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RESEARCH ARTICLE

Quantifying human-centric uncertainty in aircraft maintenance

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Abstract

Human-centric uncertainty remains one of the most persistent yet least quantified sources of risk in aviation maintenance. Although established safety frameworks such as SMS (safety management system), STAMP (Systems-Theoretic Accident Model and Processes), and FRAM (Functional Resonance Analysis Method) have advanced systemic oversight, they fall short in capturing the dynamic, context-dependent variability of human performance in real time. This study introduces the uncertainty quantification in aircraft maintenance (UQAM) framework – a novel, predictive safety tool designed to measure and manage operational uncertainty at the task level. The integrated uncertainty equation (IUE) is central to the model, a mathematical formulation that synthesises eight empirically derived uncertainty factors into a single, actionable score. Using a mixed-methods design, the research draws on thematic analysis of 49 semi-structured interviews with licensed maintenance engineers, followed by a 12-month field validation across four distinct maintenance tasks. Results demonstrate that the IUE effectively distinguishes between low, moderate and high-risk scenarios while remaining sensitive to procedural anomalies, diagnostic ambiguity and environmental complexity. Heatmap visualisations further enable supervisory teams to identify dominant uncertainty drivers and implement targeted interventions. UQAM enhances predictive governance, supports real-time decision-making and advances the evolution of next-generation safety systems in high-reliability aviation environments by embedding quantitative uncertainty metrics into existing safety architectures.

Nomenclature

Symbol

n	Number of uncertainty factors (in this study, $n = 8$)
$F_1, F_2, \ldots, F_n$	Score for the i-th uncertainty factor (range: 1 = low, 5 = high)
$C_1, C_2, \ldots, C_n$	Contextual coefficient for factor i (range: 0.5 = minimal, 2.0 = strong)
U	Scalar uncertainty score for the maintenance task
ToU	Threshold of Uncertainty; interprets U into risk categories
$\sum$	Summation operator across all n factors
$\sqrt{\ }$	Square root operator used to normalise the aggregated score
$U_{\text{low}}, U_{\text{high}}$	IUE scores resulting from low or high values of a single F_i

Acronyms

AI	Artificial Intelligence
FRAM	Functional Resonance Analysis Model
HFiE	Human Factors-induced Error
IUE	Integrated Uncertainty Equation

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ToU	Threshold of Uncertainty
SMS	Safety Management System
STAMP	Systems-Theoretic Accident Model and Processes
UQAM	Uncertainty Quantification in Aircraft Maintenance

1.0 Introduction

Aircraft maintenance environments are characterised by complexity, variability and time-sensitive operations. Yet current frameworks and safety models such as SMS, STAMP and FRAM often struggle to represent the dynamic human uncertainty involved in these settings. Despite decades of safety system evolution, the persistent challenge of modelling and predicting how human factors contribute to risk in real-world maintenance contexts remains.

1.1 Background and industry context

Human factors-induced errors (HFiEs) continue to represent a significant share of aviation maintenance incidents and remain one of the most persistent challenges in operational safety [2, 12, 44, 53, 57]. Despite decades of regulatory reform and human factors research, maintenance-related HFiEs still account for up to 42% of landing gear failures and approximately 18% of in-flight damage events [22, 49, 58]. While mitigated by frontline checks and engineering protocols, these failures still cause critical operational disruptions such as system degradation, aircraft returns and schedule delays.

Aircraft maintenance operates under stringent oversight, governed by regulatory frameworks including European Union Aviation Safety Agency (EASA) Part-145, EU Regulation 1321/2014, and International Civil Aviation Organisation (ICAO) Annex 19, all of which enforce rigorous procedural compliance and continuing airworthiness [48, 82]. The safety management system (SMS), adopted globally since 2013, is the core framework for risk identification, hazard monitoring and continuous improvement [47]. However, research increasingly points to limitations in SMS's ability to account for latent threats, context-specific variability and real-time performance fluctuations [18, 73].

Moreover, IATA's 2021 and 2022 safety data [45, 46] reveal persistent SMS challenges, particularly in risk monitoring and safety assurance, where latent conditions go undetected until incident manifestation. The evolution of SMS toward predictive and dynamic monitoring systems, accompanied by more adaptive risk-based quantification methods for managing operational complexity and uncertainty, has been recognised as essential [62]. Wachter and Yorio [107] argue that SMS frameworks cannot feasibly encompass every error-prone scenario without becoming overly complex and economically unviable. A number of researchers note the ongoing absence of predictive, interactive capabilities, while other emphasise the data-intensive requirements for implementing such features [19, 73]. SMS also struggles to model field-level performance variability, an essential factor in maintenance safety [101] and is hindered by limited analytical resources and under-reporting [4, 23, 72, 97]. Others further criticise the tendency of SMS to devolve into symbolic compliance rather than substantive safety improvement [33, 34].

1.2 The role of uncertainty in decision-making and aircraft maintenance

Uncertainty has long been understood as a major factor influencing the emergence of human error in safety-critical work. Reason [89, 90] emphasised that uncertainty distorts judgement, especially when people must switch from rule-based to knowledge-based reasoning under unfamiliar conditions. In such cases, mistakes often emerge as individuals attempt to restore control under cognitive or emotional strain. Rasmussen [87] linked uncertainty to the adaptation process during novel or dynamic scenarios, where decision-makers must act without clear precedents. Similarly, Belton et al. [7] framed uncertainty as an ever-present, but partially reducible factor in decision-making, particularly under multiple conflicting criteria. Hollnagel [43] noted that system complexity and uncertainty tend to increase together, elevating error risk, a point echoed by Wickens [110], who showed that uncertainty in information processing directly impairs decision-making accuracy.

In aircraft maintenance, uncertainty has been recognised as a destabilising factor affecting operational planning, productivity and resource allocation. Maintenance environments inherently exhibit

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stochastic variability, setting them apart from deterministic production systems and requiring dynamic, uncertainty-resilient models. A clear distinction between aleatory uncertainty (stemming from inherent variability) and epistemic uncertainty (arising from incomplete knowledge) is essential for developing effective uncertainty quantification frameworks in maintenance operations [26]. Several studies have linked unplanned maintenance to workflow disruptions, delivery delays and cost overruns. Attempts to mitigate these impacts by increasing workforce capacity can inadvertently introduce new risks, such as worker fatigue [21] or mismatched skill levels [94]. Other researchers have stressed the importance of proactively addressing uncertainty in human factors risk assessments and safety-related decision-making processes [24, 117]. Johansen [55] further argued that uncertainty must be considered when evaluating the effectiveness of safety barriers and defences. Additional studies have shown that uncertainty can distort safety defence models [68], compromise schedule integrity [35] and hinder both tactical and strategic maintenance planning [70]. Rashid et al. [85, 86] highlighted how time pressure and ambiguous cues intensify uncertainty during task execution, while others have identified its role in reducing situational awareness and increasing the likelihood of judgemental errors [50, 51]. This body of research suggests that uncertainty is not merely a contextual factor influencing human error but a fundamental operational variable that must be explicitly modelled and quantified within aviation safety systems.

1.3 Objectives

This paper introduces the uncertainty quantification in aircraft maintenance (UQAM) framework, a novel predictive model that quantifies human-centric uncertainty through the integrated uncertainty equation (IUE). Grounded in both qualitative field research and mathematical modelling, UQAM identifies eight operational dimensions of uncertainty and evaluates their predictive value through a 12-month field validation.

The rest of the paper is organised as follows. Section 2 presents the literature review and identifies theoretical limitations in current safety models. Section 3 details the methodological approach, the research gap and the conceptual development of the UQAM framework. Section 4 describes the design of the UQAM process and the mathematical derivation of the IUE. Section 5 presents the field validation results, while in Sections 6 and 7 we discuss the implications and conclude the study.

2.0 Literature review and conceptual foundations

This section reviews the evolution of safety thinking in aviation maintenance and examines how current frameworks such as SMS, STAMP and FRAM conceptualise and respond to uncertainty. It also explores the role of human variability in operational risk and the limitations of existing models in capturing real-time uncertainty. These conceptual foundations provide the basis for identifying the methodological and practical needs that the proposed UQAM framework seeks to address.

2.1 Evolution and limitations of existing safety models

The complexity of modern aviation maintenance environments necessitates a shift from linear accident models toward frameworks capable of addressing emergent behaviours and performance variability in socio-technical systems. Two of the most prominent models are STAMP (Systems-Theoretic Accident Model and Processes) and FRAM (functional resonance analysis method). However, SMS frameworks often fail to fully capture dynamic human factors such as psychological stress, environmental variability and team dynamics. At the same time, these safety models increasingly require integration with dynamic hazard detection mechanisms, moving beyond retrospective analysis towards real-time system adaptability [62, 114].

2.1.1 STAMP: a systems-theoretic approach to safety control

STAMP, developed by [66], represents a significant departure from traditional failure-event models, in the sense that it conceptualises safety as an emergent property of a system's control architecture,

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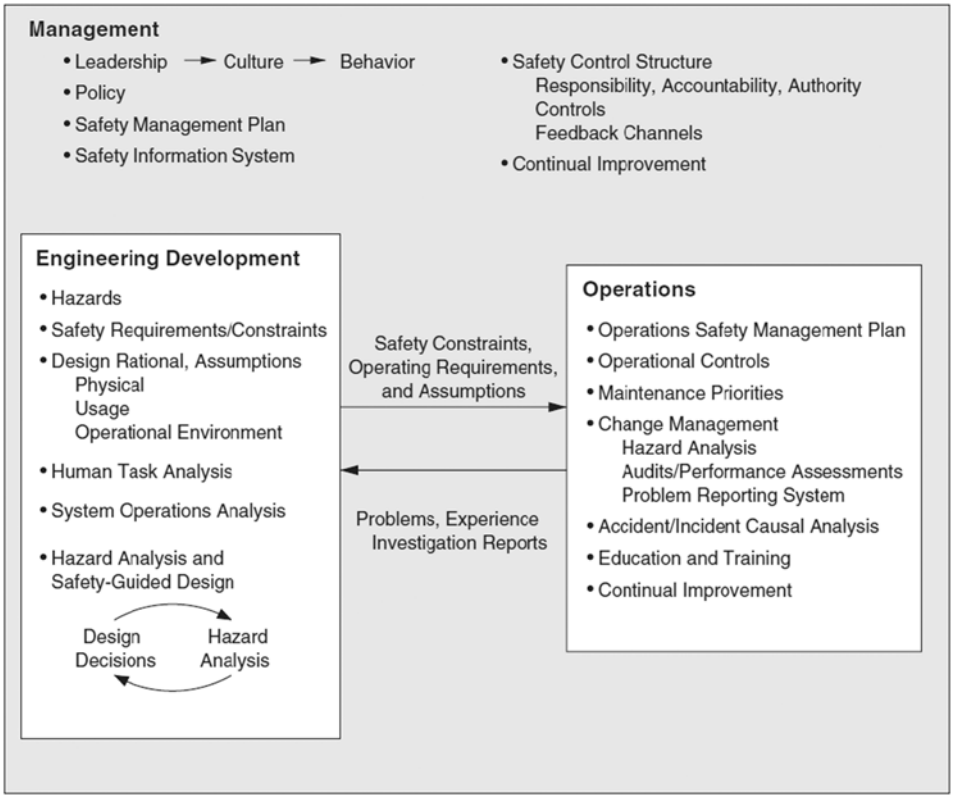


Figure 1. *The system safety engineering process components based on STAMP. Adapted from Ref. (66).*

rather than as the outcome of discrete technical failures (Fig. 1). In STAMP, accidents occur due to component malfunctions and inadequate enforcement of safety constraints across a hierarchical structure of interacting components, technical, organisational and human. STAMP is structured around the idea that each layer of a socio-technical system, ranging from frontline operators to management and regulators, exerts control through constraints, feedback loops and decision-making processes. Two critical sub-methodologies have emerged within STAMP:

- CAST (Causal Analysis based on STAMP) that focuses on identifying how systemic control failures propagate through an organisation, often uncovering mismatches between planned safety structures and actual practices.
- STPA (System-Theoretic Process Analysis) is designed to identify potential hazard scenarios proactively and inform design interventions before an accident occurs [3].

Despite its conceptual strength, STAMP faces practical limitations in contexts that demand rapid or dynamic responses, such as aircraft maintenance. While STPA offers predictive insight into potential hazards, it requires extensive qualitative data and time-intensive modelling. It also lacks built-in mechanisms for quantifying uncertainty, particularly the kind that emerges from fluctuating psychological states, resource constraints or inter-team coordination issues under time pressure. These shortcomings hinder its scalability and real-time applicability in fast-paced operational environments such as line or base maintenance, where uncertainty must be assessed and acted upon rapidly.

2.1.2 FRAM: a model of functional variability and emergent risk

The FRAM, proposed by [41], follows a different, yet complementary approach by shifting the focus from component failure to everyday performance variability (Fig. 2).

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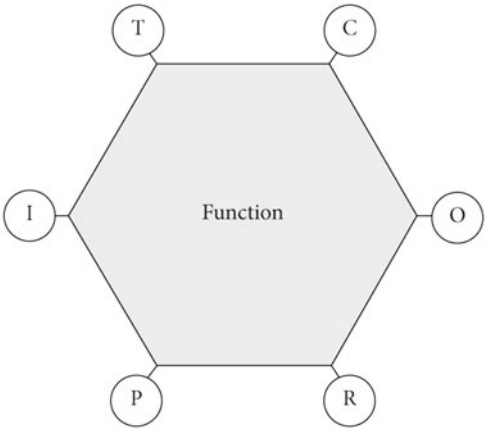


Figure 2. *A display of FRAM. A hexagon representing a function, with the six aspects of input (I), output (O), preconditions (P), resources (R), control (C), and time (T). In public domain [41].*

Nomenclature:

- I: that which the function processes or transforms or that which starts the function
- **O**: the result of the function, can be an entity or a state change
- **R**: resource(s) required for the processing performed by the function
- **T**: time required for the processing performed by the operational unit
- **C**: constraints and controls on the operational unit (procedures, methods, etc.)
- **P**: conditions that must be satisfied before a function can be carried out

It posits that both safe and unsafe system outcomes emerge from interactions between routine functions and that risk arises when these functional outputs resonate or interact in unpredictable ways. FRAM models work as nodes with six aspects (input, output, preconditions, resources, control, and time), emphasising that variability in one function can propagate through the system, potentially amplifying other minor deviations into major disruptions. This makes it particularly well-suited for analysing socio-technical systems like aircraft maintenance, where adaptive behaviour is often required to handle changing operational demands, environmental conditions or incomplete information. The strengths of FRAM lie in its ability to:

- Map complex interactions between human and technical functions.
- Capture non-linear emergent phenomena in operations.
- Recognise that variability is a normal, not an exceptional, condition in human performance.

However, as Tian et al. [104] highlight in their systematic review of 108 FRAM applications, including 26 in aviation, FRAM is primarily qualitative and lacks precise mechanisms for time-sensitive quantification or risk calculation. Its application requires intensive manual modelling and contextual knowledge, which impedes its utility in real-time decision-support systems or predictive safety monitoring. Furthermore, it struggles to incorporate dynamic human-centric uncertainty, such as fluctuating psychological load, task ambiguity, or shifting team structures – conditions common in aviation maintenance operations.

2.2 Toward uncertainty-aware safety models

Recent scholarship advocates for integrating artificial intelligence (AI) and human reliability analysis (HRA) into these frameworks to enhance real-time predictive capacity [19, 38, 73]. Walton [108]

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stresses the need for AI systems to be optimised for information flow and interpretability. However, integration challenges remain, particularly around data harmonisation and trust assurance. Tonk and Boussif [105] and Bjerga et al. [10] also note the absence of tools to communicate uncertainty effectively in decision-making environments, while Salmon et al. [95] and Mogles et al. [75] highlight ongoing problems in categorising human error and temporal effects within these frameworks. Recent advancements in intelligent hazard identification, such as deep learning models, combining contextualiser (BERT), sequencer (Bi-LSTM), and labeller (CRF) architectures, highlight the feasibility of embedding AI into real-time safety risk quantification systems [114]. Furthermore, framing maintenance management challenges through business analytics, encompassing descriptive, predictive and prescriptive layers, provides a valuable pathway for AI-driven safety system integration [26].

3.0 Research design and conceptual rationale

This section outlines the research design and the rationale underpinning the development of the UQAM framework. It details the methodological approach used to investigate uncertainty in aircraft maintenance, including the literature review process, identification of the research gap and philosophical foundations. The section also describes the data collection strategy and introduces the conceptual basis for the proposed framework, bridging empirical insights with model development.

3.1 Literature review methodology

A systematic literature review was undertaken, following a structured seven-stage protocol adapted from Booth et al. [13], Grant and Booth [36] and Okoli [79, 80], as shown in Fig. 3.

Search strategies combined Boolean logic across four academic databases (ProQuest, ScienceDirect, SAGE and EBSCOhost), applying human error, uncertainty, safety management, maintenance, STAMP, FRAM and SMS keywords. Articles were selected according to language (English or French), publication quality (peer reviewed) and domain relevance (safety critical systems), focusing on sources from 2006 to 2025 for applied studies, with broader inclusion criteria for theoretical frameworks. From an initial pool of 2244 sources, 73 articles were ultimately included in the final synthesis. Figure 4 presents the typological breakdown of the included sources, indicating that the majority were peer-reviewed journal articles (68.5%), followed by scholarly monographs (20.5%), book chapters (6.8%) and technical or institutional reports (4.1%). Thematic clustering revealed that while 64% of sources addressed human error or human factors, fewer than 7% attempted any quantitative operationalisation of uncertainty, and none provided validated tools for field-level application in aircraft maintenance. These findings align with the observations made by Reason [90] and Liu [68], who highlighted the limitations of retrospective error models and the absence of predictive frameworks.

As illustrated in Fig. 5, the thematic distribution of the selected studies reveals a prevailing research concentration on general human factors topics, particularly those situated within safety-critical industries and defence-related safety systems. In contrast, only a marginal proportion of the literature directly estimates or quantifies uncertainty. These findings also underscore the limitations of dominant human error taxonomies – slips, lapses and violations, as outlined by Reason [90] and Wickens et al. [110]. These classifications describe error as a retrospective artifact rather than a dynamic construct, influenced by evolving environmental, organisational and psychological factors. As a result, they fail to capture the cyclical, situated drivers of uncertainty that characterise real-world aviation maintenance environments.

3.2 Research gap

Despite significant advancements in aviation safety research, the current body of literature remains constrained in its ability to fully capture human behaviour's complexity, fluidity and unpredictability in aircraft maintenance. A systematic review of 73 key studies (Table 1 and Table B1 in Appendix B) revealed several persistent gaps across theoretical, methodological and practical dimensions, particularly in relation to human-centric uncertainty and its influence on safety outcomes.

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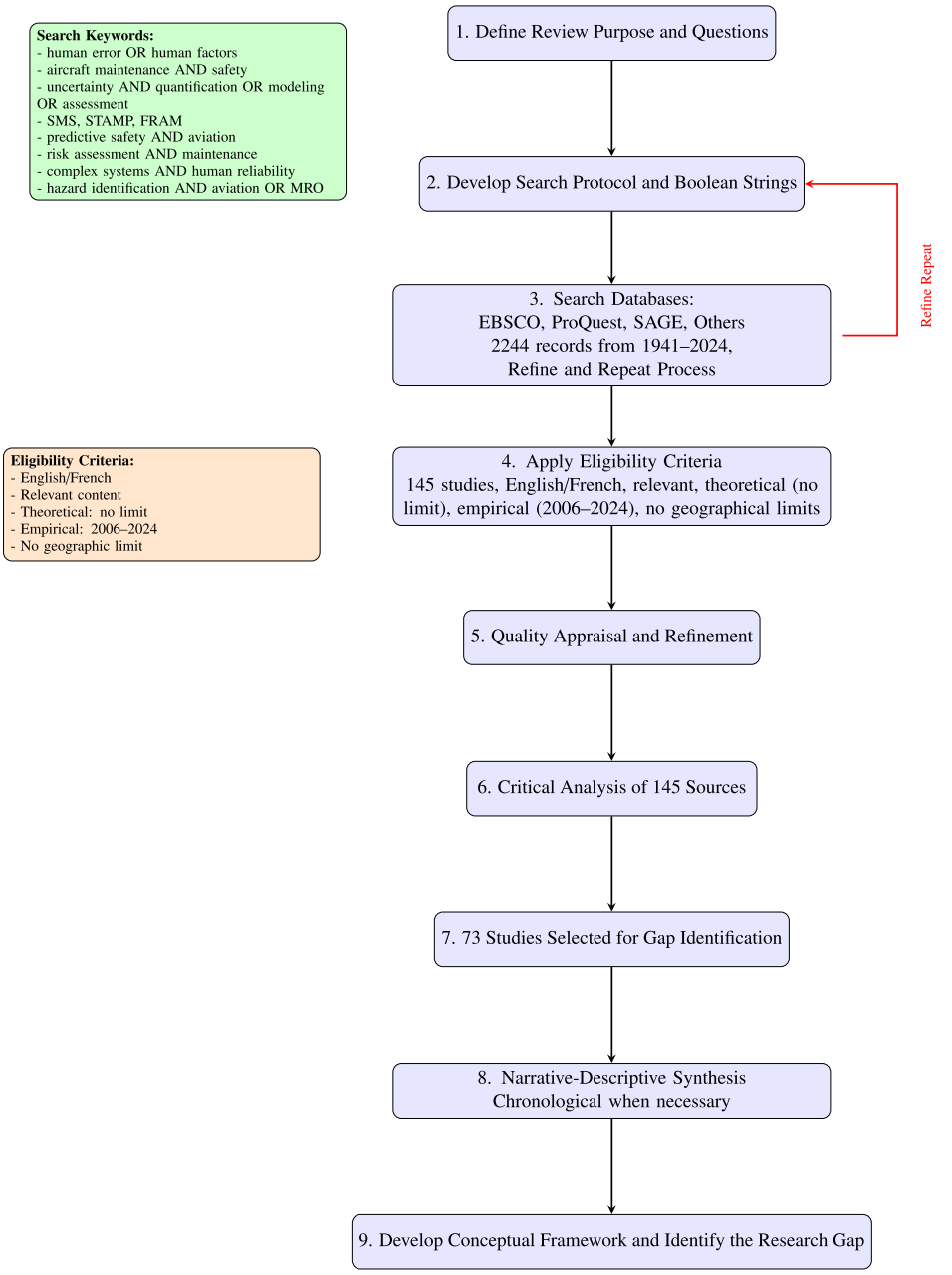


Figure 3. *The procedural steps of the literature review.*

1. Widely adopted safety models such as STAMP and FRAM emphasise systemic structures, control constraints and functional variability. However, they fail to represent the probabilistic and emergent nature of human behaviour, especially under conditions of uncertainty. These models lack mechanisms for modelling real-time variability in psychological, environmental and team-based factors that directly influence operational safety.
2. Existing approaches to human factors, including HRA and human factor analysis and classification system (HFACS), rely predominantly on qualitative or taxonomic methods, which, although

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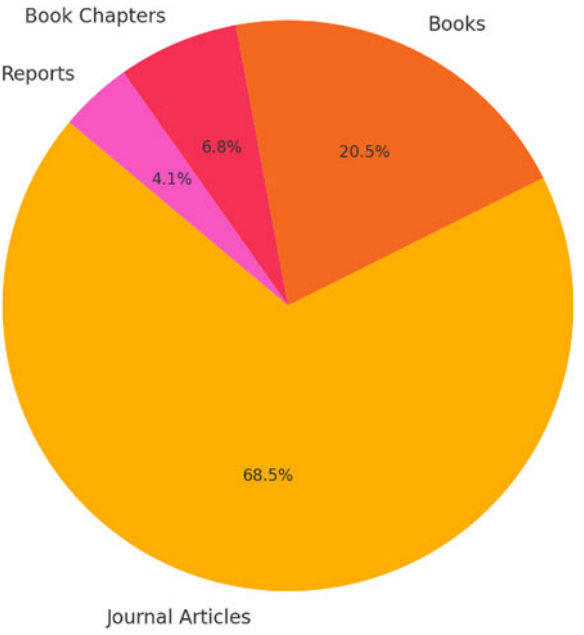


Figure 4. *Percentage distribution by publication type.*

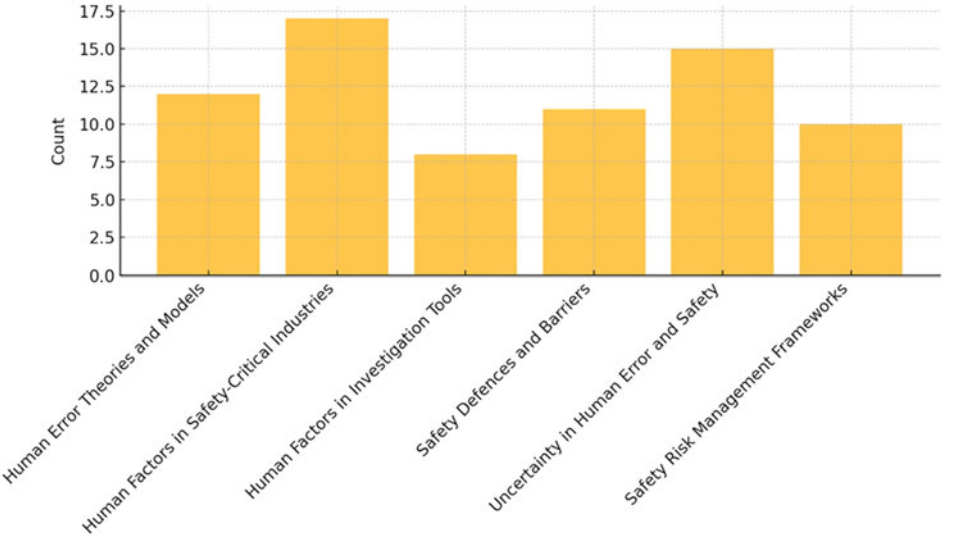


Figure 5. *The sources arranged by themes.*

insightful, do not lend themselves to proactive, quantitative risk prediction. This absence of quantitative modelling limits our ability to anticipate error emergence and implement timely interventions.

3. Most safety models in aviation maintenance remain static and retrospective in nature. They are not designed to evolve dynamically with frontline conditions or integrate live operational data. In high-risk environments like aircraft maintenance, where situational variables shift rapidly, this rigidity diminishes the practical utility of such models in real-time decision-making.
4. Prevailing positivist and deterministic paradigms underpinning most safety research, assume error to be an observable, linear output of failure chains. This view neglects the subtleties

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Table 1. *Gap domains in uncertainty modeling*

Gap Domain	Description
Conceptual	Uncertainty remains vaguely defined and conflated with complexity or variability
Methodological	Lack of mixed-method approaches merging field insight with quantitative modelling
Operational	No validated real-time tools for quantifying uncertainty in active maintenance
Model limitations	Existing frameworks lack real-time feedback loops for human variability
Ontological misfit	Current models rely on deterministic logic in dynamic, emergent settings

of human adaptation, context-driven decisions, and the subjective experience of uncertainty. Consequently, the field lacks operator-centric research that explores how frontline personnel perceive, navigate, and mitigate uncertainty before it manifests as error.

The shift from traditional compliance-driven SMS frameworks toward continuous, predictive safety systems has become increasingly vital in managing growing operational complexity and uncovering latent risks [62]. Effectively addressing both foreseeable 'grey rhino' threats and rare, high-impact 'black swan' events demand a more sophisticated, real-time approach to uncertainty modelling and hazard detection [114]. This evolving landscape highlights an urgent research imperative: developing a novel safety framework that quantitatively models human uncertainty as a dynamic and context-aware variable. Such a framework should be rooted in real-world operational insights, remain adaptable to shifting field conditions and enhance existing safety paradigms such as SMS, STAMP and FRAM.

3.3 Conceptual response: the UQAM framework

In response to the abovementioned gaps, this study introduces the (UQAM framework, a novel, hybrid model designed to mathematically represent and operationally manage human-centric uncertainty within safety-critical maintenance environments. At the core of UQAM is the IUE, a computational mechanism that synthesises field-level assessments across eight key dimensions of uncertainty:

- technical knowledge
- procedural familiarity
- psychological state
- environmental conditions
- team dynamics
- resource availability
- task complexity
- time pressure

These dimensions emerged through a constructivist analysis of interviews with 49 licensed aircraft maintenance professionals representing civil and military sectors. Unlike traditional models, UQAM does not treat uncertainty as an abstract background condition but as a measurable real-time input into safety decision making. The IUE quantifies these variables into a scalar uncertainty score that supervisors can visualise, interpret and act upon during task planning and execution. This transforms uncertainty from a latent risk into a manageable parameter, enabling predictive interventions, targeted oversight and continuous feedback within safety management systems. The UQAM framework is both theoretically grounded and practically validated. It integrates the interpretivist understanding of human experience with the precision of mathematical modelling, thereby bridging the methodological division between soft human factors inquiry and hard systems engineering. Furthermore, its compatibility with existing safety models, such as SMS, STAMP, and FRAM, offers a pathway for real-time enhancement of these

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Table 2. *The interviews outline*

Participant	Organisation	Date	Time	Recording ref.	Duration/min	Privileges	Experience	Transcript words
1	Military	10-Oct	12:00	MP001	31	Head of maintenance	23	1237
2	Military	11-Oct	9:00	MP002a, 2b, 2c	29.2	Inspector, quality control manager	12	1489
3	Military	11-Oct	12:45	MP003	19.8	Fitter, Line, Base	18	1111
4	Military	11-Oct	14:19	MP004a, 4b, 4c	33.5	Inspector, Quality manager	28	1364
5	Military	12-Oct	11:30	MP005	28.3	Inspector, Line, Base	20	1324
6	Military	12-Oct	10:55	MP006	24.8	Inspector, Line, Base	14	1015
7	Military	13-Oct	9:30	MP007	50.6	Inspector, Avionics Line, Base	22	1395
8	Military	13-Oct	10:40	MP008	24.5	Inspector, Avionics Line, Base	8	980
9	Military	13-Oct	11:20	MP009	23.2	Fitter, Line, Base	8	944
10	Military	13-Oct	12:20	MP010	16.4	Inspector, Line, Base	26	671
11	Military	13-Oct	14:00	MP011	26.2	Inspector, Line, Base	30	811
12	Military	18-Jan	10:00	MP012	34	Director Airworthiness, Inspector	26	890
13	Military	18-Jan	11:45	MP013	27.7	Inspector, Line, Base	12	819
14	Military	18-Jan	12:30	MP014	21.8	Inspector, Line, Base	17	695
15	Military	18-Jan	13:30	MP015	22.4	Inspector, Line, Base	20	1045
16	Civil	3-Apr	11:15	CP001	31	B1.1 CRS	35	1096
17	Civil	3-Apr	12:30	CP002	29	B1.1	28	1166
18	Civil	3-Apr	13:05	CP003	23	B1.1 CRS	39	1178
19	Civil	3-Apr	13:45	CP004	17.5	B1.1	4	759
20	Civil	3-Apr	14:30	CP005	22.5	B1	35	967
21	Civil	4-Apr	9:33	CP006	31.2	B1 CRS	10	1237
22	Civil	4-Apr	10:30	CP007	28.5	B1 CRS	12	1026
23	Civil	4-Apr	11:15	CP008	18.2	Mechanic	5	871
24	Civil	4-Apr	12:35	CP009	27.5	NDT Engineer	29	868

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Table 2. *Continued*

Participant	Organisation	Date	Time	Recording ref.	Duration/min	Privileges	Experience	Transcript words
25	Civil	4-Apr	13:15	CP010	24	B2	7	861
26	Civil	4-Apr	13:55	CP011	10	B2	10	569
27	Civil	4-Apr	14:30	CP012a, CP012b	15	B2	10	792
28	Civil	4-Apr	15:00	CP013	20	Mechanic	18	1057
29	Civil	5-Apr-23	9:30	CP014	20	B1 CRS	25	893
30	Civil	5-Apr	10:15	CP015	17	B1	13	866
31	Civil	5-Apr	10:50	CP016	19.4	B1 B2	12	716
32	Civil	5-Apr	11:30	CP017	23	CAT A	32	678
33	Civil	5-Apr	12:30	CP018	19	B1 Fitter	2	635
34	Civil	5-Apr	13:10	CP019	12	B1 Fitter	8	497
35	Civil	5-Apr	13:45	CP020	16	B1 B2	13	619
36	Civil	5-Apr-23	14:15	CP021	15	B1 B2 Boroscope inspector	12	605
37	Civil	6-Apr-23	10:00	CP022	22	B1 B2	14	750
38	Civil	6-Apr-23	10:50	CP023	20	Mechanic	7	616
39	Civil	6-Apr-23	11:30	CP024	22	B1 CRS	28	629
40	Civil	6-Apr-23	12:35	CP025	18	B1 B2	3	754
41	Civil	6-Apr-23	13:05	CP026	20	B1 CRS	33	740
42	Civil	6-Apr-23	13:35	CP027	21.5	B1 CRS	27	720
43	Civil	6-Apr-23	14:15	CP028	27.8	B1 CRS	26	744
44	Civil	6-Apr-23	15:00	CP029a CP029b	13.5	B1 B2	4	607
45	Civil	7-Apr-23	9:30	CP030	20.2	B1 CRS	5	690
46	Civil	7-Apr-23	10:10	CP031	22.5	B2 CRS	33	631
47	Civil	7-Apr-23	11:00	CP032	16	B2 CRS	31	648
48	Civil	7-Apr-23	11:30	CP033	16.9	B2	2	722
49	Civil	7-Apr-23	12:30	CP034	31	B1	5	880
TOTALS					1123.6		17.57142857	42,877

frameworks, transforming them from retrospective taxonomies into adaptive, anticipatory systems. In essence, UQAM proposes a paradigm shift: from error-centric to uncertainty-aware safety governance. It equips maintenance organisations with a practical tool for quantifying human variability, enhances situational awareness at the supervisory level and contributes to the long-term evolution of predictive safety science in aviation. In the next section, the paper presents the methodological design, empirical findings, and validation outcomes that support the implementation of this new framework and argues for its integration into future-oriented aviation safety governance.

3.4 Research philosophy and methodological approach

Anchored in the interpretivist paradigm, this research posits that uncertainty in aircraft maintenance stems not solely from technical anomalies but also from contextual, experiential and inherently subjective dimensions of frontline practice. The methodology embraces the complexity of socio-technical systems and recognises safety as an emergent property shaped by dynamic operational contexts [20]. Consistent with the perspective of [67], it emphasises reflexivity, context-awareness, and the co-construction of meaning. The adopted mixed-method approach (Fig. 6) unfolded across three interconnected phases, balancing theoretical depth with empirical validation. This design ensures the resulting framework is both firmly rooted in real-world practice and adaptable for broader system-level applications.

1. Qualitative exploration: In-depth, semi-structured interviews and field note observations were conducted to capture frontline perspectives on uncertainty, error genesis and safety systems.
2. Model development: Thematic patterns were translated into a conceptual framework, leading to the design of the UQAM process and the derivation of the IUE.
3. Computational formalisation: A structured mathematical formulation operationalised uncertainty as a scalar quantity, grounded in real-world inputs.

3.5 Data collection and participants

3.5.1 Sampling

A purposive, maximum-variation sampling strategy was employed to capture a broad range of expertise, operational settings and maintenance task complexities. A total of 49 licensed aircraft maintenance engineers were recruited from two major aviation maintenance organisations, one civilian, operating under the EASA Part-145 framework, and one military, compliant with European Military Airworthiness Requirements (EMAR-145). The sample was balanced across line maintenance ($n = 25$) and base maintenance ($n = 24$) personnel, reflecting routine and deep-level maintenance activities with varying technical and procedural complexity.

Participants were selected based on five key inclusion criteria:

1. Current active certification as Part-66 or EMAR-66 engineers
2. Minimum of five years' experience in maintenance operations
3. Operational familiarity with recurring tasks and airworthiness directives
4. Exposure to both routine and non-routine maintenance events
5. Willingness to participate in a study exploring uncertainty in maintenance operations

The sample included engineers from avionics, airframe, propulsion and systems specialities. Participants represented varying rank levels, technicians, team leaders, supervisors and quality assurance engineers, ensuring that both frontline and managerial perspectives were included in the data. This diversity allowed the study to capture layered understandings of uncertainty across organisational hierarchies and technical domains. Each participant was interviewed individually at their respective units (technical rooms, hangars, maintenance briefing areas), minimising workflow disruption and ensuring privacy. Interviews were conducted in English, lasted approximately 40 to 60 minutes, and were audio-recorded with full consent. This qualitative part of the research was complemented by field observation

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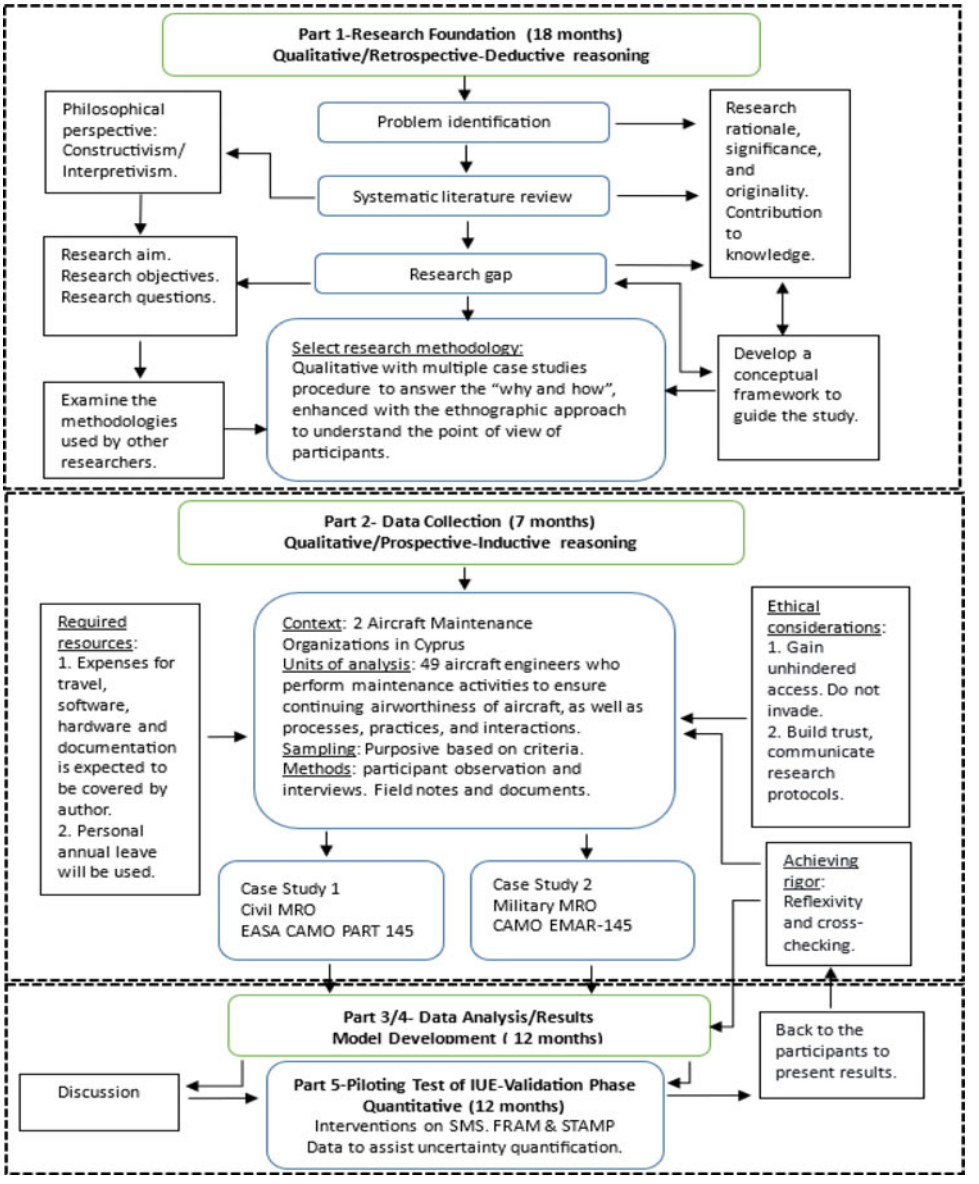


Figure 6. *The mixed method research approach.*

and note-taking. A total of 1123.6 minutes of recording time were transcribed into 42,877 words of consolidated text and cross-checked for accuracy (Table 2).

3.5.2 Interview protocol

The interview protocol was carefully developed to investigate how frontline aircraft maintenance engineers perceive, encounter and manage human-centred uncertainty within operational settings. Its design was conceptually anchored in well-established human factors frameworks, including Reason's Swiss cheese model, Hollnagel's FRAM, and Rasmussen's skill–rule–knowledge (SRK) taxonomy. Following a pilot phase involving three senior engineers (not included in the final sample), the protocol was iteratively refined to better reflect practical field conditions while maintaining theoretical coherence. Ethical

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approval for the study was obtained from the Cyprus National Bioethics Committee and the University of Nicosia Ethics Committee (Approval Code: UNIC-EHSC-21-109).

All participants were fully informed, both in writing and verbally, about the study's objectives, procedures, confidentiality provisions and their right to withdraw at any point. Informed consent was obtained before participation. All data were anonymised, securely stored and handled in full compliance with the General Data Protection Regulation (GDPR), ensuring ethical standards were upheld and participant trust maintained.

A semi-structured interview format was adopted to balance procedural consistency with exploratory flexibility. The protocol was organised around four thematic clusters:

1. The development and recognition of human error in maintenance tasks
2. The perception and sources of uncertainty in task execution
3. The interaction between human factors and formal safety systems
4. Perceived limitations of prevailing safety frameworks such as SMS, STAMP, and FRAM

A reflexive, iterative approach guided the analysis. Member checking was incorporated to enhance interpretive credibility, with selected participants reviewing emergent themes and validating their alignment with lived experience. This methodological rigour ensured the collection of rich, grounded data that was both contextually sensitive and analytically robust. The insights generated from these interviews directly informed the development of the UQAM framework. They shaped the identification of eight core uncertainty factors and the IUE design. By systematically capturing the frontline experience of uncertainty, the interview process served as a critical foundation for bridging qualitative inquiry with computational modelling in safety-critical environments.

4.0 UQAM Process Design And Mathematical Model

This section presents the structure and computational logic of the UQAM framework. Building on the thematic analysis of the qualitative findings, the framework translates eight key operational uncertainty factors into a structured process and a predictive scalar output. The section outlines the scoring mechanism's development, the IUE mathematical formulation, and the design of task-specific thresholds of uncertainty (ToU) that support supervisory decision-making in real-time contexts.

4.1 Thematic analysis and qualitative findings

Qualitative data were analysed using Braun and Clarke's [15] six-phase thematic analysis methodology, with a reflexive approach guided by Kiger and Varpio [59]. This combination provided a flexible yet rigorous structure to inductively generate themes while ensuring that the analytic process remained grounded in participants' lived experiences. As presented in Fig. 7 the analytical workflow was structured around the following iterative steps:

1. Familiarisation with the data: Audio recordings were transcribed verbatim and repeatedly reviewed alongside field notes to ensure a comprehensive understanding of contextual nuances, body language and environmental cues.
2. Initial coding: Open inductive coding was performed manually and iteratively in NVivo, generating more than 150 unique codes across the dataset. Codes reflected descriptive and interpretive insights, often capturing relational dynamics and psychological states.
3. Theme development and refinement: The codes were reviewed, clustered and abstracted into higher-order thematic categories. Themes were refined through recursive comparison and aligned with theoretical constructs and emergent operational realities.
4. Conceptual mapping and synthesis: Thematic patterns were synthesised into a conceptual map of uncertainty-inducing conditions in aircraft maintenance. This map informed the structure of the UQAM framework and directly influenced the development of the IUE.

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Table 3. *Primary dimensions of operational uncertainty in aircraft maintenance*

Code	Uncertainty Factor	Description
F_1	Technical knowledge	Individual proficiency, system familiarity, recent training
F_2	Procedural familiarity	Exposure to procedures, changes in instructions
F_3	Psychological state	Fatigue, stress, workload, distraction
F_4	Environmental conditions	Noise, lighting, workspace, ergonomics
F_5	Team dynamics	Communication, trust, coordination
F_6	Resource availability	Access to parts, tools, support
F_7	Task complexity	Diagnostic uncertainty, procedural branching
F_8	Time pressure	Deadlines, schedule constraints, shift turnover

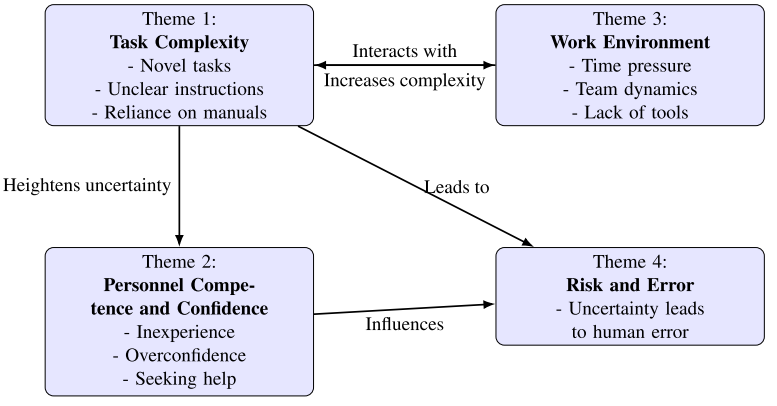


Figure 7. *Thematic map of uncertainty in maintenance tasks.*

5. Participant validation: A reflexive member-checking process was conducted with a sub-sample of 10 participants, who reviewed thematic summaries and confirmed their accuracy, clarity, and resonance with real-world practice. Their feedback led to the refinement of terminology and the clarification of two overlapping dimensions.

Through this robust analytical process, eight recurrent and interdependent factors emerged as primary dimensions of operational uncertainty. These factors were cited across civil and military contexts and consistently reflected in tasks ranging from routine line maintenance to complex base-level inspections. The final thematic structure is presented in Table 3 and serves as the conceptual foundation for the UQAM framework. These factors were not isolated or static; they operated as dynamic, interacting variables that fluctuated based on task type, personnel configuration and real-time operational pressures. This thematic foundation enabled the translation of rich qualitative insights into the formalised mathematical structure of the IUE, ensuring that the final model was theoretically sound, empirically grounded and operationally relevant.

4.2 Design of the UQAM process

The UQAM process offers a structured, dynamic and predictive framework for quantifying operational uncertainty in aviation maintenance tasks. Grounded in real-world practice and designed for adaptability, UQAM integrates human-centric factors with mathematical modelling to support proactive safety management. As seen in Fig. 8, the process begins with targeted data collection on eight key uncertainty factors (e.g., technical knowledge, team dynamics, time pressure), which are then mapped into a dynamic framework capable of incorporating evolving variables, such as new technologies or environmental changes. Each factor is assigned a dynamic coefficient, calibrated using empirical data, expert

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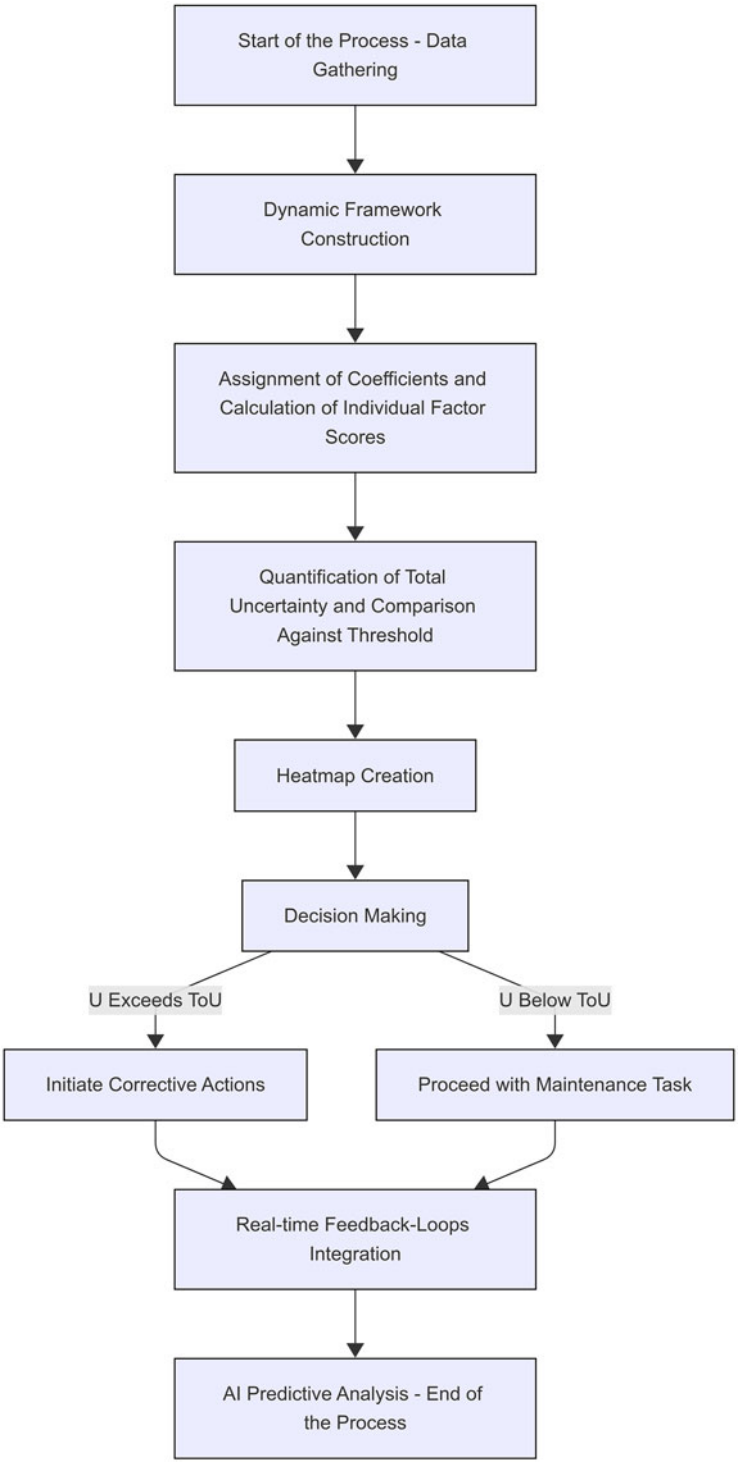


Figure 8. *The UQAM process.*

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judgement and contextual relevance. These weighted factors are synthesised using the IUE to compute a total scalar uncertainty score. This score is compared against a predefined ToU to determine whether corrective actions are required. Heatmaps visualise the distribution of factor-level uncertainty, enhancing interpretability and team-based decision-making. The process supports real-time feedback loops, updating uncertainty levels dynamically as tasks evolve. The visualisation of uncertainty contributions parallels the need to dynamically map factor propagation across maintenance environments [11]. In its final phase, UQAM could incorporate AI-driven analysis to refine coefficient weights and thresholds over time, enabling continuous learning and alignment with shifting operational risk profiles. UQAM transforms uncertainty from a latent background risk into a measurable, actionable and adaptive safety metric through its modular design, real-time responsiveness and integration with predictive analytics.

4.3 The Integrated Uncertainty Equation (IUE)

At the core of UQAM lies the IUE, a computational model that quantifies uncertainty using task-level data. The equation mathematically represents uncertainty as a function of the interaction between factor scores and contextual coefficients.

4.3.1 Conceptual rationale

The IUE was developed to address a gap in existing safety models: the lack of a real-time, quantitative mechanism for evaluating uncertainty. Traditional tools such as bowtie diagrams or risk matrices lack temporal sensitivity and are static in nature. The IUE allows for dynamic and granular modelling of fluctuating human and environmental inputs during task execution.

4.3.2 Equation derivation

The IUE aims to quantify the total uncertainty U associated with a specific aircraft maintenance task. This is achieved by aggregating the influence of eight uncertainty-inducing factors, each weighted by a context-sensitive coefficient. The objectives of the IUE are to (1) capture the individual contribution of each factor, (2) reflect the relative contextual importance of that contribution (via a weight), (3) preserve the independence and non-linearity of contributing dimensions and (4) aggregate all components into a scalar, interpretable measure of total task uncertainty.

Let:

- $i \in \{1, 2, \ldots, n\}$ denote the index for each uncertainty factor. In this model, $n = 8$.
- $F_i \in [1, 5]$: the score for the i-th factor, based on observation or expert assessment.
- $C_i \in [0.5, 2.0]$: the coefficient (weight) reflecting the contextual importance of factor i.
- U: the task's total scalar uncertainty score computed.

To ensure non-negativity and to amplify the influence of higher scores (i.e., high-risk factors), each factor value is squared:

$$F_i^2$$

This approach aligns with formulations found in kinetic energy, statistical variance and machine learning cost functions. Each squared factor score is then multiplied by its respective contextual coefficient:

$$F_i^2 \cdot C_i$$

This forms a weighted squared value that reflects both the severity and situational relevance of each uncertainty factor. To compute the combined uncertainty, all weighted squared terms are summed:

$$\sum_{i=1}^{n} F_i^2 \cdot C_i$$

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To produce a normalised, interpretable scalar score, the square root is applied:

$$U = \sqrt{\sum_{i=1}^{n} \left(F_i^2 \cdot C_i\right)}$$

Where:

- U is the total uncertainty associated with the maintenance task.
- F_i is the uncertainty score for factor i, where 1 represents very low uncertainty and 5 represents very high uncertainty.
- C_i is the real-time coefficient for factor i, ranging from 0.5 (minimal contextual impact) to 2.0 (high contextual impact).
- $n = 8$, corresponding to the eight core uncertainty dimensions listed in Table 3.

Range of Output (U):

- **Minimum Value:** $U = \sqrt{\sum F_i^2 \cdot C_i} = \sqrt{4} = 2$, represents uniformly low uncertainty.
- **Maximum Value:** $U = \sqrt{\sum F_i^2 \cdot C_i} = \sqrt{400} = 20$, represents uniformly high uncertainty.

4.3.3 Justification and mathematical properties

IUE was deliberately designed to balance mathematical rigour with practical operational relevance. IUE is inspired by principles of variance modelling (from statistics) and energy distribution (from physics). The non-linear sensitivity introduced by squaring ensures that higher-risk conditions exert proportionally greater influence on the final uncertainty score. This effect is significant in capturing the compounding nature of latent risks in high-stakes aviation environments. Capturing the compounded influence of high-risk factors through non-linear mathematical structures aligns with the need for measurable, causally linked human factor contributions, as emphasised by recent aviation maintenance research [12]. The following key mathematical properties justify its use as a predictive tool within safety-critical maintenance environments:

1. Non-negativity: All terms within the IUE are squared and multiplied by non-negative coefficients, ensuring the output is always a non-negative scalar. This preserves interpretability and aligns with the conceptual nature of uncertainty.
2. Scalability: The IUE structure is modular. While it currently includes eight uncertainty factors, the summation form allows for straightforward expansion. Additional factors can be incorporated as new domains or tasks are modelled, without affecting the underlying logic.
3. Interpretability: The resulting uncertainty score (U) maps directly onto field-validated operational thresholds (e.g., low, moderate, and high risk), making it intuitive for supervisory and planning personnel. This aligns the mathematical model with maintenance planning and decision-making workflows.
4. Interoperability: The scalar output of the IUE can be embedded into existing safety models such as SMS, STAMP and FRAM. It provides a dynamic feedback input, enhancing those frameworks' ability to monitor human factors variability in real time.
5. AI-Compatibility: The continuous, real-valued output of the IUE is compatible with machine learning pipelines. U-values can serve as training features, risk prediction inputs or anomaly detection markers within data-driven decision-support systems.

Quantifying operational uncertainty through structured models enhances the precision of task-level risk assessments, reflecting recent approaches that integrate human factors into probabilistic frameworks [12].

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Table 4. *Risk categories and recommended actions based on uncertainty score*

Uncertainty Score (U)	Risk Category	Recommended Action
$U \leq 7.0$	Low	Proceed as planned
$7.1 < U \leq 14.0$	Moderate	Increase oversight or adjust task resources
$U > 14.0$	High	Reassign, reschedule or escalate the task

4.4 Thresholds of Uncertainty (ToU)

To interpret the output of the IUE in operational terms, ToU were developed collaboratively with safety managers and engineering supervisors. These thresholds translate scalar uncertainty scores into actionable decision categories and are tailored to specific task types, as presented in Table 4. During the 12-month field validation, the ToU values were not arbitrarily set but were empirically calibrated through an iterative, data-driven process. Supervisors assigned factor scores and contextual coefficients for each maintenance task evaluated, which were then input into the IUE to produce U-values. These values were tracked alongside task performance indicators, such as deviations, delays or first-time execution issues, to assess whether elevated uncertainty levels align with observable operational risks. When U-scores consistently preceded errors or procedural breakdowns, threshold levels were adjusted downward to improve sensitivity. Conversely, if high scores were repeatedly recorded without corresponding risk manifestations, thresholds were raised to prevent over-alerting. This refinement process ensured that ToU boundaries accurately reflected both real-world variability and organisational risk tolerance.

The final thresholds guide supervisory decision-making through a three-tiered risk model:

- **Low Risk** ($U \leq 7.0$)**:** Task proceeds as planned. No additional oversight is required.
- **Moderate Risk** ($7.1 < U \leq 14.0$)**:** Task should proceed with enhanced monitoring or resource adjustments, such as experienced personnel assignment or procedural reinforcement.
- **High Risk** ($U > 14.0$)**:** Task execution should be deferred, reassigned, or escalated to a higher authority due to elevated uncertainty and potential risk exposure.

These thresholds are intentionally dynamic and responsive. They are reviewed regularly based on ongoing operational data, evolving regulatory guidance and frontline feedback. This adaptability ensures that uncertainty assessment remains aligned with aircraft maintenance environments' complex, fluid realities.

5. Field validation and results

This section presents the empirical evaluation of the UQAM framework, including its computational core, the IUE. Conducted between March 1, 2024 and March 31, 2025, the study took place within a certified EMAR-Part-145 military maintenance organisation. The objective was to assess the predictive accuracy, operational usability and contextual sensitivity of the IUE in real-world maintenance scenarios. Four recurring tasks were selected for validation, each representing distinct combinations of technical complexity, procedural frequency and operational risk.

5.1 Validation design and procedure

A supervisor-led, checklist-based scoring mechanism was implemented with safety and compliance officers. For each task, supervisors assessed eight predefined uncertainty-inducing factors (F_1) to (F_8), assigning a score between 1 and 5, and a dynamic coefficient between 0.5 and 2.0. These values were then input into the IUE:

$$U = \sqrt{\sum_{i=1}^{8} \left(F_i^2 \cdot C_i\right)}$$

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where:

- F_i represents the task-specific uncertainty score for factor i
- C_i denotes the real-time contextual weight for factor i

Risk categorisation followed pre-established ToU, developed and refined with engineering supervisors. Supervisors were instructed not to intervene based on U-scores during the trial to preserve objectivity. Instead, scores and observations were collected for post-hoc analysis, threshold calibration and model tuning.

5.2 Evaluated maintenance tasks

Four recurring maintenance tasks were selected to test the model's responsiveness across varied operational contexts. These tasks offered a spectrum of procedural regularity, technical depth and environmental variability ideal for evaluating the IUE's performance resolution and flexibility. To ensure comprehensive model validation, the tasks were deliberately chosen to reflect varying levels of technical complexity, predictability and human-centric uncertainty.

5.3 Task-specific results

5.3.1 Engine oil change

This task is moderately complex but highly predictable, with well-defined procedural steps and standardised tool usage. It was a stable reference point for evaluating whether the model could detect subtle operational deviations. This task demonstrated consistently low uncertainty ($U \approx 6$), with a single procedural deviation, incorrect torque application, elevating the score to 8.21. This validated a 'Low Risk' threshold of 7, reliably flagging emerging procedural risks without false positives. Uncertainty in this task was primarily influenced by psychological state (F_3) and time pressure (F_8).

5.3.2 Lubrication tasks

The simplest of the four tasks, routine lubrication, exhibited minimal variability and negligible uncertainty. Its high predictability and standardised execution made it ideal for validating the model's stability and resistance to noise. U-scores remained between 2.2 and 2.9 across all instances, confirming their well-controlled nature. A conservative threshold of 7 was retained to ensure any unexpected risk surge would still be promptly detected.

5.3.3 Freewheel inspection

This task exhibited higher procedural complexity and lower predictability, particularly in cases involving first-time diagnoses or atypical wear patterns. It consistently showed broader variability in U-scores, ranging from 6.4 to 9.54, with notable spikes during initial task execution and misdiagnosis incidents. These findings underscore the model's capacity to reflect diagnostic uncertainty and transitions into the 'Moderate Risk' zone when U exceeds 7. Primary contributing factors were task complexity (F_7) and technical knowledge (F_1), highlighting the critical influence of experience and context-dependent interpretation.

5.3.4 Driveshaft inspection & lubrication

This procedure was the most operationally demanding task, requiring substantial technical depth, close coordination among team members and execution under fluctuating environmental conditions. It consistently produced elevated uncertainty levels, with a baseline U-score of 9.27. Key contributing factors included environmental conditions (F_4) and team dynamics (F_5). To account for the inherent complexity of this task, a higher threshold of 10 was established, providing an operational buffer to distinguish

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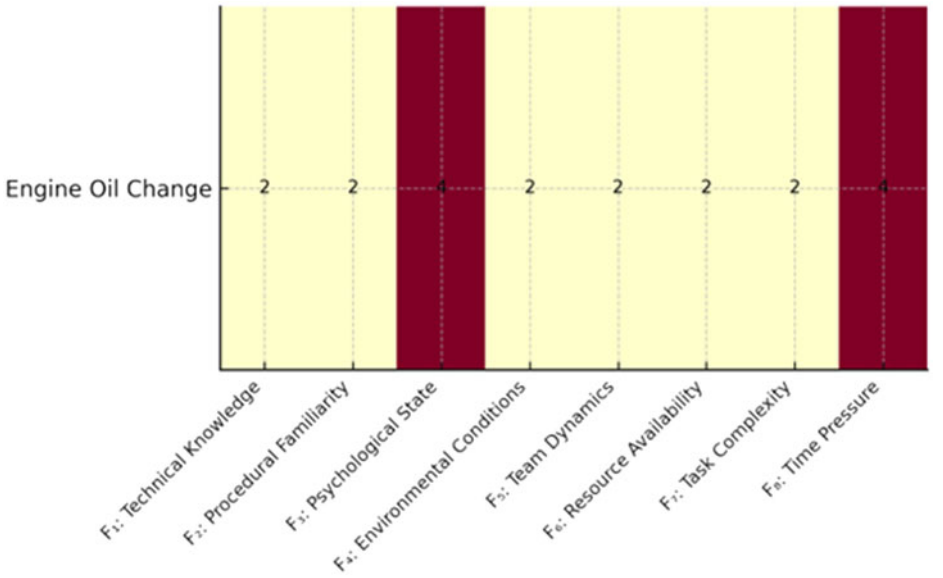


Figure 9. *Factor contribution heatmap: engine oil changes.*

between expected variability and genuinely hazardous deviations. Its inclusion enabled the model to be evaluated under conditions representing the upper bounds of operational risk and system complexity.

5.4 Heatmap analysis of uncertainty factors

In addition to scalar uncertainty scores, the UQAM framework provides visual diagnostics through heatmaps that represent the relative contribution of each factor (F_1–F_8), to the total uncertainty score (U). These visualisations offer a granular view of the dominant sources of task-related uncertainty, enabling supervisors and safety managers to pinpoint areas for targeted intervention, such as focused training, procedural reinforcement or environmental adjustments. Heatmaps were generated based on supervisor-assigned scores during live assessments for each of the four tasks evaluated. As illustrated in Figs 9–12, the heatmaps clearly differentiate the uncertainty profiles across tasks:

- Engine oil change: Heatmaps showed occasional spikes in time pressure (F_8) and psychological state (F_3), particularly during turnaround scenarios, despite the task's overall stability. These factors accounted for over 60% of total uncertainty in outlier cases.
- Lubrication: Factor contributions remained uniformly low across all observations. The heatmap validated the task's minimal uncertainty profile, with no individual factor exerting a dominant influence, confirming task predictability and model reliability in low-variance contexts.
- Freewheel inspection: High contributions were observed from technical knowledge (F_1) and task complexity (F_7), especially when inspections involved first-time execution or unfamiliar system configurations. These factors accounted for over 70% of the uncertainty, reinforcing the need for skill-based mitigation strategies in complex diagnostic tasks.
- Driveshaft inspection and lubrication: Environmental conditions (F_4) and team dynamics (F_5) emerged as dominant sources of uncertainty. Variability in workspace ergonomics and multi-person coordination increased the operational risk profile. The heatmap revealed distributed, multi-factor uncertainty, reflecting the complexity and interdependence inherent in this task.

These heatmap outputs not only confirmed the validity of the eight-factor model but also demonstrated its diagnostic value in visualising uncertainty propagation. By making the source and weight

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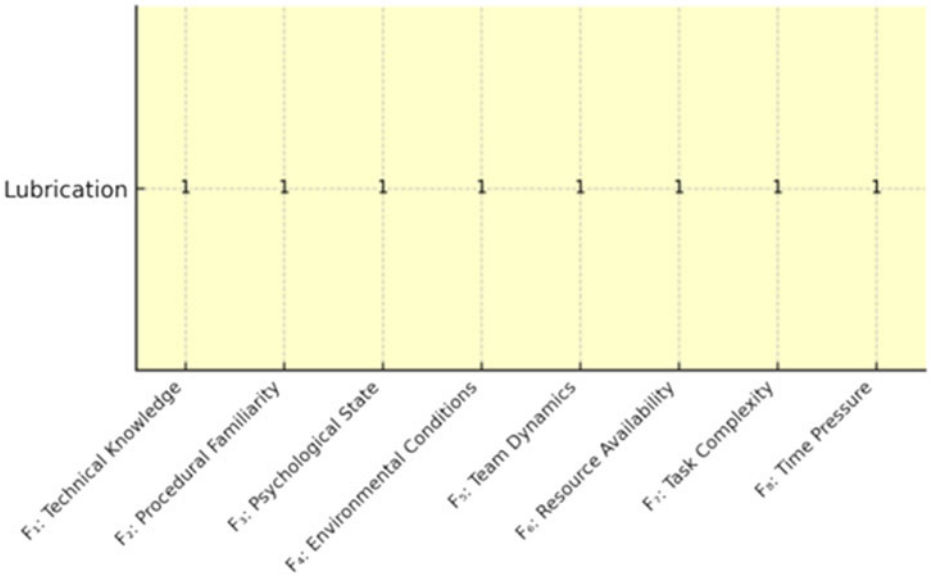


Figure 10. *Factor contribution heatmap: lubrication.*

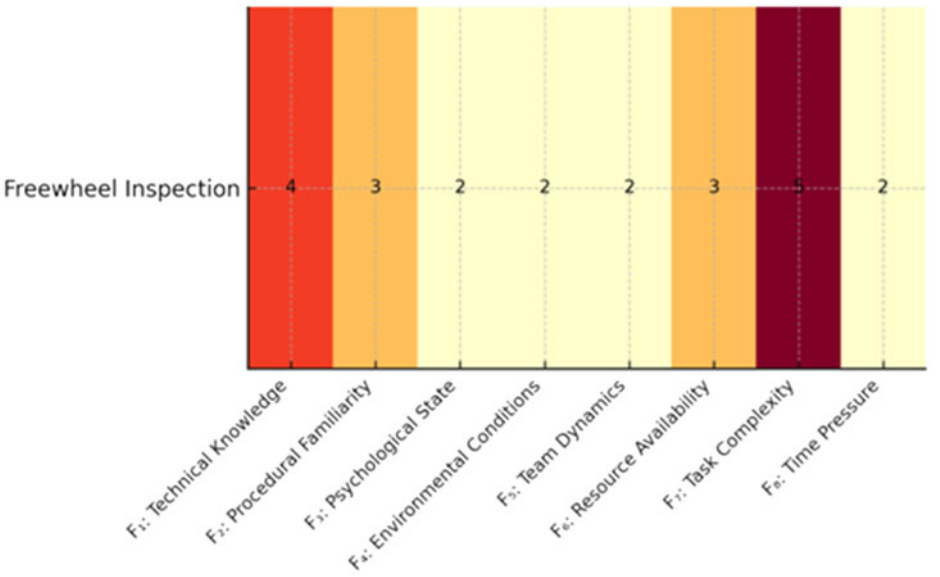


Figure 11. *Factor contribution heatmap: freewheel inspection.*

of uncertainty visible at the task level, the UQAM heatmaps support real-time risk communication, enhance supervisory awareness, and provide a feedback mechanism for continuous safety improvement.

5.5 Model sensitivity

The field validation demonstrated that the IUE is highly responsive to the variability and complexity inherent in real-world maintenance operations. Across the four evaluated tasks, the IUE consistently reflected task-specific uncertainty dynamics, distinguishing between routine, moderate and elevated risk

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Table 5. *Uncertainty observations, thresholds, and key contributors per task*

Task	Observed U	Proposed ToU	Risk Level	Key Contributors & Comments
Engine oil change (300 h/6 m)	≈ 6 (spike 8.21)	7	Low risk (≤ 7)	Resource availability (coefficient 2) drove the highest contribution; procedural deviation elevated U above 7, validating the chosen threshold
Lubrication (50 h)	2.2 – 2.9	7	Low risk (≤ 7)	Uniformly low contributions across all factors; routine nature yields minimal uncertainty; the threshold is set high to alert on any anomalous deviation
Freewheel inspection (1500 h)	6.4 – 9.54	7	Moderate risk ($7.1 < U \leq 14$)	First-time performance and misdiagnosis increased technical knowledge and complexity contributions; U above 7 signals need for training or procedural refinement
Main Driveshaft inspection lubrication (600 h/12 m)	≈ 9.27	10	Moderate risk ($7.1 < U \leq 14$)	Elevated base uncertainty due to task complexity; technical knowledge and procedural familiarity (coefficients 1.5) are primary drivers; threshold provides a buffer

conditions without producing false alerts in stable contexts (Table 5). One of the model's key strengths is its sensitivity to anomaly conditions. During the trial, the IUE successfully flagged elevated uncertainty in cases involving procedural deviation, task unfamiliarity, misdiagnosis and constrained work environments, each of which correlated with known operational disruptions. These outcomes confirm the IUE's utility as a measurement tool and an early warning indicator for supervisory decision-making. The model's scalability and adaptability were confirmed through its successful application across tasks with widely differing profiles. By dynamically incorporating contextual coefficients (C_i) and enabling modular adjustments, the IUE allowed for fine-tuned application without recalibrating the mathematical structure. This modularity supports deployment across diverse maintenance environments, from line to base operations. The model also proved to be practically usable.

Supervisors in the trial reported that the scoring process was intuitive and easily integrated into pre-task briefings or planning workflows. The heatmap visualisations were particularly valued for their ability to clearly communicate uncertainty sources, aiding task-level decisions and long-term safety planning.

Furthermore, the scalar output produced by the IUE was shown to integrate seamlessly with existing digital safety infrastructures, including SMS dashboards. Its real-valued output is also well-suited for future incorporation into AI tools and machine learning systems, opening the door to data-driven safety forecasting and autonomous decision support. The validation confirmed that the UQAM framework represents a substantive advancement in predictive safety modelling. Its ability to quantify human-centric uncertainty in real time and to do so in a flexible, scalable and interpretable way positions it as a valuable tool not only for post-hoc analysis but for shaping frontline interventions before error materialises. However, further testing in civilian Part-145 environments, integration with AI risk agents, and cross-sector validation are recommended to enhance generalisability and system-wide applicability. The model lays a foundational pathway for incorporating uncertainty as a live operational variable in future-ready safety architectures such as SMS, STAMP and FRAM.

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Table 6. *Sensitivity of IUE Score to input factors (baseline $U = 9.27$)*

Factor (F_i)	Low Score	U (Low)	High Score	U (High)	Impact Range
Technical knowledge (F_1)	1	7.13	5	11.92	−23.1% to +28.6%
Procedural familiarity (F_2)	1	7.34	5	11.21	−20.8% to +21.0%
Psychological state (F_3)	1	8.27	5	10.84	−10.8% to +16.9%
Environmental cond. (F_4)	1	6.42	5	13.03	−30.7% to +40.5%
Team dynamics (F_5)	1	6.87	5	12.61	−25.9% to +36.0%
Resource availability (F_6)	1	8.79	5	10.01	−5.2% to +8.0%
Task complexity (F_7)	1	7.65	5	11.48	−17.5% to +23.9%
Time pressure (F_8)	1	8.15	5	10.45	−12.1% to +12.7%

5.5.1 Sensitivity analysis using the driveshaft inspection and lubrication task

To evaluate the responsiveness of the IUE to fluctuations in individual uncertainty factors, a sensitivity analysis was conducted using the driveshaft inspection and lubrication task. This task, identified as the most operationally complex during field trials, provides a representative test case due to its multi-factor uncertainty profile and elevated baseline risk score.

Using a one-at-a-time (OAT) approach, each input score (F_i) was independently varied from its baseline to extreme low (1) and high (5) values, while holding contextual coefficients (C_i) and other factors constant. The resulting changes in the total uncertainty score (U) were used to calculate the impact range, reflecting each factor's marginal influence.

As shown in Table 6, the most influential variables were *Environmental Conditions* (F_4) and *Team Dynamics* (F_5), which produced the highest impact ranges (up to ±40%). Factors like *Technical Knowledge* (F_1) and *Task Complexity* (F_7) also showed considerable leverage, supporting the field-observed findings. Less sensitive variables included *Resource Availability* (F_6) and *Time Pressure* (F_8), though still relevant in high-stress contexts.

6.0 Discussion and implications

The successful field validation of the UQAM framework, anchored by the IUE, marks a significant advancement in predictive safety science. This study shifts the analytical focus from retrospective error analysis toward proactive uncertainty management, positioning uncertainty as a quantifiable, decision-driving variable in aviation maintenance safety. It responds to recent studies that advocate transitioning from descriptive to causal, probabilistic models of human factors to better reflect the dynamic nature of operational uncertainty [12].

6.1 Theoretical contribution

UQAM addresses longstanding theoretical limitations in dominant safety models – SMS, STAMP and FRAM – by introducing a formal mechanism to measure and model human-centric uncertainty in real time. While these models acknowledge complexity and emergent risk, they largely lack the capacity to assign operational value to uncertainty before errors occur. The IUE bridges this gap by transforming subjective, qualitative risk factors into measurable, scalar outputs that are actionable during planning and execution. This aligns with contemporary calls for nonlinear, probabilistic and adaptive models in safety-critical systems. Moreover, by grounding the framework in field-based qualitative data and operational context, the study offers a theoretical model that respects human factors' interpretive dimensions while enhancing their integration into systems engineering and predictive analytics.

6.2 Methodological innovation

Methodologically, UQAM represents a hybrid model that blends constructivist inquiry with computational modelling. Using thematic analysis to derive eight operational uncertainty factors ensured that

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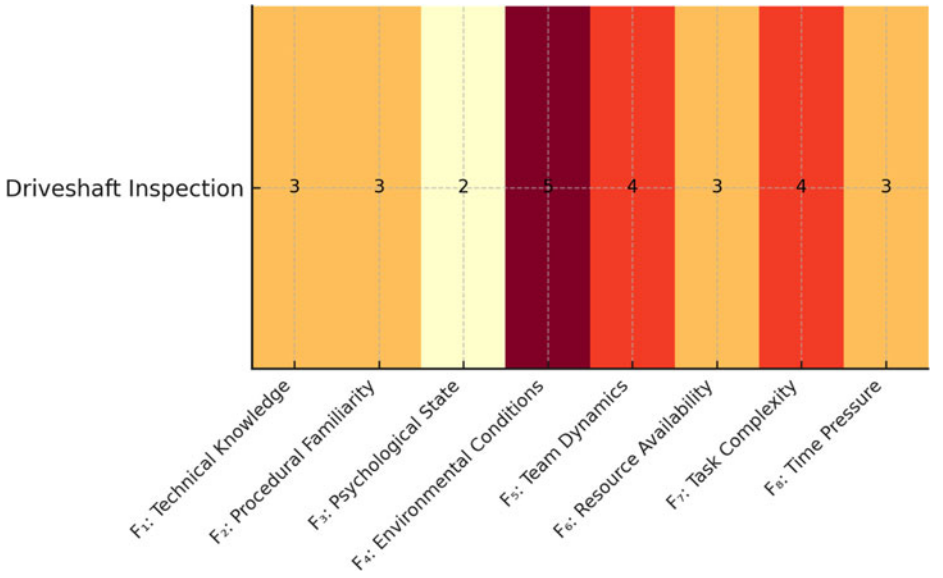


Figure 12. *Factor contribution heatmap: driveshaft inspection.*

the model reflects lived frontline experience, not just abstract constructs. The IUE's mathematical formulation, validated through a year-long field study, demonstrates how mixed-methods research can move from conceptual exploration to formalised, scalable tools. This hybrid approach also resolves a key limitation in the human factors field: the lack of quantitative methods for operationalising uncertainty in day-to-day maintenance activities. UQAM thus sets a precedent for developing rigorous, field-responsive models in other high-risk domains.

6.3 Practical applications and system integration

In practical terms, UQAM delivers a decision-support tool that is both intuitive and operationally impactful. The factor-based scoring system and associated heatmap visualisations provide clear, real-time insights into the sources and severity of task-related uncertainty. This supports informed supervisory decisions such as reallocating resources, adjusting schedules or delaying high-risk tasks. The framework is also designed for seamless integration into existing safety systems. As proposed in Figs 13–15, by embedding scalar uncertainty scores into SMS workflows and enhancing STAMP and FRAM with real-time inputs, UQAM strengthens feedback loops, enhances hazard visibility and supports dynamic intervention, transforming these frameworks from retrospective audits into proactive safety engines. Furthermore, the IUE's real-valued outputs are AI-compatible, enabling future applications, such as intelligent task planning, automated threshold tuning, and predictive risk detection through machine learning pipelines. By embedding AI-driven knowledge bases and predictive diagnostic tools into maintenance ecosystems, promises to transform aviation safety from reactive to proactive risk governance [56].

While the UQAM framework demonstrated strong usability and interpretability in field trials, certain limitations merit attention. The scoring of uncertainty factors, although guided by structured checklists, remains partially subjective and may vary depending on the assessor's experience, fatigue or situational awareness. Future iterations may benefit from incorporating automated or sensor-based inputs to complement human judgement. Additionally, the introduction of new scoring and visualisation tools may encounter cultural or operational resistance from supervisors accustomed to established routines. Early engagement, training and integration into existing workflows are essential to ensure acceptance and sustained use.

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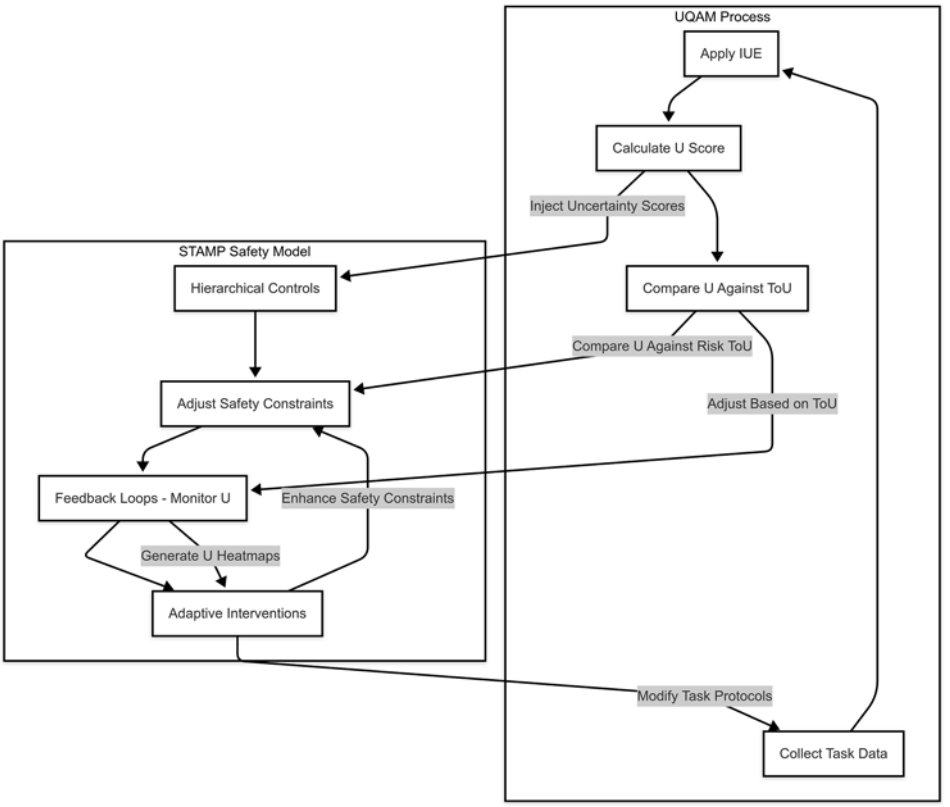


Figure 13. *UQAM potential integration into STAMP.*

6.4 Regulatory and industry relevance

Given the industry's increasing push toward predictive, performance-based safety management, UQAM aligns with evolving expectations under EASA Regulation 1321/2014, EMAR-145, and ICAO Annex 19. Its emphasis on real-time assessment, frontline usability and feedback-driven calibration directly supports emerging adaptive and evidence-based safety oversight requirements. UQAM provides a pathway for transitioning from compliance-driven audits to risk-intelligent operations – a shift vital to sustaining safety in increasingly complex maintenance ecosystems.

7.0 Conclusion

This study addressed a critical and underexplored dimension of aviation maintenance safety: the real-time quantification of human-centric uncertainty. While existing frameworks and safety models such as SMS, STAMP and FRAM have advanced the understanding of systemic risk and performance variability, they lack the tools to proactively assess uncertainty at the task level. In response, this paper introduced and validated the UQAM framework, centred around the IUE. Through a mixed-methods approach grounded in frontline operational data, the study identified eight empirically supported uncertainty factors and developed a mathematical model capable of producing scalar uncertainty scores. These scores were field-tested across four real-world maintenance tasks of varying complexity, predictability and risk. The results confirmed that the IUE captures variability in human and environmental conditions and supports predictive risk governance through actionable thresholds and visual diagnostics. The UQAM framework offers several key contributions:

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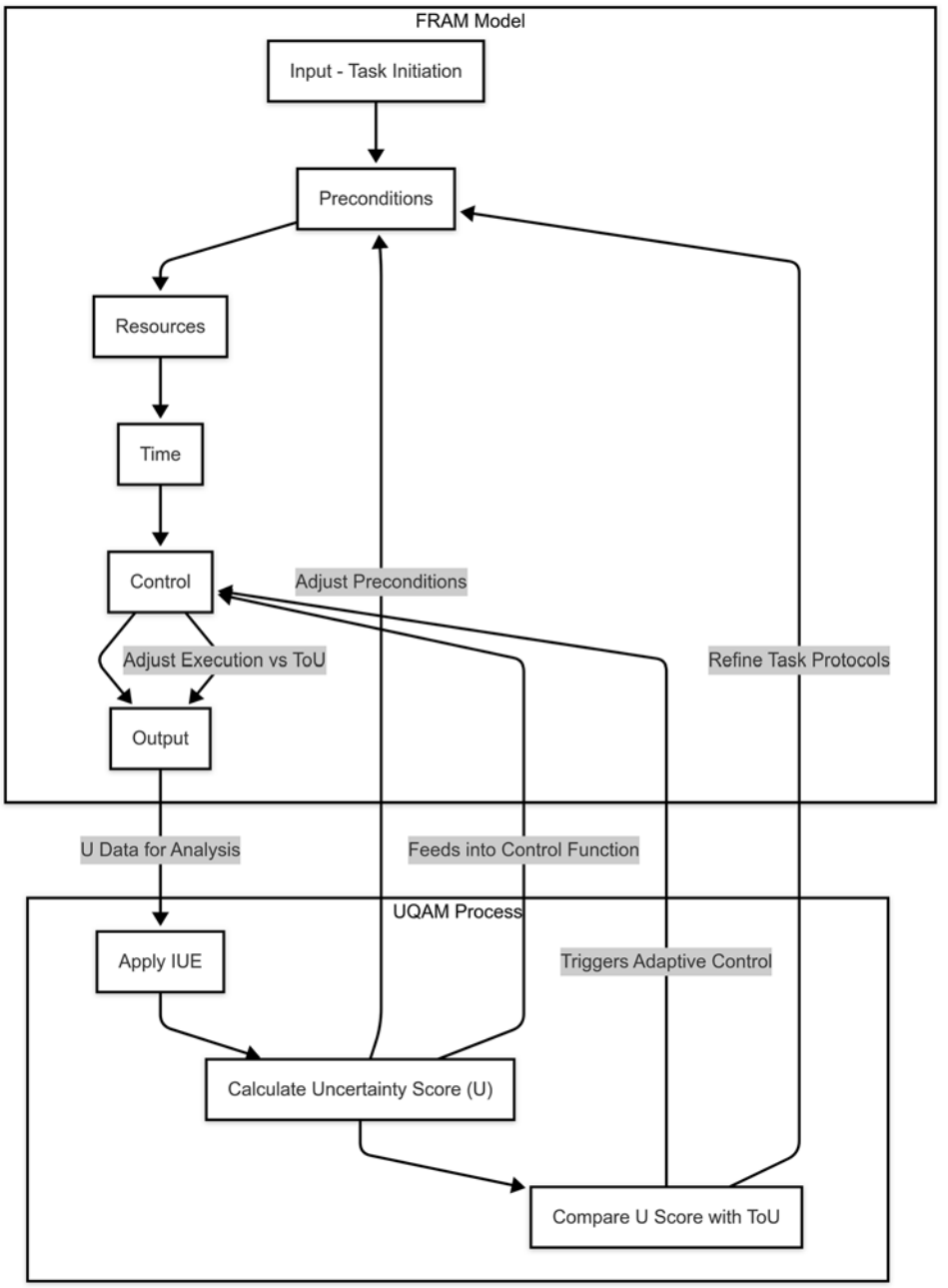


Figure 14. *UQAM potential integration into FRAM.*

- Conceptually, it reframes uncertainty as a measurable input to safety decision-making rather than a residual artifact of error.
- Methodologically, it bridges qualitative human factors analysis with quantitative systems engineering, offering a replicable structure for hybrid safety modelling.
- Practically, it provides an intuitive, field-compatible tool for supervisors, enabling proactive task-level interventions based on real-time conditions.
- Strategically, it positions safety management systems to evolve from compliance-oriented structures into adaptive, predictive architectures.

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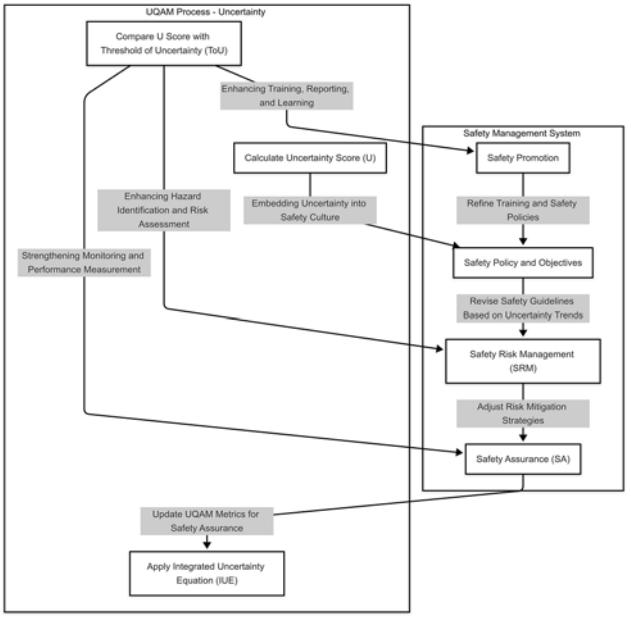


Figure 15. *Reshaping the SMS with UQAM.*

The UQAM framework holds strong potential for integration into digital safety platforms, AI-driven risk analysis and regulatory innovation. Its compatibility with existing maintenance management ecosystems allows for seamless adoption across both civil and military sectors. Future research may expand the model's scope by validating its use across different aircraft types, MRO organisations and operational contexts, as well as by exploring automated coefficient tuning through machine learning. This research advances the science and practice of predictive safety by quantifying what was previously treated as intangible. It also sets the foundation for a new generation of uncertainty-aware tools and policies capable of keeping pace with the growing complexity of aviation maintenance operations.

Future work will include uncertainty quantification methods similar to those applied in computational science and computational engineering [6, 17, 27].

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Appendix A. Mathematical Assumptions

Integrated Uncertainty Equation

$$U = \sqrt{\sum_{i=1}^{n} \left(F_i^2 \cdot C_i\right)} \tag{A1}$$

Assumptions

- Each factor F_i is treated as an independent variable representing a distinct uncertainty source.
- Squaring F_i introduces non-linearity, amplifying the influence of high uncertainty values.
- Contextual coefficients C_i are empirically derived to reflect situational importance.

The output U is a real, non-negative scalar that maps directly to risk thresholds for supervisory action.

Appendix B

The 73 studies included in the analysis for the research gap identification

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Table B1. *The 73 studies included in the analysis for the research gap identification*

Author(s), Year	Brief Comment(s) Related to This Work	Methodological Approach	Research Gap (Theory)	Research Gap (Methodology)
Senders and Moray [99]	Provided definitions of human error via causal/action theory; did not address dynamic uncertainty	Primarily conceptual/theoretical discussion	Gaps in cause-effect relationships (partial)	Lacks prospective or real-time exploration of actual operator experiences
Woods et al. [113]	Emphasised multiple regulatory definitions of human error, focusing on event chains rather than real-time uncertainty	Conceptual/analytical review of definitions	Gaps in cause-effect relationships	Focused on definitional aspects, lacking interpretivist or prospective field research
Heinrich [39]	Introduced the Domino Theory, a linear view of accident causation using large-scale industrial data	Large-scale retrospective industrial accident data analysis	Static nature of traditional model, gaps in cause-effect relationships	Universal ratio-based approach without deeper context-specific or interpretivist data collection
Dunlap et al. [28]	Revisited Heinrich's model, noting historical importance and the need for modern updates	Conceptual/historical analysis	Static nature of traditional model	Updated conceptual critique with limited new empirical data
Bird [9]	Extended Domino Theory; still sequential, lacking real-time or uncertainty-based approaches	Conceptual (theoretical extension of Domino Theory)	Static nature of traditional model	Relies on linear accident data, missing real-time or interpretivist research
Searle [98]	Linked intentionality and action theory for classifying error; no real-time uncertainty treatment	Philosophical/conceptual approach to intention and action	None	Philosophical conceptualisation with no empirical or field-based validation
Norman [77]	Explored cognitive processes leading to error; did not quantitatively model uncertainty	Cognitive/experimental psychology (theoretical discussion)	gaps in cause-effect relationships (partial)	Focused on experimental cognition; lacking field-based or interpretivist data on real-world error contexts

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Table B1. *continued*

Author(s), Year	Brief Comment(s) Related to This Work	Methodological Approach	Research Gap (Theory)	Research Gap (Methodology)
Rasmussen [87, 88]	Suggested error is embedded in event sequences; recognised complexity but did not formally quantify uncertainty	Primarily theoretical/framework development	No incorporation of human uncertainty in safety models	Primarily theoretical framework, lacking prospective or interpretivist field-based methods
Waterson [109]	Reviewed Rasmussen's impact on HF in high-risk contexts; no explicit real-time or quantitative approach	Literature review/discussion	None	Review-based conceptual discussion without empirical or prospective data collection
Hollnagel [40, 42]	Addressed causal theory and operator 'mismatches', lacking a quantitative or real-time human uncertainty model	Theoretical approach (cognitive systems engineering perspective)	No incorporation of human uncertainty in safety models, static nature of traditional model	Heavily theoretical, lacking large-scale field validation or prospective operator studies
Reason [89, 90]	Swiss cheese model; predominantly linear/qualitative approach to HF	Conceptual/qualitative model (Swiss cheese), widely used in accident investigations	Static nature of traditional model, gaps in cause-effect relationships	Retrospective focus
Wickens et al. [110]	emphasised the complexity of error but with minimal real-time integration of uncertainty	Textbook-style overview of human performance, mostly conceptual	No incorporation of human uncertainty in safety models	Largely descriptive
Woods (2018) [112]	Revisited early error theory, underscoring deeper integration of HF and system factors	Conceptual/theoretical reflection	Gaps in cause-effect relationships	Conceptual reflection lacking robust empirical field analysis
Martinussen and Hunter [69]	Overview of aviation human factors; mostly conceptual, no real-time HF modelling	Textbook-style overview (conceptual)	None	Primarily a textbook survey lacking new empirical or interpretivist approach

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Table B1. *continued*

Author(s), Year	Brief Comment(s) Related to This Work	Methodological Approach	Research Gap (Theory)	Research Gap (Methodology)
Patriarca et al. [91]	Discussed importance of HF in safety-critical industries; no robust quantitative/dynamic approach	Literature discussion/conceptual	None	Does not propose prospective or interpretivist data collection for HF research
Murie et al. [76]	Highlights HF in aviation safety management; lacks interpretivist or real-time approach	Conceptual/literature-based	None	Conceptual viewpoint without real-time or operator-centric empirical studies
Ordonez et al. [81]	Identified time pressure as an HF in aviation; does not address dynamic or quantitative modelling	Possibly experimental or survey-based approach (not fully detailed in excerpt)	None	Emphasises single-factor analysis (time pressure) with limited real-time or prospective design
Phillips et al. (2017) [83]	Examined fatigue as HF using observational-qualitative data in aviation	Observational-qualitative study	None	Retrospective, descriptive
Bendak and Rashid [8]	Investigated situational awareness as an HF factor; does not integrate broader dynamic cause-effect	Empirical study (likely observational or mixed methods)	Gaps in cause-effect relationships (partial)	Partial empirical focus but lacking prospective, real-time data collection
Yiannakides and Sergiou [116]	Studied knowledge/training HF classification; lacks robust quantitative predictive tools	Possibly case study or survey (not fully detailed)	None	Lack of quantitative approaches to human factors

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Table B1. *continued*

Author(s), Year	Brief Comment(s) Related to This Work	Methodological Approach	Research Gap (Theory)	Research Gap (Methodology)
Dos Santo et al. [96]	Investigated communication failures in aviation via retrospective analysis	Retrospective analysis of incidents	None	Retrospective
Virovac et al. [106]	Studied 28 maintenance cases focusing on communication failures; retrospective approach	Retrospective case analysis	None	Retrospective
Geibel et al. [32]	Content analysis of 1000 incident reports in aircraft maintenance; retrospective	Retrospective content analysis of incident reports	None	Retrospective
Leveson [65]	Discussed automation's effect on decision-making; early STAMP did not fully incorporate frontline uncertainty	Theoretical development (STAMP)	No incorporation of human uncertainty in safety models, static nature of traditional model	Conceptual STAMP development lacking real-time field-based testing
Illankoon and Tretten (2020) [51]	Studied judgement biases using NTSB accident data; predominantly qualitative	Retrospective qualitative analysis (NTSB reports)	None	Lack of quantitative approaches to human factors; retrospective
Chatzi [16]	Retrospective content analysis of accidents; identified trust as HF	Retrospective content analysis	None	Retrospective
Kourousis et al. [61]	Qualitative exploration of HF in maintenance tasks	Qualitative interviews or content analysis	None	Lack of quantitative approaches to human factors
Yilmaz [117]	Proposed a model with 20 HF in maintenance risk but used mostly qualitative weighting	Conceptual model development (qualitative weighting)	None	Lack of quantitative approaches to human factors

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Table B1. *continued*

Author(s), Year	Brief Comment(s) Related to This Work	Methodological Approach	Research Gap (Theory)	Research Gap (Methodology)
Yazgan [115]	Developed an HF taxonomy, noting each factor needs frequency/severity analysis but not integrated quantitatively	Conceptual taxonomy design	None	Lack of quantitative approaches to human factors
Boustras [14]	Proposed psychosocial factors in safety risk management; lacks a dynamic cause-effect approach	Conceptual/theoretical	Gaps in cause-effect relationships	Methodological limitations (mostly conceptual)
Rashid et al. [85, 86]	Examined 58 helicopter maintenance–induced errors via retrospective analysis, focusing on root causes	Retrospective analysis of aviation occurrences	Gaps in cause-effect relationships	Retrospective
Illankoon et al. (2019) [50]	Analysed 202 deviation reports (retrospective) to uncover latent conditions; no real-time or dynamic element	Retrospective content analysis of deviation reports	None	Retrospective
Thoroman et al. [103]	Used bowtie on 16 serious incidents; statistically tested Rasmussen's prevention theory	Bowtie analysis (retrospective)	Static nature of traditional model	Retrospective
Insley and Turkoglu (2020) [52]	Analysed 112 aircraft maintenance accidents for causal/contributory factors; concluded insufficient HF research	Retrospective accident data analysis	Gaps in cause-effect relationships	Retrospective

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Table B1. *continued*

Author(s), Year	Brief Comment(s) Related to This Work	Methodological Approach	Research Gap (Theory)	Research Gap (Methodology)
Wiegmann and Shappell [111] (HFACS)	HFACS is qualitative and retrospective, classifying factors in accidents rather than providing real-time adaptation	Conceptual model creation (HFACS) with subsequent widespread retrospective usage	Static nature of traditional model	Lack of quantitative approaches to human factors; retrospective
Miller and Mrusek [74]	Proposed systematic HF integration in safety management; not fully quantitative or dynamic	Conceptual proposal for HF integration	None	Lack of quantitative approaches to human factors
Rollenhagen et al. [93]	Applied HFACS to accident investigations in nuclear power; still sequential cause-effect, no real-time approach	Retrospective accident investigation approach	Gaps in cause-effect relationships	Accident investigation
Theophilus et al. [102]	HFACS in oil and gas accident reports; cause classification, retrospective	Retrospective accident-report analysis	Gaps in cause-effect relationships	Retrospective
Kim et al. [60]	HFACS in nuclear accidents; retrospective classification	Retrospective HFACS-based accident analysis	Gaps in cause-effect relationships	Retrospective
Diller et al. [25]	HFACS on 105 serious healthcare events; no dynamic or real-time approach	Retrospective HFACS analysis	Gaps in cause-effect relationships	Retrospective
Jiang et al. [54]	HFACS on 42 hazardous chemicals storage accidents; retrospective approach	Retrospective HFACS classification	Gaps in cause-effect relationships	Retrospective

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Table B1. *continued*

Author(s), Year	Brief Comment(s) Related to This Work	Methodological Approach	Research Gap (Theory)	Research Gap (Methodology)
Ergai et al. [29]	Validated HFACS across multiple industries using 125 SME inputs; no advanced quantitative or real-time approach	SME-based evaluation (likely questionnaires/Delphi-like)	None	lack of quantitative approaches to human factors
Liu [68]	Examined 'safety barriers' vs 'safety defences'; acknowledges uncertainty but not integrated in real time	Primarily conceptual	No incorporation of human uncertainty in safety models	Mainly conceptual
Johansen and Rausand [55]	Addressed safety barriers, acknowledging uncertainty; lacks a dynamic or interpretivist approach	Primarily analytical (barrier analysis), conceptual	No incorporation of human uncertainty in safety models	None
Larouzée [63]	Notes Wreathall's addition of safety defences to Reason's model; no dynamic or interpretivist dimension	Conceptual commentary	Gaps in cause-effect relationships	Purely conceptual commentary lacking prospective or operator-centric research
Sklet [100]	Defined safety barriers in oil/gas, focusing on static failures	Conceptual framework development	Static nature of traditional model, gaps in cause-effect relationships	Conceptual barrier approach lacking real-time or field-based exploration
Rollenhagen [92]	Analysed 20-year nuclear events focusing on safety barriers; retrospective perspective	Retrospective historical event analysis	Gaps in cause-effect relationships	Retrospective
McLeod [71]	Offshore incidents study; frames 'human error' as a threat, limiting deeper HF–barrier integration	Case-study/empirical approach (offshore incidents)	Ontological and epistemological considerations	Case-study approach without prospective or interpretivist analysis of real-time error experiences

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Table B1. *continued*

Author(s), Year	Brief Comment(s) Related to This Work	Methodological Approach	Research Gap (Theory)	Research Gap (Methodology)
Pitblado et al. [84]	Proposed a 'dynamic approach' to barrier management, but did not integrate human uncertainty quantitatively	Conceptual/procedural approach to barrier management	No Incorporation of human uncertainty in safety models	Conceptual proposal lacking real-time field validation or interpretivist data on barrier performance
Grattan [37]	Advocated examining low-consequence unsafe events and near-misses for improved safety learning	Conceptual/commentary	None	Lack of field studies on near-misses
Maragakis et al. [30]	Described the bowtie method for hazard identification; typically static	Conceptual introduction to bowtie	Static nature of traditional model	Conceptual introduction with no interpretivist or prospective data collection
Lauridsen et al. [64]	Applied bowtie in petroleum factoring in HF; not real-time or quantitative	Bowtie analysis (retrospective/qualitative)	None	Lack of quantitative approaches to human factors
Abdi et al. [1]	Bowtie analysis of 48 adverse healthcare events; retrospective classification of barriers	Retrospective bowtie application	Gaps in cause-effect relationships	None
Aust and Pons [5]	Proposed barrier categories (machine, mother nature, man, method, material, management); not dynamic	Conceptual classification	Static nature of traditional model	Classification-focused conceptual piece lacking empirical or field-based validation
FAA [31], PSA Norway [78]	Regulatory documents referencing barrier management/HF but not providing dynamic, uncertainty-focused frameworks	Policy/regulatory documentation	Gaps in cause-effect relationships (partial)	Policy-level guidance without real-time empirical testing or interpretivist input

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Table B1. *continued*

Author(s), Year	Brief Comment(s) Related to This Work	Methodological Approach	Research Gap (Theory)	Research Gap (Methodology)
Belton and Stewart [7]	Multi-criteria decision-making with some mention of uncertainty; not extended to real-time HF modelling	Conceptual/analytical approach to MCDM	No incorporation of human uncertainty in safety models	Conceptual/analytical approach, lacking real-world HF data or interpretivist field methods
Hollnagel [43]	Argues complexity magnifies uncertainty; FRAM remains largely qualitative, lacking a real-time or probabilistic approach	Theoretical update on FRAM	No incorporation of human uncertainty in safety models	Does not offer a new empirical or operator-centric method to address FRAM's gaps
Salazar Rosales [94]	Studied uncertainty in maintenance tasks (productivity & scheduling), not fully linked to safety models	Modeling approach (operations research/scheduling)	No incorporation of human uncertainty in safety models	Operations research perspective missing real-time safety or interpretivist dimension
Delatour [24]	Identified uncertainty as key in decision-making; no dynamic or interpretivist approach given	Conceptual discussion	No incorporation of human uncertainty in safety models	Conceptual discussion with no new empirical or field-based analysis
Goncharenko [35]	Acknowledged flight schedule uncertainty from maintenance; not integrated into real-time safety analysis	Conceptual/analytical discussion	No incorporation of human uncertainty in safety models	Conceptual approach lacking direct safety model experimentation or prospective data
Masmoudi and Haït [70]	Examined operational uncertainty in maintenance scheduling; no direct link to real-time safety modelling	Operations research approach	No incorporation of human uncertainty in safety models	Operations research approach not incorporating on-site or interpretivist safety data

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Table B1. *continued*

Author(s), Year	Brief Comment(s) Related to This Work	Methodological Approach	Research Gap (Theory)	Research Gap (Methodology)
Mendes et al. [73]	Advocated a shift from linear to nonlinear safety models, using AI for real-time measurement	Conceptual/theoretical proposal (shift to AI-based real-time modelling)	No Incorporation of human uncertainty in safety models, static nature of traditional model	Lack of prospective/operator-centric methods
Claros et al. [19]	Supported robust risk management models integrating human & machine capabilities; not specifically interpretivist or uncertainty-driven	Conceptual framework for integrated risk management	Static nature of traditional model	Conceptual framework lacking prospective or real-time empirical data collection
Walton [108]	Discussed AI's need for large datasets to predict HF; no interpretivist methodology is introduced	Conceptual discussion of AI in HF modelling	Lack of quantitative approaches to human factors	Conceptual emphasis on AI with no real-time or operator-centric field methodology
Leveson [66] (STAMP)	STAMP frames accidents as control problems; it does not fully account for frontline human uncertainty in real time; notes HRA's struggles in modelling human behaviour and complexity; partial mention of cause-effect gaps	Theoretical introduction of STAMP and HRA	No incorporation of human uncertainty in safety models, static nature of traditional model	Purely theoretical STAMP introduction lacking operator-centric empirical trials; critical review of HRA without proposing new prospective or interpretivist methods

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Table B1. *continued*

Author(s), Year	Brief Comment(s) Related to This Work	Methodological Approach	Research Gap (Theory)	Research Gap (Methodology)
Allison et al. [3] (STPA within STAMP)	STPA focuses on early hazard identification; limited real-time HF variability modeling	Theoretical extension of STAMP (STPA approach)	No incorporation of human uncertainty in safety models	Does not address ongoing, operator-driven data collection or interpretivist angles
Hollnagel [41] (FRAM)	FRAM highlights performance variability but remains mostly qualitative, lacking a probabilistic approach	Theoretical introduction of FRAM	No incorporation of human uncertainty in safety models	Lack of quantitative approaches to human factors
Salmon et al. [95]	Found STAMP/FRAM struggle with organisational/human factors and time dynamics	Conceptual/analytical critique of STAMP/FRAM	No incorporation of human uncertainty in safety models, static nature of traditional model	Conceptual critique lacking empirical data or prospective operator-centric research
Mogles et al. [75]	Addressed difficulties in capturing time dynamics for HF in FRAM; not fully real-time	Conceptual discussion/critique of FRAM	Static nature of traditional model	None

Table B1. *continued*

Author(s), Year	Brief Comment(s) Related to This Work	Methodological Approach	Research Gap (Theory)	Research Gap (Methodology)
Bjerga et al. [10]	Highlighted limitations of probabilistic approaches for human-centric systems; urged better treatment of HF uncertainty	Theoretical critique of probability-based risk methods	no incorporation of human uncertainty in safety models, lack of quantitative approaches to human factors	Critique of existing risk approaches but no new empirical method proposed
Yoe [118]	Examined micro-level uncertainties in decision-making; no new methodology introduced	Conceptual discussion	No incorporation of human uncertainty in safety models	Conceptual discussion lacking interpretivist or real-time field approach
Tonk and Boussif [105]	Conducted a comprehensive review of 72 studies on applying STAMP and STPA within the railway industry	Literature review/discussion	None	STAMP and STPA remain predominantly qualitative in nature; as a result, their effectiveness in contributing to robust and concrete safety analyses remains limited
Tian et al. [104]	Conducted a review of 108 studies employing the FRAM across various industries from 2006 to 2019, including 26 focused on aviation	Literature review/discussion	None	FRAM remains with inherent qualitative limitations; further research is needed to enhance FRAM, enabling quantitative safety analysis and interpretation

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