the aircraft turnaround are:

1. Incorrect handling or loading of passengers, baggage, mail, or cargo is likely to significantly affect aircraft mass and/or balance (including significant errors in load sheet calculations).
2. Boarding equipment removed, leading to endangerment of aircraft occupants.
3. Incorrect stowage or securing of baggage, mail, or cargo likely in any way to endanger the aircraft, its equipment, or occupants or to impede an emergency evacuation.
4. Transport, attempted transport or handling of dangerous goods which resulted or could have resulted in the safety of the operation being endangered or led to an unsafe condition (e.g., dangerous goods incident or accident as defined in the ICAO Technical Instructions).
5. Non-compliance on baggage or passenger reconciliation.

6. Non-compliance with required aircraft ground handling and servicing procedures, especially in de-icing, refuelling, or loading procedures, including incorrect positioning or removal of equipment.
7. Significant spillage during fuelling operations.
8. Loading of incorrect fuel quantities is likely to have a significant effect on aircraft endurance, performance, balance, or structural strength.
9. Loading of the contaminated or incorrect type of fuel or other essential fluids (including oxygen, nitrogen, oil, and potable water).
10. Failure, malfunction, or defect of ground equipment used for ground handling, resulting in damage or potential damage to the aircraft (e.g., tow-bar or Ground Power Unit).
11. Missing, incorrect, or inadequate de-icing/anti-icing treatment.
12. Damage to aircraft by ground handling equipment or vehicles, including previously unreported damage.
13. Any occurrence where human performance has directly contributed to or could have contributed to an accident or a serious incident.

The pandemic situation significantly impacted aviation operations, including aircraft ground handling operations. Since turnaround times have become increasingly shorter with many activities being undertaken, standard operating procedures required the development of an aircraft turnaround plan to incorporate the COVID-19 measures, both minimising the extra turnaround time with more workload (Schultz et al., 2020) and reducing in the number of safety events.

As shown in Figure 5-3, the latest safety statistics highlighted how Ground Damage, a safety event in ground operations, can be considered one of the top issues for safety and costs (IATA, 2022). Specifically on this topic, IATA estimated that the annual cost of ground damage could double to nearly $10 billion by 2035 unless preventive actions are taken (IATA, 2022).

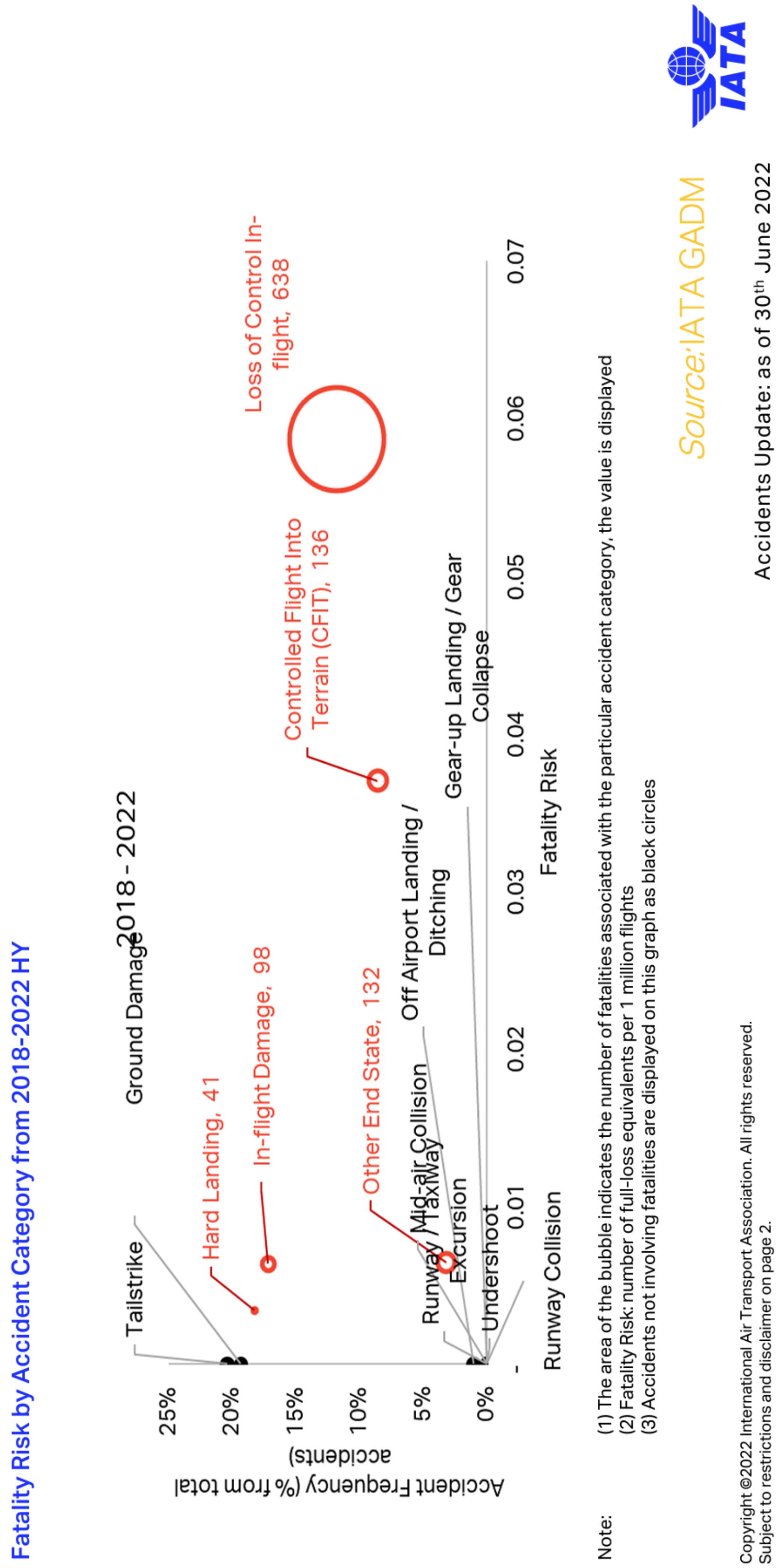


Figure 5-3 Fatality Risk by Accident Category from 2018-2022 HY (IATA, 2022)

5.2. Previous studies

A rapid review was conducted to provide a comprehensive overview of the research on using artificial intelligence (AI) based on machine learning (ML) algorithms to investigate safety events during aircraft turnaround.

The research questions were designed to investigate the data-in-data-out approach to extracting and discovering safety-relevant knowledge in large datasets to predict it:

- RQ1: Has data been integrated from multiple sources?
- RQ2: Which machine learning algorithm has been used?
- RQ3: Is the machine learning algorithm interpretable?

Concerning the RQ3 and according to Table 2-3 (Arrieta et al., 2020), the machine learning model only considered Decision Trees and Rule-Based Learner models.

The research was identified from the Google Scholar electronic database. The search string used to query this database based on metadata (title, abstract, keywords) is shown below. In addition to the papers returned by the above database, some handpicked papers recommended by domain experts but not returned by the search string were also included.

```
("artificial intelligence" OR "AI")
AND
("machine learning" OR "ML")
AND
("aircraft turnaround")
AND
("safety event" OR "safety events")
```

The search returned no papers related to the research topic. Then, a new search string was created without the keywords `("safety event" OR "safety events")`. The second search returned 185 papers with business goals in AI Operations to improve operational efficiency and profitability. The complexity of airport operations, including various activities and resource utilisation, prompted numerous studies with the primary objective of making predictions. Predict turnaround times (Halmesaari, 2020; Asadi et al., 2020; Luo et al., 2023) or specific sub-activities like passenger boarding (Schultz & Reitmann, 2018; 2019).

While these studies share a common business goal and objectives and use the same type of operational data, their analytical approaches differ significantly, suggesting that addressing a complex problem requires exploring various solutions. The validity of the approaches is measured only in terms of predictive accuracy and operational efficiency, without the conduction of the operational feedback provided by an expert as part of the process of interactions between humans and machine learning algorithms to augment the capacity to build data-efficient predictive models and increase the level of trust afforded by a given mode.

5.3. Aims and Objectives

According to the research theory, Case Study 2 was to discover “particularly dynamic and complex combinations of planned and unplanned factors” that enable a probabilistic prediction of safety events during aircraft turnaround activities. The investigation was conducted in the Ground Operations department of an Italian airline on a selected aircraft type, specifically the Airbus A320 family, a series of narrow-bodies airliners including the A321, A320, and A319.

The process started by preprocessing raw safety occurrences reported by front-line aviation personnel and operational data using computational techniques and statistical screening. Methods and tools from computer science and statistics were applied to analyse and process data. Machine learning models were trained and validated on the available data. Selection of such machine learning of higher interpretability models based on sets of 'if-then' rules served the purpose of classifying and predicting ground handling safety events.

Such decision rules return accurate and generalisable results on predicting safety versus non-safety events during aircraft turnaround activities. Such predictions would ultimately be proposed to inform decision-making to mitigate ground handling safety risks. More interestingly, such trained algorithms could even be run (scored) before the aircraft reaches the parking position after landing to anticipate the detection of the risk levels of safety events during the execution of the whole process. Thus, functioning in a fully predictive model, anticipating the risk of a highly probable safety event before the aircraft reaches the parking position after landing, and the chocks are set ('on-block time') until the aircraft is ready to leave after removing the chocks ('off-block time'). The predictive aspect of this last point has a clear safety-added value for flight planning, operations, and training.

Overall, the objective is first to investigate the phenomenon in-depth and generate evidence-based knowledge to support organisations and ground staff in identifying which factors could predictably affect a ground handling safety event. Second, to validate the prediction outcomes (the identified 'if-then' decision rules) from a machine learning modelling performance and operational feedback of an expert on such results. Third and finally, to understand where to alter or break such risk patterns operationally by acting upon and minimising the risk outcome.

5.4. Methodology

Case Study 2 of this work applied the same data analysis framework as the previous Case Study 1. The data model was not deployed and used in a real-operation context. The Cross Industry Standard Process for Data Mining (CRISP-DM) methodology (Shearer, 2000) is shown in Figure 5-4. CRISP-DM helps to plan, organise, and implement data science or machine learning projects consistently and reliably. Again, the IBM SPSS® Modeler software platform was used to build all the predictive models and conduct all the required data analytics.

Figure 5-4 Phases of the CRISP-DM Reference Model (Shearer, 2000)

The optimal learning strategy from machine learning may involve combining the complementary strengths of humans and machines (Gennatas et al., 2020). This process, called Human-in-the-loop machine learning (HITL-ML) (Monarch, 2021), has a double goal to make the machine learning process robust, optimising every step and making humans more efficient and more effective.

In this case study, as for the previous, the operational feedback provided by an expert is part of this process of interactions between humans and machine learning algorithms, which integrates the results of the Evaluation phase of the CRISP-DM model (i.e., machine) with the involvement of an expert on the topic investigated (i.e., human). The purpose is to augment the capacity to build data-efficient predictive models and increase the level of trust afforded by a given mode.

5.4.1. Stage one – Business Understanding

Business understanding focuses on describing and specifying the objective and purpose of generating predictive models. In this second case study, according to the research theory, the research question was the identification of predictors and risk patterns of ground handling safety events that occurred during aircraft turnaround activities performed by the Ground Operations department of an Italian airline in the ground handler role. A specific aircraft type series, such as the Airbus A320 family, a narrow-bodies airliner including the A321, A320, and A319, were selected to ensure uniform scientific analysis and reliable results. This objective was carried out by analysing the historical data of two-year flight operations of 195,296 flights (2019-2020). The airline's core business objective was straightforward: reduce safety events during aircraft turnaround activities by volume or frequency for the referred fleet operations. This objective was specified and supported by the following priority on safety issues for safety events in ground operations.

5.4.2. Stage two – Data Understanding

The second stage covers data understanding, translating business objectives into reliable and generalisable measures or variables. Such variables generally define what, where, when, and how to maximise, minimise, or quantify a quantity, quality, or pattern evidence of a business objective, namely the target prediction.

The steps listed in Case Study 1 were also followed in this case study. A subject-matter expert (SME) was engaged to determine the possible range of variables to consider, both planned and unplanned, selecting the proper ones, discarding those that could interfere with the data analysis problem and evaluating what variables measured might be altered or manipulated operationally.

The variables selected to model the business objectives were found by merging safety and operational data. The information extracted by the risk pattern analysis of safety events during the aircraft turnaround activities could generate safety-relevant knowledge for process optimisation and safety purposes, such as identifying leading indicators and countermeasures to mitigate the risks or designing operational scenarios to support evidence-based training.

5.4.3. Stage three – Data Preparation

The third stage, data preparation, comes after a clear view of data understanding. A wide-range integration of cross-departmental variables about the same aircraft turnaround operation was achieved. This has boosted the richness of the measurement space and depth of available conditions for investigation. This process was intended to increase the explanatory power of the tested predictive models.

5.4.3.1. Initial data collection

Data access was started by the Safety, Ground Operations and Information Technology departments involved, which supported the complete data modelling design. Data requisition was time-intensive, and the process was affected by the company's lack of transparent data governance and data policy. Technology solutions and tools adopted by some internal functions limited the data extraction of resources needed to design the complete data modelling for incompatible output formats.

Two Microsoft Excel spreadsheets were imported in IBM SPSS® Statistics ver. 28 for initial pre-screening and combined by keyed Date and Flight Number features. This final extensive dataset was imported into IBM SPSS® Modeler software (ver. 18.3). A total of 195,296 flight samples operated by the Airbus A320 Family fleets of an Italian airline, and 914 mandatory and voluntary safety occurrences reported by front-line personnel and classified as RAMP category, "occurrences during (or as a result of) ground handling operations" (Commercial Aviation Safety Team, 2021, p. 13), were collected and identified during the years 2019 and 2020. The number of safety occurrences is equivalent to 0,47% of the total flights, with a rate of 4,68 per 1,000 flights. Following the quantitative likelihood definition issued by the Federal Aviation Administration (2017) and shown in Figure 5-5 below, such volumes suggest that these event types during the aircraft turnaround activities are relatively frequent, occurring more than ten times yearly.

	Qualitative	Quantitative – Time/Calendar-based Occurrences Domain-wide/System-wide
Frequent A	Expected to occur routinely	Expected to occur more than 10 times per year
Probable B	Expected to occur often	Expected to occur between one and 10 times per year
Remote C	Expected to occur infrequently	Expected to occur one time every 1 to 3 years
Extremely Remote D	Expected to occur rarely	Expected to occur one time every 3 to 10 years
Extremely Improbable E	Unlikely to occur, but not impossible	Expected to occur less than once every 10 years

Figure 5-5 Likelihood Definitions – Commercial Operations/Large Transport Category (Federal Aviation Administration, 2017)

Table 5-1 shows the number of variables (last column) grouped by two primary databases: Operational and Reporting System (SDS) (first, second and third table rows, respectively).

The data unavailability on staff scheduling, such as the number of ground staff, composition, experience, and type of contract involved in the aircraft turnaround activities, limited the research to investigate the phenomenon in-depth and generate safety-relevant knowledge and impaired efforts to augment the predictive capacity and the potential associative or causal paths behind safety occurrences.

Table 5-1 Data sources

Index	Database	Number of variables
1	Operational	51
2	Reporting System	16

The operational database (Operational) contains planned and unplanned data for each operated flight. Planned data refer to flight plan information such as Flight Number, Departure, Arrival, and Operated Fleet. Some other variables, such as the aircraft turnaround time, were calculated as the difference between the time of arrival and the time of departure of the next flight. In contrast, unplanned data refers to mapping the changes to the scheduled operation, such as Delay Code and Delay Amount in

Departure and Arrival. The Reporting System database contains information about safety occurrences such as Type of Event, Occurrence Category, and Occurrence Class.

The list of the variables and the relative descriptions for each database have been attached in Appendix 4 at the end of the thesis.

Notably, the role or importance of any individual variable or their combination to predict a safety event in the aircraft turnaround process is unknown.

5.4.3.2. Data pre-processing

All available data were preliminarily screened for data/feature completeness, values distributions, control of missing data patterns, duplicates, out-of-threshold values, feature engineering, feature selection, and balancing. The process is fully described in Table 5.2.

Table 5-2 Data screening process

Data/Feature screening criteria	**Solutions implemented**
Completeness	The initial merged dataset is almost complete after data pre-processing. Only 21 out of 935 ground safety occurrences were not combined (2,24%) with the 195,296 operated flights.
Value distributions	Almost all variables were transformed as a categorical feature to optimise tree-like algorithm processing.
Control of missing data	No null values.
Duplicates	The Data Audit executed before and after the merging revealed a minimal difference in the number of cases. Of 23 cases out of 195,296 (0,01%), they were considered duplicates.
Out-of-threshold values	None.
Feature engineering	The binning technique was applied to reclassify the variables into homogeneous and parsimonious classes.
Feature selection	Filter feature selection methods evaluated the relationship between input and target variables.
Balance (for imbalanced targets)	The Synthetic Minority Oversampling Technique (SMOTE) was used as the standard algorithm to balance the underrepresented class in the target feature (i.e., safety occurrences).

After completing all pre-processing solutions, the data was ready to learn a set of dedicated baseline machine-learning models.

5.4.4. Stage four – Modelling (Data Analysis)

A selection of baseline machine learning models brought the CRISP-DM process (Shearer, 2000) into the fourth phase: Modelling. In this case, the primary objective was to achieve an accurate and generalisable safety event prediction. Technically, the goal was to result in highly interpretable overall baseline models and decision tree-type algorithms. Specifically, CHAID (Chi-square automatic interaction detection), C5.2, and C&R Tree (Classification and Regression Tree) algorithms were implemented for 40 baseline models.

Following the method employed in the previous case study, to better determine how well the models work and estimate how they generalise consistently to new data, all data was split into training, validation and test sets using the partition sizes 60%, 30%, and 10%, respectively. As discussed in the previous case study, no clear evidence shows which method and parameter combination would consistently outperform others (Birba, 2020). The method for data splitting and the parameters to use would vary depending on the data and the dataset size (Muraina, 2022) and cannot be predetermined. The objective was to fit the models on the training set, select the final model on the validation set, and finally cross-validate its performance levels on the test set (Cawley & Talbot, 2010).

After fitting all available models on the training set, the best accurate predictive models were selected based on performance on the validation set. Finally, cross-generalisation was performed in the test set. The purpose of the validation set was to avoid a model selection bias by minimising the selection of over-optimistic models if chosen from the training set directly. The Area Under the Curve (AUC) prediction accuracy level was set as the main model performance criteria for the assessment.

The model evaluation results are presented in the subsequent section (i.e., Evaluation). However, the general performance rate at the test set was generally moderate-low across various decision rule extractions. The range of the overall accuracy was between 61 and 74 per cent, with AUC values ranging between 0.58 and 0.60. When $AUC < 0.5$ indicates that the model is worse than the random guess; $AUC = 0.5$, the model is the same as a random guess, and the model has no predictive value; when $0.5 < AUC < 1$, the model is better than a random guess, and has particular predictive value, and the closer to 1, the better classifier performance; when $AUC = 1$, the model has perfect prediction function (Fawcett, 2006). The best tree-based algorithms selected in this first assessment were CHAID 1 and C&R Tree 1.

CHAID 1

The CHAID 1 decision tree algorithm is a favourably explainable glass-box model: the feature predictor's importance to the model prediction is differentiated and exposed. Combining planned and unplanned factors as 'if-else' statements or decision rules can explicitly lead to a risk pattern identification in the sampling space available. The CHAID 1 decision tree algorithm generated three rules for safety events in aircraft turnaround class prediction, reaching an overall minimal test set accuracy between 60 and 70 per cent for any of the decision rules. Figure 5-6 reports three examples of a decision rule.

Rule 1 for 1.0 (336; 0.705)

```
if OTPD > 2
and OperatedDeparture_reclassified in [ "LIN" "OTH" "FCO" ]
then 1.000
```

Rule 2 for 1.0 (83; 0.614)

```
if OTPD <= 1
and OperatedArrival_reclassified in [ "CTA" "PMO" "CAG" ]
then 1.000
```

Rule 3 for 1.0 (108; 0.602)

```
if OTPD > 1
and OTPD <= 2
and FlightType in [ "DOM" ]
then 1.000
```

Figure 5-6 CHAID 1 – Example of Rule for Safety Event in Aircraft Turnaround True (1.0)

The rule sets combine two types of variables:

1. Airline on-time performance in departure (OTPD) (see Table 5-3 for explanation)
2. Departure/Arrival airports (see Table 5-4 for explanation)

Table 5-3 OTPD variable information **(Airline Cost Management Group, 2022)**

Value	Label	Description
1	D0	On-Time Departure
2	D15	Departure with a delay of 15 minutes and less
3	D90	Departure with a delay of 90 minutes and less

Table 5-4 OperatedDeparture_reclassified variable information

Value	Description
CAG	Cagliari
CTA	Catania
FCO	Roma Fiumicino
LIN	Milano Linate
PMO	Palermo
OTH	Other airports

Rule 1 describes the configuration of an aircraft departing with delays of more than 16 minutes at airports like Roma Fiumicino ("FCO"), Milano Linate ("LIN"), or minor airports transformed to "OTH". During aircraft turnaround, the data preprocessing step may configure a safety event True with a 70% probability (0.705).

Rule 2 describes the configuration of an aircraft departing on time and arriving at airports like Catania ("CTA"), Palermo ("PMO") or Cagliari ("CAG"). The data preprocessing step may configure a safety event True with a 60% probability (0.614) during aircraft turnaround.

Rule 3 describes the configuration of an aircraft departing with a delay of 15 minutes or less for a domestic flight ("DOM"). The data pre-processing step may configure a safety event True with a 60% probability (0.602).

The decision rule describes the configuration of factors as the combination of values of variables increasing the risk of a safety event. The prediction target in the tree classifier. The numbers in bold red show the number of records where the rule applies (Instances) and the proportion of those for which the rule is True (Confidence), namely the likelihood of occurrence. The role of the On-Time Performance Departure (OTPD) variable is significant. The values were labelled to categorise three operational situations following the format used by the IATA Airline Cost Management Group (2022) and reported in Table 5-3. The rules are completed by combining the OTPD variable with the Domestic (DOM) flight type, namely a flight that stays within the same country and specific departure airports. The encoded values of the departure airports are shown in Table 5-4.

A top-down-oriented chart containing the rules generated by the model has been appended to Appendix 5.

Classification and Regression Tree 1 (C&R Tree)

Classification and Regression Tree is a simple and intuitive algorithm that can handle categorical and continuous variables. The C&R Tree generated two rules for safety events in the aircraft turnaround class prediction (Figure 5-7), reaching an overall minimum test set accuracy between 60 and 80 per cent for any of the decision rules, a slightly better performance than the previous CHAID 1 model results.

Rule 1 for 1.0 (95; 0.821)

```
if DelayCodeI_reclassified in [ "HANDLING" "PASSENGER/BAGGAGE" ]

then 1.000
```

Rule 2 for 1.0 (183; 0.612)

```
if DelayCodeI_reclassified in [ "ATC" "WEATHER" "MISCELLANEOUS" "OPERATION"
"CARGO/MAIL" "DAMAGE/FAILURE" "INTERNAL" "NOCODE" "TECHNICAL" ]

and OTPD in [ 3.000 ]
```

Figure 5-7 C&R Tree 1 – Example of Rule for Safety Event in Aircraft Turnaround True (1.0)

The rule sets combine two types of variables:

1. IATA Delay Codes
2. Airline on-time performance in departure (OTPD) (see Table 5-3 for explanation)

IATA delay codes (IATA, 2023) were introduced to establish a standardisation reporting system for commercial flight departure delays by airlines. Before this standardisation, each airline employed its own system, complicating the sharing and consolidation of flight delay data. IATA's solution was to standardise the format for reporting flight delays using codes, allowing for clear attribution of the causes and responsibility for the delays. The rules evidenced the precursor role of the delay reasons categorised per the IATA standardisation format combined with the On-Time Performance Delay (OTPD), as shown in Table 5-3.

Rule 1 describes the configuration of an aircraft departing with delays caused by aircraft and ramp handling or baggage processing. The data preprocessing step may configure a safety event True with an 80% probability (0.821).

Rule 2 describes the configuration of an aircraft departing with delays of more than 16 minutes caused by several categories. The data preprocessing step may configure a safety event True with a 60% probability (0.612).

A top-down-oriented chart containing the rules generated by the model has been appended to Appendix 6.

5.4.5. Stage five – Evaluation

The model performance is shown in Table 5-5. The performance evaluation of the model resulted in a minimal discrete performance estimation, considering criteria such as

Accuracy and AUC on the testing set. The accuracy value achieved was 74.306%, and the AUC (Area Under the Curve) was 0.601. The choice of the performance metric was influenced by the nature of the machine learning problem, which is classification, and the specific objective of the analysis. Based on the evaluation, the C&R Tree 1 model was selected due to its better performance in overall accuracy (74.306%), while the CHAID 1 model was chosen for its result in the Area Under the Curve (AUC) (0.601), suggesting that the model is better than a random guess, and has certain predictive value (Fawcett, 2006).

Table 5-5 Performance Model (Testing Set)

	Model	No. Fields Used	Overall accuracy (%)	Area Under Curve	Accumulated accuracy (%)	Accumulated AUC
1	CHAID 1	5	61.031	0.601	61.031	0.601
2	C5.2	5	66.698	0.588	66.698	0.588
3	C&R Tree 1	7	74.306	0.583	74.306	0.583
4	Quest 2	12	59.373	0.447	59.373	0.447
5	C&R Tree 2	20	63.609	0.423	63.609	0.423

5.4.6. Stage six – Deployment

The data model was not deployed and used in a real-operation context.

5.5. Operational feedback validation

As explained in the methodology section of this case study, operational feedback is the identified solution to integrate expert knowledge and machine-learned models. The purpose is to assess whether the decision rules are "useful" to satisfy target users' needs in the valid usage scenario and are easy to understand and interpret (i.e., "usable") (Xu, 2019).

A Nominated Person for Ground Operation in Italy's former largest airline and flag carrier was selected and contacted as a subject-matter expert. The machine learning model results were discussed around two open-ended questions in an arranged face-to-face meeting:

- RQ1: Are the decision rules plausible outputs to describe safety events during turnaround activities?
- RQ2: Are the decision rules easy to understand and interpret safety events during turnaround activities?

Positive feedback was given by the expert involved. The available data, only limited to safety occurrences and operational data, did not allow the identification of potential unknown and hidden patterns. The decision rules with the most significant number of instances have been considered plausible for understanding safety events in aircraft turnaround activities. The 'if-then' statements have been found easy to interpret, providing information to address the actions for risk mitigation. However, the suggestion for future research is to extend the range of the variables to the identified issues of any safety occurrence, specifically those related to human factors, for ascertaining explanatory aspects with people and organisations.

5.6. Summary

The data analysis generated clear and simple patterns. However, the predictive potential of the data model indicates that more extensive and diverse data sources could reveal more intricate patterns, better capturing the configuration of a safety event with their planned and unplanned factors.

The results from this case study suggest that using the rule sets to understand what caused or could cause safety events in the aircraft turnaround activities with a certain degree of confidence is possible. The combination of planned and unplanned factors in an 'if-else' statement explains the circumstances surrounding the safety events with a discrete degree of the predictive capacity of such machine learning models.

From the original plan, the unavailability of data on staff scheduling, such as the number of ground staff, composition, experience, and type of contract involved in the aircraft turnaround process, impaired much of the efforts to reach a more robust predictive capacity. The potential associative or causal paths behind safety events during the aircraft turnaround are still to be verified due to the present limitations in the data requisition process. However, the analysis results suggest a very moderate but promising perspective on the model's ability to generate plausible predictions and cross-generalisations.

The data mining process of deducing 'if-then' rules from a data set, also called rule induction, identifies the inherent relationship between the variables. Based on the available data, the analysis of the rules with the highest number of instances indicates that the combination of aircraft delays in departure, either per amount or root cause, indicates to be a strong predictor, alongside planned variables like certain departure or arrival airports, or it is operated a domestic flight.

As for the previous case study, although the case study aimed to empirically demonstrate the reconceptualisation of the safety event by identifying combinations of planned and unplanned factors, it produced several specific rules linking predictor variables to safety events during the aircraft turnaround process. These rules were validated by confirming with an expert that they are interpretable and plausible. However, despite the research limitation previously discussed and the lack of available data not covering all potential threat situations, some consideration can be advanced regarding what the rules tell us about causal patterns and how this information could be translated into effective safety measures.

This case study further suggests that implementing the 'breaking the risk pattern' approach in daily operational scenarios may prove challenging or unfeasible. Consequently, when the precursor cannot be eliminated, the strategy shifts towards managing it effectively. The findings underscored the importance of departure delays. The complexity of the precursor requires more comprehensive data to pinpoint the critical task or tasks necessitating specific corrective actions. Identifying the most common human factor-related causes would require a deeper understanding of the underlying dynamics. Therefore, applying existing occurrence-reporting taxonomies on any reported safety occurrence would ensure the identification of Human Factors/Human Performance-related variables.

5.7. Recommendation

The case study review found that a positive reporting culture intended to cultivate an organisational atmosphere where people have the confidence to report safety concerns without fear of blame is essential to allow a better assessment of the predicted target, while an improvement of data quality in occurrence analysis encompass aspects leading to Human Factors/Human Performance-related variables.

CHAPTER 6. ORGANISATIONAL IMPACT

6.1. Introduction

The analysis of the case study results revealed that establishing the proposed data model solution by integrating diverse sources into a unified database was a non-trivial task, highlighting its inherent complexity. It became evident that the successful implementation of AI-based applications like predictive analytics necessitates comprehensive change management involving organisation, personnel, and technology.

The industry is moving into the digital era at an unprecedented pace, and digital transformation is on the agenda of many industrial sectors and organisations. It specifically concerns the changes such innovations can bring to the business model, products, processes, and organisational structure (Hess et al., 2016). Introducing AI-based applications like predictive analytics is perhaps the most pervasive managerial challenge. Thanks to new data processing frameworks, applying ever more sophisticated algorithms to a large volume and a wide variety of information revolutionises traditional business models. The potential to transform all information sources into knowledge by discovering hidden patterns, correlations and trends is crucial to impact multiple domains, including organisations' risk management, safety performance monitoring and measurement, and the decision-making process.

As shown in Figure 6-1, the results came from a recent survey by O'Reilly Media (Loukides, 2021), evidencing AI usage across significant industries and showing where the AI adoption initiative is heading. Computers, electronics, and technology lead the ranking with 17%, followed by financial services (15%), healthcare (9%), and education (8%). New and recent statistics confirm this trend, reporting that Artificial intelligence (AI) adoption is growing across industries. In 2023, 35% of companies are using AI in their business. The industries with the highest AI adoption rates include financial services, healthcare, retail, and manufacturing. They use AI platforms and tools to automate tasks, improve workflows, and create new services and products (Hostinger, 2024).

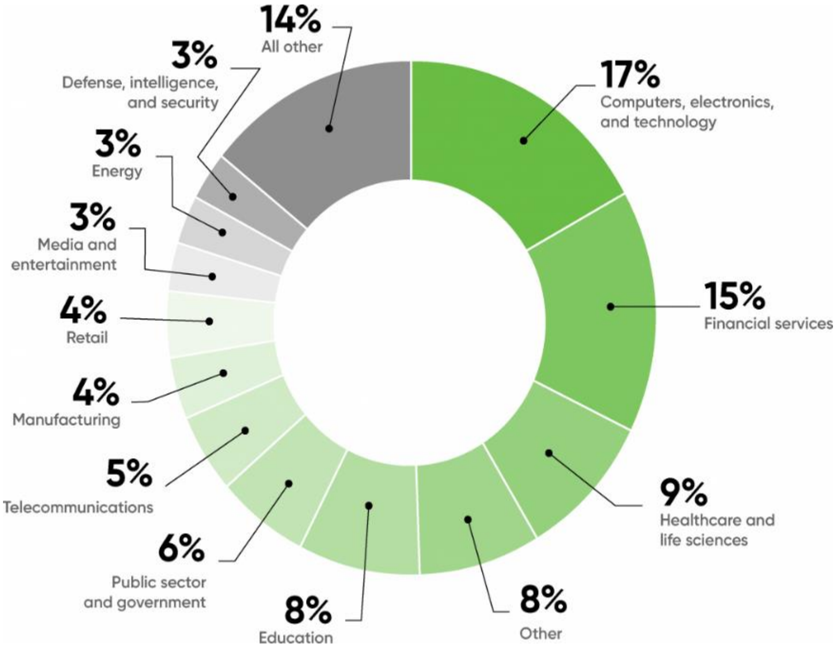


Figure 6-1 Industries using AI (Loukides, 2021)

The aviation system is missing from the list, suggesting that AI adoption is still ongoing. The European Union Aviation Safety Agency (EASA) has started some initiatives to fill the gap with the other industrial sectors. The publication of some white papers (EASA, 2020; 2023) is an attempt to allow for an exchange of views and vision with the aviation stakeholders on AI implementation and its potential impact on all affected domains. EASA identified safety risk management as one of the key opportunities and challenges created by introducing this technology in aviation, empowering safety intelligence, and providing solutions to infer knowledge by detecting hidden correlations in the data.

Big Data Analytics comprises two ideas: Big Data and Data Analytics. Big Data is defined as a massive data set with large, more varied, and complex structures that have difficulties storing, analysing, and visualising the processes or results (Sagiroglu, 2013). Data Analytics is simply the process of extracting meaningful information from data. Applying machine learning and pattern recognition technologies allows for the discovery and scaling of more complex insights.

Implementing AI-based applications like predictive analytics or Big Data Analytics can become one of the organisation's most valuable resources. However, the evidence highlighted from case studies from the literature is that the implementation process is not trivial and requires systematic approaches to operationalise data science initiatives (Braganza et al., 2017). It showed how this activity impacts the socio-technical system in every aspect, from the technological, human and organisational points of view. The constraints that stand in the way between the definition of the business problem and the model deployment require a change management approach where people and technology are equally involved.

In 1995, John Kotter published what many consider to be pivotal work in change management. From his book "Leading Change: Why Transformation Efforts Fail", many articles followed, agreeing with the assumption that some two-thirds of all change initiatives fail. The causes of the widely-quoted 70% change failure rate are multiple. Mosadeghrad and Ansarian (2014) used a systematic and meta-analysis review of the literature published between 1980 and 2011 to examine the significant reasons for organisational change failure. Unsuccessful change programmes were attributed more to the organisational values than technical aspects such as insufficient education and training, employees' apathy, inadequate management support, poor leadership, inappropriate organisational culture, inadequate resources, poor communication, inappropriate planning, insufficient customer focus, and lack of a monitoring and measurement system.

More recent work on analysing 200 organisational change case studies identified factors that enable successful change in a constructive leadership style with effective communication, teamwork, and employee engagement (Jones et al., 2019). Successful change management requires a significant commitment from executives and senior managers. Control of all changes' lifecycles is necessary to increase the odds of success and enable beneficial changes to be made with minimum disruption.

6.2. Aims and Objectives

Over the past two years, the pandemic made it impossible to evaluate the organisational impact of this emerging technology on the execution of some specific safety risk processes, such as risk assessment and safety performance monitoring. Then, it was necessary to review the research project and adopt a new strategy to replace those tasks initially set in the plan.

A series of one-to-one semi-structured interviews have been conducted with the aim to be an initial approach to change management, performing a gap analysis in the process of implementing AI-based solutions (i.e., predictive analytics or Big Data Analytics) in complex organisations. Namely, large volumes and large varieties of data from several repositories are collected and integrated into one storage space for intelligent analysis to extract insights, patterns, and information. The reason for conducting this study is to collect a preliminary sample of data, test the adequacy of the proposed research method, and assess its potential in a future full-scale project.

The objective was to identify criticalities, evaluate solutions, and exploit opportunities to implement the process of big data in organisations. Specifically, descriptive data will be gathered and analysed to understand the systematic approach to dealing with organisational change in the execution of two specific risk management activities: risk assessment and safety performance monitoring. The involvement of selected aviation professionals and researchers with expertise in Safety Management Systems helped to understand the current state of the organisation's processes. To capture an accurate visual picture and visualising process breakdowns and areas of risk ('as-is') and how to model the impact of this future process could change ('to-be').

This study is intended to be a small-case test used to assess the feasibility of a future and subsequent more extensive analysis, evaluating whether the proposed method is appropriate to investigate the research topic. The strategy to adopt the semi-structured interviews relies on the objective to provide more discussion than a straightforward question-and-answer format, allowing interviewers to open up about sensitive issues thanks to their expertise and background and the use of qualitative analysis techniques provided to extract meaningful findings from the interviews and identify patterns of meaning across the data to derive topics of interest.

6.3. Methodology

The study employed a one-to-one semi-structured interview and thematic content analysis to elicit in-depth thoughts and information from selected safety practitioners to identify and assess the key themes in ensuring a successful implementation of AI-based applications like predictive analytics in organisations by combining open-ended and structured questions.

The cross-case analysis of the findings and lessons learned from the case studies regarding implementation challenges informed the development of the interview guide. This process facilitated the refinement of interview questions to encompass the study's pivotal elements effectively. The analysis incorporated discerned patterns, themes, and areas of interest derived from the execution of the case studies.

Pilot interviews anticipated the main study through the conduction of three interviews. The objective was to test the interview guide with a small sample of participants, assess question clarity, appropriateness, and effectiveness, and identify any issues with the sequencing of the questions or emerging new themes. This preliminary step also helped to refine, if necessary, the question list and verify the interview duration. The remaining eight one-to-one semi-structured interviews completed the process, as shown in Figure 6-2.

First step: Pilot interviews (Pilot study)

- Carried out three interviews
- Consolidated the content of interview guides, new themes emerging and the length of interviews.

Second step: Followed semi-structured interviews (Main study)

- Conducted eight semi-structured interviews

Figure 6-2 The Interview Process

Participants were selected based on their expertise, extensive experience, and backgrounds relevant to the study's objectives. By deliberately including safety professionals and researchers with diverse backgrounds in fields such as aviation operators, aerodrome organisations, and air traffic providers, it sought to encompass a broad range of perspectives.

Initial contact with potential participants was made through email, explaining the purpose of the study and inviting their voluntary participation. Interested participants were given an informed consent form outlining the study's objectives, confidentiality measures, and their rights as participants. Only those who sent participants' consent were included in the study.

The interviews were conducted individually in virtual mode using video conferencing tools for online video calls (Microsoft Teams). The interviews, primarily conducted in the Italian language, were audio-recorded with the participant's permission to ensure accurate data capture, later automatically transcribed and then translated into English with specific features available in Microsoft Word.

The objective of the interview was to collect and analyse descriptive data to comprehend the structured methodology employed for addressing organisational change during the implementation of two distinct risk management tasks: risk assessment and safety performance monitoring. A predetermined set of three broad headings to primarily explore the existing state (‘as-is’) and the desired state (‘to-be’), emphasising aspects beyond user profiling. Furthermore, the study aimed to identify potential opportunities for incorporating AI-based solutions within organisational frameworks. See the interview questions in Appendix 7. The interview transcripts are in a separate file with the raw data.

The role of the interviewer was to act as an active listener and facilitator of the interview process. Open-ended questions encouraged participants to share their experiences, opinions, and reflections on organisation, human and technology integration. Probing questions were employed to delve deeper into specific areas of interest and to elicit more detailed responses.

The Thematic Analysis based on Braun & Clarke's framework (2006) was applied to the interview analysis. The method is widely used across various disciplines to explore and understand the meaning and patterns in textual, visual, or audio data. The general process is shown in Figure 6-3.

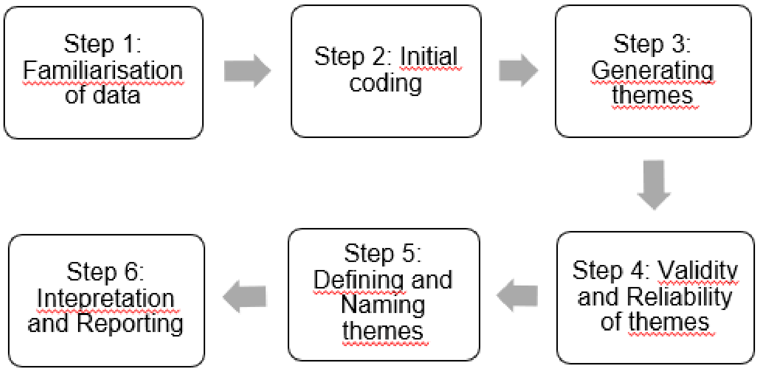


Figure 6-3 Thematic Analysis by Braun and Clarke (2006)

The six-phase process for thematic analysis, illustrated in Table 6-1, was employed to address various tasks systematically. Each broad heading was subjected to this process individually. The initial phase involved participant profiling. Subsequently, the second and third phases of questioning focused on identifying meaningful patterns within current operational practices ('as-is') and recognising obstacles and solutions during implementation ('to-be'). The fourth phase adopted an open conversational approach, seeking insights regarding potential opportunities and advantages of integrating AI technologies.

Table 6-1 Phases of thematic analysis by Braun and Clarke (2006)

PHASES	DESCRIPTION OF THE PROCESS
1. Familiarising yourself with your data:	Transcribing data (if necessary), reading and re-reading the data, noting down initial ideas.
2. Generating initial codes:	Coding interesting features of the data in a systematic fashion across the entire data set, collating data relevant to each code.
3. Searching for themes:	Collating codes into potential themes, gathering all data relevant to each potential theme.
4. Reviewing themes:	Checking if the themes work in relation to the coded extracts (Level 1) and the entire data set (Level 2), generating a thematic 'map' of the analysis.
5. Defining and naming themes:	Ongoing analysis to refine the specifics of each theme, and the overall story the analysis tells, generating clear definitions and names for each theme.
6. Producing the report:	The final opportunity for analysis. Selection of vivid, compelling extract examples, final analysis of selected extracts, relating back of the analysis to the research question and literature, producing a scholarly report of the analysis.

The CUBE methodology (McDonald, 2017), a comprehensive and evidence-driven assessment methodology for social-technical modelling, was used to consolidate the evidence gathered from the thematic analysis. This methodology provided valuable insights into assessing risks at a specific time and determining the necessary steps to transition from the current state ('as-is') to the complexities of implementing AI-based applications in organisations ('to-be').

6.4. Cross-case report

This report aims to highlight and consolidate the findings and lessons learned from the case studies concerning the implementation challenges. As evidence of reflective thinking, reflective writing attempts to report the experience made during the case studies, analyse what did and did not work, what to do differently in the future, and why. The initial description of the problem space came from the evidence of the criticalities that emerged from the data collection to integrate information from multiple sources to produce specific, comprehensive, unified data about an entity's process.

The most significant barrier experienced during the case studies was the capacity to move big data processing forward for two main reasons:

1. Most of the data needed to carry on the case studies were sensitive and could not be accessed easily for data protection and legal issues, thus making it challenging to collect.
2. A manual effort was necessary to solve the multiple data formats. Data was stored in separate business systems with different tools and technologies,

undermining the data quality or integrity and the unmanageability of the data itself, limiting the research project.

In many large and complex organisations, each department or business unit needs specific and different information to do the job. Data is collected and stored in separate repositories on which technology solutions and tools adopted are often different, resulting in a data or information silos condition with a rigid compartmentalised structure or organisation.

Even if data silos and information silos are sometimes used as synonyms, their meaning and root causes differ. Data silos primarily arise in a technological issue where a data repository controlled by one department or business unit is isolated from the rest of an organisation. Storing data in several repositories harms the quality and integrity of the information because each repository requires diverse methods and language, or it requires simply storing the same type of data in different and incompatible formats. Information silos are repositories of information not shared with other repositories. Creating an environment with disparate systems inside a company undermines the capability to have accessible and free communication. Silo mentality in organisations is the consequence of this situation.

Silo mentality refers to departments or business units that operate independently—reluctance to share information with employees of different divisions in the same company. The pyramidal organisational structure of the Safety Management System, with one leader at the top, a small executive leadership team below, and tiers of managers leading down to the bottom team of employees, tends to favour this situation. Therefore, is the Safety Management System's organisational structure designed to support the implementation of Artificial Intelligence applications?

Another aspect of the case studies was improving competence regarding Artificial Intelligence and its applications. Knowledge is a crucial building block for successful change management. To ensure the adoption of AI, companies need to educate everyone from the top leaders down (Fountaine et al., 2019). A report published by McKinsey Global Institute study (Manyika et al., 2017) found that the more familiar companies become with AI and its applications, the more opportunity they see for it in their business. The findings of the case studies show that making the most of value from AI requires a different way of investigating the problems. It is strategic to have a robust theoretical foundation to support the objective and strategy of the investigation to make suitable predictions and identify patterns in data rather than collecting and integrating data. These conditions are necessary for maintaining clarity regarding the business problem, which negatively affects the project's focus. A lack of expertise to support the critical AI initiative also makes the awareness of the potential organisational benefits ineffective.

The cross-case report was prepared to summarise and consolidate the findings and lessons from the case studies focused on the challenges encountered while implementing the data model solution. These studies revealed two primary themes. Firstly, they highlighted the sensitivity of the required data, which posed challenges in data collection due to data protection and legal compliance issues. Secondly, the studies emphasised the necessity of manual efforts to handle various data formats stored across different business systems, each using distinct tools and technologies. This diversity in data handling methods posed potential risks to data quality, integrity, and overall manageability, imposing constraints on the research project.

6.5. Pilot Study

6.5.1. Interviews

The preliminary study included three safety practitioners from distinct professional domains: air traffic control, aviation operations, and aircraft production. They all possessed expertise in Safety Management Systems (SMS). Their experience with data management and data analytics (DA) varied, ranging from beginner (novice) to experienced professionals. Refer to Table 6-2 for a summary of each participant's user profile.

Table 6-2 Participants in the Pilot Study

ID	AREA	SMS DOMAIN	EXPERIENCE ROLE	EXPERIENCE SMS	EXPERIENCE DA
1	SMS	Air Navigation Service Provider	10+	10+	Intermediate
2	CONSULTING	Commercial Air Transport	1-5	10+	Intermediate
3	SMS	Aircraft Production/Design	6-10	1-5	Novice

The pilot interviews took place in January 2023. During these interviews, participants were prompted to discuss (i) how risk assessment and safety performance management procedures are applied within their organisations, (ii) what socio-technological aspects organisations need to confront and overcome to implement AI-based solutions successfully, (iii) exploration of the most significant advantages and opportunities associated with the adoption of this technology within organisations. The questionnaire list has been appended to the Appendix 7. Notes were taken by an assistant supervisor in the role of a second researcher (DB) present at the time of the interviews.

6.5.2. Data Analysis

The Thematic Analysis (Braun & Clarke, 2006) was applied to manage and analyse the interview data collected. The researcher (FT) and research supervisors (SC, NM) thoroughly reviewed the interview transcriptions. After becoming familiar with the content, each individual (FT, SC, NM) independently conducted coding of the interviews as a first step. This process led to the development of a preliminary analytical framework consisting of distinct categories and corresponding themes over a series of meetings to ensure inter-rater reliability.

The assigned codes were subsequently grouped into categories based on shared contextual meaning. Through collaborative discussions, FT, SC, and NM refined the initial analytical framework, striving to define key categories accurately and consolidating into broader themes categorised under two main perspectives: the current state of the system ('as-is') and its potential future state ('to-be').

The thorough analysis of interview data in the pilot study showed emergent themes and patterns, offering valuable insights into the process of conducting a gap analysis within the context of implementing Big Data Analytics in organisations. It was agreed that these emerging findings could guide the course of the main study, determining which factors drive the change, understanding the current state, identifying critical challenges, and assessing solutions for successfully integrating Big Data Analytics within organisations. The outcomes of the pilot study underscored the consistency of the topic guide design. No modifications were required.

6.6. Main Study

6.6.1. Interviews

Between February and March 2023, eight individual semi-structured interviews were conducted with safety professionals. These professionals were selected based on their expertise in Safety Management Systems (SMS) across various domains, including aviation, aerodrome-certified operators, research and development, and academic organisations (R&D). Their familiarity with data management and analytics (DA) spanned a range from beginners (novices) to experts. For a concise overview of each participant's user profile, please refer to Table 6-3.

Table 6-3 Participants in the Main Study

ID	AREA	SMS DOMAIN	EXPERIENCE ROLE	EXPERIENCE SMS	EXPERIENCE DA
4	SMS	Aerodrome operator	1-5	10+	Intermediate
5	SMS	Aerodrome operator	1-5	6-10	Novice
6	SMS	Aerodrome operator	10+	10+	Novice
7	R&D		1-5	10+	Expert
8	R&D		1-5	1-5	Expert
9	SMS	Commercial Air Transport	10+	10+	Intermediate
10	R&D		10+	10+	Expert
11	R&D		10+	10+	Expert

The approach employed for the preliminary study regarding the topic guide's design proved effective. The feedback from the pilot study indicated that no modifications were necessary, so participants were prompted to discuss the same three broad headings questioned in the pilot study. The questionnaire list has been appended to the Appendix 7. Notes were taken by an assistant supervisor in the role of a second researcher (DB) present at the time of the interviews.

6.6.2. Data Analysis

The Thematic Analysis method outlined by Braun and Clarke (2006) was applied to organise and examine the data from the eight one-to-one interviews, which must be added to the three conducted during the pilot study. The 11 interview transcriptions were read and re-read by the researcher (FT) and the research supervisors in the role of reviewers (SC, NM). After familiarisation, all reviewers independently generated the initial codes and collated codes in provisional categories. Codes were organised into categories based on similar meanings.

The three reviewers worked together to improve the analytical framework. They turned categories into potential themes. As they continued analysing, they made each theme more detailed, building the overall story of the analysis. This process also helped them develop clear names and descriptions for each theme. The data analysis was applied individually to the system's current state ('as-is') and how it might be, including potential limitations and suggested solutions ('to-be').

After a thorough analysis based on interviews, the same five themes emerged for how things are right now ('as-is') and how they could be in the future ('to-be'). Table 6-4 shows the outcomes at the different stages of the ongoing analysis to refine the specifics of each theme, starting from codes and moving to categories and final themes. An arbitrary distinction was applied: (i) Major themes occurring in over 50% of the interviews; (ii) Minor themes occurring in under 50%.

Table 6-4 Defining and Naming Themes: Codes, Categories and Themes

	CODES	CATEGORIES	THEMES
as-is	72	17	5
to-be	63	20	4
Total	135	37	9

Five dominant themes describing how risk assessment and safety performance management procedures are applied within the organisations ('as-is') were identified across the interviews. No minor themes were identified. Refer to Table 6-5 for a summary of the themes related to 'as-is'.

Table 6-5 Themes ('as-is')

THEMES ('as-is')	NO. OF INTERVIEWS	PERCENTAGE
Data management	11	100%
Process execution	10	91%
Use of experts	9	82%
Culture (People/Organisations)	8	73%
Technology development	7	64%

Three dominant themes describing what socio-technological aspects organisations need to confront and overcome to implement Big Data Analytics successfully ('to-be') were identified across the interviews. One minor theme was identified. Refer to Table 6-6 for a summary of the themes related to 'to-be'.

Table 6-6 Themes ('to-be')

THEMES ('to-be')	NO. OF INTERVIEWS	PERCENTAGE
Use of experts	10	91%
Data management	10	91%
Culture (People/Organisations)	9	82%
Technology development	3	27%

6.6.2.1. System's current state ('as-is')

The data analysis of the system's current state ('as-is') identified five major themes comprised of 17 categories.

Data management

The interviewees collectively provided valuable insights into data management, shedding light on its critical role as the foundation of the entire risk management process. The complex nature of this subject prompted the emergence of various distinct categories, each of which contributed to the overall understanding without one dominating the rest. This highlighted the multifaceted nature inherent in this theme, from lack of data to data sharing, integration, or interpretation.

Participant ID #2

Regarding safety processes, data collection does not go beyond the Reporting System and Flight Data Monitoring. As I can say, someone considers hazards and then analyses them, but only in limited cases; the findings come from the Quality Assurance process.

Participant ID #3

A series of data cannot be shared in any way. Some data can certainly be shared within the company. There is no will, or at least it is thought it cannot be a problem. The spread to the outside, and in some cases, this is objectively true. There is no culture of sharing, especially with the outside, for prevention. We are working slowly on this problem, but we are still really at the basics. There is sharing for the sole purpose of prevention, not with the outside. It is still very, very limited.

Participant ID #9

So, let us try to cross the data. The limits are sometimes in trying to export them to make them readable. Moreover, from that point of view, I tell you, I have direct contact with IT, and eventually, I have access to databases so that I can do it with SQL.

Step by step, it is not like you can turn the key, you say, free everyone, and away I give you the data, and you can play it as you want. Because? Data used incorrectly can create even more problems than it is.

Refer to Table 6-7 for a summary of the categories related to data management and their incidence per number of contributions.

Table 6-7 Data management ('as-is') categories

CATEGORIES	NO. OF INTERVIEWS	PERCENTAGE
Lack of data	5	49%
Data sharing	5	49%
Data integration	5	49%
Data interpretation	3	27%
Data accessibility	2	18%
Data analysis	1	9%

Process execution

Most interviewees, 10 out of 11 (91%), discussed how risk assessment and safety performance management procedures are applied within the organisations. It emerged that regulations govern both processes. The execution of risk assessment occurs either in response to significant changes within organisations (i.e., management of change) or as prompted by the National Aviation Authority to analyse emergent safety issues (64%). In most cases, the approach is very simplified and mainly based on a qualitative approach (64%) without established standard methods (36%).

Participant ID #1

It is a structured process that is activated whenever there is any change. The risk assessment process is primarily the change management process. The risk assessment, as well as at the preventive level, is also done at the post level, following an event or a group of events. In which the event is studied and analysed.

Participant ID #5

Risk assessment is considered a prescriptive activity or mandatory to have the various approvals and authorisations from (the National Aviation Authority) or to comply with the standardisation. In addition, it remains a document of exclusive use that is the sole responsibility of the Safety Manager.

Participant ID #8

More qualitative. Then, the more mature ones will try to use quantitative approaches. So, they use data to reinforce their analysis, but in the first instance, it is largely qualitative.

Concerning safety performance management, the industry provides guidelines that assist these organisations in proposing a standard list of safety indicators. The indicators selection process is commonly delegated to the organisation's experts. This expertise allows for identifying the most relevant and meaningful indicators for assessing performance and risks. It can differentiate between indicators that are merely data points from those that are relevant and significant for tracking performance and anticipating future outcomes (55%).

Participant ID #1

We make use of both leading and lagging indicators. Mainly, they are those provided for by the procedures and European regulations connected within our (domain). Lagging is much easier because it derives from data collection.

Participant ID #6

The starting point was the adoption of the indicators proposed by (the National Aviation Authority).

Refer to Table 6-8 for a summary of the categories related to process execution and their incidence per number of contributions.

Table 6-8 Process execution ('as-is') categories

CATEGORIES	NO. OF INTERVIEWS	PERCENTAGE
Process activation	7	64%
Risk Assessment approach	7	64%
Safety Performance Management approach	6	55%
Standard method	4	36%

Use of experts

Competence and skills are essential for effectively applying risk assessment and selecting safety indicators. 7 out of 11 interviewees discussed the importance of experts in this process, while 3 out of 11 (27%) highlighted a lack of necessary skills.

Participant ID #1

A qualitative evaluation is made based on experience.

Participant ID #6

Risk-based mainly on the expert's judgment rather than on the data analysis themselves.

Participant ID #8

The other thing is definitely the experience of the staff who work there. I have always dealt with very competent people who have at least a decade of experience in safety performance management, risk management, and other areas.

Participant ID #7

A lack of background or knowledge is something as simple as that; that is, in my opinion, most people have always conducted their risk assessment in a certain way. Changing and trying other things, trying something you do not know clearly, is a barrier.

Refer to Table 6-9 for a summary of the categories related to using experts and their incidence per number of contributions.

Table 6-9 Use of experts ('as-is') categories

CATEGORIES	NO. OF INTERVIEWS	PERCENTAGE
Use of SMEs	7	64%
Skills	3	27%

Culture (People/Organisations)

In an organisation, culture encompasses the values, beliefs, behaviours, and norms that define how individuals operate and engage with one another. While culture may be intangible, its impact on employee morale, productivity, and overall success is undeniable. Notably, collaboration emerged as a dominant theme among the seven interviewees, with 7 out of 11 (64%) emphasising its significance.

Participant ID #3

We certainly try to do joint and shared work, but in practice, the condition of silos often goes outside. Unfortunately, and often, theory, which is what is written, deviates from practical activities. In a specific team or, in any case, a team member, activities are started together, and then everything is dispersed over time. Especially at the level of mitigation actions, it is necessary to carry out punctual monitoring over time to verify the results.

Participant ID #5

No, there is always more than one operational area. Too much. It has rarely happened to me that there is only one area involved and, from a synergy point of view, of collaboration. No, there is not.

Organisations are dedicated to promoting collaboration between departments; however, the organisational structure of a Safety Management System, with distinct operational areas such as flight, training, maintenance, and ground, may inadvertently encourage a siloed mentality.

Participant ID #11

Nevertheless, there was probably some of that. However, we did try. To collaborate, the way the organisation was structured was the flight safety departments independent of any other department. So, it did not come under flight operations. It did not come under ground operations, and so on and so on. Thus, it was reported directly to the Accountable Manager. And so, we would. We would have—representatives from the engineering, ground, and flight operations teams. So yes, we would be working across different parts of the organisation.

A blend of internal and external factors intricately shapes system maturity within organisations. The continuous improvement process began in 2012 when the Safety Management System was made mandatory for aircraft operators and extended to ground operations and maintenance later. This evolution, particularly in a risk management application, positioned the aviation sector far ahead of other industries, such as maritime and rail.

Participant ID #8

Here, the level changes a lot depending on who the partner you are talking to is. You know better than I do; in short, from the point of view of risk assessment, the aviation sector is far ahead of other sectors. We have also dealt with rail and maritime partners, and of course, aviation has a couple of geological eras ahead.

Participant ID #10

Safety management in the aviation sector is even more advanced than in the chemical and medical domains.

Refer to Table 6-10 for a summary of the categories related to culture and their incidence per number of contributions.

Table 6-10 Culture ('as-is') categories

CATEGORIES	NO. OF INTERVIEWS	PERCENTAGE
Collaboration	7	64%
System maturity	3	27%
Siloed mentality	1	9%

Technology development

Currently, implementing these technologies is not on the agenda of organisations. Although its importance is recognised, the lack of knowledge and application hampers its development. The aspects related to the tools emerged as a minor category (9%).

Participant ID #5

No way. No, then, at the moment, we do not talk about it because, for us, it is an unknown world. Indeed, our Accountable Manager would be very inclined to experiment with any systems that can improve performance or support the business.

Participant ID #6

There is no plan for implementing AI technologies in the organisation, although I support its importance.

Refer to Table 6-11 for a summary of the categories related to technology development and their incidence per number of contributions.

Table 6-11 Technology development ('as-is') categories

CATEGORIES	NO. OF INTERVIEWS	PERCENTAGE
BDA implementation	7	64%
Tools	1	9%

6.6.2.2. Potential limitations and suggested solutions ('to-be')

The data analysis of the system's potential changes, including its limitations and suggested improvements ('to-be'), revealed three major and one minor theme. Identical themes were generated to ensure a fair comparison between the current and future states, resulting in 20 categories.

Use of experts

Most participants recognised a need for specialised skills, knowledge, and competent staff, which are currently lacking within organisations. The training was identified as a solution. A campaign to raise awareness and enhance basic managerial-level competence could serve as a starting point to familiarise individuals with new technology.

Participant ID #2

The competence of the responsible figures is the attention that a specific company, company or organisation places on correctly applying the SMS. It is still impossible to understand the advantages that can be derived from implementing a mature SMS. And so many companies have stopped, stopped, and slowed down evolution. The level of competence certainly has to do with the lack of awareness of the opportunity to have extensive data collection and consequently have an effective Data Analysis process.

There is not much expertise in Data Analytics.

Participant ID #3

Surely, knowledge is needed. I challenge anyone who does not want to use something that is not there. A basic mistrust of what is unknown, so a transition period, training and training is still necessary to make the tools available and easily usable.

Participant ID #4

Machine learning and big data processes are very innovative, and not always in all areas have received the necessary generational change. Then, internally, we do not have people with this skill. This must be bought outside.

Participant ID #7

To do statistical things or to do analytical things, advanced data like that, you must have studied different things, or you really have to be studying these things later. So let us say that maybe there are also a few people who have both skills and a good view of both points of view.

Refer to Table 6-12 for a summary of the categories related to using experts and their incidence per number of contributions.

Table 6-12 Use of experts ('to-be') categories

CATEGORIES	NO. OF INTERVIEWS	PERCENTAGE
Lack of skills	9	82%
Competent staff	5	49%
Training	3	27%

Data management

The complex nature of this theme and its multifaceted nature prompted the emergence of various distinct categories related to each other, each of which contributed to the overall understanding. Most participants discussed the need for data integration and sharing to address the challenges posed by data silos conditions, which are isolated collections of data stored independently by different organisational departments, hindering accessibility and collaboration.

Participant ID #1

Technical problems of connecting interconnect the various sources of data production. These are absolutely trivial solutions when these skills are available at the software management and data analysis level.

Participant ID #7

In most cases, it is an individual dataset.

Data sensitivity and quality are dependent categories stemming from data integration, sharing and managing data sensitivity, and ensuring data quality present challenges in safeguarding sensitive information and maintaining accurate, reliable data.

Participant ID #3

First, it is difficult to identify databases by type of information. If we can find them, the next problem is the quality of the data, for example, on maintenance records of paved surfaces. Already, it is not easy to find historical data. Once found, the difficulty lies in exporting a manageable file.

Participant ID #4

So, the biggest obstacles are the non-homogeneity of the sources of information and the lack of homogeneity of historical data, which does not allow the use of preventive and predictive analysis methods.

Participant ID #9

Then, try to figure out all the databases you need and get them to talk to each other. So, as usual, maybe 50 different databases with different languages should be integrated, and then work on creating a valid data model.

Moreover, that is why I am working with a Power BI; let us call it parallel because, at the moment, I am unable to throw out the data if they cannot guarantee confidentiality and security.

During the discussion, additional minor categories related to data management emerged, including data governance, data security, data encryption, data reliability, and data trustworthiness, all interrelated with the previously mentioned categories.

Refer to Table 6-13 for a summary of the categories related to data management and their incidence per number of contributions.

Table 6-13 Data management ('to-be') categories

CATEGORIES	NO. OF INTERVIEWS	PERCENTAGE
Data integration	6	55%
Data sharing	5	49%
Data sensitive	4	36%
Data quality	4	36%
Data governance	2	18%
Data security	1	9%
Data encryption	1	9%
Data reliability	1	9%
Data trustworthiness	1	9%

Culture (People/Organisations)

The majority of participants identified leadership and Accountability as critical factors for achieving complete success in implementation. Active management involvement is mandatory given the extensive changes impacting various facets of the organisation, including its structure, personnel, and IT systems. Hence, it is emphasised that the role of the Accountable Manager should align with that of the CEO, given the substantial investments required in this management of change.

Participant ID #2

Seeing Accountable Managers illuminated is increasingly rare. So, this process could change through regulatory aspects or the cultural growth of Accountable Managers. No legislation in Europe or other parts of the world requires specific skills from the Accountable Managers.

Participant ID #3

It must start from the top; otherwise, it does not work…. Also, in general, it requires investments of a certain importance. Surely, it is a trivial thing, but we should still act from the top down and get from the bottom up. I know, starting from the production workshops. Digitalise the operational departments.

Participant ID #4

One of the six pillars of Business Continuity is embedding. So, it means lowering safety within the organisation, giving it more power to transmit the concept of safety within the whole organisation. For this reason, it would be important to make the role of Accountable Manager coincide with the role of CEO.

Participant ID #6

Matching the role of Accountable Manager to the position of CEO to convey the message of the organisation's strong commitment to safety with effects in terms of investment capacity and to ensure the success of initiatives.

In many organisations, safety initiatives, particularly those involving changes and investments, are typically implemented under two main circumstances: compliance with norms and alignment with industry standards, often driven by institutions or leading companies.

Participant ID #11

From (organisation disclosed)'s point of view. They are a big competitor at the time in a (country disclosed) was (organisation disclosed), and if (organisation disclosed) were not doing it, then why would be am I? Do it. Another thing was the regulatory background, *which the regulator was not requiring. So, you know you talked to an Accountable Manager or CEO in an airline. Moreover, say, well, it is not the regulator requirement.*

Regarding organisational challenges, some participants emphasised expanding the current SMS organisational structure beyond operational areas, such as human resources, finance, and procurement departments. They also advanced the need to update the structure to support the implementation process better.

Participant ID #2

The SMS was introduced by the will of the stakeholders, but it was limited only to the operational aspects. It is clear that having an involvement through regulation in all other areas within an operator, as well as the areas of human resources, finance, and procurement, is clear that you would take a step forward. I hope that SMS can evolve in this direction soon.

This process also necessitates a cultural shift to address resistance to change, encompassing both in the way of working and for new analysis techniques.

Participant ID #3

Lack of willingness to change on the part of the staff. The older a company is, pass me the term, formed by people of a certain age and with some work experience, the more this thing, in my opinion, becomes difficult. If, on the other hand, you are in a young and dynamic environment with open minds, then the propensity to change is much and, therefore, more easily implemented.

Participant ID #6

The resistance of some managers to change.

Participant ID #7

A group within the company wanted to analyse things, yet they could not do it. On the side of the pilots, they did not want to analyse any performance that was even minimally related to safety because they saw it as a form of control and could be an excuse to fire pilots.

Refer to Table 6-14 for a summary of the categories related to data management and their incidence per number of contributions.

Table 6-14 Culture ('to-be') categories

CATEGORIES	NO. OF INTERVIEWS	PERCENTAGE
Leadership and Accountability	6	55%
Organisational challenges	5	49%
Change dynamics	4	36%

Minor themes are less representative of the interviews overall; the three interviews contributing to the discussion of Technological development identified the importance of identifying suitable and supportive tools to handle the whole data process and starting with small case studies to explore the potential benefits: from enhancing decision-making to provide practical examples and promoting problem-solving skills.

6.6.2.3. Potential future benefits and opportunities of developing AI

The last part of the interview was designed to capture the knowledge or awareness of participants on AI implementation in their operational environment and pinpoint potential areas of improvement.

In general terms, all interviewees emphasised the significance of developing an all-encompassing strategy concerning AI. The data analysis identified one dominant theme comprised four categories and one minor.

Refer to Table 6-15 for a summary of the themes related to Potential future benefits and opportunities of developing AI.

Table 6-15 Themes for Potential future benefits and opportunities of developing AI

THEMES	NO. OF INTERVIEWS	PERCENTAGE
Enhancing Operations	9	91%
Knowledge Enhancement	1	9%

Nine participants emphasised the value of AI in enhancing operations such as decision-making and maximising cost-efficiency, which can be summarised as process optimisation. Additionally, other minor categories emerged, including predictive maintenance of facilities and cost-benefit analysis.

Participant #ID 3

In successive steps, starting with digitalising work in general. Then, try to digitalise the various activities as much as possible. In some environments I know, paper is still very much used, apart from the computer, which, more or less, everyone has it. Yes, digitalisation. Then, however, it is necessary to make a general analysis of the data that you want to make available and understand how to automate their transfer as much as possible. Automation, that is it... The process optimisation. Definitely. Process optimisation could bring benefits in terms of process efficiency (time) and economics (savings).

Participant #ID 4

On decision-making. However, you have to pay attention to how the data is managed. An incorrect analysis of the data could lead to wrong decisions. Having detailed analysis is the request of every manager because it allows you to select the information and initiatives to be undertaken. Also, when the Accountable Manager, the CEO, goes to the Board of Directors, the safety numbers alone are insufficient. There is a need to extend the analysis to the economic aspects, the impact on the passenger, the quality of the service provided, and so on.

Participant #ID 5

The process becomes more objective and less, shall we say, personal.

Participant #ID 11

Whether we have quantitative or qualitative data bringing those things together and reflecting our uncertainty around those inputs in the output we get, they lend themselves very well to risk assessment and decision-making in aviation operations.

Only 1 out of 11 participants (9%) mentioned knowledge enhancement as a potential benefit.

Participant #ID 11

I think it is more in-depth safety knowledge. I think we would. Yeah, we will. More anomalies. We will do better-informed risk assessment. I think. We will probably. We should be able to direct resources better if we do risk assessment better. Then, we *should be able to direct resources better and not waste our time on things where it is just.*

Refer to Table 6-15 for a summary of the categories related to Enhancing Operations.

Table 6-16 Enhancing Operations categories

CATEGORIES	NO. OF INTERVIEWS	PERCENTAGE
Decision-making process	6	55%
Optimisation process	3	27%
Predictive maintenance of facilities	1	9%
Cost-Benefit analysis	1	9%

The professional role, experience, and background of the participants played a role in shaping their perception of the potential benefits that the implementation of Artificial Intelligence can bring to their organization and activities. In fact, all of them focused on enhancing operational processes. Only one participant's academic experience led to an orientation toward improvement in the knowledge aspect.

6.7. Discussion

This study intended to initially explore the challenges associated with implementing data science initiatives, or predictive analytics more broadly, within complex organisations. A series of 11 one-to-one semi-structured interviews with safety professionals from various domains within the aviation industry, including aviation operators, aerodrome-certified operators, research and development experts, and academic organisations, all with expertise in Safety Management Systems (SMS) were conducted to uncover patterns and themes of the research topic.

The thematic analysis outlined by Braun and Clarke (2006) encompassed a systematic and flexible approach to organise and examine the data focused on three overarching themes:

1. The application of risk assessment and safety performance management procedures within the/their organisations.
2. The socio-technological challenges organisations face when implementing Big Data Analytics successfully.

3. Identifying the significant advantages and opportunities associated with adopting this technology within organisations.

Through collaborative discussions with two reviewers, the initial analytical framework was refined. The goal was to accurately define key categories, consolidating the first two broader themes categorised under two main perspectives: the current state of the system ('as-is') and its potential future state ('to-be'). The third and last aimed to enhance participants' awareness of AI implementation in their operational environment and identify potential areas for improvement.

The data analysis of the system's current state ('as-is') revealed that certified organisations, like those under analysis, demonstrated well-defined and documented processes.

In the context of risk assessment, these processes occur in three distinct phases: prospective analysis for change management, retrospective analysis of specific safety issues, or upon request by the National Aviation Authority. A qualitative approach is often employed, with a significant reliance on experts. Additionally, in the domain of safety performance management, experts play a pivotal role in identifying the key indicators for monitoring. However, the industry's governing bodies often propose standardised and common indicators.

The interviewees provided valuable insights into data management, emphasising its central role as the basis of the entire risk management process. They specifically highlighted three key challenges: the lack of data, challenges associated with internal and external data sharing with stakeholders, and issues related to data integration.

Regarding organisational culture, respondents underscored the significance of collaboration, noting that it is most successful in organisations with more mature and efficient systems.

Finally, implementing these technologies is not currently a priority for organisations. Despite the interviewees recognising its importance, a lack of knowledge and practical application impedes its progress.

The data analysis of the system's potential changes, including its limitations and suggested improvements ('to-be'), revealed that the lack of knowledge in understanding these new technologies and the absence of specialised skills within organisations represent significant limitations. Several interviewees recommended, as a solution, initiating training sessions on this subject, a top-down approach commencing with top-level management and cascading down to lower organisational levels. Launching an awareness campaign and enhancing fundamental managerial-level competencies could be an initial step to informing individuals about the practical applications of these new technologies.

In line with what emerged from the previous data analysis (i.e., 'as-is'), the complex nature of data management led to various distinct categories, all interconnected and contributing to the overall comprehension of the theme. Most interviewees emphasised the importance of data integration and sharing to overcome the challenges posed by data silos, namely isolated data collections stored independently across different organisational departments, which hinder accessibility and collaboration. Two key categories, data sensitivity and data quality, are closely linked to data integration and sharing. Managing data sensitivity and ensuring data quality present challenges in safeguarding sensitive information and maintaining accurate and reliable data.

Most participants highlighted that Leadership and Accountability are crucial factors for successful implementation. Given the extensive changes affecting various aspects of the organisation, including its structure, personnel, and IT systems, active management involvement is essential. Therefore, it is emphasised that the role of the Accountable Manager should align with that of the CEO, especially considering the substantial investments required to manage this change effectively.

It would be inaccurate to suggest that only large companies can invest in AI. AI adoption is influenced by multiple factors, with the company's size being just one of them. Adopting these new technologies is expected to be on the agenda for both large and small companies as they become more common and prescriptive by norms or standardisation.

Regarding organisational challenges, some participants emphasised the importance of expanding the current SMS organisational structure beyond operational areas, such as human resources, finance, and procurement departments. They also stressed the need to update the current structure to support the implementation process better.

The data analysis of the last part of the interview, which aimed to raise participants' awareness of AI implementation in their operational environment and identify potential areas for improvement, underscored the strategic significance of implementing these technologies within organisations. It also highlighted the specific benefits that could be realised, particularly in enhancing decision-making and optimising operational processes.

In summary, through the analysis of evidence gathered during case studies and interviews, the study highlights the inherent complexity in implementing AI-based applications (i.e., Big Data Analytics or predictive analytics), necessitating significant organisational changes involving people and technology. Within the aviation industry, the adoption of such technologies remains relatively undeveloped. In this highly regulated and complex environment, initiatives tend to be started in response to prescriptive norms, industry standards or standardisation efforts, mainly when driven by influential institutions or large organisations.

During the discussions, participants identified potential barriers hindering successful implementation and emphasised the need for specific initiatives to overcome these challenges. As a relatively new technology, one major obstacle is the lack of knowledge about the technology itself and its potential benefits. To address this, participants recommended developing an information and training program to reach all organisational levels, bridging the gap between technology and humans. Furthermore, given that this represents a profound change requiring investments in both human resources and technology, active engagement from management is essential, particularly from the CEO or Accountable Manager, who possesses decision-making authority. Without their support and commitment, the likelihood of success in the implementation process would be significantly compromised.

In terms of the potential of this new technology, there is a shared awareness of its strategic importance in implementation. The majority of the participants emphasised its potential benefits for enhancing operations. The optimisation of processes with cost-saving advantages, along with a more structured and objective decision-making process, were the most frequently cited benefits. It is worth noting that one participant also highlighted the potential for this technology to impact safety knowledge to enhance risk management.

6.8. CUBE

The CUBE methodology (McDonald, 2017) allows for a rich understanding of a socio-technical system to be built around four domains: the system, the action, the sense-making, and the culture:

1. System functioning: incorporates Perrow's functional focus on complexity and coupling (Perrow, 1984) and accounts for both formal and informal elements (i.e., Policies, Procedures, Protocols and Guidelines (PPPGs)), as well as the sequence of activities that generally takes place.
2. Action: incorporates the flows of information, knowledge and understanding and anything that happens in the system that is recordable or measurable (Turner,

1997) e; this can be analysed at different levels, such as individual actions, team performance against a standard, activity sequences, or key outcome, process and balancing measures concerning system performance (McDonald, 2017).

3. Sense-making: incorporates Weick's work on how individuals operating within the system make sense of it, often through practical action.

4. Culture: incorporates Schein's (Schein, 2010) and Pigeon and O'Leary's (1994) work on culture.

The CUBE comprises four system aspects: Goals, Process, Social Relations, and Information and knowledge. Figure 6-4 shows the 16 dimensions of the CUBE across the five project phases.

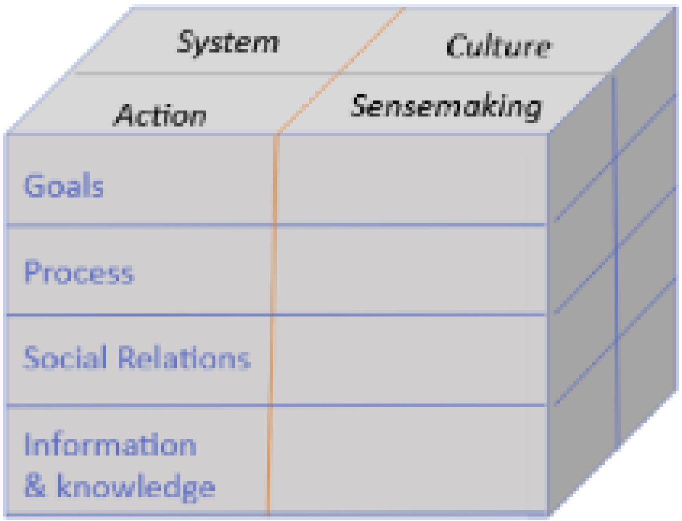


Figure 6-4 Dimensions of the CUBE (McDonald, 2017)

Data and insights from interviews and lessons learned from the case studies were used to assess 16 dimensions. These dimensions relate to the system's current state or initial description ('as-is') and its envisioned future state or what could change ('to-be'). The comprehensive analysis of all 32 dimensions can be found in Annexes 8 and 9.

The analysis of the current state ('as-is') revealed that regulations govern both processes. Operators need to establish, implement, and maintain a management system to ensure alignment in systems and processes. The distinctions between operators can be drawn from differences in sensemaking and culture. Variations in sensemaking at the individual or small team level and differences in culture related to a community can be attributed to a silo mentality. These discrepancies become evident when assessing the maturity of an operator's system, which essentially reflects the level of development, implementation, and effectiveness of the organisation's Safety Management System (SMS).

The analysis of what could change ('to-be') confirms that implementing AI-based applications requires profound change management. While awaiting industry regulations to align with adopting new technology in AI governance (Stix, 2022), the change affects every dimension of the CUBE. Extracting interpretable patterns to identify the combination of planned and unplanned factors and understanding a safety event's dynamic and complex nature requires primarily a sensemaking and cultural shift. The challenge is to change from siloed work to interdisciplinary collaboration with cross-sectional teams of individuals with diverse skills and perspectives. Collaboration is aimed at developing data models, and data scientists and stakeholders must work closely together during the whole data analytics process to deploy reliable and usable models within the context of the operational scenario.

Resistance to change, tied to implementing new technology and its potential negative impacts on daily work, as well as the fear of being replaced by machines or feeling obsolete, necessitates strong management commitment (Fountaine et al., 2019). In this context, a positive leadership style is essential for reinforcing the Safety Policy towards a new set of values, beliefs, attitudes, and behaviours to change how safety is perceived, prioritised, and practised. Open communication with employees emphasises the opportunities and benefits, fostering expertise on AI and thrusting in its outcomes (Tabesh et al., 2019). The importance of managerial roles is also addressed in the capacity and the decision-making to launch economic investments.

AI is also rapidly advancing in several fields. For example, big data from electronic health records can be utilised in healthcare to support evidence-based clinical decisions and value-based care. A strategic focus on leadership, teamwork, culture, and collaboration is crucial for successful implementation. Technology alone is insufficient to drive healthcare transformation; it requires people to derive value and create impact across the organisation (Chen & Decary, 2020).

CHAPTER 7. DISCUSSION AND CONCLUSION

The discussion chapter aims to interpret and contextualise the thesis results. In contrast to the results chapter, which presents and describes the analysis findings, this chapter elaborates on and evaluates the research findings. It also discusses their significance and implications.

In this chapter, the research findings are linked to the research questions or hypotheses and connected to prior studies and literature reviews. Furthermore, the relevance and significance of the findings in the research field are assessed, supporting the conclusions drawn from the analysis. It serves as the final research wrap-up and provides a comprehensive summary of the findings and their implications.

7.1. Discussion

A key achievement of the research is empirically demonstrating the dynamic nature of safety events by redefining them as a combination of planned and unplanned factors. This redefinition seeks to transform safety events from unplanned or unintended situations into predictable ones, progressing its conceptual understanding intricately linked to the evolution of safety thinking.

The research objectives encompassed the following:

1. A reconceptualisation of the safety event definition and its validation, clarifying its dynamic nature and implications on the safety thinking striving to improve the safety processes and risk management in quantitative and probabilistic terms;
2. Building a data model solution grounded in the novel definition of safety event, enabling the extraction of interpretable patterns from merged and extensive datasets;
3. Foster an innovative and evolving risk management approach and strategy in predictive terms, spanning from hazard identification to risk monitoring, driven by insights derived from patterns;
4. Identify the potential barriers to implementing AI-based applications like Big Data Analytics in a complex organisational context and propose solutions for managing an organisational change.

This dynamic perspective to relate a safety event as a complex pattern of precursors potentially contributes to fostering an innovative and evolving risk management approach and strategy in predictive terms, spanning from hazard identification to risk monitoring, driven by insights derived from patterns.

Case studies were designed to validate the research theory, investigating two different safety issues within an ultra-safe system like the commercial air transportation domain, with the goal of extracting interpretable patterns from merging and extensive datasets using a data model solution grounded in the principles used to reconceptualise safety events.

The implementation of such a data model solution was a complex endeavour. The research shed light on the profound changes necessary to successfully implement data science initiatives through a specific study to initiate change management, identify critical issues, evaluate potential solutions, and capitalise on opportunities when implementing AI-based applications like predictive analytics. A series of one-to-one semi-structured interviews were conducted involving aviation safety professionals. A thematic analysis was used to identify, analyse, and report patterns or themes from the interview transcriptions on three overarching topics: (i) how risk assessment and safety performance management procedures are applied within their organisations, (ii) what socio-technological aspects organisations need to confront and overcome to implement data science initiatives successfully, (iii) exploration of the most significant advantages and opportunities associated with the adoption of this technology within organisations.

7.1.1. Methodology, implementation and findings

The primary aim of the literature review was to identify relevant theories, concepts, and frameworks developed over the last century, starting from Heinrich to Hollnagel. These insights were the foundation for progressing from a conceptual understanding of safety event complexity towards empirically demonstrating safety events as sets of proven precursors.

The data model solution was developed around integrating planned and unplanned variables and transforming the target event as a binary condition of success and failure, drawing inspiration from Hollnagel's FRAM (2012; 2017). Hollnagel's principles assert that operational activities are seldom entirely routine, and problems typically arise not from explicit failures, errors, or violations but rather from the unexpected aggregation of variability in everyday performance.

Despite some limitations, such as the difficulties of collecting data in the case studies, the analysis suggests the data model's ability to produce accurate predictions with a significant degree of predictive capability. The extraction of interpretable patterns empirically demonstrated the dynamic nature of the safety events under investigation to some extent.

Refer to Figure 7-1, an example of a pattern for Unstable Approach True, and Figure 7-2, an example of Safety Events during Aircraft Turnaround.

Rule 48 for 1.0 (773; 1.0)

```
if @DeltaDelay > -14.003
and @eventtype.1_cat in [ "OtherEvents" "Speed high between 5000-3000 feet" ]
and @eventtype.2_cat in [ "OtherEvents" ]
and @eventtype.3_cat in [ "Flap late setting above 500 AFE" ]
and @Severity_Max_cat in [ "3.0+" ]
then 1.000
```

Figure 7-1 Example of Rule for UA True (1.0)

The rule set combines three types of variables:

1. Recovery delay from departure (@DeltaDelay).
2. Sequence of Flight Data Monitoring events occurred at different times during the descent/approach phases (@eventtype.X_cat).
3. Severity class of the Flight Data Monitoring events (@Severity_Max_cat).

An unstabilised approach is indicated True with a probability of 100% (1.000) when a recovering departure delay of approximately 15 minutes or more (@DeltaDelay) combines with a specific sequence of Flight Data Monitoring events (@eventtype.X_cat). This sequence starts with a high speed between 5,000-3,000 feet (["OtherEvents" "Speed high between 5,000-3,000 feet"]) and ends with a late flap setting between 1000-500 feet (["Flap late setting above 500 AFE"]). Additionally, this sequence may include at least one event with a severity class of 3 or higher (@Severity_Max_cat in ["3.0+"]). As part of the data preprocessing step, certain Flight Data Monitoring events have been reclassified as ["OtherEvents"] to address outliers, ensuring that extreme data points do not unduly impact the analysis or machine learning models.

Rule 3 for 1.0 (336; 0.705)

```
if OTPD > 2
and OperatedDeparture_reclassified in [ "LIN" "OTH" "FCO" ]
then 1.000
```

Figure 7-2 Example of Rule for Safety Event in Aircraft Turnaround True (1.0)

The rule set combines two types of variables:

1. Airline on-time performance in departure (OTPD).
2. Departure airport

Aircraft departing with delays of more than 16 minutes (OTPD > 2) at airports like Roma Fiumicino ("FCO"), Milano Linate ("LIN"), or minor airports transformed to "OTH" during the data pre-processing step may configure a safety event (True) with a 70% probability (0.705) during aircraft turnaround.

Both case studies employed operational feedback to integrate expert knowledge and machine-learning models. The positive feedback from experts indicated that the identified sets of precursors were valuable for meeting the needs of target users in valid usage scenarios. These rules were considered usable because they were easy to understand and interpret, potentially changing the game for risk management in practice. The experts involved in the operational feedback indicated that the identified sets of precursors were valuable for meeting the needs of target users in valid usage scenarios, suggesting that the data model solution enabled the extraction of interpretable and reader-friendly machine learning models in both case studies.

These models facilitate a better understanding of the dynamic features that contribute to explaining the target safety event. Essentially, this approach, known as Explainable AI (XAI) (Molnar, 2022), supports reimagining safety events as dynamic phenomena that can be readily interpreted.

Both case studies were not designed to identify the intrinsic dynamic nature of the two comprehensively investigated safety events. Instead, they aimed to empirically validate the research's proposed theory, training the data model with the available data. The data analysis generated clear and simple patterns. However, the predictive potentiality of the data model indicates that more extensive and diverse data sources could reveal more intricate patterns, better capturing the configuration of a safety event with their planned and unplanned factors. Given the complexity of both safety events, gathering additional data sources, such as meteorological information, would have been necessary to map all potential conditions in everyday performance fully.

The semi-structured interview questionnaire was developed based on the CUBE methodology (McDonald, 2017), which follows socio-technical systems change analysis principles. The question list was designed to uncover the complex challenges associated with adopting AI-based solutions within organisational contexts, such as predictive analytics or Big Data Analytics. It sought to explore the system's current state ('as-is') and identify potential limitations while suggesting possible improvement solutions ('to-be'). The study specifically examined the influence of two pivotal tasks within risk management—risk assessment and safety performance monitoring. The thematic analysis (Braun & Clarke, 2006) highlighted the multifaceted nature of these challenges, encompassing organisational dynamics, human factors, and technological integration.

7.1.2. Literature review and reconceptualisation of Safety Event

The reconceptualisation of safety events began with a comprehensive historical analysis of how safety thinking evolved over the last century. This analysis aimed to highlight its innovative aspects up to the present day. While the initial idea originated during the Master's thesis (Toti, 2017), a thorough review of existing literature encompassing theories, concepts, and models played a pivotal role in refining and enhancing the theoretical hypothesis. Every concept that emerged in the development of safety science, even seemingly unrelated ones, contributed to shaping the final definition, with some proving to be more crucial than others.

An event encompasses any unplanned or unexpected situation that has the potential to cause consequences. Assessing the effects for type and entity determines the category (e.g., safety, security, or financial) and its class (e.g., accident or incident). The event definitions discussed during the thesis have highlighted that each was developed to identify and explain the circumstances and potential outcomes rather than delving into understanding their dynamic aspects and nature. Cacciabue describes it as "a situation leading to a change of state" (2010, p. 123), while Hollnagel refers to it as performance variability (2012; 2017). In the healthcare domain, it is "a deviation from generally accepted practice or process that reaches the patient and causes severe harm or death" (Hoppes & Mitchelle, 2014, p. 3) or "a situation where the best or expected practice does not occur" (Nationwide Children's Hospital, 2021), underlining the role of deviation from the intended process (Surry, 1969).

Even though the definitions are neutral, they commonly address negative aspects because they are applied in causal models where the ultimate state is represented by losses that systems aim to prevent (Reason, 1997). However, the same definitions can also be applied to positive situations, transforming negative threats into opportunities (ISO, 2018). Events are then recognised for their outcomes rather than their inherent nature. The research delves deeper by not only considering events as fixed or static phenomena but by conceptualising them as dynamic combinations of co-occurring factors, both related and unrelated, within a specific space-time context. This latter view forms the core of this research. Although the research focuses on safety events, the concept is broad and adaptable to any event type with applications across diverse domains.

The novel and proposed definition of a safety event comprises two essential elements: the combination of factors and their inherent different nature. James Reason's original model first advanced that disasters in socio-technical systems typically arise from multiple causal factors, underscoring the critical importance of combinations, as each element, though necessary, remains insufficient to lead to a catastrophic outcome. The significance of these combinations, often regarded as random factors to emphasise their unpredictability, in influencing accident outcomes, whether resulting in injury or not, was first introduced by Wigglesworth (1972) and later taken up by Lawrence in his causal models (1974).

The diverse nature of the factors as elements of explaining the change of state, variability of the performance or deviation from the expected process was first advanced by Leplat (1985), who advocated that performance and activity are closely influenced by the dichotomy condition of the task as prescribed by designers or managers and as conceived by individuals. The distinction between planned and unplanned factors, which are elements of explaining the change of state or the deviation from the expected process, was addressed by Hollnagel in his FRAM (2012; 2017), emphasising that work conditions often deviate from what is strictly specified or prescribed within many socio-technical systems. This distinction underscored the difference between Work-As-Done (WAD) and Work-As-Imagined (WAI).

The integration of the FRAM principles 'Work-As-Imagined' (WAI) and 'Work-As-Done' (WAD), and the 'Equivalence of Successes and Failures' in the data model solution acknowledged the idealised vision of the data structure. Each data record was structured to depict the working conditions comprehensively and as fully as possible. This process involved merging both planned variables, which reflect the intended aspects of the work as envisioned in the 'Work-as-Imaged' perspective, and unplanned variables, which encompass unforeseen elements or conditions that emerge during work execution, often deviating from the initially intended plan. The management of the target event as binary, indicated as either successful or not at the end of each record, favoured the deployment of highly interpretable risk patterns in the forms of sets of 'if-then' rules, as opposed to 'black box' algorithms, where the underlying reasons behind the results may not be immediately apparent.

7.1.3. Case studies and consolidation of the theory

The data model solution was applied in two separate case studies. The first case study focused on uncovering specific combinations of planned and unplanned factors that attempted to explain the dynamic nature of unstable approaches within a selected fleet at a regional airline. The second case study focused on identifying the planned and unplanned factors contributing to safety events during aircraft turnaround activities in a selected fleet at a specific airport in ground operations. Differentiating the case studies into two distinct operational areas was strategic, aiming to facilitate theory validation across different contexts and enhance their generalisability.

Case Study 1. An unstabilised approach occurs when the aircraft's landing approach deviates from established stable approach criteria. Identifying such situations involves a systematic analysis conducted by experts to measure the deviation from the Company's Standard Operating Procedures. By integrating operational data with flight data events captured by the Flight Data Monitoring System, automatic data collection ensures reliability and data quality. The highest number of instances highlighted that the severity class of specific unplanned Flight Data Monitoring events, notably 'Flap late setting above 500 ft' and 'Gear late extension', emerged as repetitive predictors, especially when combined with some planned variables like specific routes or crew composition.

Case Study 2. The aircraft turnaround defines the servicing process while an aircraft is parked between the execution of two successive flights. It consists of a tight sequence of activities from arrival to departure, generally carried out by different handling companies and ground vehicle types in a relatively limited space. Integrating operational data with safety records to identify planned and unplanned factors contributing to safety incidents during aircraft turnaround. The analysis results proved the data model's ability to generate plausible and widely applicable predictions, confirmed by the positive operational feedback given by the expert involved. The analysis of the sets of precursors highlighted that departure delays, whether due to specific causes or durations, can be considered a strong predictor, specifically when considered alongside planned factors such as departure airports and flight types. Nevertheless, in the data understanding phase, a deep understanding of the data emphasised the significance of fostering an effective reporting culture for a more accurate representation of the phenomenon and an efficient occurrence analysis process to extract insights about the underlying causal factors.

The selection of a relevant sample of past and recent studies in some industrial fields and aviation to extract safety-relevant knowledge and patterns from large datasets provided a literature background of the data-in-data-out approach used to investigate specific events (Yang et al., 2018; Yu, 2020; Kumar, 2021). The research questions were designed to explore the following themes: (i) Has data been collected and integrated from multiple sources? (ii) Which relevant machine learning models have been used?; and (iii) Is the machine learning model interpretable? The goal is to show the distinctive approach of the proposed data model solution to this body of evidence.

The analysis revealed two major themes within the case studies. The first theme involved the prevalent use of 'uninterpretable' or 'black-box' machine learning models, where only the input and output are known, with little insight into the model's inner workings (Movin et al., 2023). In contrast, Kumar (2021) employed a different approach to predict sales and orders in the binary category of fraud or not. This approach produced interpretable results, utilising Decision Tree Classifiers and achieving high accuracy.

The practical implication of moving from a conceptual understanding of the complexity of a safety event to an empirical demonstration of a safety event as an empirically demonstrated set of precursors could potentially impact the practice of risk management significantly. The Domino Model or Domino Theory was developed by Heinrich (1931) and later taken up by Weaver (1971), Bird and Loftus (1974) (Othman et al., 2018) and Adams (1976), as part of their efforts to prevent accidents and improve safety, emphasised the importance of identifying and addressing the root causes and contributing factors before they can lead to an accident. The linear sequence toward an accident can be stopped by breaking the chain at any point. On the other hand, in the concept of ‘breaking the risk pattern’ (Baranzini et al., 2013; Baranzini & Zanin, 2015), the risk can be mitigated by breaking at any point, the combination of the planned and unplanned factors configuring a safety event. Hence, this novel conceptual framework aims to introduce an additional risk mitigation strategy by identifying and intervening in the fertile conditions that facilitate a safety event, preventing it rather than relying solely on implementing recovery or consequences/containment barriers. The linear or non-linear sequence toward an accident or incident can be stopped by breaking the chain or combination at any point.

The data analysis conducted in the Master's thesis (Toti, 2017) discovered that late flap configurations increased the likelihood of an unstable approach by 30 times. A subsequent analysis of three years' performance data from two airline companies confirmed a significant correlation between the 'Late Flap extension below 1000 ft' event in Flight Data Monitoring and unstable approaches. The results suggested that by addressing the identified precursor as a leading indicator, organisations can identify trends or issues early and take preventive measures to improve future outcomes (i.e., lagging indicators) positively or negatively. Refer to Tables 7-1 and 7-2 for a summary of the performance results.

Table 7-1 Unstabilised approach Performance Company 1

Company 1	**2018**	**2019**	**2020**
Flight cycles	140,343	139,286	54,978
UA events rate per 1,000 flights	2,47	1,99	1,60
Late Flap events rate per 1,000 flights	2,30	1,66	1,27

Table 7-2 Unstabilised approach Performance Company 2

Company 2	**2018**	**2019**	**2020**
Flight cycles	40,087	40,424	14,385
UA events rate per 1,000 flights	1,37	0,64	1,25
Late Flap events rate per 1,000 flights	1,30	0,54	0,90

The cross-case report was prepared to summarise and consolidate the findings and lessons from the case studies focused on the challenges encountered while implementing the data model solution. These studies revealed two primary themes. Firstly, they highlighted the sensitivity of the required data, which posed challenges in data collection due to data protection and legal compliance issues. Secondly, the studies emphasised the necessity of manual efforts to handle various data formats stored across different business systems, each using distinct tools and technologies. This diversity in data handling methods posed potential risks to data quality, integrity, and overall manageability, imposing constraints on the research project.

These findings support and align with the results and implications from previous research on the same themes. For example, the operational constraints and related trade-offs between disclosure protection and multiple dimensions of data quality (accuracy, accessibility, relevance, coherence, granularity, punctuality, and interpretability) in disseminating statistical information products and services were discussed by Eltinge (2022). Tayefi et al. (2021) discussed healthcare organisations' challenges in using patient data for analytics while ensuring data privacy and accuracy. Electronic Health Records (EHRs) are rich sources of information, encompassing structured and unstructured data with immense potential for healthcare insights. Besides structured data, unstructured data in EHRs can provide valuable information, but the analytics processes are complex, time-consuming, and often require excessive manual effort. Advanced statistical techniques like natural language processing, machine learning, deep learning, and radiomics have emerged to address this, albeit with unresolved hurdles: restricted data access due to sensitivity and ethical concerns persists, alongside data quality issues.

It became evident that introducing the data model solution represented a significant change management endeavour involving organisations, people, and technology. In their book, Provost and Fawcett (2013) explored various aspects of data science, including its impact on organisational change. In contrast, Marr (2016) covered the strategic aspects of implementing big data and AI initiatives and how these technologies impact organisational change management. A series of one-to-one interviews captured participants' perspectives and experiences regarding transforming input into output and identifying the obstacles hindering the execution of two critical risk management tasks such as risk assessment and safety performance monitoring through the implementation of AI-based solutions, a series of semi-structured interviews were conducted with safety professionals from diverse backgrounds to gain insights into their systematic approach to managing organisational change during the execution of these two specific risk management activities.

7.1.4. Semi-structured interview and CUBE

A series of semi-structured interviews were conducted involving aviation professionals with different backgrounds and expertise based on the basic principles of the CUBE methodology (McDonald, 2017) as part of a socio-technical systems analysis to deploy an AI-based solutions system change. The CUBE was developed over several years through research programs in aviation, including the MASCA Project—Managing System Change in Aviation (European Commission, 2022), PROSPERO—Proactive Safety Performance for Operations (European Commission, 2017) and ACROSS—Advanced Cockpit for the Reduction Of StreSs and Workload (European Commission, 2022). It was also applied in healthcare studies, such as managing the risk of Retained Foreign

Objects (Corrigan et al., 2018) and hospital operations and processes (Geary et al., 2022; Prescott et al., 2022; Ward et al., 2022).

The primary objective of the CUBE was to support organisational change efforts by providing a structured and systematic analysis approach. It facilitated transitioning from the current 'as-is' condition to the desired 'to-be' state. Today, the ARK Platform allows users to annotate risk management data described using the CUBE ontology with qualitative operational risk data, for example, in the study to address risk management for the prevention and control of healthcare-associated infections (HCAIs) (McDonald et al., 2021).

Braun and Clarke's (2006) approach was applied as a methodology for conducting thematic analysis of the management and analysis interview. The researcher and two supervisors discussed and refined the working analytical framework in the role of reviewers to establish key themes and categories. Pilot interviews anticipated the main study through the conduction of three interviews. The objective was to test the interview guide with a small sample of participants, assess question clarity, appropriateness, and effectiveness, and identify any issues with the sequencing of the questions or emerging new themes. This preliminary step also helped to refine, if necessary, the question list and verify the interview duration. Participants were selected based on their expertise, extensive experience, and backgrounds relevant to the study's objectives. By deliberately including safety professionals and researchers with diverse backgrounds in fields such as aviation operators, aerodrome organisations, and air traffic providers, it sought to encompass a broad range of perspectives.

The thematic analysis of the system's current state or 'as-is' on the application of risk assessment and safety performance monitoring tasks in organisations generated five main themes: (i) data management, (ii) process execution, (iii) use of experts, (iv) culture (people/organisations), and (v) technology development.

The participants emphasised that regulations govern both processes. In the realm of air operations, the European Regulation (EU) 965/2012, at the point ORO.GEN.200 Management System requires certain technical requirements and administrative procedures. According to this regulation: “(a) The operator shall establish, implement and maintain a management system that includes:” “(3) the identification of aviation safety hazards entailed by the activities of the operator, their evaluation and the management of associated risks, including taking actions to mitigate the risk and verify their effectiveness;” (EASA, 2023, p. 333). In addition to the core regulation, the European Regulation provides further guidance through AMCs (Acceptable Means of

Compliance) documents. AMC1.ORO.GEN.200(a)(3) specifically offers explanations, examples, recommended procedures, and best practices for the following processes: (a) Hazard identification processes, (b) Risk assessment and mitigation process, (c) Internal safety investigation, and (d) Safety performance monitoring and measurement (EASA, 2023, p. 334). It is worth noting that correlated regulations have been implemented in other domains to regulate management systems.

7 participants out of 11 (64%) discussed that the execution of risk assessment occurs either in response to analyse emergent safety issues or for significant changes within organisations and that the approach is very simplified and mainly based on a qualitative approach. The lack of standard methods was highlighted by 4 participants out of 11 (36%).

Participant ID #1

It is a structured process that is activated whenever there is any change. The risk assessment process is primarily the change management process. The risk assessment, as well as at the preventive level, is also done at the post level, following an event or a group of events. In which the event is studied and analysed.

Participant ID #5

Risk assessment is considered a prescriptive activity or mandatory to have the various approvals and authorisations from the National Aviation Authority or to comply with the standardisation. In addition, it remains a document of exclusive use that is the sole responsibility of the Safety Manager.

Concerning safety performance management, the industry provides guidelines that assist these organisations in proposing a standard list of safety indicators. The indicators selection process is commonly delegated to the organisation's experts. This expertise allows for identifying the most relevant and meaningful indicators for assessing performance and risks.

Participant ID #6

The starting point was the adoption of the indicators proposed by (the National Aviation Authority).

The application and execution of risk assessment and selection of safety indicators requires competence and skills. 9 out of 11 interviewees (82%) discussed the crucial role of experts in their application.

Participant ID #6

Risk-based mainly on the expert's judgment rather than on the data analysis themselves.

Participant ID #8

The other thing is definitely the experience of the staff who work there. I have always dealt with very competent people who have at least a decade of experience in safety performance management, risk management, and other areas.

The participants provided valuable insights into data management, emphasising its central role as the basis of the entire risk management process. They specifically highlighted three key challenges: the lack of data, challenges associated with internal and external data sharing with stakeholders, and issues related to data integration.

Participant ID #3

A series of data cannot be shared in any way. Some data can certainly be shared within the company. There is no will, or at least it is thought it cannot be a problem. The spread to the outside, and in some cases, this is objectively true. There is no culture of sharing, especially with the outside, for prevention. We are working slowly on this problem, but we are still really at the basics. There is sharing for the sole purpose of prevention, not with the outside. It is still very, very limited.

Participants emphasised the importance of collaboration in terms of organisational culture, particularly highlighting its effectiveness in organisations with well-established and efficient systems.

Participant ID #5

No, there is always more than one operational area. Too much. It has rarely happened to me that there is only one area involved and, from a synergy point of view, of collaboration. No, there is not.

Even if the participants recognised the strategic importance of implementing AI-based solutions, the data science initiatives are not on the agenda of the organisations.

Participant ID #6

There is no plan for implementing AI technologies in the organisation, although I support its importance.

The thematic analysis of the system's potential changes or 'to-be', including its limitations and suggested improvements on the application of risk assessment and safety performance monitoring tasks in organisations, generated the same themes of the current state ('as-is') except for process execution: (i) data management, (ii) use of experts, (iii) culture (people/organisations), and (iv) technology development.

Participants acknowledged a shortage of specialised skills, knowledge, and competent staff within their organisations and identified training as a potential solution.

Participant ID #2

The competence of the responsible figures is the attention that a specific company, company or organisation places on correctly applying the SMS. It is still impossible to understand the advantages that can be derived from implementing a mature SMS. And so many companies have stopped, stopped, and slowed down evolution. The level of competence certainly has to do with the lack of awareness of the opportunity to have extensive data collection and consequently have an effective Data Analysis process.

There is not much expertise in Data Analytics.

Participant ID #4

Machine learning and big data processes are very innovative, and not always in all areas have received the necessary generational change. Then, internally, we do not have people with this skill. This must be bought outside.

Cultural competencies are dynamic components within organisational processes and are equally crucial in machine learning systems. Despite technical intricacies often taking precedence, it is essential to acknowledge that cultural competencies and organisational processes are pivotal in ensuring the safety and performance of machine learning models (Pandey, 2023). Launching an awareness campaign and enhancing fundamental managerial-level competencies could be an initial step to informing individuals about the practical applications of these new technologies.

As revealed by the analysis of the system's current state, the intricate and multifaceted nature of data management gave rise to several distinct yet interconnected categories, each contributing to a comprehensive understanding.

Participant ID #1

Technical problems of connecting interconnect the various sources of data production. These are absolutely trivial solutions when these skills are available at the software management and data analysis level.

Participant ID #4

So, the biggest obstacles are the non-homogeneity of the sources of information and the lack of homogeneity of historical data, which does not allow the use of preventive and predictive analysis methods.

Participant ID #9

Then, try to figure out all the databases you need and get them to talk to each other. So, as usual, maybe 50 different databases with different languages should be integrated, and then work on creating a valid data model.

Moreover, that is why I am working with a Power BI; let us call it parallel because, at the moment, I am unable to throw out the data if they cannot guarantee confidentiality and security.

The majority of participants, 6 out of 11 (55%), identified Leadership and Accountability as pivotal factors for achieving total success in implementation. Considering the extensive changes affecting various aspects of the organisation, such as its structure, personnel, and IT systems, active involvement from top management is essential. Therefore, it is emphasised that the role of the Accountable Manager should align with that of the CEO, especially given the substantial investments required for this change management process.

Participant ID #2

Seeing Accountable Managers illuminated is increasingly rare. So, this process could change through regulatory aspects or the cultural growth of Accountable Managers. No legislation in Europe or other parts of the world requires specific skills from the Accountable Managers.

Participant ID #3

It must start from the top; otherwise, it does not work…. Also, in general, it requires investments of a certain importance. Surely, it is a trivial thing, but we should still act from the top down and get from the bottom up. I know, starting from the production workshops. Digitalise the operational departments.

Participant ID #6

Matching the role of Accountable Manager to the position of CEO to convey the message of the organisation's strong commitment to safety with effects in terms of investment capacity and to ensure the success of initiatives.

The final part of the interview was thought to facilitate participants' discussion on AI implementation within their operational context and identify potential areas for improvement. Overall, all interviewees stressed the importance of making a comprehensive AI strategy. An overwhelming majority, 9 out of 11 participants (91%), highlighted AI's potential to enhance operations, particularly in streamlining decision-making processes and process optimisation.

In this study, the CUBE, a model and methodology designed for conducting comprehensive analyses of socio-technical systems and processes, was employed to consolidate the evidence collected to assess how to effectively implement AI-based applications within organisations to enhance their risk management processes, specifically on two specific tasks: risk assessment and safety performance monitoring and measurement—defining the initial problem space as a collection of requirements that should be fulfilled. This initial step helped to establish a set of prerequisites for an effective system, which, in turn, served as the foundation for a subsequent validation exercise.

7.2. Limitation of the Study

Both case studies were not designed to identify the intrinsic dynamic nature of the two comprehensively investigated safety events. Instead, they aimed to empirically validate the research's proposed theory, training the data model with the available data. Hence, once the business problems of the case studies were well-defined, the difficulties related to data acquisition required a constant update of the projects, limiting the exploration of the phenomena. Moreover, a manual effort was necessary to address various data formats stored across different business systems, each utilising distinct tools and technologies. This diversity in data handling methods posed potential risks to data quality, integrity, and overall manageability, thereby imposing constraints on the research project.

The data analysis generated clear and simple patterns. However, the predictive potentiality of the data model indicates that more extensive and diverse data sources could reveal more intricate patterns, better capturing the configuration of a safety event with their planned and unplanned factors. Given the complexity of both safety events, gathering additional data sources, such as meteorological information, would have been necessary to map all potential conditions within the operational scenarios fully. For example, in the second case study, the difficulties of exporting staff scheduling data, including details like the number of ground staff, composition, experience, and contract types involved in the aircraft turnaround process, presented a limitation in the research efforts to enhance predictive capabilities and identify potential human and organisational factors contributing to safety events.

The semi-structured interviews served as an initial step in change management, involving a gap analysis for implementing AI-based solutions within complex organisations. This process addressed the challenges of handling extensive and diverse data from various sources, fusing them into a single database for intelligent analysis to extract valuable insights, patterns, and information. Due to the complexity of the subject matter and the limited number of participants, a criterion-based selection approach was employed. By deliberately including safety professionals and researchers with diverse backgrounds in fields such as aviation operators, aerodrome organisations, and air traffic providers, it sought to encompass a broad range of perspectives to ensure their insights aligned with the research objectives and questions.

7.3. Recommendations

The objective of predictive analytics is continually expanding as organisations generate and collect more data. The case studies reveal that including more data sources, a more accurate representation of a real-world situation involving people, technology, and the environment helps to predict and uncover hidden combinations of factors. This, in turn, allows us to gain valuable insights and make data-driven decisions in various areas.

Both case studies provide spaces for implementation and future research. For example, in Case Study 1, a single flight can generate multiple Flight Data Monitoring events or exceedances if various parameters or conditions deviate from established safety criteria or Standard Operating Procedures at different times during the flight. As a recommendation for future initiatives, analysing Flight Data Monitoring events as multivariate time series data rather than separately can help identify and leverage temporal dependencies to enhance the predictive capabilities of unstabilised approaches.

The findings from the thematic analysis of the requirements for successful data science initiatives within organisations underscored the intricacy of this project. Despite the interviews involving a limited number of participants, they yielded a preliminary list of themes for developing feasible solutions and an overarching strategy, encompassing both organisational and technical aspects. The CUBE, introduced in this study as an initial step, established a set of prerequisites for an effective system, emerging to be an effective analytical tool for exploring the dynamics of socio-technical systems in the context of organisational change.

7.4. Future Research and Practice

Industry 4.0, the fourth industrial revolution, reshapes how businesses oversee their value chains. Real-time data analysis and decision-making are crucial, making data a vital asset in Industry 4.0. Effective Data Governance is essential (Zorrilla & Yebenes, 2022) to accept data science results and efficiently manage organisational changes (Brous & Janssen, 2020). In the aviation industry, the European Union Aviation Safety Agency (EASA) is outlining its vision for AI safety and ethics in aviation. Its Artificial Intelligence Roadmap (EASA, 2020; 2023) provides a comprehensive action plan for the EASA AI Programme, guiding the development of conceptual guidance materials and forthcoming regulatory rules. In the context of rapidly advancing data science initiatives across industries and the evolving landscape of AI implementation, especially considering the complexity of this emerging field and the unique historical moment, it becomes recommendable as future research and practice to prioritise exploratory research to strengthen ongoing development efforts.

The field of AI governance studies how humanity can best navigate the transition to an advanced AI system, focusing on the multifaceted aspects of political, economic, military, governance, and ethical dimensions (Dafoe, 2018). It is a relatively new field, and as a result, there are limited dedicated governmental institutions exclusively focused on supporting these initiatives for the proper development, support, and implementation of AI governance efforts (Stix, 2022). Analysing this aspect would close a gap in the current AI governance literature, providing valuable support to organisations that are pivotal in implementing AI governance in their operations (Mäntymäki et al., 2022).

AI governance is strongly connected to the trustworthiness of data. It encompasses the rules, procedures, and methods organizations employ to ensure ethical, responsible, and lawful development and implementation of AI. Data trustworthiness focuses on the reliability, accuracy, and integrity of the data utilised in training and operating AI systems. The experts involved in the operational feedback indicated that the identified sets of precursors were valuable for meeting the needs of target users in valid usage scenarios, suggesting that the task could be researched as a solution to be developed within a trustworthy Artificial Intelligence (AI)-supported Knowledge Management System (KMS) (Vining et al., 2022).

Even if the data analysis solution is not yet mature enough, the initial results indicate the predictive capacity to generate interpretable and usable patterns. The BOB (Before-Of-Before) model could represent an evolutionary step forward from the proposed data model solution, with a primary objective of enhancing predictive capabilities. By designing the data structure to capture both planned and unplanned variables comprehensively, mirroring real working conditions, and shifting the predictive focus from safety events to precursor elements, it is theoretically possible to uncover their dynamic nature. The BOB model empowers systems to detect weak signals, spot trends or emerging issues early, and predictively implement preventive measures to enhance future outcomes. This approach extends the time gap between detection and potential incident scenarios, encapsulating the concept of being predictive.

One of the objectives of this research was the development of new ideas that could be adaptable to all contexts, not just limited to the field of commercial aviation, which was central in the theory validation process. The reconceptualisation of a safety event as a complex entity, dynamically composed of various and diverse factors, opens up the possibility for experimentation in all those contexts where research aims to understand the conditions under which a specific phenomenon occurs. Therefore, this research has the potential to be applied in other domains, such as healthcare or automotive.

7.5. Summary

Safety events occur spontaneously or unexpectedly without prior planning. They are recognised for the potential consequences they may cause to people or objects and classified as accidents or incidents based on the extent of these consequences. A safety event can potentially cause harm to individuals or damage to objects. Similarly, a security event is explicitly recognised when there is a likelihood of posing a threat to people, property, the environment, or, in the context of a financial event, disrupting the regular functioning of a system, process, or operation.

The reconceptualisation of a safety event stems from the need to evolve its unpredictable nature into a predictable one. This entails shifting the focus from understanding how a safety event occurs with its underlying causes to identifying the combinations of co-occurring factors, planned or unplanned, within a specific space-time context in probabilistic terms, bringing out its dynamic and complex nature. The objective is to make it interpretable, evolving the field of safety thinking with implications in evolutionary and systemic risk management approaches.

The literature review uncovered that an event, regardless of the type and scale of the potential consequences, is recognised as a deviation from the intended process (Surry, 1969) and declined successively as a change of state (Cacciabue, 2010) or performance variability. The novel definition of a safety event is "a particularly dynamic and complex combination of planned and unplanned factors" that enables a probabilistic predictor, highlighting the intricate relationship among the factors contributing to those deviations from the normal process rather than solely relying on outcome assessment for identification.

The development of causal models in the last 100 years since the 'accident proneness' proposed in 1919 (Greenwood & Woods, 1919) shows the evolution of safety science in supporting the investigation of accidents or incidents with their contributing factors and played a central role in describing the increasing complexity of the models that had to adapt to the increasing complexity of systems depending on the application area.

The conclusions from the Master's thesis (Toti, 2017) generated diverse findings, revealing the complexity and dynamicity of a safety event and indicating that specific conditions during a normal operation elevate the odds of this happening. Applying predictive analysis techniques on data integrated from diverse sources into a unique dataset helped the retrospective identification of correlations between factors and the specific contextual conditions in which they emerge, differentiating between planned and unplanned. The underlying premise of this approach challenged the assumption that safety events are inherently unforeseen or unpredictable, suggesting instead that they occur in combination with specific conditions in a given space-time window. This work inspired and prepared an investigation that laid the groundwork for the current research.

The data analysis of two case studies generated clear and simple patterns. However, the predictive potentiality of the data model indicates that more extensive and diverse data sources could reveal more intricate patterns, better capturing the configuration of a safety event with their planned and unplanned factors. Given the complexity of both case studies, gathering additional data sources would have been necessary to fully map a wide range of potential conditions in everyday performance.

The positive feedback from experts indicated that the identified sets of precursors were valuable for meeting the needs of target users in valid usage scenarios. These rules were considered plausible and usable because they were easy to understand and interpret, potentially changing the game for risk management in practice. The experts involved in the operational feedback indicated that the identified sets of precursors were valuable for meeting the needs of target users in valid usage scenarios, suggesting that the data model solution enabled the extraction of interpretable and reader-friendly machine learning models in both case studies.

In theory, the analysis of risk patterns derived from implementing this predictive analysis methodology within a so-organised database can effectively depict the dynamic nature of a safety event. Exploring the hypothesis of likening a safety event to a risk pattern can pave the way for new and innovative applications in the risk management process in every sector, domain or situation. Presently, safety risks are typically managed by deploying suitable safety barriers. In scenarios where a safety event is unforeseeable and unpredictable, risk reduction is achieved by applying preventive or recovery measures to lower the associated risk level. The concept of 'breaking the risk pattern' (Baranzini et al., 2013; Baranzini & Zanin, 2015) could offer an innovative, novel and further risk mitigation strategy, moving the mitigation measures directly on the combination of the factors configuring a safety event breaking its conditions-fertile.

To be realistic, applying the 'breaking the risk pattern' in the everyday operational realm may not always be possible or, at the very least, challenging. Therefore, if the condition cannot be removed, the strategy is to attempt to manage it. This requires more organisational knowledge and expertise. Simple possession of data and a model is insufficient; the research demonstrated that interpreting the patterns to identify appropriate control measures is essential. Model validation cannot rely solely on statistical parameters analysis. Expert validation is necessary to evaluate the results concerning usability in operational contexts and improve the model's predictive capacity. These tasks require human factors, socio-technical systems and operational knowledge, which may not always be available in current organisational settings. Therefore, organisational readiness must be to implement and interpret AI models to devise suitable countermeasures to mitigate the risk, which is a novel challenge for the predictive approach.

Integrating AI implementation with organisational requirements presents a challenge that needs to be addressed. It encompasses adopting new technology and understanding the profound complexity of safety events and their management to identify appropriate actions for reducing the risk level. This necessitates human and organisational factors together with a socio-technical systems framework to support the analysis of these factors, thus advocating for a methodology like CUBE (McDonald, 2017), a comprehensive and evidence-driven assessment methodology for social-technical modelling to drive organisational change and provide for a structured and systematic approach to analysis and aid in the transition from the current 'as-is' condition to the desired 'to-be' state.

7.6. Conclusion

The core of the research was the reconceptualisation of the safety event and its validation. Then, implementing a data model solution enabled a probabilistic prediction of a safety event, extracting interpretable patterns from a merged and complex database to demonstrate the theory that a safety event is “a particularly dynamic and complex combination of planned and unplanned factors”. By leveraging the synergy between the data model and the advanced analytical techniques, it is possible to uncover meaningful insights from patterns for an innovative systemic approach to risk management. Moreover, to identify the potential barriers to implementing AI-based applications in a complex organisational context and propose solutions for managing an organisational change.

The research empirically demonstrated the dynamic and complex nature of the safety event, making it predictable and advancing its conceptual understanding and connection to the evolving field of safety thinking. The data analysis of both case studies generated clear and simple patterns. However, the predictive potentiality of the data model indicated that more extensive and diverse data sources could reveal more intricate patterns that would otherwise remain obscured within the data. The concept of ‘breaking the risk pattern’ (Baranzini et al., 2013; Baranzini & Zanin, 2015) can potentially change the practice of risk management, providing a further strategy for risk mitigation. The research also demonstrated that implementing AI-based applications like predictive analytics in organisations is not trivial and requires profound change management where organisation, people and technology are equally involved. A series of semi-structured interviews were conducted involving aviation professionals with different backgrounds and expertise based on the basic principles of the CUBE methodology (McDonald, 2017) as part of a socio-technical systems analysis to identify constraints and deploy an AI-based solutions system change.

An underlying objective of this research was to propose a versatile approach applicable to all types of events in various risk management contexts. The theory, the demonstrated validation process, and the results indicate that the research could have universal applications in diverse domains that manage risks, such as healthcare and automotive, where analysing conditions for success and failure is crucial to be resilient and have a sustainable business, dealing daily with the management dilemma to balance production and protection by controlling the safety risks.

REFERENCES

Adams, E. E. (1976). Accident causation and the management system. *Professional Safety*, 26-29.

Airbus. (2024). *Skywise*. Retrieved from Airbus: https://aircraft.airbus.com/en/services/enhance/skywise

Airline Cost Management Group. (2022). *2022 Data Collection for Fiscal Year 2021 (FY2021) .* IATA.

Amalberti, R. (2001). The paradoxes of almost totally safe transportation systems. *Safety Science*, 109-126.

Amalberti, R. (2017). The paradoxes of almost totally safe transportation systems. In R. Amalberti, *Human Error in Aviation* (p. 101-118). Routledge.

Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., . . . Herrera, F. (2020, June). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, p. 82-115.

Asadi, E., Evler, J., Preis, H., & Ficke, H. (2020). Coping with uncertainties in predicting the aircraft turnaround time at airports. *Selected Papers of the Annual International Conference of the German Operations Research Society (GOR), Dresden, Germany, September 4-6, 2019* (p. 773-780). Dresden, Germany: Springer International Publishing.

Aven, T. (2016). Risk assessment and risk management: Review of recent advances on their foundation. *European Journal of Operational Research, 253(1)*, 1-13.

Baranzini, D., & Zanin, M. (2015). *Risk Prediction & Risk Intelligence in Aviation – the next generation of aviation risk concepts from PROSPERO FP7 Project.*

Baranzini, D., McDonald, N., Corrigan, S., Kontogiannis, T., Zanin, M., Ureta, H., & Nugent, T. (2013). *D3. 6 Functional specification for the design and preparation of PROSPERO approach to safety performance management.* Deliverable to EC as part of PROSPERO project grant agreement 314822.

Barry, D. J. (2021). Estimating runway veer-off risk using a Bayesian network with flight data. *Transportation Research Part C: Emerging Technologies, 128*, 103180.

Bell, J., & Holroyd, J. (2009). *Review of human reliability assessment methods.* Buxton, Derbyshire: Health and Safety Laboratory.

Bergamaschi, S., Guerra, F., Interlandi, M., Trillo Lado, R., & Velegrakis, Y. (2013). QUEST: A keyword search system for relational data based on semantic and machine learning techniques. *Proceedings of the VLDB Endowment, 6*, 1222-1225.

Birba, D. E. (2020). *A Comparative study of data splitting algorithms for machine learning model selection.*

Bird, F. E., & Germain, G. L. (1966). *Damage Control: A New Horizon in Accident Prevention and Cost Improvement.* New York: American Management Association.

Braganza, A., Brooks, L., Nepelski, D., Maged, M., & Russ, R. (2017). Resource management in big data initiatives: Processes and dynamic capabilities. *Journal of Business Research, 70*, 328-337.

Branford, K. (2011, January). Applying the AcciMap Approach to Analyze System Accidents. *Aviation Psychology and Applied Human Factors*.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research In Psychology, 3*(2), 77-101.

Brous, P., & Janssen, M. (2020). Trusted Decision-Making: Data Governance for Creating Trust in Data Science Decision Outcomes. *Admninistrative Sciences, 10*(4), 81.

Cacciabue, P. C. (2010). *Sicurezza del trasporto Aereo.* Milano: Springer-Verlag Italia.

Cawley, G. C., & Talbot, N. L. (2010). On Over-fitting in Model Selection and Subsequent Selection Bias in Performance Evaluation. *Journal of Machine Learning Research, 11*, 2079-2107.

Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: synthetic minority over-sampling technique. *Journal of artificial intelligence research, 16*, 321-357.

Chen, M., & Decary, M. (2020). Artificial intelligence in healthcare: An essential guide for health leader. *Healthcare management forum* (p. 10-18). Los Angeles, CA: SAGE Publications.

Chubb, J., Cowling, P., & Reed, D. (2022). Speeding up to keep up: exploring the use of AI in the research process. *AI & society, 37(4)*, 1439–1457.

Collins. (2024). *Event*. Retrieved from Collins: https://www.collinsdictionary.com/it/dizionario/inglese/event

Commercial Aviation Safety Team. (2021). *Aviation Occurrence Categories.* ICAO.

Corrigan, S., Kay, A., O'Byrne, K., Slattery, D., Sheehan, S., McDonald, N., & Cromie, S. (2018). A socio-technical exploration for reducing & mitigating the risk of retained foreign objects. *International Journal of Environmental Research and Public Health, 15*(4), 714.

Dafoe, A. (2018). *AI governance: a research agenda.* Future of Humanity Institute, University of Oxford: Oxford, UK.

de Ruijter, A., & Guldenmund, F. (2016). The bowtie method: A review. *Safety Science*, 211-218.

Drucker, P. F. (1968). *The Practice of Management.* London: Pan Books.

Dunlop, E. S., Basford, B., & DePoy Smith, M. L. (2019). Remodeling Heinrich: An Application for Modern Safety Management. *Professional Safety 64 (05)*, 44-52.

Dwivedi, R., Dave, D., Naik, H., Singhal, S., Omer, R., Patel, P., & Ranjan, R. (2023). Explainable AI (XAI): Core ideas, techniques, and solutions. *ACM Computing Surveys, 55(9)*, 1-33.

Earnest, R. (1997, November). Characteristics of proactive & reactive safety systems. *Professional Safety*, p. 27.

EASA. (2014, 05 27). *Regulation (EU) No 376/2014.* Retrieved from EASA Pro: https://www.easa.europa.eu/en/document-library/regulations/regulation-eu-no-3762014

EASA. (2017). *European Plan for Aviation Safety (EPAS) 2018-2022.* Cologne: EASA.

EASA. (2020). *Artificial Intelligence Roadmap 1.0.* Cologne, Germany: EASA.

EASA. (2022). *Annual Safety Review 2022.* Cologne, Germany: European Union Aviation Safety Agency.

EASA. (2022). *EASA Research Agenda 2022-2024.* Cologne, Germany: EASA.

EASA. (2023). *Artificial Intelligence Roadmap 2.0.* Cologne, Germany: EASA.

EASA. (2023). *DATA4SAFETY.* Retrieved from EASA Pro: https://www.easa.europa.eu/en/domains/safety-management/data4safety

EASA. (2023, 09 21). *Easy Access Rules for Air Operations (Regulation (EU) No 965/2012).* Retrieved from EASA Pro: https://www.easa.europa.eu/en/document-library/easy-access-rules/easy-access-rules-air-operations-regulation-eu-no-9652012

ECCAIRS 2020. (2020). *ECCAIRS 2*. Retrieved from ECCAIRS Taxonomy: https://aviationreporting.eu/en/taxonomy-browser

Eltinge, J. (2022). Disclosure Protection in the Context of Statistical Agency Operations: Data Quality and Related Constraints. *Harvard Data Science Review. Published online June, 24*.

European Commission. (2017, 02 06). *PROactive Safety PERformance for Operations*. Retrieved from CORDIS EU research results: https://cordis.europa.eu/project/id/314822

European Commission. (2022, 05 25). *Advanced Cockpit for Reduction Of StreSs and workload*. Tratto da CORDIS EU research results: https://cordis.europa.eu/project/id/314501

European Commission. (2022, 05 25). *MAnaging System Change in Aviation*. Retrieved from CORDIS EU research results: https://cordis.europa.eu/project/id/266423

Eurostat. (2023, 03 23). *Fatal Accidents at work by NACE Rev. 2 activity.* Retrieved from Eurostat Data Browser: https://ec.europa.eu/eurostat/databrowser/view/hsw_n2_02/default/table?lang=en

Farmer, E. (1927). The Study of Personal Differences in Accident Liability. *Journal of the National Insititute of Industrial Psychology*, 432-6.

Farmer, E., & Chambers, E. G. (1929). A Study of Personal qualities in Accident Proneness and Proficiency. In M. R. Council, *Industrial Health Research Board Report* (p. vii-80 ref.8).

Fawcett, T. (2006). An introduction to ROC analysis. *Pattern recognition letters, 27*(8), 861-874.

Federal Aviation Administration. (2017). *Order 8040.4B Safety Risk Management Policy.* Federal Aviation Administration.

Fitouri-Trabelsi, S., Cosenza, C. A., Gustavo, Z. C., & Mora-Camino, F. (2013). An operational approach for ground handling management at airports with imperfect information. *ICIEOM 2013, 19th International Conference on Industrial Engineering and Operations Management.*

Fountaine, T., McCarthy, B., & Saleh, T. (2019). Building the AI-Powered Organization. *Harvard Business Review, 97*(4), 62-73.

FSF. (2000). *FSF ALAR Briefing Note 7.1 - Stabilized Approach.* Flight Safety Foundation.

Fu, G., Xie, X., Jia, Q., Li, Z., Chen, P., & Ge, Y. (2020, Febbraio). The development history of accident causation models in the past 100 years: 24Model, a more modern accident causation model. *Process Safety and Environmental Protection, 134*, 47-82.

Geary, U., Ward, M. E., Callan, V., McDonald, N., & Corrigan, S. (2022). A socio-technical systems analysis of the application of RFID-enabled technology to the transport of precious laboratory samples in a large acute teaching hospital. *Applied Ergonomics, 102*, 103759.

Gennatas, E. D., Friedman, J. H., Ungar, L. H., Pirracchio, R., Eaton, E., & Valdes, G. (2020). Expert-augmented machine learning. *Proceedings of the National Academy of Sciences, 117*(9), 4571-4577.

Goh, Y. M., Love, P. E., Brown, H., & Spickett, J. (2012, December 16). Organizational Accidents: A Systemic Model of Production Versus Protection. *Journal of management studies, 49(1)*, 52-76.

Gordon, R., Rose, D. M., & Bushel, H. (2009). Testing planning organising, leading and controlling (POLC): an empirical examination of the functions of management through a pilot study developing the 'POLC-BMS'. *Proceedings of the 23rd Australian and New Zealand Academy of Management Conference (ANZAM 2009).*

Great Britain. Health and Safety Executive. (1992). *The Tolerability of Risk from Nuclear Power Stations.* H.M. Stationery Office.

Greenwood, M., & Woods, H. M. (1919). *Greenwood, M., & Woods, H. M. (1919). The incidence of industrial accidents upon individuals: With special reference to multiple accidents.* HM Stationary Office: Darling and son, Limited, printers.

Gunning, D. (2017). Explainable artificial intelligence (xai). *Defense advanced research projects agency (DARPA)*.

Haddon Jr, W. (1995). Energy damage and the 10 countermeasure strategies. 1973. *Injury Prevention, 1(1)*, 40.

Hale, A. R., & Hale, M. (1970). Accidents in perspective. *Occupational Psychology, 44*, 115-121.

Halmesaari, E. (2020). *Interpretable machine learning for prediction of aircraft turnaround times.*

Heinrich, H. W. (1931). *Industrial Accident Prevention: a Scientific Approach.* New York, NY, US: McGraw-Hill.

Heinrich, H. W. (1959). *Industrial accident prevention: a scientific approach (4th ed.).* McGraw-Hill.

Hess, T., Matt, C., Benlian, A., & Wiesböck, F. (2016). Options for Formulating a Digital Transformation Strategy. *MIS Quarterly Executive, 15*(2).

HFACS Inc. (2014). *The HFACS Framework*. Retrieved from The HFACS Framework: https://hfacs.com/hfacs-framework.html

Hollnagel, E. (1998). *Cognitive reliability and error analysis method (CREAM).* Elsevier.

Hollnagel, E. (2012). *An Application of the Functional Resonance Analysis Method (FRAM) to Risk Assessment of Organisational Change.*

Hollnagel, E. (2017). *FRAM: the functional resonance analysis method: modelling complex socio-technical systems.* CRC Press.

Hollnagel, E., Braithwaite, J., & Wears, R. L. (2013). *Resilient Health Care.* Taylor & Francis Ltd.

Hollnagel, E., Braithwaite, J., & Wears, R. L. (2015). *From Safety-I to Safety-II: A White Paper.*

Holste, A. (2021, 06 07). *Volume of data/information created, captured, copied, and consumed worldwide from 2010 to 2025.* Tratto da Statista: https://www.statista.com/statistics/871513/worldwide-data-created/

Hopkins, A. (2001). *Lessons from Longford: The Esso Gas Plant Explosion.*

Hopkins, A. (2009). *Thinking about process safety indicators.*

Hoppes, M., & Mitchelle, J. (2014). *Serious Safety Events: Getting to Zero.* American Society for Healthcare Risk Management.

Hostinger. (2024). *Hostinger Tutorial*. Retrieved from hostinger.com: https://www.hostinger.com/tutorials/ai-statistics#:~:text=In%202023%2C%2035%25%20of%20companies,create%20new%20services%20and%20products.

IATA. (2022). *2021 Safety Report.* International Air Transport Association.

IATA. (2022). *2022 Mid-Year Accident Update.* Montreal, Canada: IATA.

IATA. (2022). *IATA Ground Damage Report.* Montreal, Canada: IATA.

IATA. (2023). *IATA Airport Handling Manual.* International Air Transport Association.

IATA. (2023). *Interactive Safety Report.* Retrieved from IATA: https://www.iata.org/en/publications/safety-report/interactive-safety-report/

IATA. (2024). *Global Aviation Data Management (GADM)*. Retrieved from IATA: https://www.iata.org/en/services/statistics/gadm/

ICAO. (2016). *Annex 19 to the Convention on International Civil Aviation.* Montréal: ICAO.

ICAO. (2016). Global Safety Strategy. In ICAO, *Doc 10004, Global Aviation Safety Plan* (p. 17-19). Montréal, Canada: ICAO. Tratto da ICAO Safety.

ICAO. (2018). *Safety Management Manual (SMM) Fourth Edition.* Montréal, Canada: ICAO.

ISO. (2018). *ISO 31000 Risk Management.* Geneve, Switzerland: ISO.

ISO. (2018). *ISO 31000:2018(en) - Risk management guidelines.* Retrieved from Online Browsing Platform: https://www.iso.org/obp/ui/#iso:std:iso:31000:ed-2:v1:en

ISO. (2019). *IEC 31010:2019*. Retrieved from ISO: https://www.iso.org/standard/72140.html

Jones, J., Firth, J., Hannibal, C., & Ogunseyin, M. (2019). Factors Contributing to Organizational Change Success or Failure. In *Evidence-Based Initiatives for Organizational Change and Development* (p. 155-178). Hershey, PA: IGI Global.

Joslin, R., & Odisho, E. (2020, 01 28). *Rethinking unstable approach training.* Retrieved from Royal Aeronautical Society: https://www.aerosociety.com/news/rethinking-unstable-approach-training/

Kaplan, R. S., & Norton, D. P. (1992). The Balanced Scorecard - Measures That Drive Performance. *Harvard Business Review*.

Kelly, D., & Efthymiou, M. (2019). An analysis of human factors in fifty controlled flight into terrain aviation accidents from 2007 to 2017. *Journal of safety research, 69*, 155-165.

Kiss, C. (2005). The Human Factors SHELL Model. *Academia Edu, 80*, 152-155.

Kumar, A. (2021). Ensemble Technique on Predictive Analysis and Fraud Orders Detection using Supervised Machine Learning Algorithms in Supply Chain Management. *Turkish Online Journal of Qualitative Inquiry, 12*(7).

Kune, J. B. (1985). Accident liability. *British Journal of Industrial Medicine*, 336-340.

Lakey, J. R., & Lewins, J. (1987). *ALARA - Principles, Practice and Consequences, Proceedings of the Symposium onALARA - Quantitative Techniques for Radiation Protection in the Nuclear Industry, Held at The Institution of Civil Engineers, London, September 1986.* Taylor & Francis.

Lališ, A., Socha, V., Kraus, J., Nagy, I., & Licu, A. (2018). Conditional and unconditional safety performance forecasts for aviation predictive risk management. *2018 IEEE aerospace conference.* IEEE.

Laurozee, J., & Le Coze, J. C. (2020, June). Good and bad reasons: The Swiss cheese model and its critics. *Safety Science (126)*.

Lawrence, A. C. (1974). Human error as a cause of accidents in gold mining. *Journal of Safety Research, 6(2)*, 78-88.

Leplat, J. (1989). Error analysis, instrument and object of task analysis. *Ergonomics, 32(7)*, 813-822.

Leveson, N. G. (2004). A new accident model for engineering safer systems. *Safety Science, 42 (4)*, 237-270.

Li, Y., & Guldenmund, F. W. (2018). Safety management systems: A broad overview of the literature. *Safety science, 103*, 94-123.

Loh, W. Y. (2011). Classification and regression trees. *Wiley interdisciplinary reviews: data mining and knowledge discovery, 1*(1), 14-23.

Loukides, M. (2021, 04 19). *AI Adoption in the Enterprise 2021*. Retrieved from O'Reilly media: https://www.oreilly.com/radar/ai-adoption-in-the-enterprise-2021/

Lukáčová, A., Babič, F., & Paralič, J. (2014). Building the prediction model from the aviation incident data. *2014 IEEE 12th International Symposium on Applied Machine Intelligence and Informatics (SAMI)* (p. 365-369). IEEE.

Luo, M., Schultz, M., Fricke, H., & Desart, B. (2023). Data-driven fusion of turnaround subprocesses to predict aircraft ground time. *Date accessed, 6(05*.

Luttwak, E. (2016). *The Grand Strategy of the Roman Empire: From the First Century CE to the Third.* JHU Press.

Mäntymäki, M., Minkkinen, M., Birkstedt, T., & Viljanen, M. (2022). Defining organizational AI governance. *AI and Ethics, 2*(4), 603-609.

Manyika, J., Lund, ,. S., Chui, M., Bughin, J., Woetzel, J., Batra, P., . . . Sanghvi, S. (2017). *Jobs lost, jobs gained: What the future of work will mean for jobs, skills, and wages.*

Marr, B. (2016). *Big Data in Practice: How 45 Successful Companies Used Big Data Analytics to Deliver Extraordinary Results.* Wiley Online Library.

Martinez, D., Fernández, A., Hernández, P., Cristóbal, S., Schwaiger, F., Nunez, J. M., & Ruiz, J. M. (2019). Forecasting unstable approaches with boosting frameworks and lstm networks. *9th SESAR Innovation Days.*

Mathur, P., Kathri, S. K., & Sharma, M. (2017). Prediction of aviation accidents using logistic regression model. *2017 International Conference on Infocom Technologies and Unmanned Systems (Trends and Future Directions)(ICTUS).* IEEE.

McCarthy, J. (2007). *What is Artificial Intelligence?* Stanford, CA: Stanford University.

McDonald, N. (2014, May). The evaluation of change. *Cognition Technology and Work 17(2)*, p. 193-206.

McDonald, N. (2017). Using the SCOPE Analysis Cube for STSA. *M.SC. in Risk and Change Management.* Dublin, Ireland: Trinity College Dublin.

McDonald, N., McKenna, L., Vining, R., Doyle, B., Liang, J., Ward, M. E., . . . Brennan, R. (2021, Nov). Evaluation of an Access-Risk-Knowledge (ARK) Platform for Governance of Risk and Change in Complex Socio-Technical Systems. *Int J Environ Res Public Health*.

Mintz, A., & Blum, M. L. (1949). A re-examination of the accident proneness concept. *Journal of Applied Psychology*, 195-211.

Molnar, C. (2022). *Interpretable Machine Learning: A Guide for Making Black Box Models Explainable (2nd ed.).*

Monarch, R. M. (2021). *Human-in-the-Loop Machine Learning: Active learning and annotation for human-centered AI.* Simon and Schuster.

Mosadeghrad, A. M., & Ansarian, M. (2014). Why do organisational change programmes fail? *International Journal of Strategic Change Management, 5*(3), 189-218.

Movin, M., Junior, G. D., Hollmén, J., & Papapetrou, P. (2023). Explaining black box reinforcement learning agents through counterfactual policies. *International Symposium on Intelligent Data Analysis* (p. 314-326). Cham: Springer Nature Switzerland.

Muraina, I. (2022). Ideal dataset splitting ratios in machine learning algorithms: general concerns for data scientists and data analysts. *7th International Mardin Artuklu Scientific Research Conference*, (p. 496-504).

Nationwide Children’s Hospital. (2021). *Serious Safety Event Rate (SSER)*. Retrieved from Nationwide Children’s: https://www.nationwidechildrens.org/impact-quality/patient-safety/serious-safety-event-rate-sser

NTSB. (2004). *Aircraft Accident Report NTSB/AAR-04/01.* National Transportation Safety Board.

Odisho II, E. V. (2020). *Predicting Pilot Misperception of Runway Excursion Risk Through Machine Learning Algorithms of Recorded Flight Data.* Embry-Riddle Aeronautical University.

Oehling, J., & Barry, D. J. (2019). Using machine learning methods in airline flight data monitoring to generate new operational safety knowledge. *Safety Science, 114*, 89-104.

Othman, I., Majid, R., Mohamad, H., & Shafiq, N. (2018). Variety of Accident Causes in Construction Industry. *MATEC Web Conf. 203 02006.*

Pandey, P. (2023, 09 23). *Organizational Processes for Machine Learning Risk Management.* Retrieved from Toward Data Science: https://towardsdatascience.com/organizational-processes-for-machine-learning-risk-management-14f4444dd07f

Pandya, R., & Pandya, J. (2015). C5. 0 algorithm to improved decision tree with feature selection and reduced error pruning. *International Journal of Computer Applications, 117*(16), 18-21.

Perrow, C. (1984). *Normal Accidents: Living with High-Risk Technologies.* Basic Books.

Pidgeon, N., & O'Leary, M. (1994). Organizational safety culture: Implications for aviation practice. *Aviation psychology in practice*, 21-43.

Prescott, E., Reynolds, A., Kennedy, C., Kennedy, B., O'Callagan, S., Geary, U., & Ward, M. E. (2022). Ward rounds–A socio-technical system informed analysis of the perceptions of intern and senior house office doctors. *Human Factors in Healthcare, 2*, 100027.

Provost, F., & Fawcett, T. (2013). *Data Science for Business: What you need to know about data mining and data-analytic thinking.* O'Reilly Media, Inc.

Rajnarayan, D., & Wolpert, D. (2008). *Bias-variance tradeoffs: Novel applications.* arXiv preprint arXiv:0810.0879.

Rasmussen, J. (1997). Risk management in a dynamic society: a modelling problem. *Safety Science. 27 (2–3)*, 183-213.

Reason, J. (1990). The Contribution of Latent Human Failures to the Breakdown of Complex Systems. *Human Factors in Hazardous Situations*, 475-484.

Reason, J. (1997). *Managing the Risks of Organizational Accidents (1st Edition).* London: Routledge.

Reason, J. (2000). Human error: models and management. *Clinical research ed., 320(7237)*, 768-770.

Ritschard, G. (2013). CHAID and earlier supervised tree methods. In *Contemporary issues in exploratory data mining in the behavioral sciences* (p. 48-74).

Robertson, M. M., Hettinger, L. J., Waterson, P. E., Ian Noy, Y., Dainoff, M. J., Leveson, N. G., & Courtney, T. K. (2015). Sociotechnical approaches to workplace safety: Research needs and opportunities. *Ergonomics, 58(4)*, 650-658.

Sagiroglu, S. (2013). Big Data: A Review, Collaboration Technologies and Systems (CTS). *2013 International Conference on* (p. 42-47). IEEE.

Schein, E. H. (2010). *Organizational culture and leadership. Vol.2.* John Wiley & Sons.

Schmidt, M. (2017). A review of aircraft turnaround operations and simulations. *Progress in Aerospace Sciences, 92*, 25-38.

Schultz, M., & Reitmann, S. (2018). Prediction of aircraft boarding time using LSTM network. *2018 Winter Simulation Conference (WSC)* (p. 2330-2341). IEEE.

Schultz, M., & Reitmann, S. (2019). Machine learning approach to predict aircraft boarding. *Transportation Research Part C: Emerging Technologies, 98*, 391-408.

Schultz, M., Evler, J., Ehsan, A., Preis, H., Fricke, H., & Wu, C.-L. (2020). Future aircraft turnaround operations considering post-pandemic requirements. *Journal of Air Transportation Management*.

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

Shearer, C. (2000). The CRISP-DM Model: The New Blueprint for Data Mining. *Journal of Data Warehousing, 5*(4), 13-22.

Stitching Tripod Foundation. (2015). *Guidance on using Tripod Beta in the investigation and analysis of incidents, accidents and business losses.* London: Energy Institute.

Stix, C. (2022). Foundations for the future: institution building for the purpose of artificial intelligence governance. *AI and Ethics, 2*(3), 463-476.

Surry, J. (1969). *Industrial accident research: A human engineering appraisal.* University of Toronto, Department of Industrial Engineering.

Swain, A. D. (1974). *The human element in systems safety; a guide for modern management.* London: Industrial and Commercial Techniques.

Tabesh, P., Mousavidin, E., & Hasani, S. (2019). Implementing big data strategies: A managerial perspective. *Business Horizons, 62*(3), 347-358.

Tayefi, M., Ngo, P., Chomutare, T., Dalianis, H., Salvi, E., Budriones, A., & Godtliebsen, F. (2021). Challenges and opportunities beyond structured data in analysis of electronic health records. *Wiley Interdisciplinary Reviews: Computational Statistics, 13*(6), e1549.

The BIM Engineers. (2023, 03 03). *Understanding the Different Dimensions of BIM: A Guide to 8D, 9D, and 10D BIM.* Retrieved from The BIM Engineers: https://thebimengineers.com/blog/view/understanding-the-different-dimensions-of-bim-a-guide-to-8d-9d-and-10d-bim

The House Committee on Transportation & Infrastructure. (2020). *Final Committee Report on the design, development & certification of the Boeing 737 MAX.*

Toti, F. (2017). *Model of Predictive Analysis in an Ultra-Safe System.* Trinity College Dublin.

Trist, E. L., & Bamforth, K. V. (1951). Some social and psychological consequences of the Longwall method of coal-getting. *Human Relations, 4*, 3-38.

Turner, B. A. (1997). *Man-made disasters.*

Venkatasubramanian, V., & Zhang, Z. (2016). TeCSMART: A hierarchical framework for modeling and analyzing systemic risk in sociotechnical systems. *AIChe Journal, 62 (9)*, 30675-3084.

Vining, R., McDonald, N., McKenna, L., Ward, M. E., Doyle, B., Liang, J., & Brennan, R. (2022). Developing a framework for trustworthy AI-supported knowledge management in the governance of risk and change. *International Conference on Human-Computer Interaction.* Cham: Springer International Publishing.

Wagner, D. C., & Barker, K. (2014). Statistical methods for modeling the risk of runway excursions. *Journal of Risk Research, 17(7)*, 885-901.

Ward, M. E., Daly, A., McManara, M., Garvey, S., & Teeling, S. P. (2022). A case study of a whole system approach to improvement in an acute hospital setting. *International Journal of Environmental Research and Public Health, 19*(3), 1246.

Wigglesworth, V. B. (1972). *Behaviour. The Principles of Insect Physiology.* Netherlands: Springer.

Xu, W. (2019). Toward Human-Centered AI: A Perspective from Human-Computer Interaction. *Interactions, 26*(4), 42-46.

Yang, C., Qian, Z., Pei, Y., & Wei, L. (2018). A Data-Driven Approach for Condition Monitoring of Wind Turbine Pitch Systems. *Energies, 11*(8), 2142.

Yin, R. K. (2009). *Case study research: Design and methods.* London, UK: SAGE.

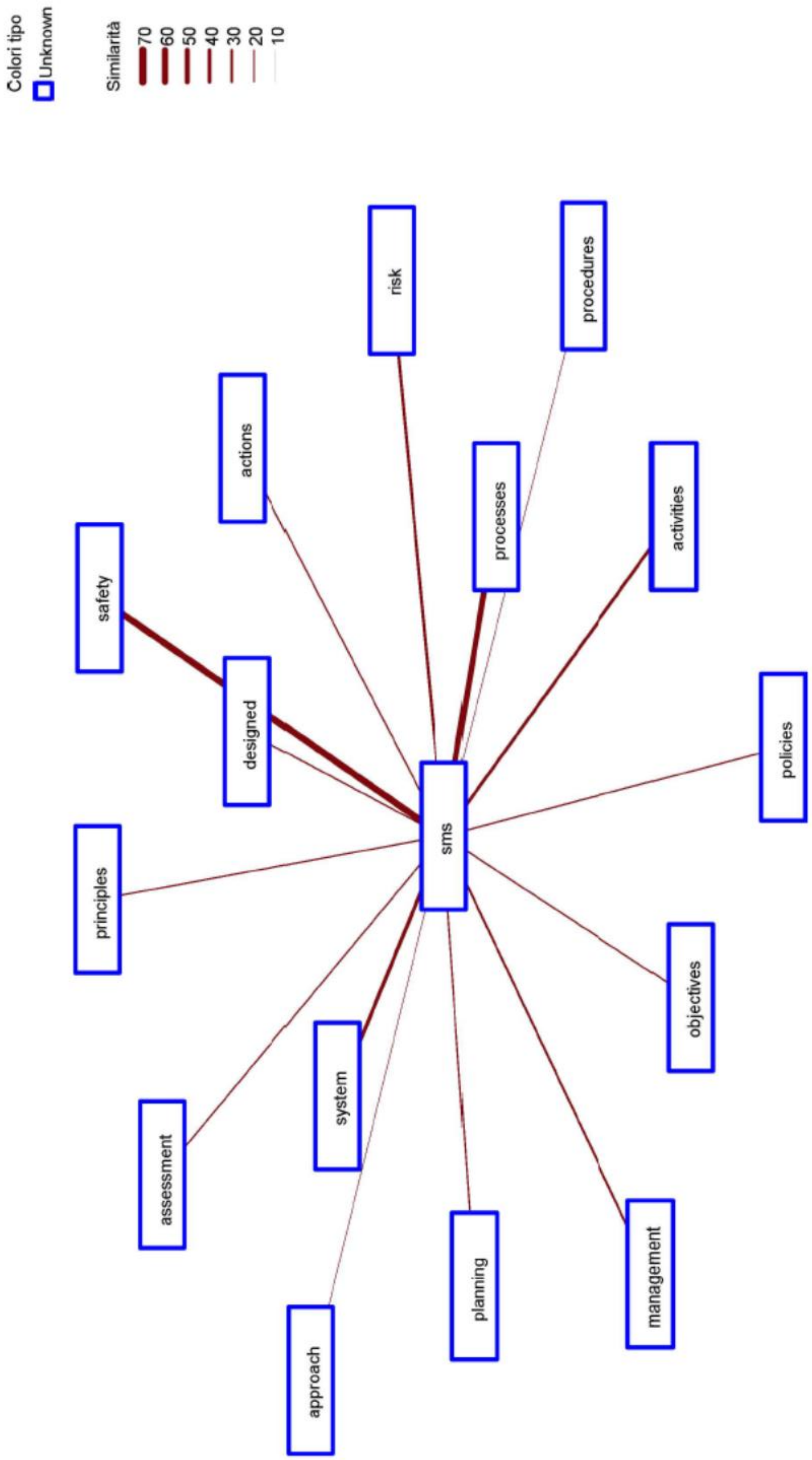
Yu, X. (2020). Risk Interactions of Coronavirus Infection across Age Groups after the Peak of COVID-19 Epidemic. *International journal of environmental research and public health, 17*(14), 5246.

Zhang, X., & Mahadevan, S. (2019). Ensemble machine learning models for aviation incident risk prediction. *Decision Support Systems, 116*, 48-63.

Zorrilla, M., & Yebenes, J. (2022). A reference framework for the implementation of data governance systems for industry 4.0. *Computer Standards & Interfaces, 81*, 103595.

APPENDICES

Appendix 1 Concept Map on SMS Definitions



Appendix 2 Inputs Model Case Study 1

Variable	Description
@FDMVol_cat	Amount of flight data events generated by aircraft and recorded by the Flight Data Monitoring during a flight.
@Fleet	Aircraft Model
@From_rec	Departure Airport
@To_rec	Arrival Airport
@ETDBin_R	Estimated Time of Departure
@ETABin_R	Estimated Time of Arrival
@Route_cat	Departure and Arrival Airports
@DelayDep_Cat	Amount of delay in Departure
@DelayArrival_Cat	Amount of delay in Arrival
@DeltaDelay	The difference between arrival delay and departure delay
@Crew Volume_Cat	Number of flight crew members
@CPFHT.1_Cat	Total flight hours carried out by the Captain
@CPAge_cat	Captain's Age
@FOFHT_cat	Total flight hours carried out by the First Officer
@FOAge_cat	First Officer's Age
@Severity_Max_cat	The highest severity class value generated by the aircraft and recorded by the Flight Data Monitoring during a flight.
@eventtype.X_cat	Flight data event type. The number indicates the sequential order when multiple flight data events occur during a flight.

Appendix 3 Rule Sets Case Study 1 – CHAID 4

- @Severity_Max_cat in ["2.0" "no event"] [Mode: 0] => 0.0
- @Severity_Max_cat in ["3.0+"] [Mode: 1]
  - @eventtype.2_cat in ["Derotation"] [Mode: 0] => 0.0
  - @eventtype.2_cat in ["Flap late setting above 500 AFE"] [Mode: 1]
    - @FDMVol_cat in ["FDM <3"] [Mode: 1]
      - @eventtype.1_cat in ["Derotation" "Flap late setting above 500 AFE" "Gear Late Extension" "Long Flare below 30 ft" "Speed high between 3000-1000 feet" "Speed high between 5000-3000 feet"] [Mode: 1] => 1.0
      - @eventtype.1_cat in ["OtherEvents"] [Mode: 1]
        - @DeltaDelay <= 1.111 [Mode: 1] => 1.0
        - @DeltaDelay > 1.111 [Mode: 1] => 1.0
    - @FDMVol_cat in ["FDM >=3"] [Mode: 1]
    - @Route_cat in ["CAGLIN" "CTALIN" "FCOGOA" "LINCAG" "LINCTA" "LINLCY" "LINTXL" "MXPFCO" "NAPLIN"] [Mode: 1] => 1.0
      - @Route_cat in ["FCOGVA" "FCOLIN" "LCYLIN" "LINBRU" "TXLLIN"] [Mode: 0] => 0.0
      - @Route_cat in ["FCOMXP" "LINFCO" "LINFRA" "LINNAP" "OtherRoutes"] [Mode: 1]
        - @DelayArrival_Cat in ["+10 delay" "5-10 delay"] [Mode: 1]
          - @Route_cat in ["FCOMXP" "LINFCO" "LINFRA" "LINNAP"] [Mode: 1] => 1.0
          - @Route_cat in ["OtherRoutes"] [Mode: 1] => 1.0
        - @DelayArrival_Cat in ["+5 early" "OnTime"] [Mode: 1] => 1.0
      - @Route_cat in ["FCOVRN" "FRALIN"] [Mode: 1] => 1.0
  - @eventtype.2_cat in ["Gear Late Extension"] [Mode: 1]
    - @CPAge_cat in ["CPAge +52" "CPAge 43-52"] [Mode: 1]
      - @eventtype.3_cat in ["Flap late setting above 500 AFE"] [Mode: 1]
        - @Fleet in ["E75"] [Mode: 1]
          - @DelayDep_Cat in ["+60min" "30-60min"] [Mode: 1] => 1.0
          - @DelayDep_Cat in ["1-10min" "10-30min" "OnTime"] [Mode: 1] => 1.0
        - @Fleet in ["E90"] [Mode: 1] => 1.0
      - @eventtype.3_cat in ["Gear Late Extension" "OtherEvents" "no event"] [Mode: 1]
        - @Route_cat in ["BRULIN" "CAGLIN" "CTALIN" "FCOGOA" "FCOGVA" "FCOMXP" "FCOVRN" "GOAFCO" "GVAFCO" "LINBRU" "LINCAG" "LINCTA" "LINFRA" "LINLCY" "LINNAP" "LINTXL" "MXPFCO" "TXLLIN"] [Mode: 1] => 1.0
        - @Route_cat in ["FCOLIN" "NAPLIN" "OtherRoutes"] [Mode: 1]
          - @Crew Volume_Cat in ["+3 crew"] [Mode: 1]
            - @Fleet in ["E75"] [Mode: 1] => 1.0
            - @Fleet in ["E90"] [Mode: 1] => 1.0
          - @Crew Volume_Cat in ["1-2 crew"] [Mode: 1] => 1.0
        - @Route_cat in ["FRALIN" "LINFCO"] [Mode: 1]
          - @ETABin_R in ["06-12" "18-24"] [Mode: 1]
            - @CPAge_cat in ["CPAge +52"] [Mode: 1] => 1.0
            - @CPAge_cat in ["CPAge 43-52"] [Mode: 1] => 1.0
          - @ETABin_R in ["12-18"] [Mode: 1] => 1.0
        - @Route_cat in ["LCYLIN"] [Mode: 1]
          - @FOFHT_cat in ["FOFHT < 1500"] [Mode: 1] => 1.0
          - @FOFHT_cat in ["FOFHT >= 1500"] [Mode: 1] => 1.0
    - @CPAge_cat in ["CPAge <43"] [Mode: 1] => 1.0
  - @eventtype.2_cat in ["Long Flare below 30 ft"] [Mode: 1]
    - @To_rec in ["FCO"] [Mode: 1]

@eventtype.1_cat in ["Derotation" "Speed high between 5000-3000 feet"] [Mode: 0] => 0.0

@eventtype.1_cat in ["Flap late setting above 500 AFE" "Gear Late Extension" "OtherEvents" "Speed high between 3000-1000 feet"] [Mode: 1]

@FOFHT_cat in ["FOFHT < 1500"] [Mode: 1]

@DelayArrival_Cat in ["+10 delay" "OnTime"] [Mode: 1]

@CPAge_cat in ["CPAge +52"] [Mode: 1] => 1.0

@CPAge_cat in ["CPAge 43-52" "CPAge <43"] [Mode: 0] => 0.0

@DelayArrival_Cat in ["5-10 delay"] [Mode: 1] => 1.0

@FOFHT_cat in ["FOFHT >= 1500"] [Mode: 1]

@CPAge_cat in ["CPAge +52" "CPAge <43"] [Mode: 0] => 0.0

@CPAge_cat in ["CPAge 43-52"] [Mode: 1] => 1.0

@eventtype.1_cat in ["Long Flare below 30 ft"] [Mode: 1] => 1.0

@To_rec in ["LIN" "MXP-VRN-NAP-LCY" "OTHERS"] [Mode: 1]

@CPAge_cat in ["CPAge +52" "CPAge 43-52"] [Mode: 1]

@FDMVol_cat in ["FDM <3"] [Mode: 1]

@Route_cat in ["BRULIN" "FRALIN" "LINFRA" "TXLLIN"] [Mode: 1]

@Fleet in ["E75"] [Mode: 1] => 1.0

@Fleet in ["E90"] [Mode: 1] => 1.0

@Route_cat in ["CAGLIN" "FCOLIN" "FCOVRN" "LINBRU" "NAPLIN"] [Mode: 1]

@DeltaDelay <= -0.000 [Mode: 1]

@Fleet in ["E75"] [Mode: 1] => 1.0

@Fleet in ["E90"] [Mode: 1] => 1.0

@DeltaDelay > -0.000 [Mode: 1] => 1.0

@Route_cat in ["CTALIN" "FCOGOA" "FCOGVA" "FCOMXP" "GOAFCO" "LCYLIN" "LINCTA" "LINFCO" "LINLCY" "LINNAP" "LINTXL" "MXPFCO"] [Mode: 1] => 1.0

@Route_cat in ["OtherRoutes"] [Mode: 1]

@ETDBin_R in ["06-12" "12-18"] [Mode: 1]

@FOAge_cat in ["FOAge +48" "FOAge < 37"] [Mode: 1] => 1.0

@FOAge_cat in ["FOAge 37-48"] [Mode: 1] => 1.0

@ETDBin_R in ["18-24"] [Mode: 1] => 1.0

@FDMVol_cat in ["FDM >=3"] [Mode: 1]

@ETDBin_R in ["00-06"] [Mode: 1] => 1.0

@ETDBin_R in ["06-12" "12-18" "18-24"] [Mode: 1] => 1.0

@CPAge_cat in ["CPAge <43"] [Mode: 1]

@FDMVol_cat in ["FDM <3"] [Mode: 1] => 1.0

@FDMVol_cat in ["FDM >=3"] [Mode: 1] => 1.0

@eventtype.2_cat in ["OtherEvents"] [Mode: 1]

@eventtype.1_cat in ["Derotation"] [Mode: 1]

@Route_cat in ["BRULIN" "CAGLIN" "FCOLIN" "FRALIN" "LINFCO" "OtherRoutes"] [Mode: 0] => 0.0

@Route_cat in ["LCYLIN" "LINBRU" "LINFRA" "LINLCY" "NAPLIN"] [Mode: 1]

@ETABin_R in ["06-12" "18-24"] [Mode: 1] => 1.0

@ETABin_R in ["12-18"] [Mode: 1] => 1.0

@Route_cat in ["LINNAP"] [Mode: 1] => 1.0

@eventtype.1_cat in ["Flap late setting above 500 AFE" "Long Flare below 30 ft"] [Mode: 1]

@DelayDep_Cat in ["+60min"] [Mode: 1] => 1.0

@DelayDep_Cat in ["1-10min" "10-30min"] [Mode: 1]

@DeltaDelay <= -0.000 [Mode: 1] => 1.0

@DeltaDelay > -0.000 and @DeltaDelay <= 8 [Mode: 1]

@FDMVol_cat in ["FDM <3"] [Mode: 1] => 1.0

@FDMVol_cat in ["FDM >=3"] [Mode: 1] => 1.0

@DeltaDelay > 8 [Mode: 1] => 1.0

@DelayDep_Cat in ["30-60min" "OnTime"] [Mode: 1]

@CPAge_cat in ["CPAge +52" "CPAge 43-52"] [Mode: 1]

@Route_cat in ["BRULIN" "CAGLIN" "CTALIN" "FCOGOA" "FCOGVA" "FCOLIN" "FCOMXP" "FRALIN" "GOAFCO" "GVAFCO" "LCYLIN" "LINCAG" "LINCTA" "LINFRA" "LINLCY" "LINNAP" "LINTXL" "MXPFCO" "NAPLIN" "OtherRoutes" "TXLLIN"] [Mode: 1] => 1.0

@Route_cat in ["LINBRU" "LINFCO"] [Mode: 1] => 1.0

@CPAge_cat in ["CPAge <43"] [Mode: 1]

@FOAge_cat in ["FOAge +48"] [Mode: 1] => 1.0

@FOAge_cat in ["FOAge 37-48" "FOAge < 37"] [Mode: 1] => 1.0

@eventtype.1_cat in ["Gear Late Extension" "Speed high between 3000-1000 feet"] [Mode: 1]

@eventtype.3_cat in ["Flap late setting above 500 AFE" "Gear Late Extension"] [Mode: 1]

@Route_cat in ["BRULIN" "CAGLIN" "CTALIN" "FCOGOA" "FCOGVA" "FCOLIN" "FCOMXP" "FCOVRN" "FRALIN" "GOAFCO" "LINBRU" "LINCAG" "LINCTA" "LINFCO" "LINFRA" "LINLCY" "LINNAP" "LINTXL" "MXPFCO" "NAPLIN" "OtherRoutes" "TXLLIN" "VRNFCO"] [Mode: 1] => 1.0

@Route_cat in ["GVAFCO" "LCYLIN"] [Mode: 1] => 1.0

@eventtype.3_cat in ["OtherEvents" "no event"] [Mode: 1]

@Crew Volume_Cat in ["+3 crew"] [Mode: 1] => 1.0

@Crew Volume_Cat in ["1-2 crew"] [Mode: 1]

@ETDBin_R in ["00-06"] [Mode: 1] => 1.0

@ETDBin_R in ["06-12" "12-18" "18-24"] [Mode: 1]

@From_rec in ["FCO" "MXP-VRN-NAP-LCY" "OTHERS"] [Mode: 1]

@CPAge_cat in ["CPAge +52" "CPAge 43-52"] [Mode: 1] => 1.0

@CPAge_cat in ["CPAge <43"] [Mode: 1] => 1.0

@From_rec in ["LIN"] [Mode: 1]

@DeltaDelay <= -0.000 [Mode: 1] => 1.0

@DeltaDelay > -0.000 and @DeltaDelay <= 0 [Mode: 1] => 1.0

@DeltaDelay > 0 [Mode: 1] => 1.0

@eventtype.1_cat in ["OtherEvents" "Speed high between 5000-3000 feet"] [Mode: 1]

@eventtype.3_cat in ["Flap late setting above 500 AFE"] [Mode: 1]

@DeltaDelay <= -14.003 [Mode: 1] => 1.0

@DeltaDelay > -14.003 [Mode: 1] => 1.0

@eventtype.3_cat in ["Gear Late Extension" "OtherEvents"] [Mode: 1]

@To_rec in ["FCO"] [Mode: 0] => 0.0

@To_rec in ["LIN" "MXP-VRN-NAP-LCY"] [Mode: 1]

@ETABin_R in ["06-12" "12-18"] [Mode: 1] => 1.0

@ETABin_R in ["18-24"] [Mode: 1]

@FOAge_cat in ["FOAge +48"] [Mode: 1] => 1.0

@FOAge_cat in ["FOAge 37-48"] [Mode: 1] => 1.0

@To_rec in ["OTHERS"] [Mode: 1]

@eventtype.1_cat in ["OtherEvents"] [Mode: 1] => 1.0

@eventtype.1_cat in ["Speed high between 5000-3000 feet"] [Mode: 1]

@DelayArrival_Cat in ["+10 delay"] [Mode: 1] => 1.0

@DelayArrival_Cat in ["OnTime"] [Mode: 1] => 1.0

@eventtype.3_cat in ["no event"] [Mode: 1]

@Route_cat in ["CAGLIN" "LCYLIN" "LINCAG" "LINFCO" "TXLLIN" "VRNFCO"] [Mode: 0] => 0.0

@Route_cat in ["FCOGVA" "FRALIN" "GOAFCO" "LINFRA" "LINLCY" "LINTXL" "MXPFCO" "NAPLIN"] [Mode: 1] => 1.0

@Route_cat in ["FCOLIN" "LINNAP"] [Mode: 1] => 1.0

@Route_cat in ["FCOVRN" "GVAFCO" "OtherRoutes"] [Mode: 1]

@ETDBin_R in ["00-06" "06-12"] [Mode: 0] => 0.0

@ETDBin_R in ["12-18" "18-24"] [Mode: 1]

@FOFHT_cat in ["FOFHT < 1500"] [Mode: 1] => 1.0

@FOFHT_cat in ["FOFHT >= 1500"] [Mode: 1]

@DeltaDelay <= -2.834 [Mode: 1] => 1.0

@DeltaDelay > -2.834 and @DeltaDelay <= 0 [Mode: 1] => 1.0

@DeltaDelay > 0 [Mode: 1] => 1.0

@eventtype.2_cat in ["Speed high between 3000-1000 feet"] [Mode: 1]

@eventtype.1_cat in ["Derotation" "Speed high between 5000-3000 feet"] [Mode: 1]

@Route_cat in ["BRULIN" "FCOLIN" "FCOMXP" "LINBRU" "LINCTA" "LINNAP" "LINTXL" "MXPFCO" "OtherRoutes"] [Mode: 1]

@ETDBin_R in ["00-06" "18-24"] [Mode: 1] => 1.0

@ETDBin_R in ["06-12" "12-18"] [Mode: 1]

@From_rec in ["FCO" "LIN" "MXP-VRN-NAP-LCY"] [Mode: 1] => 1.0

@From_rec in ["OTHERS"] [Mode: 1]

@Crew Volume_Cat in ["+3 crew"] [Mode: 1] => 1.0

@Crew Volume_Cat in ["1-2 crew"] [Mode: 1] => 1.0

@Route_cat in ["CAGLIN" "FCOVRN" "FRALIN" "GOAFCO" "LCYLIN" "LINFCO" "TXLLIN"] [Mode: 0] => 0.0

@eventtype.1_cat in ["Flap late setting above 500 AFE" "Gear Late Extension" "Long Flare below 30 ft" "Speed high between 3000-1000 feet"] [Mode: 1] => 1.0

@eventtype.1_cat in ["OtherEvents"] [Mode: 1]

@ETABin_R in ["06-12"] [Mode: 1]

@To_rec in ["FCO" "OTHERS"] [Mode: 0] => 0.0

@To_rec in ["LIN" "MXP-VRN-NAP-LCY"] [Mode: 1] => 1.0

@ETABin_R in ["12-18"] [Mode: 1]

@From_rec in ["FCO"] [Mode: 1]

@eventtype.3_cat in ["Gear Late Extension" "OtherEvents"] [Mode: 1] => 1.0

@eventtype.3_cat in ["no event"] [Mode: 1] => 1.0

@From_rec in ["LIN" "MXP-VRN-NAP-LCY" "OTHERS"] [Mode: 1] => 1.0

@ETABin_R in ["18-24"] [Mode: 0] => 0.0

@eventtype.2_cat in ["no event"] [Mode: 1]

@eventtype.1_cat in ["Derotation"] [Mode: 0] => 0.0

@eventtype.1_cat in ["Flap late setting above 500 AFE" "Gear Late Extension" "Speed high between 3000-1000 feet"] [Mode: 1] => 1.0

@eventtype.1_cat in ["Long Flare below 30 ft"] [Mode: 0]

@Route_cat in ["BRULIN" "CTALIN" "FCOGVA" "FCOMXP" "FCOVRN" "GOAFCO" "GVAFCO" "LINBRU" "LINFCO" "LINFRA" "LINNAP" "LINTXL" "VRNFCO"] [Mode: 0] => 0.0

@Route_cat in ["CAGLIN" "FRALIN" "NAPLIN" "TXLLIN"] [Mode: 1] => 1.0

@Route_cat in ["FCOLIN" "MXPFCO" "OtherRoutes"] [Mode: 0]

@To_rec in ["FCO"] [Mode: 0] => 0.0

@To_rec in ["LIN" "OTHERS"] [Mode: 1]

@Fleet in ["E75"] [Mode: 1]

@CPAge_cat in ["CPAge +52" "CPAge <43"] [Mode: 0] => 0.0

@CPAge_cat in ["CPAge 43-52"] [Mode: 1] => 1.0

@Fleet in ["E90"] [Mode: 1] => 1.0

@eventtype.1_cat in ["OtherEvents"] [Mode: 1]

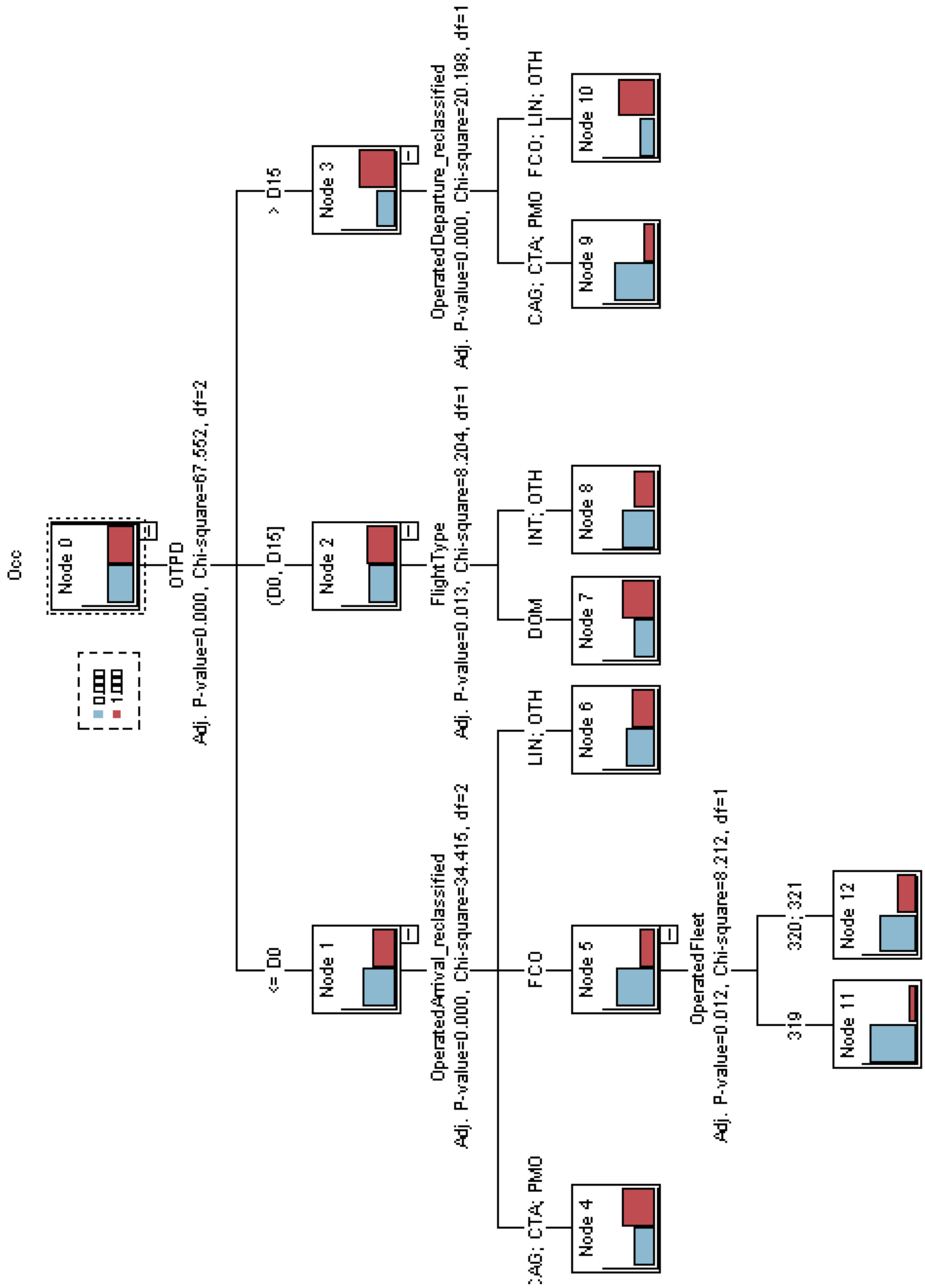
@Route_cat in ["BRULIN" "FCOGOA" "FCOGVA" "FCOMXP" "FRALIN" "GOAFCO" "GVAFCO" "LCYLIN" "LINBRU" "LINCAG" "LINCTA" "LINFCO" "LINFRA" "LINLCY" "LINNAP" "TXLLIN" "VRNFCO"] [Mode: 0] => 0.0

```
@Route_cat in [ "FCOVRN" "MXPFCO" "NAPLIN" ] [ Mode: 1 ]
    @FOAge_cat in [ "FOAge +48" ] [ Mode: 1 ] => 1.0
    @FOAge_cat in [ "FOAge 37-48" ] [ Mode: 1 ] => 1.0
@Route_cat in [ "OtherRoutes" ] [ Mode: 1 ]
    @ETABin_R in [ "00-06" "06-12" "18-24" ] [ Mode: 0 ]
        @CPFHT.1_Cat in [ "CPFHT < 1500" ] [ Mode: 0 ] => 0.0
        @CPFHT.1_Cat in [ "CPFHT >= 1500" ] [ Mode: 0 ] => 0.0
    @ETABin_R in [ "12-18" ] [ Mode: 1 ]
        @Fleet in [ "E75" ] [ Mode: 1 ]
            @Crew Volume_Cat in [ "+3 crew" ] [ Mode: 1 ] => 1.0
            @Crew Volume_Cat in [ "1-2 crew" ] [ Mode: 0 ] => 0.0
        @Fleet in [ "E90" ] [ Mode: 1 ] => 1.0
```

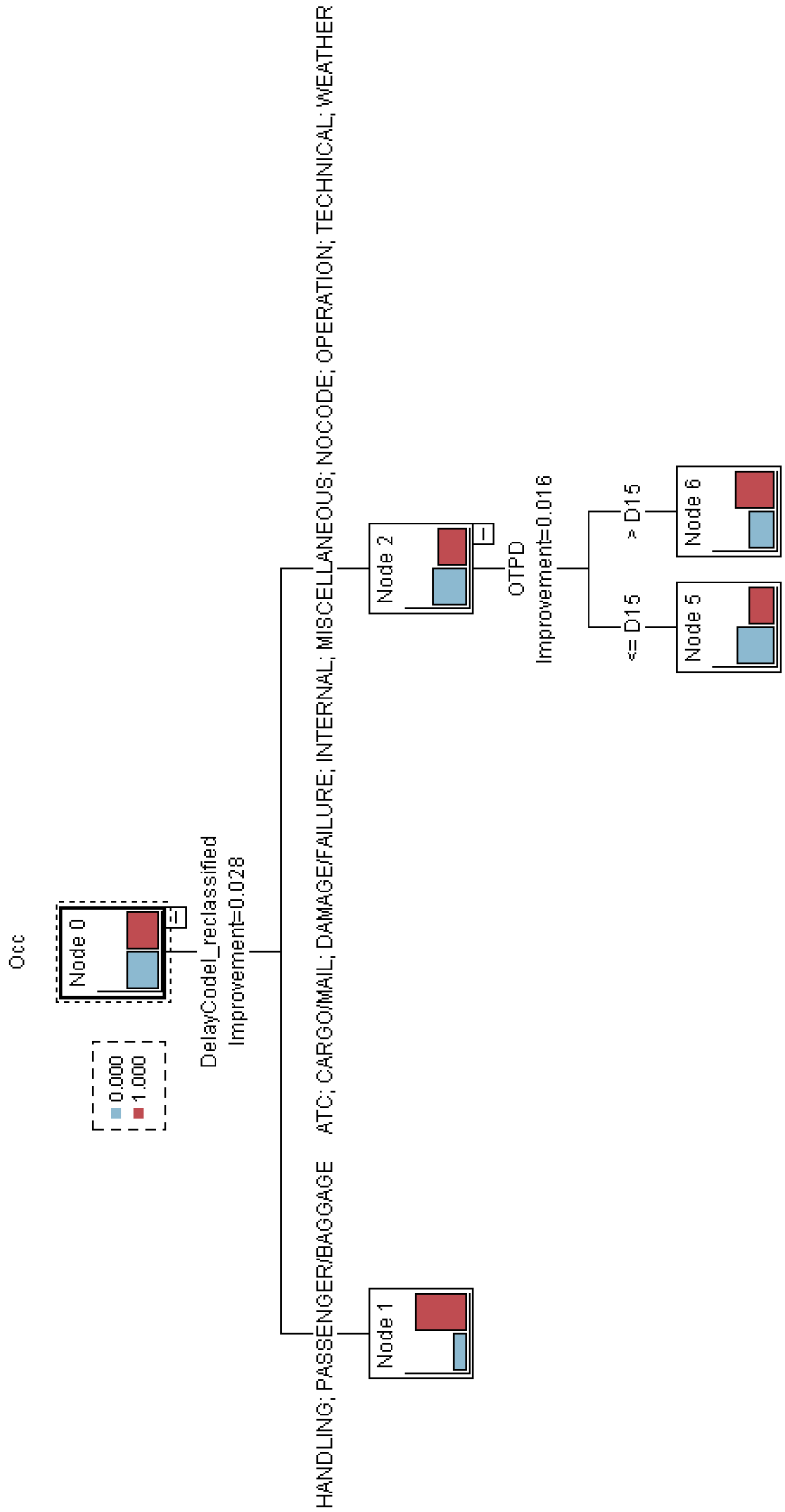
Appendix 4 Inputs Model Case Study 2

Variable	Description
OTPD	On-Time Performance in Departure
OTPA	On-Time Performance in Arrival
OperatedDeparture_reclassified	Departure Airport
OperatedArrival_reclassified	Arrival Airport
OperatedFleet	Aircraft Model
FlightType	Type of Operated Flight. For example, a 'domestic flight' refers to a flight that operates exclusively within the boundaries of a single country.
DelayCodeI_reclassified	An ‘aircraft delay code’ refers to a system or code used in aviation to categorise and monitor the reasons for delays or disruptions in aircraft operations. The Roman number indicates the sequential order when multiple reasons for delay or disruption in aircraft operation occur.
DelayCodeII_reclassified	An ‘aircraft delay code’ refers to a system or code used in aviation to categorise and monitor the reasons for delays or disruptions in aircraft operations. The Roman number indicates the sequential order when multiple reasons for delay or disruption in aircraft operation occur.
FarePayingPassengers	Number of fare-paying passengers
BaggageTransported	Amount of baggage transported
LoadFactor	The percentage of available passenger seats on an aircraft occupied during a flight.

Appendix 5 Rule Sets Case Study 2 – CHAID 1



Appendix 6 Rule Sets Case Study 2 – C&R Tree 1



Appendix 7 Semi-structured interview questionnaire

PART 1 – Participant/Industry Profile

The first part focuses on clustering participants to enhance result reliability and generalisability and uncover associations between roles or expertise and topics.

- Q1. In what industry field do you work?
- Q2. What role do you play in your organisation?
- Q3. How long have you been employed in this role?
- Q4. How long have you been working in risk and safety?
- Q5. What is your background experience in data management and data analytics?

PART 2 – Current operational practices ('as-is')

The second part discusses how organisations apply risk assessment procedures and measure operational safety performance.

- Q6. Could you describe the risk assessment process in your organisation and your involvement in the task?
- Q7. When is a risk assessment activated or required?
- Q8. Could you describe the performance management process in your organisation, from identifying the indicators to their measurement and your involvement in the task?
- Q9. Are big data processing and analytics implemented or to be implemented in your organisations to support the risk assessment and safety performance management processes?

PART 3 – Challenges to implementation ('to-be')

The third part seeks to uncover interviewers' perspectives on socio-technological challenges in implementing big data processing and analytics.

- Q10. Considering your experience, what could be or have been the main obstacles to implementing big data processing and analytics in your organisations?

- Q11. Considering your experience, which solutions would you adopt or have adopted to introduce big data processing and analytics in your organisations?

PART 4 – Potential future benefits and opportunities of developing AI

The fourth part explores AI technology development's compelling benefits and opportunities in aviation.

- Q12. What other benefits do you expect from introducing AI technologies in risk management?
- Q13. Are you aware of the potential of implementing AI technologies in organisations?
- Q14. Something else to add…

Appendix 8 The CUBE – Initial description ('as-is')

	SYSTEM	ACTION	SENSEMAKING	CULTURE
GOALS	Establish, implement, and maintain a management system that includes the identification of aviation safety hazards entailed by the operator's activities, as well as evaluating and managing associated risks, including taking actions to mitigate the risks and verifying their effectiveness.	Develop and maintain a formal risk management process that ensures hazard identification, assessment and control of risks to an acceptable level. Develop and maintain a Safety Performance Monitoring and Measurement to verify the operator's safety performance compared to the safety policy and objectives.	Establish, implement and maintain the process of collecting and analysing safety-related data, understanding the context in which safety events occur, making informed decisions, and communicating these insights throughout the organisation.	Establish, implement and maintain a shared set of values, beliefs, attitudes, and behaviours within the organisation that collectively influence how safety is perceived, prioritised, and practised. Install a positive safety culture, promote open communication, encourage reporting of safety concerns and incidents without blaming, and foster a strong commitment to safety at all levels of the organisation. It also supports sensemaking by ensuring that safety-related information is readily shared, understood, and acted upon.
PROCESS	The key activity of the risk assessment is to evaluate hazards, measure the correlated risks and identify proper measures to mitigate them. The key activity of the Safety Performance Monitoring and Measurement is to select the safety metrics and performance indicators to monitor.	The risk assessment is activated either in response to significant organisational changes or to analyse emergent safety issues. Monitoring safety metrics and performance indicators is a routine activity based on safety data collection.	Achieving a precise and comprehensive risk assessment and selecting the most appropriate performance indicators aligned with the organisation's objectives demands competence and specific expertise. Typically, the activities are delegated to qualified experts (i.e., SMEs).	Each operational area operates the processes independently, utilising its data and analysis techniques. A strong need for interdepartmental collaboration emerged as a prevailing theme. However, the integration between the operational areas is influenced by the level of development, implementation, and effectiveness of the organisation's SMS.

SOCIAL	The operator's lines of responsibility and accountability are well-defined, with the Accountable Manager holding direct safety responsibility. In larger and more complex organisations, the structure is divided into distinct operational areas, each with its dedicated safety management framework.	Each operational operational area has established its own Safety Action Group to review safety-related information specific to its domain. These Safety Action Groups across various operational areas support the Safety Review Board, a high-level committee responsible for addressing strategic safety issues and assisting the Accountable Manager in maintaining safety accountability.	Understanding, making sense of, and sharing safety-related information and events internally across operational areas or externally across organisations is influenced by the maturity of a system, which refers to the level of development, implementation, and effectiveness of the SMS of the organisation.	The division into distinct operational areas promotes the development of distinct subcultures and mindsets specific to their respective domains—a tendency to work in silos.
INFORMATION	Isolated collections of data within an organisation or system that are not easily accessible or shared with other parts of the organisation limit the view of data—using a wide range of applications threatens data integrity. Also, data limitation and quality limit the view of data and affect the quantitative approach in risk management.	Safety data is limited to occurrence reporting and operational flight data events, known as Flight Data Monitoring (FDM). Notably, safety data remain in isolated datasets without the possibility of fusing with other source data (e.g., operational) for data security and privacy concerns.	Data silo favours the use of qualitative approaches and expert judgment to fill the gap between the norms and the complexity of the risk management tasks. The execution of risk assessment and selection of indicators requires competence and experienced staff instead of having a quantitative approach using numerical data.	Silo mentality affects the development of a culture of collaboration, open communication, and shared understanding.

Appendix 9 The CUBE – What could change ('to-be')

	SYSTEM	ACTION	SENSEMAKING	CULTURE
GOALS	Implement AI-based applications to enhance the management system, which includes the identification of aviation safety hazards entailed by the operator's activities, evaluating and managing associated risks, taking actions to mitigate the risk, and verifying their effectiveness in predictive terms.	Extracting interpretable patterns to identify the combination of planned and unplanned factors to understand a safety event's dynamic and complex nature.	Stakeholders must agree to a common understanding, making sense of and sharing safety-related information and events to benefit the safety knowledge generated from the data analysis methodology.	Stakeholders must share the same common values on data and information sharing.
PROCESS	Implement a data analysis methodology that facilitates the extraction of easily understandable risk patterns, enabling the advancement of a predictive risk management approach and strategy. This approach should cover the whole process, from identifying hazards to monitoring risks.	Knowledge of the nature of a safety event provides a new strategy for risk mitigation and the identification of leading indicators.	Extracting interpretable and reader-friendly machine-learning patterns requires employing the operational feedback to integrate expert knowledge and machine-learning models before deployment in a valid usage scenario.	Implementing a data analysis methodology revolutionises traditional risk management practices.
SOCIAL	Changing from siloed work to interdisciplinary collaboration by forming cross-functional teams with diverse skills and perspectives.	The process application in data science and data analytics like KDD, Agile Data Science, and CRISP-DM requires a tight collaboration between data scientists and stakeholders to deploy a reliable predictive model for enabling readable patterns.	Implementing a leadership style to maintain ongoing commitment and support, facilitate effective communication and coordination, foster expertise in big data, and provide thrust in the outcomes.	Implement open communication with employees to highlight opportunities and benefits, overcoming the resistance to change. Focusing on specific tasks such as explaining the tool's potential and associated opportunities while reducing concerns deriving from perceived threats.

INFORMATION	Implementing a data model resulting from merging data sources from various operational areas into a single dataset for extracting interpretable patterns.	Integrating into a single dataset safety, operational, and every data source enables the mapping of all conditions of operational activities.	Implementing the data model and analysis of the data effectively, the organisation requires specialised resources and a comprehensive understanding of the new technology at all organisational levels.	Implement collaborative or integrated thinking to foster open communication, cooperation, and the breaking down of barriers between different departments or teams within an organisation. Fear of AI comes from concerns about its potential to replace individuals and make their skills obsolete by introducing a new way of working.

Appendix 10 Ethical Approval Letter

Trinity College Dublin
Coláiste na Tríonóide, Baile Átha Cliath
The University of Dublin

14/07/2022

Study Title: Predictive risk management: a novel approach in complex organisations

Dear Fabio

I have reviewed the Data Protection Risk Assessment and supporting documentation (Participant Information Leaflet, Consent Form) in respect of this research study and am satisfied that the intended processing of personal data for the purposes of the study as described therein is in compliance with data protection legislation, specifically the EU General Data Protection Regulation 2016 (GDPR), Data Protection Acts 1988-2018 and Health Research Regulations 2018.

Please note that the completion of a risk assessment is not a one-time exercise, but a continual process. If at any stage there are changes to the processing envisaged by this assessment please contact me.

Be advised that the Trinity College Data Protection Office may carry out a review to assess if the processing is being performed in accordance with the information provided.

I wish you the very best of luck with your research.

Sincerely,

John Eustace
Data Protection Officer
Secretary's Office
Trinity College Dublin
Dublin 2, Ireland

Appendix 11 Additional Information

Separated documents with the raw material related to the research have been stored in a shared folder created by Trinity College Dublin for the thesis examination.