Advanced System Engineering Approaches to Dynamic Modelling of Human Factors and System Safety in Sociotechnical Systems

By

Esmaeil Zarei

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This research is dedicated to my wife Reihane Akbari, my Mother Fatemeh Zarei, and my late father Mohammad Zarei for their loyal support in all ways.

ABSTRACT

Sociotechnical systems (STSs) indicate complex operational processes composed of interactive and dependent social elements, organizational and human activities. This research work seeks to fill some important knowledge gaps in system safety performance and human factors analysis using in STSs. First, an in-depth critical analysis is conducted to explore state-of-the-art findings, needs, gaps, key challenges, and research opportunities in human reliability and factors analysis (HR&FA). Accordingly, a risk model is developed to capture the dynamic nature of different systems failures and integrated them into system safety barriers under uncertainty as per Safety-I paradigm. This is followed by proposing a novel dynamic human-factor risk model tailored for assessing system safety in STSs based on Safety-II concepts. This work is extended to further explore system safety using Performance Shaping Factors (PSFs) by proposing a systematic approach to identify PSFs and quantify their importance level and influence on the performance of sociotechnical systems' functions. Finally, a systematic review is conducted to provide a holistic profile of HR&FA in complex STSs with a deep focus on revealing the contribution of artificial intelligence and expert systems over HR&FA in complex systems. The findings reveal that proposed models can effectively address critical challenges associated with system safety and human factors quantification. It also trues about uncertainty characterization using the proposed models. Furthermore, the proposed advanced probabilistic model can better model evolving dependencies among system safety performance factors. It revealed the critical safety investment factors among different sociotechnical elements and contributing factors. This helps to effectively allocate safety countermeasures to improve resilience and system safety performance. This research work would help better understand, analyze, and improve the system safety and human factors performance in complex sociotechnical systems.

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NOMENCLATURE

Acronyms

ATHEANA	A technique for human event analysis
AMCR	Advanced main control rooms
AGAPE-ET	A guidance and procedure for human error analysis for emergency tasks
ANP	Analytic network process
BPL	Bayesian parameter learning
BWM	Best worst method
CORE-DATA	Computerized operator reliability and error database
MCR	Main control rooms
CREAM	Cognitive reliability and error analysis method
CPS	Computerized procedure systems
CESA	The commission errors search and assessment
DST	Dempster-Shafer evidence theory
DBN	Dynamic Bayesian networks
DEMATEL	Decision making trial and evaluation laboratory
DCS	Digital control systems
ELECTRE	Elimination and choice translating reality
ETA	Event tree analysis
EER	Escape and rescue
FST	Fuzzy set theory
FBN	Fuzzy Bayesian network
CPIs	Chemical process industries

CBM	Condition-based maintenance
HEP	Human error probability
HR	Human reliability
HRA	Human reliability analysis
HR&FA	Human reliability and Factors Analysis
HMI	Human- machine interference
HEART	Human error assessment and reduction technique
HERA	Human event repository and analysis
HEPI	Human error probability index
HRMS	Human reliability management system
HAZOP	Hazard and operability study
HFIs	Human factor issues
HFEPRM	Human Factor Engineering Program review model
HSIs	Human-system interfaces
HED	Human error database
HuRAM+	Human related event root cause analysis method plus
HENT	Human entropy
INTENT	Method for Estimating HEPs for decision-based errors
IDAC	The information, decision, and action in crew context
Petro-HRA	Petroleum human reliability analysis
MCDM	Multi-criteria decision-making
NPPs	Nuclear power plants
NASA	National aeronautics and space administration

OTHEA	Organization-oriented technique of human error analysis
Phoenix-PRO	Phoenix-petroleum refining operations
OPERA	Operator performance and reliability analysis
PSFs	Performance shaping factors
PRA	Probabilistic risk assessment
PdM	Predictive maintenance
RBM	Risk-based maintenance
RCM	Reliability centered maintenance
SA	Situation awareness
SPAR-H	The standardized plant analysis risk-human reliability analysis
SOHRA	Shipboard operation human reliability analysis
SLIM	Success likelihood index method
STSs	Sociotechnical systems
STs	Secondary tasks
SD	System dynamics
SEM	Structural equation modeling
SACADA	The scenario authoring, characterization, and debriefing application
TOPSIS	Technique for the order of prioritisation by similarity to ideal solution
TBM	Time-based maintenance
QRA	Quantitative risk analysis
VOE	Virtual offshore evacuation
WoS	Web of science

CHAPTER 1

INTRODUCTION

1.1. Background

The sociotechnical systems (STSs) (e.g., oil and gas, healthcare, aviation, manufacturing, construction, power industry, and automotive) indicate complex operational processes composed of interactive and dependent social elements, organizational and human activities. These systems are mainly attributed to dynamic complexity, relative ignorance, interactable and non-linear operations [1,2]. Chemical process industries (CPIs) as a salient example of STSs are indicated by nature as one of the most high-tech workplaces, where potentially catastrophic accidents can occur, owing to their intensive operations, a huge amount of hazardous material, complicated chemical process, rapid developments, complex business systems, and demanding interactive co-operation from humans. Recent process installations are equipped with significant reliable devices, advanced automation, and control, and various safety management systems to prevent incidents. However, major accident analysis reveals extensive continuous improvement is still required in process safety, particularly in the area of human and organizational factors [3]. For instance, a quarter of the 20 catastrophic accidents in CPIs in the four decades from 1974-2014, occurred recently in the five years from 2009 [4].

Human factors play a crucial role in this industry life cycle including design, construction, normal operations, maintenance, emergency operations, and decommissioning. However, human behavior and decision-making have been recognized as the main contributing and prevalent factors in abnormal situations and accident causation. A detailed analysis of incidents reveals that Texas City Disaster (1947), Piper Alpha disaster (1988), Texaco Refinery fire (1994), Bhopal gas leak tragedy (1984), Texas City Refinery explosion (2005), and Deepwater Horizon oil rig (2010), and Chevron

Richmond Refinery Accident (2012) are some examples of such major accidents and disasters which have received much publicity over past decades all of which have human errors either as a main direct cause or as an indirect cause. These accidents imposed countless losses so that a real estimation of all social, economic, and environmental damages may be impossible. The lists and statistical damage analyses of these catastrophic accidents can be found in numerous pieces of literature (Swuste et al., 2020). Human error directly or indirectly, in both individual and organizational perspectives, has therefore been recognized as the most responsible, complicated, and latent factor contributing substantially to an initiating event of an accident. Retrospective studies of major accidents and disasters in critical systems such as CPIs confirm that more than 80% of accidents in the process industries, 75%–96% of casualties in marine operations, and more than 90% of accidents in nuclear power plants (NPPs) have been caused by human failure [7,8]. To address this issue therefore human performance indicators such as human error probability (HEP) must be carefully and continuously assessed to identify its possible influence on systems failure. Human reliability and Factors analysis (HR&FA) have been utilized and then developed as the main proactive strategy to tackle this challenge through identifying vulnerabilities within tasks and operations, understanding of error cycle and shaping factors, quantifying potential errors, and finally, guiding how to improve reliability and safety of the system. It also helps to enhance human-centered and error-tolerant design to make socio-technical systems inherently suited to operation by humans. Regardless of conducting HR&FA studies to acquire their benefits, successful development of other domains of process safety system requires integrating it into them, i.e. risk analysis, accident investigation, and safety culture. For instance, Noroozi et al. (2013) proved that including human error in the risk analysis of simple process equipment containing a pump, a valve, and a separator, added $ 68,615 to the total amount of estimated risk in terms of asset loss, human loss, environment loss, and reputation loss for the accidents scenario [9]. Considering these losses in a large complex plant adds an enormous amount of risk value [10]. As another example, the National Transportation Safety Board (NTSB, US) has reported that among 18 accidents, in ten of them (1996-2000), human operator failure significantly contributed to the occurring initial events while material released to the atmosphere was 11,474,530 L and the overall financial damage was more than US $185 million [11]. As a result, the timely establishment HR&FA paves the way for a real investment in critical systems.

Human performance in system safety focus has been investigated from two distinctive perspectives of human reliability analysis (HRA) or human factors. The former mainly emphasizes predicting human performance (e.g., error probability), while improving human performance by optimizing system or task design is a major concern from the latter point of view. HRA has been developed closely tied to nuclear safety and subsequently progressively become a research and applied area that is more connected with reliability engineering than human factors [12]. However, they are closely intertwined, and the benefit is reciprocal. For instance, human factors present an empirical basis to predict human error probability, as the most common human performance manifestation in HRA. On the other side, HRA paves the way to technically model human performance and incorporated it in an engineering perspective which consequently can be employed in the system design [12,13]. However, the quality of HRA relies on an understanding of human performance nature which it mainly most readily built on a human factors foundation [12]. Furthermore, human error risk analysis and HRA often produced specific probability values regarding human-oriented functions, while failing to deliver deep insights concerning the sources of vulnerability, and complex resonance mechanisms resulted in adverse events, despite the minor improving new HRA techniques [13]. Therefore, this is significant room for human factors and HRA to contribute to the science in which a more effective and firmer estimation of human performance and error can be obtained [14]. In this sense, there has been a strong interest within both HRA and human factors societies to explore the human role in contributing to safer and more resilient systems [15]. One of the increasingly emerging paradigms is resilience engineering. Safety sciences and subsequently HRA have customarily centered on revealing factors that undermine existing safety instead of designing systems, processes, and organizations that optimize safety, while the latter is a core part of resilience engineering. Subsequently, decision makings in designing safety countermeasures are according to system thinking focus which will monitor performance variability and dampening critical. Therefore, there is more rooms to scholarly understand how individuals and teams contribute to system resilience and safety [16].

Several techniques and models have been proposed to analyze human factors and reliability to improve system safety in sociotechnical systems. Although these models have brought significant improvement in safety and risk models, some significant drawbacks remain. These shortcomings include the following; 1) static structures of these models, while most process and human factors are variable and often occur in the operational time of a system; 2) uncertainty in input and output data, particularly in the form of probability or frequencies due to the lack of enough precise data of young emerging technologies; 3) inability to consider conditional dependencies among the root failures of complex systems; 4) inability to use predictive modeling to simulate system safety barrier's behavior, and 5) incorporating often operational or mechanical failures into probabilistic safety analysis modeling, while human and organizational failures which are the deeper and more fundamental cause of accidents are ignored in most models. In other words, the conventional approaches cannot be utilized to model dynamic hazards, conditional dependencies, and common cause failure modes and they also use crisp and precise data that is rarely available or highly uncertain. However, the existence of great uncertainty in these studies, because of a lack of data, is a strong reason to move towards employing probabilistic tools such as Bayesian Networks (BN) [17,18]. Therefore, the current research work aimed at developing holistic models for addressing some substantial concerns and demonstrating the importance of a dynamic approach in the HR&FA in STSs.

1.2. Motivation and Objectives

HR&FA plays an essential role in the entire life cycle of complex systems to develop and maintain sustainable and resilient operations. These factors significantly contributed to the design, construction, normal operation, maintenance, emergency preparedness, and decommissioning of complex systems.

Several techniques, models, or concepts have been proposed for HR&FA in high-risk systems and these may be classified into two general approaches. The first classification is based on probabilistic risk assessment (PRA), while the second comes from the cognitive theory of control. The former was the first introduced while cognitive studies mainly concentrate on studying human primary cognitive operations (i.e. perception, understanding, and reasoning tasks) to analyze mental workload, decision-making, planning, and situation awareness [19]. In the two general research streams, since the ‘70s, many scholars have made both theoretical and empirical investigations to improve this domain, and consequently enhance process safety and risk analysis. However, there is no comprehensive knowledge in critically analyzing the HR&FA literature on CPIs, despite their importance both for the science of process safety and concerning its practical implications in decision-making to improve system safety from the human perspective. The research work is designed to fill this knowledge gap as well as identify the needs, gaps, and challenges of HR&FA.

However, traditionally established HR&FA models and techniques mainly rely on four main assumptions: a) a system can be fully decomposed into clear elements and accordingly events into individual acts, b) elements have functioned in a bimodal manner; either work or fail (Fig. 1), c) the sequence of events have preestablished and firmed as examined by selected representation and finally d) event combinations are linear either straightforward or complex and orderly [2,20]. While these assumptions may be partially true for technological systems, it is highly arguable to apply for STSs neither for risk assessment nor for accident analysis perspective [21,22].

Conventional techniques significantly improved our understanding of human behavior and error mechanisms and enhanced system safety and resilience in socio-technical systems. However, there are still some crucial challenges in establishing conventional techniques because of either insufficient classified data or emerging extensive databases (e.g., accidents data), subjective uncertainty and bias, emerging new performance shaping factors (PSFs) associated with Industry 4.0, industrial internet of things (IIoT), and increasing complex system's attributes (e.g., dynamic complexity, relative ignorance, interactable and non-linear operations) [23].

Moreover, most scientific endeavors to replace expert-driven HR&FA methods with empirical data-driven methods have failed due to significant uncertainty in human reliability databases and the incapability of conventional techniques to relax them. Despite the emerging Bayesian and credal networks and their invaluable contributions, tackling data scarcity using the tacit knowledge of domain experts is still the most prevalent and practical way [24]. Hence, it is vital to propose a rigor model to address the critical challenges of incomplete and imprecise data in knowledge engineering, while it also should help to better understand, analyze, and improve the safety performance of complex sociotechnical systems.

This research is aimed at developing a dynamic risk-based human factors assessment tool for complex systems with a primary focus on CPIs. The model integrates the complex, non-linear and unstable dependencies among a wide range of endogenous and exogenous factors that contribute to system safety in sociotechnical systems. Hence, the research goal is achieved through the following objectives. Each of these research objectives is translated into a research task presented in Figure 1.1.

i) Develop a critical analysis of HR&FA which reveals engineering challenges and research opportunities. This will serve as a useful mechanism for designing the methodology developments, in this study, to improve HR&FA domain

ii) To develop a dynamic and predictive system safety assessment model considering the integration of human failures into mechanical and operational failure, and safety barriers under uncertainty. The proposed model can serve as a useful tool for the operational safety management of complex engineering systems.

iii) To propose a dynamic model to analyze human-factor risk in sociotechnical systems. The proposed model is built considering the advanced canonical probabilistic approaches (e.g., Noisy Max and Leaky models) that address the critical challenges of incomplete and imprecise data. The proposed dynamic model would help better understand, analyze, and improve the system safety performance of complex sociotechnical systems.

iv) To introduce an advanced approach to system safety in sociotechnical systems. The model proposed a novel Taxonomy of PSFs, a systematic procedure to quantify the importance level and influence of PSFs over the performance variability of sociotechnical systems' functions (e.g., organizational, human, and technological). It also deals with key challenges in knowledge engineering associated with HR&FA in complex systems.

Vi) To examine the models developed with real-life case studies in various complex systems.

i) To develop critical analysis in the knowledge engineering process in HR&FA using artificial intelligence (e.g., Machine learning, Deep learning) and knowledge-driven systems (e.g., Fuzzy expert systems). This will help to properly and healthy direct future research projects in HR&FA in complex systems considering the gained first-hand experiences in this research.

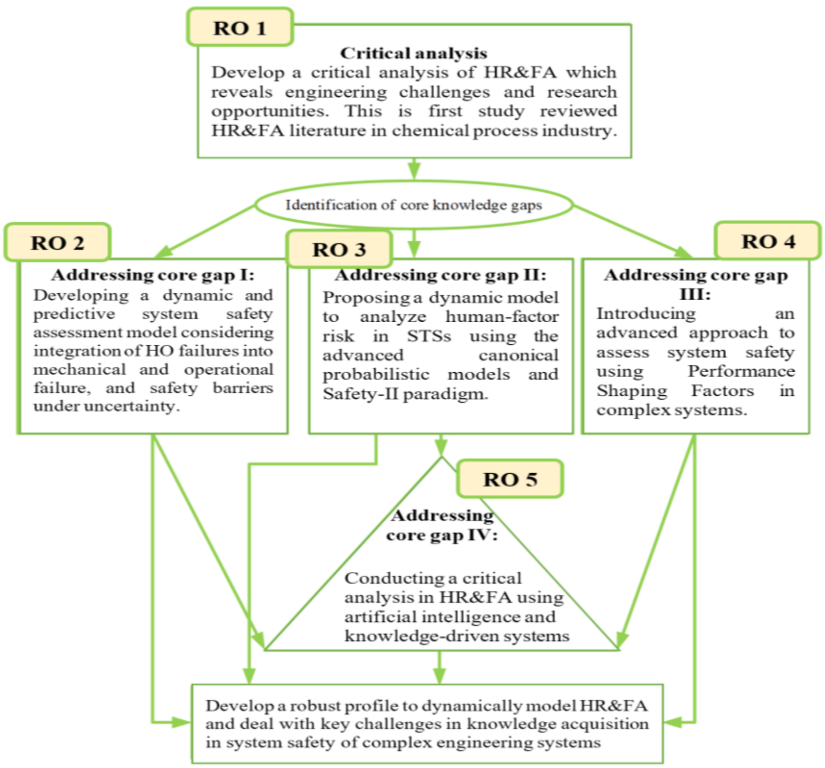

Figure 1. 1 An algorithm showing the workflow to meet the present research objectives (RO)

1.3. Research questions

This section present research questions associated with research objectives (ROs) illustrated in Fig

Grand research question:

- How can we improve the system safety and human factors techniques in STSs?

Research questions associated with RO1:

- What research streams have been investigated in the three elements of process systems from the HRA perspective?
- How have previous investigations contributed to HRA, and what needs and gaps remain in these studies?
- How should the current drawbacks be dealt with, and what challenges are HRA analysts facing in this journey?

Research questions associated with RO2:

- How can we address insufficient system safety-driven knowledge in emerging critical technologies?
- How can we deal with subjective uncertainty in knowledge acquisition of system safety assessment in emerging critical technologies?
- How can we dynamically model the evolving risks and system safety barriers' failures?

Research questions associated with RO3:

- Which internal and external factors are associated with the performance variabilities of human, organizational, and technical functions in STSs?
- How can we predict the probability of performance variability and deal with its uncertainty?
- How can we quantify the intra-effects (coupled dependencies) among VSFs?
- How can we update the prior probability distributions, given the new evidence?
- How can we dampen the critical variability in a risk-based decision-making process?

Research questions associated with RO4:

- How can we model system safety using performance-shaping factors in STSs?

- How can we efficiently deal with subjective uncertainty, fuzziness, and vagueness in system safety assessment in STSs?
- What are the most critical performance shaping factors contributing to system safety performance variability and system functions?

Research questions associated with RO5:

- How do advanced intelligence approaches apply to risk and safety assessment of human activities in complex operations?
- Do machine learning techniques pave new insights and capabilities in accident learning using textual and numerical data?
- How do fuzzy expert systems quantify the influence of PSFs on human reliability and integrate HEP into quantitative risk analysis?
- Which myths, misapplications, and critical concerns should be considered using these advanced intelligent approaches?
- Using bibliometric data analysis, how is the intellectual structure of knowledge in human factors in chemical process industries?

1.4. Scope and Limitations

This study is developed for complex sociotechnical systems, specifically oil and gas operations. This research proposal uses advanced probabilistic and knowledge-driven techniques to focus on dynamic risk-based system safety and human factors in complex systems. This study is instrumental in understanding, analyzing, and predicting system safety and human performance to support dynamic decision-making under uncertainty.

System safety and human-factor risks are complex challenges in sociotechnical systems since These systems are mainly attributed to dynamic complexity, relative ignorance, and interactable and non-linear operations [1,2]. Moreover, it poses critical challenges in their prediction and management because of its stochastic nature, subjectivity, and data scarcity. Analyzing the safety of these critical systems suffering from human performance variability requires robust and dynamic models to capture the associated complexity and uncertainties in system modeling and knowledge engineering. There are several uncertainties with the formation, key parameters, and variabilities mechanisms involved in this serious problem. This study is not an attempt to address all research gaps associated with the dynamic risk-based assessment of system safety suffering from human-factor risks but an attempt to tackle some of the research gaps related to oil and gas operations stemming from human and system performance resonance.

The unavailability of industrial human data implies that some of the models developed cannot be tested and validated with the real operational data set.

1.5. Co-authorship statement

The contributions of Esmaeil Zarei, Prof. Dr. Faisal Khan, and Dr. Rouzbeh Abbassi towards the research work and the thesis are discussed here.

Esmaeil Zarei: Conceptualization and idea formulation, development of methodology, human factors, and system safety risk model development, performing data analysis, and model testing; writing the original draft of the manuscript along with all supporting documents for submission to journals; Reviewing and editing the manuscripts based on feedback from co-authors and journal reviewers.

Faisal Khan: Idea formulation of research, development of the methodology, development of model algorithms, guidance in data analysis, and re-organizing and review of the manuscripts and thesis.

Rouzbeh Abbassi: Idea formulation of research, guidance in data analysis, and re-organizing and review of the manuscripts and thesis.

1.6. Organization of the Thesis

This thesis is written in a manuscript-based format. The overall outcomes of this thesis are represented in five peer-reviewed journal chapters. In general, chapter 1 is devoted to the introduction, while Chapter 8 presents the Summary, Conclusions, and Recommendations. Chapters 2 to 6 of this thesis are developed based on the chapter submissions to peer-reviewed journals.

Chapter 2 presents a critical analysis of the state-of-the-art theoretical and empirical findings concerning HR&FA in CPIs. This chapter is published in *Reliability Engineering & System Safety 211 (2021): 107607.*

Chapter 3 presents an innovative and dynamic risk model to analyze hydrogen infrastructure. This chapter is published in *International Journal of Hydrogen Energy 46, no. 5 (2021): 4626-4643.*

Chapter 4 introduces an innovative and dynamic human-factor risk model to analyze safety in sociotechnical systems. This chapter is published in *Process Safety and Environmental Protection 164 (2022): 479-498.*

Chapter 6 proposed an advanced approach to the system safety in sociotechnical systems. This chapter is accepted in *Safety Science.*

Chapter 6 illustrates how have artificial intelligence and expert systems contributed to HR&FA in complex systems. This chapter is accepted to present in the *2022 Mary Kay O'Connor Safety and Risk Conference. Texas A&M University, Oct 2022.* It is also published in *Process Safety and Environmental Protection* (*2023), 171: 736-750.*

It should be noted that the literature is done for each task and included in each chapter rather than presented as a separate chapter.

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CHAPTER 2

Importance of human reliability in process operation: A critical analysis

Preface

A version of this chapter has been published in ***Reliability Engineering & System Safety 211 (2021): 107607****. I am the primary author along with the Co-authors, Faisal Khan, and Rouzbeh Abbassi. I developed the critical analysis of stat-art-of-the theoretical and empirical findings, shedding light on the strengths and shortcomings of current literature and identifying the needs, gaps, and challenges of HRA in CPI. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' and peer review feedback. Co-author Faisal Khan helped in the concept development, design of methodology, reviewing, and revising the manuscript. Co-author Rouzbeh Abbassi provided fundamental assistance in validating, reviewing, and correcting the model and results. The co-authors also contributed to the review and revision of the manuscript.*

Abstract

Chemical process industries (CPIs) work with a variety of hazardous materials in quantities that have the potential to have large health, environmental and financial impacts and as such are exposed to the risk of major accidents. The experience with accidents in this domain shows many cases which involve complex human-machine interactions. Human Reliability Analysis (HRA) has been utilized as a proactive approach to identify, model, and quantify human error highlighted as the leading cause of accidents. Consequently, researchers have actively worked on enhancing process safety and risk engineering since the '70s. However, despite its importance and practical implications for improving human reliability, there has not been a review of human reliability related to processing systems. The present study is aimed at presenting a systematic attempt to identify the needs, gaps, and challenges of HRA in CPI. An in-depth analysis of the literature in

Web of Science core collection and Scopus databases from 1975 to August 2020 is conducted. This analysis focuses on human factors in three critical elements of CPIs: maintenance operations, emergency operations, and control room operations. The analysis synthesizes the theoretical and empirical findings, shedding light on the strengths and shortcomings of current literature and identifying research opportunities. A comparison of HRA in CPIs is undertaken with nuclear power plants (NPPs) to better understand the current stage of research and research challenges and opportunities.

Keywords: Human Reliability Analysis; Human error; Process industry; Emergency management; Control room; Maintenance operations.

2.1. Introduction

Chemical process industries (CPIs) are indicated by nature as one of the most high-tech workplaces, where potentially catastrophic accidents can occur, owing to their intensive operations, a huge amount of hazardous materials, complicated chemical processes, rapid developments, complex business systems, and demanding interactive co-operation from humans. Recent process installations are equipped with significant reliable devices, advanced automation, and control, and various safety management systems to prevent incidents. However, major accident analysis reveals extensive continuous improvement is still required in process safety, particularly in the area of human and organizational factors [1]. For instance, a quarter of the 20 catastrophic accidents in CPIs in the four decades from 1974-2014, occurred recently in the five years from 2009 [2].

Human factors play a crucial role in this industry life cycle including design, construction, normal operations, maintenance, emergency operations, and decommissioning. However, human behavior and decision-making have been recognized as the main contributing and prevalent factors in abnormal situations and accident causation. A detailed analysis of incidents reveals that Texas City Disaster (1947), Piper Alpha disaster (1988), Texaco Refinery fire (1994), Bhopal gas leak tragedy (1984), Texas City Refinery explosion (2005), and Deepwater Horizon oil rig (2010), and Chevron Richmond Refinery Accident (2012) are some examples of such major accidents and disasters which have received much publicity over past decades all of which have human errors either as a main direct cause or as an indirect cause. These accidents imposed countless losses so that a real estimation of all social, economic, and environmental damages may be impossible. The lists and statistical damage analyses of these catastrophic accidents can be found in numerous pieces of literature [3,4]. Human error directly or indirectly, in both individual and organizational perspectives, has therefore been recognized as the most responsible, complicated, and latent factor contributing substantially to an initiating event of an accident. Retrospective studies of major accidents and disasters in critical systems such as CPIs confirm that more than 80% of accidents in the process industries, 75%–96% of casualties in marine operations, and more than 90% of accidents in nuclear power plants (NPPs) have been caused by human failure [5,6]. To address this issue therefore human error probability (HEP) must be carefully and continuously assessed to identify its possible influence on systems failure. Human reliability analysis (HRA) has been utilized and then developed as the main proactive strategy to tackle this challenge through identifying vulnerabilities within tasks and operations, understanding of error cycle and shaping factors, quantifying potential errors, and finally, guiding how to improve reliability and safety of the system. In other words, HRA aims at identifying, modeling, and quantifying human error that may occur in different activities. HRA also helps to enhance human-centered and error-tolerant design to make socio-technical systems inherently suited to operation by humans. Regardless of conducting HRA studies to acquire their benefits, the successful development of other domains of process safety systems requires integrating HRA into them, i.e. risk analysis, accident investigation, and safety culture. For instance, Noroozi et al. (2013) proved that including human error in the risk analysis of a simple process equipment containing a pump, a valve, and a separator, added $ 68,615 to the total amount of estimated risk in terms of asset loss, human loss, environment loss, and reputation loss for the accidents scenario [7]. Considering these losses in a large complex plant adds an enormous amount of risk value [8]. As another example, the National Transportation Safety Board (NTSB, US) has reported that among 18 accidents, in ten of them (1996-2000), human operator failure significantly contributed to the occurring initial events while material released to the atmosphere was 11,474,530 L and the overall financial damage was more than US $185 million [9]. As a result, timely establishing HRA paves the way for a real investment in critical systems.

Several techniques, models, or concepts have been proposed for analyzing human reliability in such high-risk systems and these may be classified into two general approaches. The first classification is based on probabilistic risk assessment (PRA), while the second comes from the cognitive theory of control. The former was the first introduced while cognitive studies mainly concentrate on studying human primary cognitive operations (i.e. perception, understanding, and reasoning tasks) to analyze mental workload, decision-making, planning, and situation awareness [10]. In the two general research streams, since the ‘70s, many scholars have made both theoretical and empirical investigations to improve this domain, and consequently enhance process safety and risk analysis. However, there is no systematic study to review the available HRA literature on CPIs, despite their importance both for the science of process safety and concerning its practical implications in decision-making and improving human reliability. However, several review investigations have been made in similar safety-critical industries (i.e. NPPs, presented in Table 3.4) and even in operations that are less sensitive to safety and risk issues than CPIs. Considering this vital interest, the present study is the first study that aims at conducting a systematic investigation of HRA in CPIs through an in-depth analysis of the literature in Web of Science core collection and Scopus databases from 1975 to 2020. It is noteworthy that there are critical operations in hazardous process systems where human interference has enormous potential for human error, and subsequently for major accident occurrence. In this critical analysis, hazardous and essential operations are classified into control, maintenance, and emergency operations and more details are provided in the following sections. Studies have concluded that hydrocarbon companies should concentrate their main programs on human factor management in these three critical elements [9,11]. Accordingly, the review article focuses on HRA in these three critical elements of CPIs including maintenance operations, emergency operations, and control room operations (Human- machine interference (HMI)) where most catastrophic accidents have arisen.

It is believed that managing some emergency operations may need the involvement of control room operators to bring an abnormal situation to a normal or safe condition. This condition is common in some critical sectors such as NPPs. It is important to notice that emergency response management requiring control room interventions is rarely investigated concerning HRA in CPIs. Moreover, the vast majority of human reliability literature on control room operations of CPIs has focused on normal operations which required intervention by operators. In other words, the HRA of control room activities involving managing emergencies has not been investigated enough in CPIs yet. Accordingly, we focused on operator reliability analyses that have been conducted in normal operations and are considered to be *control room operations (section 3.4)*, while emergency operations management which did not have any involvement of control room operators is considered to be *emergency operations (section 3.3)*. It is worth paying attention to this matter once there are sufficient investigations of emergency operations in which control room activities play a role and which become available in future review studies.

The main objectives of the present study were to synthesize the theoretical and empirical findings, to recognize the main research streams as well as to shedding light on the strengths and shortcomings of literature to enable exploration of the research and practice opportunities. Moreover, the authors demonstrate a comparison of HRA investigations in CPIs with nuclear power plants as similar social-technical systems in a safety-critical perspective to better understand the current stage of research in this domain. To this end, the main research questions addressed in this review are as follows:

- What research streams have been investigated in the three elements of process systems from the HRA perspective?
- How have previous investigations contributed to HRA and what needs and gaps remain in these studies?
- How should the current drawbacks be dealt with and what challenges are HRA analysts facing in this journey?

The rest of the paper proceeds as follows. In Section 3.2, the applied methodology is provided, while in Section 3.3, the results and discussions are presented. Section 3.4 is given to the conclusions of this review.

2.2. Research Methodology

This critical review study was conducted based on available literature in the HRA domain in the process industry sector in Web of Science (WoS) core collection and Scopus databases from 1975 to 2020. After selecting appropriate keywords and combining them with Boolean operators (AND, OR, NOT, or AND NOT), advanced search operations were conducted in both databanks. Fig. 2.1. illustrates the six main steps of the employed framework in the present study.

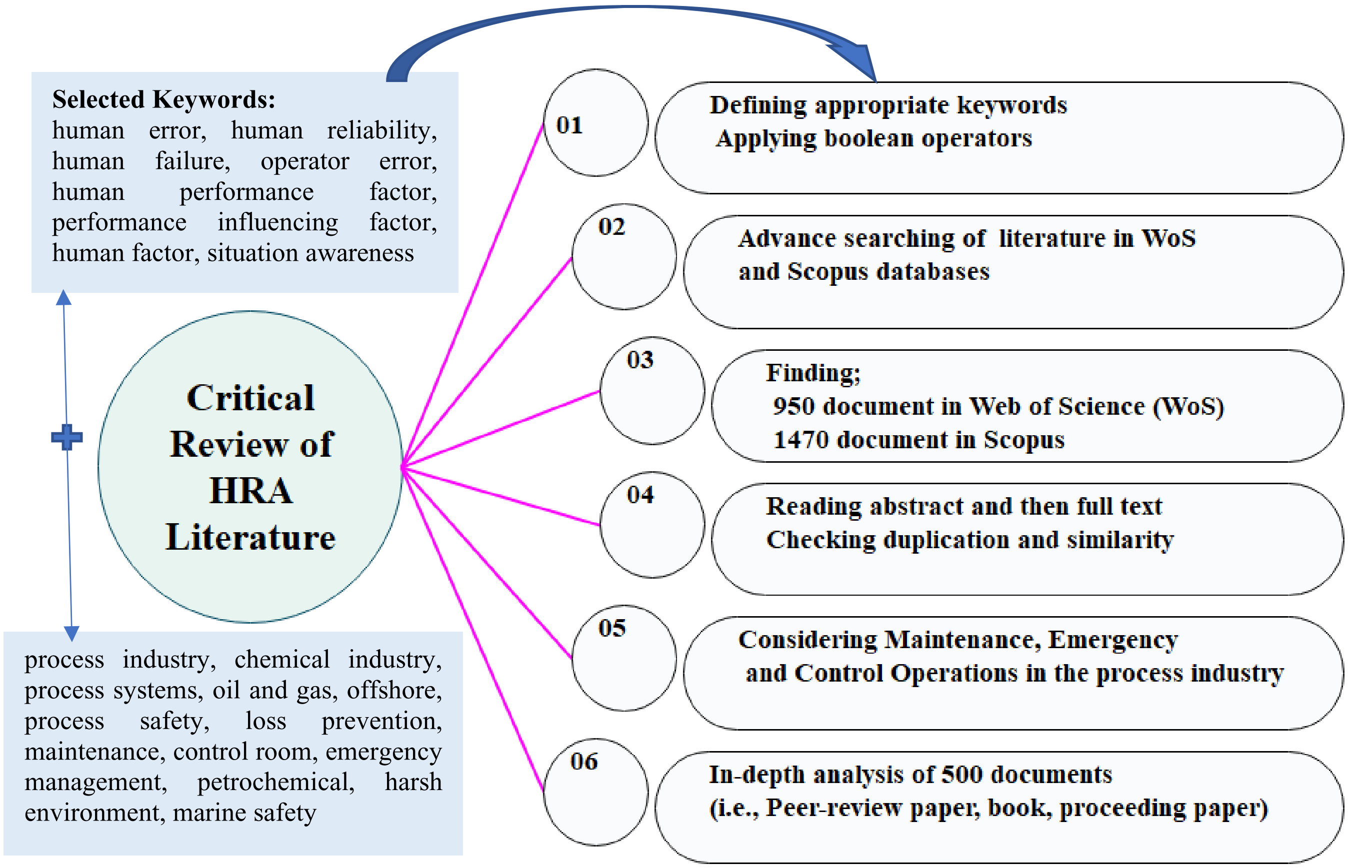

Figure 2. 1 The research methodology adopted for the HRA critical review in the process industry

As can be seen, as around 950 (WoS) and 1470 (Scopus) documents were found in the first selection, it was necessary to apply exclusion criteria to allow for a review investigation. This research focused on HRA studies in three hazardous elements of CPIs containing maintenance operations, emergency operations, and control room operations which were substantially prone to catastrophic accidents contributed to by human failure. Hence, studies beyond this scope, HRA in beyond maintenance, emergency response, and control room activities in the process industry, were excluded from the next steps in the present research. In the following steps, firstly all abstracts, and then full texts of vague abstracts were reviewed by the research team. Considering the duplicated documents and ignoring highly similar papers in methodology and case study perspective, 500 credible pieces of literature were finally selected for an in-depth analysis. Moreover, the references in the selected papers were also reviewed for further investigation of potential omissions of the papers. Finally, we scrutinized the selected documents to respond to the research question.

2.3. Results and Discussion

In this section, firstly, a brief review of HRA studies is provided and then literature on three considered elements (i.e. maintenance, emergency, and control operations) is discussed. The authors tried to define the main gaps, needs, and challenges of HRA in the domains of oil and gas operations. Moreover, dominant research lines to date, as well as streams and directions for future investigations, are specified.

2.3.1. A brief review of HRA Literature

From the initial academic publications (i.e. the '60s) on the general introduction of human error to the present (2020), approximately 500 pieces of scientific literature have been published based on a core collection of the Web of Sciences database on HRA in CPIs. Fig. 2.2 shows the number of scientific publications based on two previous study results and the present study from 1987 to Aug 2020. Amin et al. (2018) aimed to analyze process safety and risk analysis literature in the process industry by August 2020 using WoS Core Collection, Scopus, and Compendex database [12], while Tao et al. (2020) analyzed the HRA literature generally in various fields (i.e. NPPs, healthcare, chemical plants) by 2018 using Web of Science Core Collection [13]. These review studies have been selected to provide a reference comparison with the present study to illustrate the total number of publications and the general trend in these fields.

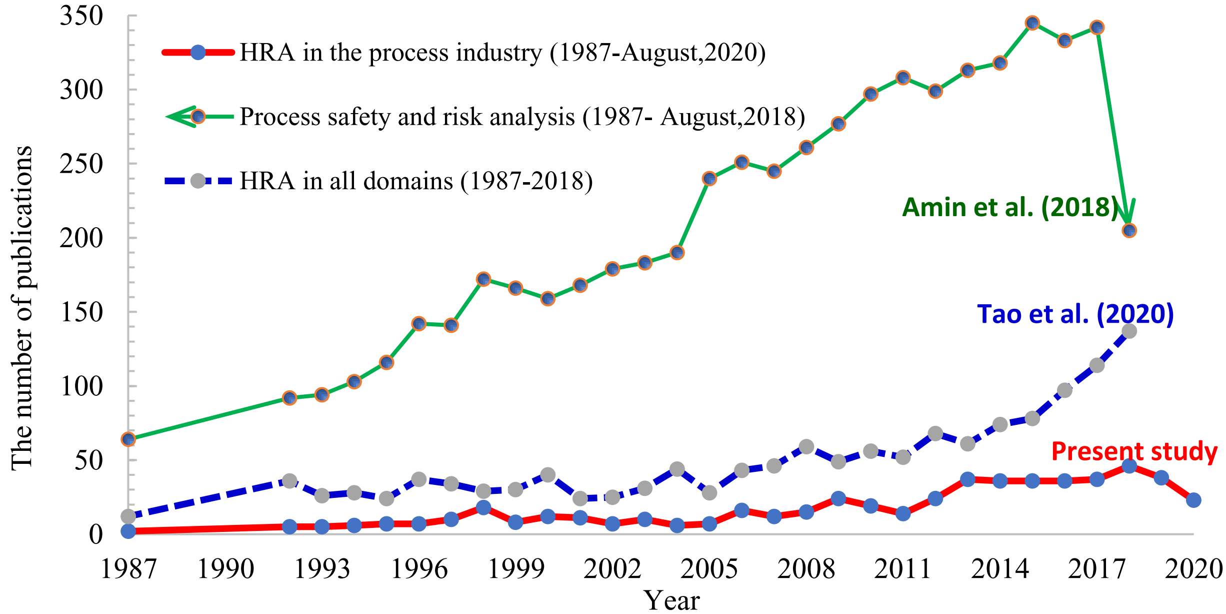

Figure 2. 2 The number of scientific publications in process safety and human reliability

Overall, the findings illustrated an increasing level of academic publications in three domains over the time frame. However, as can be seen, the HRA in the process industry receives much less attention in comparison with other sectors. Even considering the study of Tao et al. (2020), which reviewed HRA investigations in various domains, there is a marked difference in the number of studies conducted in safety and risk analysis in CPIs. The findings of the present research were confirmed by other studies. For instance, Ramos et al. (2020) recently argued that the most well-known HRA techniques have been proposed and utilized in NPPs, whereas the process industry has mainly concentrated on process safety in terms of technical aspects of the operation and equipment as well as quantitative risk analysis (QRA) [14,15]. Considering the human role as the factor most contributing to major accidents, there is, therefore, an urgent call for leading researchers and academic centers to pay more attention to this domain. To add a value for HRA practitioners, Table 2.1. presents some examples of CPI facilities addressed by HRA studies where human error probability is predicted in sub-task activities in each considered element (i.e. maintenance, emergency, and control operations) of CPIs operations.

Table 2. 1 Some examples of human tasks in each operation category and corresponding HEP value

Typical CPI facilities	Operation type	Sub task example	HEP value
Oil and gas facility [16]	Maintenance (i.e. condensate pump)	Conducting pressure and isolation leak tests	1.54E-0.1
		Closing the isolation valve	2.31E-02
		Depressurizing the drain lines	1.54E-04
Maritime [17]	Emergency management (i.e. fire pump on-board ship)	Monitoring water pressure (Pre-activity)	7.46E-03
		Monitoring water pressure (Post-activity)	3.64E-02
		Opening inlet and outlet valves	1.77E-01
Petrochemical plant [18]	Control room	Commissioning boiler	1.44E-01
		Controlling warning signs	4.34E-01
		Controlling of production	4.97E0-1

2.3.2. Maintenance operations

Maintenance is one of the most vital operations to maintain the desired profitability of the process and to optimize the life cycle cost by increasing the availability and reliability of the system [19]. It is reported that more than $300 billion is spent annually on industrial maintenance and operation in the US and around 80% of this value is allocated to addressing the correction of the chronic failures of machines, systems, and people [20]. There are different strategies such as budget, resources, goals, and types of maintenance according to national standards and internal requirements of companies. There are two general types of maintenance philosophy, namely proactive (i.e. Predictive maintenance (PdM), Condition or risk-based maintenance (CBM, RBM), Time-based maintenance (TBM), Reliability centered maintenance (RCM)) and secondly reactive types (i.e. Emergency maintenance, Deferred corrective maintenance). Personnel is the most common and main elements of the maintenance operations in every employed strategy. Moreover, human activities are the core ingredient of any maintenance steps, which involves developing an action plan, disassembling, inspecting, repairing, reassembling equipment, and reoperation. These activities are performed under various and often harsh circumstances which may lead to human error such as installing or replacing a wrong part or assembling the part in the wrong sequence despite all technological enhancements. Buncefield explosion (2005) (total losses over £1 billion, injured 43 people), as the largest peacetime explosion in European history, is a concrete example, caused mainly due to lack of understanding of relatively new technology and insufficiently detailed procedures in maintenance organization. A study revealed that among 60 possible human factors, nearly half of them contributed to this explosion occurrence [21]. Bhopal gas leak tragedy (1984, claimed death toll over 16,000, at least 558,125 people injured), Piper Alpha disaster (1988, 167 death toll and $3 billion lost) were also attributed to maintenance failures such as inexperience, poor maintenance procedures, and deficient learning mechanisms [22]. Hence, human error occurrence in maintenance activities not only increases the overall risk which may result in such disasters, but it also fails (maintenance organization in attaining their philosophy of increasing productivity, reliability, and availability of a system.

It is reported that around 20% of all accidents and about 10–15% of all fatalities have occurred in maintenance operations in Europe [23]. Furthermore, Reason and Hobbs (2003) pointed out that human performance problems that had arisen from maintenance activities comprised the highest level of between 42% - 65% compared to levels of other activities within NPPs in the United States [22]. Therefore, reaching the desired targets in maintenance operations is required to allow successful HAR to minimize the risk of possible errors. To adhere and highlight this philosophy, more than 25 studies were conducted by various researchers in the CPIs. Table 2.2 illustrates the most relevant studies to HRA in maintenance operations in the process industries. It is worth noting that the studies which had the same findings or aims or applied the same methods, were those that brought significant influence on HRA in maintenance activities as shown in Table 2.2.

Table 2. 2 Human reliability analysis studies in maintenance operations in the process industry

Year	Method	Main objectives	Domain	Main findings
2019[16]	Evidence theory, HEART	Addressing HEART's deficiency	Condensate pump in Offshore facility	Estimating HEP more accurately
2019[21]	Questionnaire-based on Reason's model	Identifying causality of HFs	Instrumentation and electrical devices in Buncefield explosion (BE)	28 human factors contributed to BE from 60 possible factors
2019[24]	SOHRA	Effect of maintenance 4.0 and PMS on HR	Diesel generator in Marine system	HEP reduced by 83%
2018[25,26]	Structured questionnaire, BN	Developing data collection and analysis procedures	Marine Engine and Deck Departments	Identifying and weighing PSFs, HEP estimation
2017[27,28]	SLIM, Modified HEART	Development of a monograph for HEP assessment	Condensate pump in Marine engines	Rapid and accurate estimation of HEL
2017[29]	Genetic algorithm, Simulated annealing	Effect of fatigue and time pressure on grouping maintenance activities	Petrochemical plant	HE increased by simultaneous activities
2016[30]	Questionnaire	Maintainer's perceptions of organizational effectiveness and operational reliability	Nine petroleum production facilities	Identified significant contributing factors to MTTF

2016 [31]	SLIM	Considering HE in maintenance interval estimation	Gas chilling and liquefaction units in LNG facility	Shutdown maintenance activities become safer and more reliable
2015[32]	SLIM, THERP, RFID	HEP prediction and reduction	Offshore condensate pump	A net HEP reduction of 1.09% using RFID tools
2014[33]	SLIM, Fuzzy cognitive maps (FCM)	Optimization of condition-based maintenance by human error	Five petrochemical plants	HE had a significant effect on system average unit cost
2013[34]	Questionnaire-based on HFIT and interview	Identify the human factors contributing to maintenance failures	Petroleum industry	Prevalent failures attributed to assumptions (79% of the case, and communication 66%)
2013[7]	SLIM	Integrating human error into risk analysis (ETA)	Offshore facilities (pump, separators)	A significant difference in risk value occurs if HEP is ignored in QRA.

As has been indicated, all investigations that have been conducted in recent decades frequently employed the conventional HRA techniques (1st and 2nd generations) to assess human reliability. As can be seen from Table 2.2, some principal steps have been established in HRA in marine maintenance activities. For instance, Islam et al. (2020) integrated evidence theory into the HEART method to reduce uncertainty in HEP prediction [16], developed data collection and analysis procedures to explore the relative importance of performance-affecting factors [25,26], and proposed a monograph for human error likelihood assessment to rapidly and accurately estimate HEL (Islam et al. 2017b) for maintenance operations of marine systems. Moreover, a specific method based on HEART, named SOHRA, accompanied by marine-specific errors-producing conditions was developed by [35], although it covers the entire scope of marine activities not only maintenance. However, such fundamental attempts have not been observed in maintenance operations of onshore facilities where most of the high-risk oil and gas operations are performed. Hence, developing and validating more specific techniques and PSFs for these activities requires further investigations.

Another example of studies is the questionnaire-based survey according to Reason's accident model which was investigated to identify the causality of HFs in instrumentation and electrical devices' maintenance [21]. This study is a qualitative investigation and suffers from strong causation modeling to illustrate how and to what extent the latent factors/errors, directly and indirectly, contribute to HRA. As a result, efforts are needed in future studies to draw detailed attention to the causality modeling of HFs using advanced modeling techniques.

Another valuable research employed a new machine-assisted digital approach based on the maintenance 4.0 approach, to perform maintenance activities. This investigation showed) that HEP decreased by 83% compared to planned maintenance schedule (PMS), the most commonly used maintenance approach on board a ship, by mainly reducing the human workload in maintenance operations [24]. This effectiveness also proved that considering human error in condition-based maintenance had a significant effect in reducing system average unit cost [33]. This found the importance of optimization of the conventional maintenance approaches by considering HRA perspective in future research.

There is a shortage in considering human errors in risk analysis of maintenance operations in CPIs. Noroozi et al. (2013), was the only study that presented an excellent attempt at considering human error recovery as a safety barrier using the event tree analysis method where maintenance error was placed as the initial event. Although this study focused on simple process equipment including a valve, a pump, and a separator in offshore facilities, findings confirmed that a significant difference in the risk level occurs when human error is included in the risk analysis, and it could add $68,615 to the risk value. Nonetheless, this necessity has not received the attention it deserves, and more studies are required to incorporate human error into other popular quantitative risk analysis methods in complex maintenance operations. Furthermore, integrating human error into the risk assessment process of the causal modeling process and mechanical failures needs more investigation of maintenance activities.

Among the available HRA techniques, SLIM, HEART, SOHRA (a specialized version of HEART for the maritime field), and THERP methods were frequently employed to assess human reliability in maintenance activities. These studies brought significant improvement to HRA in maintenance activities, particularly in marine operations. However, the employed methods are located in the first-generation category of HRA approaches and suffer from some important methodological drawbacks, as follows:

- Lack of an enough tailored set of PSFs focused on maintenance operations (M-PSFs) in CPIs.

- Heavy reliance upon experts' opinions for selecting M-PSFs and assigning a value to estimate HEP.
- Great epistemic (subjective) and aleatory (objective) uncertainties in human error identification and quantification.
- Inability in human error modeling to illustrate the root cause and their mechanism and latent interactions between internal and external factors contributed to error occurrence.
- Too great a concentration on external influencing factors (i.e., organization, task, operator, system) and not enough on internal factors (i.e. Memory faults, Decision-making failures) as well as failing to identify error types.
- Failing to model potential dependencies among PSFs, different tasks performed simultaneously, and different groups (HSE, operations, engineering, maintenance) in a maintenance cycle.
- Assigning only binary criteria to human performance (success/failure).
- Lack of empirical data for model development and validation, and HEP prediction in various maintenance tasks.
- Linear quantification for HEP using multiplying PSFs value by a nominal error rate.
- Heavy focus on executing the work step and ignoring HRA in other important maintenance phases (i.e., system configuration, maintenance plan review).
- Static structural nature of techniques and inability to capture and model dynamic behaviors of the system.

These drawbacks and corresponding challenges have been emphasized in different studies [7,16,20,36,37] hence further research and challenges call for future efforts in this research stream. As a case in point in NPP's maintenance, Heo and Park (2010) developed a tailored framework for risk analysis of human errors [38], Khalaquzzaman et al. (2010) proposed a model to estimate system unavailability owing to human failure, while Prasad and Prabhu (2010) conducted a systematic review of human error in aviation maintenance and inspection [39].

2.3.3. Emergency operations

Emergency operations as a last and critical defense layer are a core section of reactive safety measures to mitigate potential losses (i.e., the death toll and injures economic and environmental damage) and improve the resilience of critical systems when a major accident occurs. These operations may be divided into three phases: (1) pre-emergency, (2) emergency response, and (3) post-emergency. Prevention and mitigation accompany preparedness measures in the first step, while response and recovery actions are utilized in the two last phases, respectively. Although emergency or crisis management inherently attempts to minimize the risk of catastrophic consequences such as fires, explosions, and toxic release scenarios, any human failure can not only fail to successfully implement a scheduled plan but can also result in irreversible damage in oil and gas installations. Increasing complexity in the real-world, less opportunity to practice, massive exposure to the hazardous and harsh physical environments, applying high time pressure, unfamiliar situations with incomplete information, simultaneous involvement with different disciplines, degradation of infrastructure and plant equipment, and failing safety and control systems are the main reasons giving rise to the more likely occurrence of human error in emergency operations [40,41]. Moreover, most activities in emergency management are performed by, or rely on, human activities or decisions that increase human susceptibility to failure in their desired performance.

Bhopal (1984) and Piper Alpha disasters (1988), Vermilion Block incident (2010), the Gulf of Mexico [40], BP Grangemouth Refinery incidents (2010) [42], and Bouali Sina Petrochemical Plant fire (2016), the largest fire in Iran's petrochemical industry to date, are some well-known instances of catastrophic events where human error played a substantial role in increasing devastating effects during emergency management. It is highly acknowledged that most of these accidents could have been prevented if human factors had been adequately considered during design and emergency planning [40]. Furthermore, the vital importance of human factors in emergency operations has been identified by several reports published by the HSE UK dealing with the inclusion of human factors in CPIs, and the HRA of safety-critical tasks in the offshore industry [43,44]. As a result, effectively assessing human reliability in all phases of the emergency management cycle plays an important role in operating safer and more resilient organizations. To achieve this philosophy, since the 1980s, 20 investigations have been conducted to explore HRA in emergency operations of offshore and onshore facilities. The employed methodology, main objectives, and achievements of the important and most relevant of these studies are presented in Table 3.3.

Table 2. 3 Human reliability analysis studies in emergency operations in the process industry

Year	Methodology	Main objectives	Domain	Main findings
2020[45]	BN-CREAM, BN-SLIM, BPL, BN-SPARH	Validation of some BN-HRA methods by simulation data	Virtual offshore evacuation (VOE)	BN-SLIM is more accurate and outperforms others
2020[46]	HFACS, Fuzzy-TOPSIS	Qualitatively evaluate the influence of human various factors and errors	Hypothetical platform	Enhancing decision making during emergency response
2019[47]	Virtual offshore emergency training simulator, BN	Presenting computational human behavior simulation model	Offshore emergencies	Modeling human behavior variability in emergency operations
2019[48]	Interpretative structural modeling (ISM), BN	Causal factors analysis in emergency processes of fire accidents	Oil-gas storage and transportation	Integrating HFs into causality modeling in emergency processes
2018[17]	FST, SOHRA	HE assessment during operating procedures of an emergency fire	Pump at the on-board ship unclear	Estimation of HEP
2016[49]	Simulator, BN, questionnaire	Modeling unobservable person-based PIFs by behavior indicators	VOE	Quantifying unobservable PIFs using VE and BN
2014[50]	Evacuation protective layers diagram, ETA	Discussing the human and organizational factors (HOFs) in HE	Evacuation operations on BP Deepwater Horizon accident	Identifying HOFs contributed to the unsuccessful evacuation operations
2014[51]	Computer-aided simulation, BN	Handling the data scarcity problem in HRA	VOE	Developing a data collection methodology
2013[52]	Evidence theory, BN, Expert judgment, SLIM	Reducing the uncertainty and conflict in HEP estimation	Offshore Emergency conditions	Providing more reliable and precise human error estimation
2010[53]	HAZOP, Bow-tie Risk graph and Matrix,	Human error risk analysis	Muster process in offshore installations	Developing an HR risk assessment method
2006[54]	HEPI, SLIM	Risk management of human error	Emergency offshore musters	Developing an HR risk management method
2005[44]	SLIM, Questionnaires	Prediction of HEP in the emergency musters	Offshore production platforms.	Presenting HEP data for offshore musters
1998[55]	Data collections	Generating HEPs data	Lifeboat evacuation in offshore installations	Qualitative and quantitative data were collected successfully.
1993[56]* 1995[57]* 2013[40]	The EER HAZOP methodology	Identifying systematically the EER hazards	Offshore installations	Incorporating human failure into systematic hazard analysis in EER
1987[58]	Operator Action Event Trees, database	Assessing HR during the detailed engineering phase	Offshore emergency blowdown system	Increasing the design's margin of safety by HRA

* Technology Report

Retrospective purpose-based analysis of these articles reveals the main research streams of HRA in emergency management as illustrated in Fig. 2.3.

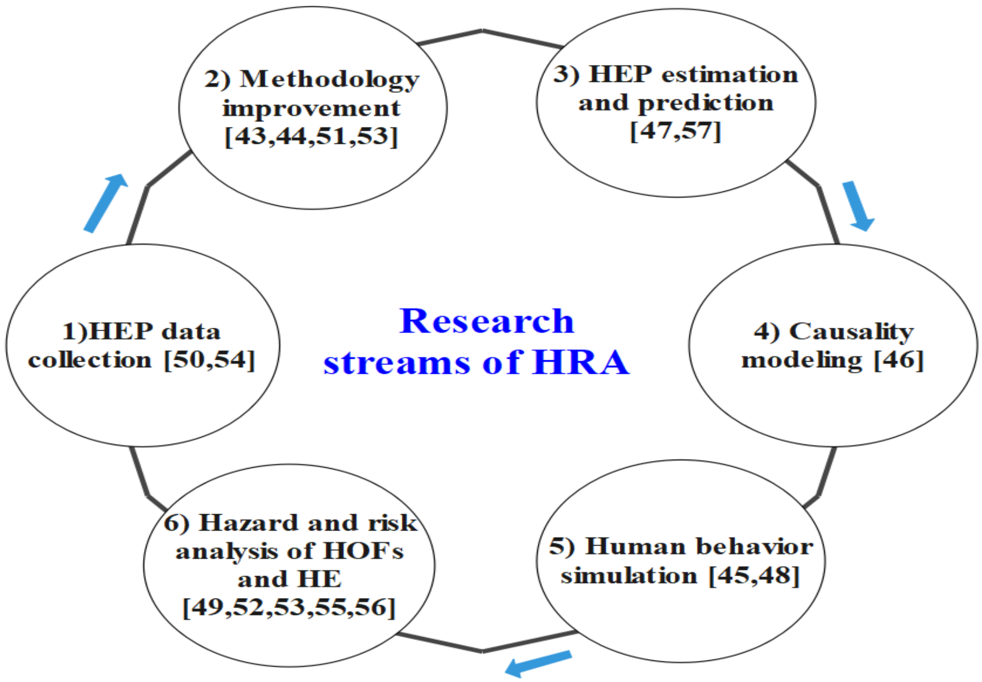

Figure 2. 3 Main research streams in HRA of emergency operations in the process industry

One of the fundamental needs and challenges in HRA already exists in the first research stream being the lack of a human error database in emergency activities. The databank is a vital factor influencing HRA quality, particularly HEP prediction [59]. Thanks to the availability of virtual simulators, significant efforts in recent years have been made by researchers to compensate for data scarcity in this research area [47,49,51]. Nevertheless, in comparison with similar critical systems like NPPs (i.e. OPERA [60], HERA [61], SACADA [59], CORE-DATA [62]) and the aviation domain, developing a structural procedure, the theoretical foundations, and subsequently HRA database should be urgently established through active and mutual cooperation by both academic and leading oil and gas organizations. Moreover, developing operator training and simulating programs that support mutual databanks can be a genuine attempt at HRA. Although retrospective accident analysis demonstrated that the frequency of major accidents and disasters, which occurred mainly due to human error in CPIs, is higher than NPP, fewer fundamental theoretical and technical developments in this critical domain are presented in comparison to NPP. For instance, several specific methods (i.e. AGAPE-ET [63]) and standard taxonomies of PSFs [64] for emergency tasks in NPP, or even for railway [65] were developed, while they exist as main shortcomings in the process industries.

Some attempts have been made in the second research line (methodology improvement) category by employing the Dempster -Shafer Evidence Theory (DST) and BN techniques. The former was used to address uncertainty due to partial ignorance and subjectivity and variability in multi-expert judgments, while the latter was utilized to solve unrealistic independence assumptions through dependency modeling among human factors and corresponding activities, in the awareness phase of muster action [52]. Although DST is a popular tool to deal with uncertainty modeling, it suffers however from some important drawbacks, including conflict management when evidence conflicts within a scenario. Further, the elements in the frame of discernment must be mutually exclusive in DST. These shortcomings have greatly affected the theory's practical application in uncertainty modeling [66,67]. There are huge technical and social differences among potential emergency scenarios in oil and gas operations. This issue along with the numerous uncertainty sources in expert knowledge elicitation, as the most popular HEP prediction approach, stimulate demand for utilizing advanced both non-probabilistic and probabilistic methods or hybrid approaches to tackle these issues. For instance, interval or fuzzy calculus, p-box formulations, information theory, game-theoretical foundations, Monte Carlo simulation, D Number theory are non-probabilistic, while credal set, probability box, and probability distributions as probabilistic techniques can integrate into conventional HRA approaches to simultaneously take an advantage of both common

HRA and these advanced methods. For example, D Numbers Theory as a novel and efficient alternative way to express uncertain information was systematically developed to tackle these drawbacks [68] and was employed by researchers to deal with these issues, i.e. uncertainty, in another study [69]. Moreover, these powerful tools have been introduced in the past two decades and their applications toward the realistic engineering domain, particularly in human reliability, call for new challenges, and further research by HRA practitioners. Other issues arise when expert judgments are affected by their multi-background criteria (i.e., different experience, positions, educations level, safety attitude, and beliefs) which need to employ some advanced multi-criteria decision-making (MCDM) methods to address uncertainty and decision-making challenges. Various MCDM methods are available which can be suitable based on study scope and concerns to reach a more reliable results [70,71]. Some of these popular MCDM methods include the (fuzzy) Best Worst Method (BWM), Analytic network process (ANP), Markovian Multi-Criteria Decision Making, VIKOR method, Elimination and Choice Translating Reality (ELECTRE), (fuzzy) decision making trial and evaluation laboratory (DEMATEL), and (fuzzy)Technique for the Order of Prioritisation by Similarity to Ideal Solution (TOPSIS). Some applications and potential extensions of these approaches to deal with probability elicitation issues, using expert judgments, were demonstrated in previous studies [72–77]. Recently a constructive validation of BN-HRA methods (i.e. BN-CREAM, BN-SLIM, BN-SPARH, BPL), as the third-generation techniques, was conducted using offshore evacuation virtual environment data [45]. Apart from proposing new generation HRA methods, findings were presented showing that data-based techniques such as BN-SLIM and BPL are more successful than the rule-based methods. Nonetheless, further investigations must be performed using actual, appropriate, and different context data under different assumptions and model modifications with fewer restriction criteria to reach concrete conclusions [45]. Apart from the EER, the HAZOP methodology proposed in the early period of HRA studies as a technology report [56,57], a tailored HRA method for emergency operations able to address the forgoing methodology shortcomings (see in maintenance operation section), is one of the main gaps from a methodological perspective. This is also true for human error risk analysis methods utilizing offshore and onshore installations.

A new advancement in HRA has been recently demonstrated in the human behavioral simulation research line to model human behavior variability and unobservable person-based PIFs using a virtual offshore emergency training simulator [47,49]. In the former study, the variability arises from psychological differences, while the morale, motivation, and attitude of emergency responders using behavioral indicators were modeled in the later experiment. These research lines may open useful new horizons in the HRA domain and will be great advantages to HR analysts to assess HEPs more preciously. Human behavior modeling is a great challenging research stream that requires at the least, both simulation as well as physical and cognitive psychology considerations [47,78]. As a result, more concerted experiments are required to develop different powerful simulators, mechanisms to incorporate all aspects of human performance (i.e., mental, physical, emotional) as well as all PSFs hierarchy (i.e., organization, machine, task, environment) into new models in future studies. Another need is in exploring potential benefits and challenges of using the virtual environment to assess human performance and reliability in emergency operations [49,52].

2.3.4. Control room operations

Main control rooms (MCR) are the focal point to efficiently sustain operations in hazardous installations, where operators must direct normal tasks and safely deal with all safety-critical situations using complex interfaces. In other words, they are expected to continuously monitor activities, identify all abnormalities, and respond quickly to unsafe events occurring in the onsite operations. Although these rooms have been substantially equipped with automation, human performance remains a vital element to real-time supervision and safe control of the systems [79,80]. The main reason is that operation designers are unable to predict all potential failure scenarios and cannot provide pre-defined safety measures for every contingency [9]. Furthermore, human operators are more flexible and have a great ability in learning and adapt to the peculiarities of the system since they are expected to plug the holes in the designer's imagination [81].

However, human error in these operations has been a leading factor in the occurrence of catastrophic accidents such as the Milford Haven refinery explosion [82] and more recently, the Texas City refinery explosion [83]. Analyzing 500 pipeline incidents revealed that operator errors, the most contributing failure among direct causes, were responsible for around 31% of accidents [84]. Hence, the prevention of these failures can significantly improve system safety in the oil and gas industries.

Control rooms are substantially complex socio-technical environments and various factors, directly and indirectly, influence operator performance. Furthermore, operator performance forms a crucial and last layer for addressing abnormal situations when process variables cross their safe limits. Occasionally, the operators fail to bring the plant to normal operating conditions due to human failures which arise from various latent factors. These variables fluctuate considerably including; individual (i.e. situation awareness, fatigue, competency, expertise, experience) ; organizational (i.e. safety culture, procedure, communication process, workload, maintenance programs, training courses); physical environment (i.e. room layout, poor lighting, noise, glare, automation systems, non-ergonomic workstation), and task; (i.e. task attribute/requirement, level of detail, type of HMI interaction, clarity of instruction and terminology) [85]. As a result, if these contributing factors do not receive enough attention there is a great potential for human error to occur and subsequently major accidents. Moreover, Iqbal et al. (2018) argued that the risk which arises from a plant is reliant on the operator's performance. It thus needs to analyze the operator reliability considering latent interactions among these contributing factors which hasn't received enough attention in CPIs.

To address this important issue, several researchers have sought the HRA of MCRs in chemical process systems. These investigations might be classified into two main groups. The first group focuses on employing probability theory to estimate HEP, while the second group measures operators' performances and subsequently their reliability in terms of cognitive and behavioral functions such as eye movement, situation awareness (SA), and soft controls. In the first study, Vaez. and Nourai. (2013) analyzed the reliability of the combined automatic-operator emergency response plan considering operator errors using SPAR-H and the reliability block diagram technique to improve the drawbacks of the response plan [86]. A self-developed questionnaire, to collect the operators' opinions regarding common performance conditions, and fuzzy rules, to quantify them, accompanied by CREAM-BN, to estimate HEP, was used in another study [87]. These studies investigated HR from a probabilistic perspective to estimate HEP in control room operations, while in recent years new concepts investigated operator performance and reliability using cognitive indices. However, some researchers believed that the monitor and inference of cognitive and behavioral functions of the operator to understand or diagnose a real-time situation might provide numerous opportunities for useful applications. These usages include analyzing operator reliability, improving operator training programs, developing a new type of operator support system, and human performance measures for human reliability validation [1,88,89]. To this end, a second group of researchers conducted several theoretical and experimental studies. From the first group for instance, Zarei et al. (2016) developed an intelligent Adaptive Neuro-Fuzzy Inference System model to predict operator's efficiency considering human reliability and decision-making styles in petrochemical plant's control rooms [90], whilst several advancements in experimental attempts have been conducted in recent years. In this sense, Ikuma et al. (2014) measured operator performance in terms of speed and accuracy by assessing subjective workload, eye movement, and situation awareness using a desktop computer-based simulation of a control room with two interface designs (i.e. black and gray) [91]. Iqbal and Srinivasan, (2018) considered two performance metrics (the margin-to-failure and the available-time) and proposed a strategy for estimating control room operators' reliability using a simulated ethanol production plant. In this human subject-based experimental investigation, 128 participants in two groups of experts and novice students participated as control room operators to investigate to what extent operator reliability is affected by an operator's experience level [89]. They used failure of operators to direct the virtual plant from abnormal situation to the normal limits of their reliability using the above-mentioned indices.

Moreover, in recent years, SA, as one of the most influential factors on the cognitive abilities of operators and prerequisites of their safety performance, was investigated. The first step in SA is the perception of a situation or task element, then the understanding of its meaning, and finally, the projection of its status in the future [92]. Sharma et al. (2016) used the information obtained from the eye tracker to complete twelve control scenarios during process disturbances using a simulated ethanol plant [1,93]. They concluded that successful participants in completing their tasks followed distinct eye gaze patterns so that each SA element (i.e. orientation, diagnosis, and execution) revealed a particular eye gaze pattern [1,93]. In another study, they proposed gaze transition entropy and dwell time entropy as new quantitative measures of eye gaze tracking [94]. They argued that SA estimated by eye tracking is a pertinent online indicator of human error. However, they also mentioned that this is the first step and further research needs to be conducted because the investigation only focused on outcome-oriented metrics especially work or failure of task or completion time (dwell time). Additionally, detailed cognitive level, multivariate behavior model of operators, and other eye-tracking measures such as saccadic duration, saccadic peak velocity, and pupil dilation should be included in realistic research of SA. Naderpour and et.al (2015) investigated the role of SA in three different major accidents and presented an SA error taxonomy. They concluded that SA errors contributing to these accidents can be mainly classified as errors due to poor design of operator support systems, inappropriate presentation of information in human–system interfaces, and error due to poor mental models [95]. They highlighted an urgency in exploring cognitive support systems to decrease the workload and stress of operators, and a virtual plant simulator presented as operator training method to improve SA. Nevertheless, this is a qualitative effort narrating the SA errors and there is urgent need to develop strong approaches able to quantify the different errors in three levels of SA, modeling dynamic dependencies and common causes. Mohammadfam et al. (2019) argued that many organizational, situational, and individual factors influence SA and modeling their interactions is a key factor in accident prevention [96]. Nonetheless, this important issue has received little attention in the process safety domain by researchers to date. Therefore, identifying, modeling, and quantifying the various latent variables adversely affecting the SA, investigating which error type (i.e. mistakes, lapses, and slips) occurs in different SA levels, the causes behind them, and which methodology is most suitable and reliable for studying SA in advanced main control rooms (AMCR) of CPIs should all be deeply researched in future studies. In addition, quantifying the effect of various variables and modeling their dependencies presents a real challenge for researchers because HRA practitioners suffer from access to sufficient data regarding human failures in process industries. For instance, Kulkarni et al. (2019) mentioned that fatigue has been identified as an underlying factor in major accidents such as the NASA Challenger explosion, the Exxon Valdez oil spill, the Bhopal gas tragedy, and the Three Mile Island nuclear incident [97]. As an exemplifier, operators must be at the height of their mental performance to safely recover from abnormalities in such high-risk plants. However, fatigued operators in such a stressful condition substantially fail to prevent the escalation due to poor decision making because fatigue can greatly affect operator capabilities to problem solving, alertness, and mental calculations by a decline in electrical activity in parts of the brain [97]. Fatigue which reduces mental or physical performance comes from prolonged exertion or insufficient quantity and quality of sleep which indicates a complex and latent relationships of these factors [97]. Therefore, simulation-based studies using virtual control room operations to investigate the operator performance under different scenarios, can substantially contribute to addressing these issues and provide more realistic results for effective intervention.

Another important human reliability issue arises from the increasing level of automation in digital control systems (DCS) that has emerged in the AMCR in recent decades. These main rooms are adapting by adopting digital and computer technologies such as large display panels, computerized displays, soft controls, and computerized procedure systems (CPS) that introduce new ergonomic and safety risk factors in this complex environment [98]. For instance, Jou et al. (2011) pointed out that HMI digitalization can decrease alertness and human SA, which in turn may result in failures in decisions made in an emergency situation [99]. Several studies argue that by changing from conventional displays to computer workstations and soft controls, requiring different human behavior and performance influencing factors, presenting new human error, the way error occurs, and PSFs in DCS [100,101]. New PSFs come from new systems of procedures, alarms, decision-making, and MHI as well as communication differences in size, structure, and team perspective [100,102]. Moreover, this digitalization can present a great deal of data and can automatically complete many operation interactions at the same time. In this situation, control room operators must pay close attention to monitors and analyze systems operation messages and are thus often faced with a huge mental workload. If the operators suffer from a lack of SA or are faced with other issues, they may be unable to give an accurate and timely response. Consequently, errors of omission or errors of commission commonly occur [99]. Zou et al. (2017) argue that HRA methods which are used for analog control rooms are unable to meet the requirements of HRA in new rooms, and that new operator reliability assessment methods that can consider the characteristics of digitalization related to human factors should be developed accordingly [103]. In stark contrast, however, human operators do not provide the appropriate training schedule as well as guidelines to identify and deal with these factors. Most importantly, less effort are made to develop specific methods to identify, quantify and model PSFs and their causal influencing relationships in the chemical process systems. Ramos et al. (2020) believed that operators in NPPs are mainly controlling nuclear reactivity and generating electricity, whereas oil and gas refineries can contain up to 15 units or more. Each of the units, including a great number of instruments and equipment, accompanied by various chemical operations, require controlling and monitoring by control room operators [14]. Nevertheless, great efforts have been established to investigate these challenges in other safety-critical systems (i.e. NPPs, aviation) [99,103]. For instance, Zou et al. (2017) listed different investigations conducted by the US Nuclear Regulatory Commission, the Electric Power Research Institute HRA, and the Korea Atomic Energy Research Institute to research these challenges [103]. They aimed to emphasize the required modifications and considerations which must be improved in conventional HRA approaches to minimize the new human and organizational risk factors of DCS [103]. There are also some review investigations that discussed the effect of digitalization in NPPs [104] which may mean maturity of literature for this issue in NPPs, and new HRA techniques (i.e. OTHEA [100]) to meet the requirements of DCS in NPPs. As a result, these scientific gaps should be immediately addressed through experimental studies by cooperation of scientists and experts of leading oil and gas organizations before major losses occur. Although Lee et al. [101] focused on NPPs, the results can be used as a primary foundation to analyze HR of AMCR in the process industry. They analyzed 110 PSFs considering the 1st generation HRA techniques (i.e., SLIM, HEART, THERP) and 49 PSFs from 2nd generation HRA techniques (i.e. CREAM, SPAR-H, ATHEANA). These 159 PSFs were then categorized into nine main classes according to findings achieved by mapping each PSF to others, considering their concept and application in HRA methods and the context changes in AMCR to be used in HRA of this domain. The terms used for these nine candidate groups of PSFs are *Stress level, Action type, Experience, Time constraints, Places where operator actions are taken, Procedures, Training, HMI, and Teamwork*. Considering Human Factor Engineering Program review model (HFEPRM) based on Nureg-0711 [102] and several investigations for HF issues (HFIs) in advanced MCR [101,105], indicated human factor and performance analysis outputs can be considered as input data to determine PSFs. Accordingly, Lee et al [101] identified 46 HFIs mainly either merged in AMCR or remaining from conventional MCR in advanced MCR. They classified them into four groups being HFIs which come from computerized procedure system (N=13), acquisition of HSI information (N=11), HSI control (N=14) and related to training (N=8). The HFIs mainly arise from HSIs such as CPS, advanced information systems, soft control, and their related training mainly based on reviewing NUREG reports [102]. More details regarding the systematic approach are utilized to ensure this classification can consider the context changes in AMCR are available [101] and readers are referred to the original resource to obtain more information. However, an attempt has been made to clearly visualize which and how human factors issues cause or impact on PSFs in the AMCR based on Lee et al.'s (2011) findings [101]. Therefore, to better understand the potential complex integrations among the influencing factors, a qualitative causation model among these HFIs in each group and common PSFs in HRA is developed using Bayesian networks (Fig 4), which is powerful tools in graphical causation modeling. As can be seen from the proposed model, complex relationships exist between the human factor challenges in four HFIs groups and corresponding PSFs. For instance, HIS as one of PSFs, is influenced by 23 human factor issues from four groups. A clear example of these relationships could be the impact of *poor operator's situation awareness* on *HIS* and *implementation of procedure* which is demonstrated using a directed arc from the former node to two later nodes (Fig. 2.4) in which each edge corresponds to a conditional dependency, and each node corresponds to a unique random variable.

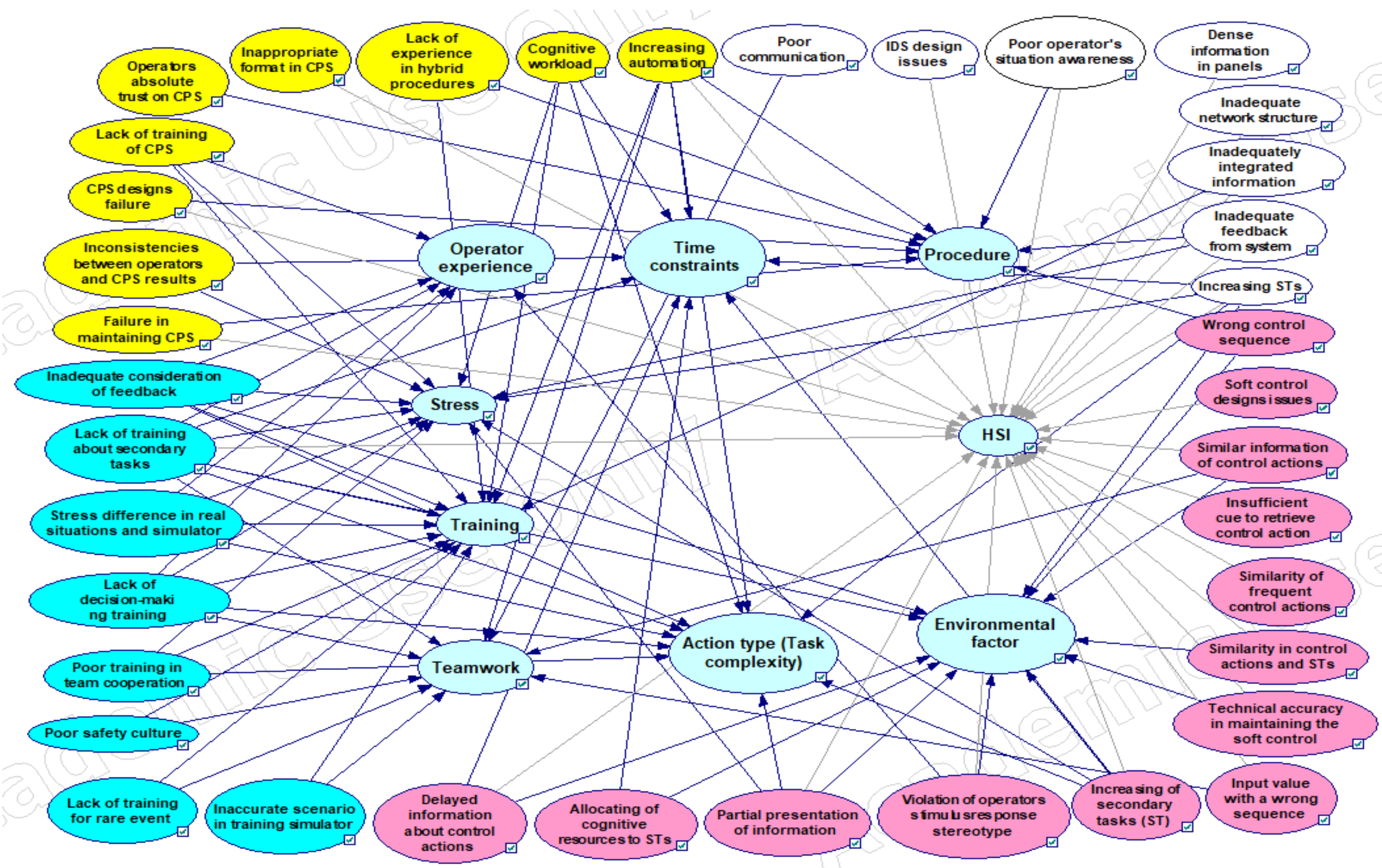

Figure 2. 4[1] Human factor issues (HFIs) and their influence on nine performance shaping factors in AMCR based on Lee et al.'s (2011) findings

Although the authors made efforts to provide a comprehensive model with the evidence-based causal relations, the developed model needs to be improved as per availability and context of new evidence or specific characteristics of studied system. Moreover, establishing empirical studies for quantifying the impact of these HFIs and investigating new emerging PSFs as well as utilizing new techniques for dependencies modeling, and dynamic modeling of HR are important challenges and research opportunities of HRA in oil and gas operations. Hybrid models using dynamic

[1] The causal arcs among PSFs and HIS are presented by different colors for the sake of increasing the readability

Bayesian networks (DBN) and System dynamics (SD) have top priority to present holistic and precise causal models of nonlinear behaviors in these complicated systems. Developing data-driven PSFs assessment models with enough transparency between models and source data, to deal with data scarcity and the uncertainty of expert judgments' should be investigated as novel steps in CPIs. It is noteworthy that validation of these models, as well as expert judgment models to generalize their applications and results, introduces a set of challenges for HRA practitioners due to vast differences between real operational conditions and simulator characteristics [106]. Advanced statistical approaches such as Structural Equation Modeling (SEM) and Path Analysis methods enable simultaneous modeling, of both direct and indirect (latent) relationships of variables recommended for future research. The results of these tools can be incorporated into probabilistic approaches such as BNs as a novel step in the quantification of HEP.

2.3.5. Comparison of HRA in CPIs with NPPs

Investigations comparing two similar safety-critical domains may accurately reveal the quality and quantity of scientific findings. To this end, this section compares fundamental HRA studies in CPI with NPPs in terms of five important criteria including review studies, human error databases, PSF taxonomy, special HRA technique, and empirical study in control rooms operations.

Overall, as seen in Table 2.4, significant efforts in all criteria have been made in NPPs (N=39), whereas several studies were conducted in the only simulation-based investigation and methodology development in CPIs (N=9). Ten studies focused on reviewing research on different HRA concerns (i.e. man-machine interface design, effects of digitalization, cognitive aspects, benchmarking issues) in NPPs from 1990 to 2020 (on average three investigations per year). This means there has been steady progress towards HRA in this industry. However, to the best of the authors' knowledge, any scientific inquiry into HRA has not to date been set up in CPIs. Considering various issues in HRA, this crucial gap would be highly recommendable to explore the main needs and challenges in different aspects of human reliability in such high-risk industries. This is true for the existing noticeable gap in the human error database (HED) in CPIs which is very important at least to provide reliable data to quantify the HEP in various operations (emergency, maintenance control, and normal operations). It is clearly understood that insufficient human performance data is identified as a vital factor and main fundamental issue affecting HRA quality, particularly in the estimation of HEP [59,107,108], and even in NPPs where significant efforts have been made to develop HEP databanks and simulators. As a result, there is an urgent need to address these gaps by collaborating in both industrial and academic settings where numerous leading companies and universities are involved in the oil and gas industries. Nevertheless, in this regard, several international organizations have been developing HRA databases and collecting data through comprehensive control room simulator studies. As seen in Table 3.4, for instance, SACADA [59], OPERA [60], and HURAM+ [107] are among several HRA databases developed from NPP control room simulator studies.

Kim and Jung [64] concluded that at least 220 PSFs exist in available taxonomies and Lee et al. [101] identified 159 PSFs from nine HRA methods. These factors vary from one technique or operation to another. Moreover, the number and value of each PSF can substantially change the HEP value since it is estimated by multiplying the nominal HEP in PSF values which are mainly selected based on expert judgments under great uncertainty. Therefore, developing specific taxonomies of PSFs for hazardous activities such as emergency tasks and AMCR operations is vital to obtain an accurate HEP estimation. Furthermore, as PSFs have a considerable influence on operator performance and reliability, having a standard set of them, can improve human error modeling and consequently, the decision-making process to prevent human errors. As illustrated in Table 2.4, only one study has been made to propose HRA taxonomy for marine and offshore applications, whereas six types of taxonomy were developed in NPPs. It should be highlighted that quantification, intra and inter-dependency modeling, and causality modeling of PSFs require urgent efforts to develop advanced methods or models in this field.

Furthermore, it is believed that most of the first and second-generation HRA methods originally developed are based on findings into human behavior and performance data adapted to NPP characteristics, while methodology initiatives are less established in other critical domains such as CPIs. In recent years, reasonable efforts have also been made to propose new methods to deal with new concerns or to improve the conventional methods in both CPIs and NPPs which can be observed in Table 2.4. Generally, the number of these methods in NPPs is around double those in CPIs. HEPI [54] was proposed for human error estimation in offshore operations, and Petro-HRA [109] as a general method for human reliability analysis in the petroleum industry, while Phoenix-PRO [14] was adjusted for oil and gas operation from original Phoenix which is a qualitative general HRA method. In contrast, more specific techniques were presented to be addressed especially human error concerns. For instance, AGAPE-ET [63] method for emergency tasks, CESA [110] for errors of commission, IDAC [111] for HRA of control room-operating crew during an accident, and OTHEA [100] for digital NPPs were recently proposed.

Table 2. 4 Comparison of HRA studies in CPIs with NPPs with respect to five criteria in HRA perspective

Type of literature	Nuclear power plants	Chemical process industry
Review study	HRA in man-machine interface design [112] Effects of digitalization in CR[104] Cognitive basis for HRA [113] HRA techniques applied for PRA [114] Issues in benchmarking HRA methods [115] HRA techniques for risk assessment [116,117] EOC identification [118], quantification[119] Need, Status, Trends, and Limitations [120]	The present study
Human error database (HED)	OPERA[60], HERA[61], SACADA[59], CORE-DATA[62], OPERA [60]	
Taxonomy of PSF	Extreme external hazards[121] Emergency tasks [64] Advanced main control rooms [101,122] HRA and system design [123] A hierarchical standard set of PIFs[124]	HENT [125]
Special HRA technique (apart from 1st and 2nd generation methods)	OTHEA[100], NARA[126] AGAPE-ET [63], CESA [110], IDHEAS [127], Phoenix [128], IDAC [111]	HEPI [54] Petro-HRA [109] Phoenix-PRO [14]
Control room simulator (Empirical study)	• Effects of PSFs on HRA [129–131] • HRA in AMCR: Communication characteristics in CPS [132] Effects of automation decisions [133] Error recovery in soft controls [134] Diagnosis error [135] Reliability in Analog vs. Digital [136] Thoughts inferencing by eye movement [88] Personality effects on diagnosis errors [137] • HRA and the Safety-II concept [138]	Eye-gaze behavior to quantifying SA and operator reliability [1,89,93,94] Assessing operator performance using speed and accuracy, workload, SA, and eye-tracking [91]

Empirical studies using control room simulators are the last criterion to compare the advancements in the two industries. Srinivasan et al. (2016) believe that conventional human error approaches mainly focused on likelihood approaches to analyze human reliability hinder the role of the cognitive capabilities of the operators [1,93,94]. His research team conducted several experimental investigations by interacting with senior students with the HMI using a simulator of chemical process operations (i.e. ethanol plant). Participants' eye movements were captured employing eye trackers while they completed some cognitive tasks (i.e. Successful disturbance rejection, failed disturbance rejection) or managing process abnormalities. They used area of interest (AOI) of fixation duration, fixation count, dwell duration, saccade duration, and fixation rate distribution over the period ranging as cognitive functions of operators and margin-of-failure and available-time to respond to process events as operator performance indicators [1,93,94].

On the other hand, several investigations were conducted in NPPs to examine the effects of PSFs (i.e. task complexity, training level, operator experience, secondary operation numbers, HSI type (digital or analog), mode conversion) on AMCR's operator performance by participating graduate students and licensed operators in which they had to complete various simulated process scenarios. Operator performance was estimated in terms of different dependent variables such as operation time, error rate, workload, SA, and response time [129–131,135,136]. Moreover, several empirical studies were conducted to assess new concerns arising from MACR from in HRA perspective which means substantial attention has been paid to digitalization in NPPs compared to CPIs where rare efforts have been reported. Some noticeable studies in NPPs include communication characteristics in CPS [132], effects of automation decisions [133], error recovery failure probability in soft controls [134], diagnosis error [135], and personality effects on diagnosis errors [137].

2.3.6. HRA and new safety management paradigms

In recent decades, safety science has been increasingly changed by introducing new paradigms such as Resilience Engineering (2006) [139], Safety Differently (2014) [140], and Safety-II (2014) [141]. According to resilience engineering, error or failure is not necessarily a consequence of malfunction or poor design, but it arises from the adaptations required to address the real-world complexity instead of a breakdown or poor function, although it has already been mentioned that task analysis will emphasize the identification of error-likely situations not error-likely people [142].

People and organizations' performance should be adjusted appropriately based on the current circumstances because resilient performance requires more than incident prevention which is at the heart of the conventional safety management systems (named Safety-I). In Safety-II, the main objective is not just hazard elimination and failure prevention but also how to maximize an organisation's potential for resilient performance through responding, monitoring, learning, and anticipating [139]. Moreover, Safety differently introduced by Dekker (2014) as a new human factors era, introduces a different type of safety thinking which considers individuals as the main origins of diversity, insight, creativity, and wisdom regarding safety instead of risk sources [140]. With this end in view, it should take as a solution people to harness, not as a problem to control, and safety should be introduced as the presence of positive capacities rather than as an absence of negatives [140]. Safety-I presented a protective safety through concentrating on how things can go wrong, whereas Safety-II paves a different way to achieve productive safety by mainly focusing on how things can and do go right. In this new concept the safety purpose does not just consider failure prevention and hazard control, but also how people can maximize the potentials of the organization to achieve a resilient performance in the way it responds, monitors, learns, and anticipates [141,143]. To this end, the mechanism and vocabulary used in human error management should be changed. For instance, in Safety-I, operator performance measures are as a set of limited unsuccessful outcomes such as human errors or failing to manage an abnormal situation, while it should be changed to one of many diverse successful results along with a set of limited unsuccessful consequences based on Safety-II [141,143]. Ham et al. (2020) is the only study in the HRA domain based on this new paradigm that attempts to obtain HRA data from event investigation reports using large data analysis in NPPs [138]. To achieve that, they claimed that there are at least three challenges including collecting vital information from reports concerning the dominant PSFs, considering data from success outcomes, and analyzing the massive amount of information [138]. Accordingly, safety can be improved by investing in potential factors required for successful cases to occur as well as preventing failed cases. Furthermore, the ways to define and measure the value of PSFs concerning success outcomes represent new challenges and perhaps strong validation as further research directions to take more advantage of Safety-II concept in HRA. Analyzing both success and failure data calls for an urgent need to integrate big data mining and learning techniques into conventional HRA methods. Furthermore, HRA practitioners should focus on developing a systematic combination of the two approaches of safety thinking in the HRA domain especially in complex socio-technical systems because it does not claim to entirely substitute the conventional safety thinking with the new [144].

2.4. Conclusions

The present study reviewed the current knowledge regarding HRA in three critical elements of chemical process systems in human reliability perspective, namely maintenance operations, emergency management operations, and control room operations. A systematic study, as the first review investigation, was conducted to shed new light on the main needs and gaps in the available literature and upcoming challenges in future research necessities and opportunities in this domain. Moreover, the main research streams and contribution of previous studies into HRA are specified, and some novel approaches are suggested to deal with the dominant drawbacks of current HRA knowledge. Importance and necessity of a new thinking system about human reliability to take more advantages of results of new safety management paradigms is also highlighted. Most of the studies have been focused on HEP estimation using conventional methods in maintenance activities, while they continue to be accompanied by the virtual offshore simulator and hybrid models (i.e., fuzzy theory, BN and TOPSIS) to analyze human error and develop HRA data in the emergency management sector. In contrast, some new experiments are performed to assess operator reliability and performance using cognitive functions that have not been given the attention they deserve in two previous elements of CPIs operations. Fundamental steps should be taken to develop HE/HRA database, tailored HRA techniques, and PSFs taxonomies for oil and gas operations as well as new advancements of performance simulators and novel human reliability modeling methods. Furthermore, integrating dynamic models and human cognitive and behavioral theories into conventional HRA techniques can provide a better understanding of human performance variability and reliability. This is the first attempt to review the current knowledge in this area which can be benefited by further research. It is worth noting that the present study does not cover all potential human activities in CPIs. Important operations such as permit to work, confined space activities, shutdown and pre-startup of units and management of change are some common activities prone to human error in this industry. Exploring available investigations into these activities to deal with difficulties and to give research opportunities can be revealed in future academic efforts.

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CHAPTER 3

A Dynamic Risk Model to Analyze Hydrogen Infrastructure

Preface

A version of this chapter has been published in ***International Journal of Hydrogen Energy 46, no. 5 (2021): 4626-4643****. I am the primary author along with the Co-authors, Faisal Khan, and Mohammad Yazdi. I developed the dynamic risk model to analyze hydrogen infrastructures. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' and peer review feedback. Co-author Faisal Khan helped in the concept development, design of methodology, reviewing, and revising of the manuscript. Co-author Mohammad Yazdi provided support in testing the model. The co-authors also contributed to the review and revision of the manuscript.*

Abstract

Safety management of hydrogen infrastructure is vital for sustainable progress in the hydrogen economy. Accordingly, this paper presents a dynamic and holistic risk model to address some significant shortcomings of the current hydrogen risk analysis models. The hydrogen release scenarios are modeled using the Bow-tie technique integrated with improved D Numbers Theory and Best-Worst Method. This helps to analyze epistemic uncertainty in the prior probabilities of the causation factors and barriers. Subsequently, a Dynamic Bayesian Network (DBN) model is developed to analyze dynamic risk and deal with aleatory uncertainty. An epistemic uncertainty refers to deficiencies by a lack of knowledge or information. The application of the proposed model is demonstrated in a water electrolysis process. The results of the case study provide a better understanding of the causal modeling of accident scenarios, associated evolving risks with uncertainty. The proposed model will serve as a useful tool for the operational safety management of the hydrogen infrastructure or other complex engineering systems.

Key words: Dynamic risk analysis; hydrogen safety; dynamic Bayesian network; D-number theory; Best-Worst Method.

3.1. Introduction

The advantages of hydrogen over other conventional energy sources have drawn considerable attention to the hydrogen economy in recent years. There are many valuable properties of hydrogen including viable clean and green energy, a promising alternative fuel for our future, the highest energy content [1,2], its abundance and production using a widely varied combination of energy sources, an important role in energy storage and energy security [3], and a universal demand for hydrogen gas. Further, global environmental challenges, like global warming, increasing greenhouse gas emissions, climate changes, and depleting hydrocarbon resources have resulted in an immediate need to transition to a "hydrogen society".

In addition to above-mentioned advantages, hydrogen also presents some serious safety risks. It is potentially extremely devastating because of its wide explosion limit range (4%-75%), much lower minimum ignition energy (0.017 mJ), high deflagration index (DI=550 bar m/s) in comparison with methane (DI=55 bar m/s) and gasoline (DI=100–150 bar m/s), high air diffusion coefficient (0.61 cm/s), low density and significantly greater flame speed compared with other gases [4,5], the possibility for spontaneous ignition of hydrogen release [6], and the ability to easily release from sealing parts, for instance, valves and flanges, since it is the smallest molecule [7,8]. These issues result in increasing public concern about hydrogen-related safety risks. These concerns have been exacerbated by catastrophic disasters such as the hydrogen explosions in the Hindenburg disaster (1937, 36 fatalities), Polyethylene plant in Pasadena, Texas (1989, 22 death and 100 people injured), the US Space Shuttle challenger (1986, 7 death) [9], Chernobyl disaster (1986, 4000 death toll, the maximum severity (Level 7) [10], Fukushima nuclear plant (2011, 1 death, 37, maximum severity (Level 7)) [11]. Moreover, even non-catastrophic hydrogen accidents, particularly in facilities that are located in residential zones such as fuel stations, may result in substantial hindrances to the development of hydrogen technologies and subsequent decreases in public acceptance [11,12]. Furthermore, there is a probability of major accidents occurring because of escalated operations at the hydrogen facilities [13]. Moradi and Groth, (2019) indicated safe and reliable systems play an indispensable role in the acceleration of the progress and deployment of hydrogen infrastructures. Thus, the safety of the required infrastructure is a vital factor for the hydrogen economy to become a reality.

Several risk models have been developed to assess the safety of hydrogen infrastructures. Rosyid et al., (2007) proposed a Bow tie and consequence modeling-based model to analyze the risk of hydrogen economy infrastructures, and likewise, a semi-quantitative model using the Hazard Identification (HAZID) technique, Process Hazard Analysis Software Tool (PHAST) software accompanied by a risk matrix was proposed by Moonis et al., (2010). In other studies, a comprehensive risk analysis framework to model safety risks and catastrophic accidents of hydrogen dispersion was applied by some researchers [17–19]. Mohammadfam and Zarei, (2015) built Hazard and Operability (HAZOP), Preliminary Risk Analysis (PRA), Event Tree Analysis (ETA), and PHAST simulator into a safety and risk analysis model. Moreover, a risk matrix-based model to incorporate potential risk influence was developed using fuzzy probability and Bayesian belief network models [20]. Recently, some new safety and risk models have been developed, for instance, Hydrogen Risk Assessment Model (HyRAM) [21], and 3D risk management (3DRM) [22], dynamic Bayesian network-based model [23], Computational Fluid Dynamics (CFD) simulation and experimental model [24], and a Bayesian Regularization Artificial Neural Network (BRANN) model for parameter uncertainty modeling in fire risk analysis of urban hydrogen fueling stations [25].

Although these models have brought significant improvement in safety and risk models of hydrogen infrastructures, some significant drawbacks still remain. These shortcomings include the following; 1) static structures of these models, while most process and human factors are variable and often occur in the operational time of a system; 2) uncertainty in input and output data, particularly in the form of probability or frequencies due to the lack of enough precise data of young emerging technologies like hydrogen; 3) inability to consider conditional dependencies among the root failures of complex systems; 4) inability to use predictive modeling to simulate system safety barrier's behavior, and 5) incorporating often operational or mechanical failures into probabilistic safety analysis modeling, while human and organizational failures which are the deeper and more fundamental cause of accidents are ignored in most models. In other words, the conventional approaches cannot be utilized to model dynamic hazards, conditional dependencies, and common cause failure modes and they also use crisp and precise data that is rarely available or highly uncertain. The above-mentioned studies are good instances of applying conventional Quantitative risk assessment (QRA) to hydrogen facilities using generic data, assumptions, and estimations. However, the existence of great uncertainty in these studies, because of a lack of data, is a strong reason to move towards employing probabilistic tools such as Bayesian Networks (BN) [14,26]. Moradi and Groth (2019) pointed out that the employment of QRA methods along with BN techniques is necessary to have robust system-level studies.

Therefore, the current study aimed at developing a holistic model for addressing some substantial concerns and demonstrate the importance of a dynamic approach in the safety analysis of hydrogen infrastructures. In this approach, first, a causal model of hydrogen release scenarios was developed through holding focus group meetings with the process, safety, maintenance, instrument, and electrical experts (see experts' profile in Table 4.2 in the appendix). These scenarios begin from root events that lead to top events and end with potential consequences by considering the function of existing safety barriers, e.g., release or dispersion prevention barriers. After that, this model was created in the Bayesian network to provide a clear and graphical model of the accident. Then, a new and improved algorithm called D Number Theory along with expert elicitation, and Best-Worst Method (BWM), were applied to calculate the occurrence probability of root events, the failure probability of safety barriers, and uncertainty treatment in the input data. Finally, a predictive Dynamic BN (DBN) model was developed to tackle other limitations of the current risk analysis models of hydrogen infrastructures which are very important in quantifying conditional dependencies, risk updating, and predicting safety barriers' behavior. To present the capabilities of the model, a real case study was conducted on a hydrogen generation plant by water electrolysis which was located in a combined-cycle power plant. It is noteworthy to mention that BWM, as a new multi-criteria decision-making (MCDM) method, is according to a systematic pairwise comparison of the decision criteria to evaluate a set of alternatives with respect to a set of decision criteria [27], while D Number Theory as a new theory is a generalization of Dempster-Shafer evidence theory for efficient modeling of uncertain information [28].

The rest of the paper proceeds as follows. In Section 2, the developed model is provided, while in Section 3, the model application is presented with results and discussion, and in Section 4, the conclusion is presented.

3.2. The proposed dynamic risk model

This section provides an overview of the proposed dynamic risk model. The model was built applying an improved D Number Theory, BWM, System Hazard Identification, Prediction and Prevention (SHIPP) methodology, and DBN to safety and risk assessment of hydrogen infrastructure under uncertainty. The framework of the model development is illustrated in Fig .3.1.

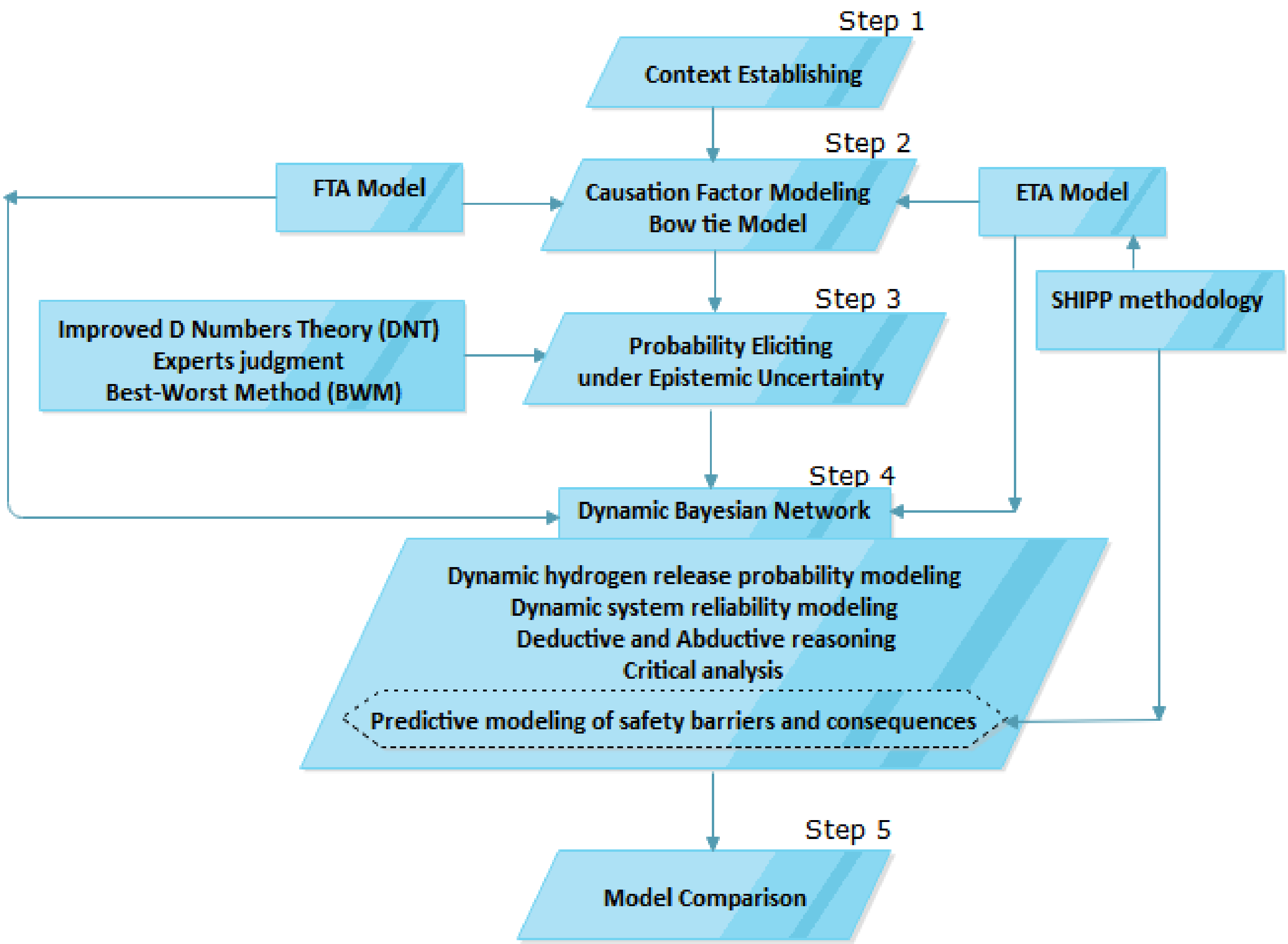

Figure 3. 1 The framework of the proposed dynamic risk model

3.2.1. Establish the Context (Step 1)

In this step, first, the main study objectives, which were provided in the last section of the introduction section, were defined. Then, according to the main goals and scope and context of the study, all the available materials such as process description, process flow, and pipeline & instrument diagrams (PFD, P&ID) and operations and maintenance procedures were investigated to identify the system, subsystems, and their functions (see the first section of the model application). The developed model can serve for achieving different targets, and as the selected aims substantially influence the framework and details of the study, it should be determined at the first step.

3.2.2. Causation Factor Modeling (Step2)

Hydrogen release scenarios on a real hydrogen generation plant by water electrolysis, situated in a combined-cycle power plant, were developed. To reach this aim, first of all, PFD and P&ID of the plant were studied. Then, the plant was divided into three sections according to the main functions and labeled: 1) Chemical section, 2) Mechanical section, and 3) Storage section. In each section, all possible failures of the main equipment that could lead to a hydrogen release were identified. After that, a deductive failure analysis using fault tree analysis (FTA) to identify how failures (root and intermediate events) are connected and how they can logically lead to the accident scenario in each section was performed. In addition, the potential consequences of the hydrogen release were specified via an event tree analysis (ETA) considering the functions (e.g. work or fail) of safety barriers including release prevention barrier (RPB), dispersion prevention barrier (DPB), ignition prevention barrier (IPB), and escalation prevention barrier (EPB). Finally, a comprehensive cause-effect model of the hydrogen release scenario was proposed through ten safety meetings with the process, safety, maintenance, instrument, and electrical experts.

3.2.3. Probability Elicitation under Epistemic Uncertainty (Step 3)

3.2.3.1. The D number theory

Dempster-Shafer (D-S) evidence theory is one of the well-known approaches for uncertainty modeling among all the available methods. However, it suffers from some limitations, including conflict management when evidence conflicts within a scenario. Also, the elements in the frame of discernment must be mutually exclusive. These limitations have greatly limited the theory's practical application in uncertainty modeling [29,30]. D Numbers Theory, as a new and efficient alternative way to express uncertain information, was systematically developed to tackle these drawbacks [28]. Hence, the present work is the first study aiming to present an attempt at improving and then integrating this novel theory into DBN for effective probability elicitation under uncertainty. The main advantages of this theory are provided in the appendix (Section 1). The main definitions are as follows.

Definition One: (D Number), Assuming that Ω is a finite non-empty set, a D number can be formulated as Equation 3.1:

$$D: \Omega \to [0,1] \qquad (3.1)$$

where $(\varphi) = 0$, and satisfy $\sum_{A \subseteq \Omega} D(A) \leq 1$. The φ in an empty set and A is a subset of φ.

It can be concluded that the definition of D number and basic belief assignment are similar. The difference is that according to the D number theory, the elements Ω are not necessarily mutually exclusive and Ω will be acceptable if it can satisfy $\sum_{A \subseteq \Omega} D(A) \leq 1$.

If we assume that the problem set as: $\Omega = [a_1, a_1, \ldots, a_n]$, and $a_n \in R$. In addition, $a_i \neq a_j$ if $i \neq j$. According to the aforementioned issue, another form of D numbers can be defined by Equation 3.2:

$$D(\{a_1\}) = \mu_1\,,\ D(\{a_2\}) = \mu_2\,, \ldots., D(\{a_n\}) = \mu_n \qquad (3.2)$$

Simply put, it can be denoted as $D = \{(a_1, \mu_1), (a_2, \mu_2), \dots, (a_n, \mu_n)\}$, where $\mu_i \geq 1$ and satisfies $\sum_{i=1}^{n} \leq 1$.

Definition two: (The D combination rule), Assuming that D_1 and D_2 are two independent D numbers and defined as:

$D_1 = \{(a_1^1, \mu_1^1), (a_2^1, \mu_2^1), \dots, (a_n^1, \mu_n^1)\}$

$D_2 = \{(a_m^2, \mu_m^2), (a_m^2, \mu_m^2), \dots, (a_m^2, \mu_m^2)\}$,

The combination of D_1 and D_2 are indicated as $D = D_1 \oplus D_2$ and can be defined via Equation 3.3:

$$D(a) = \mu \qquad (3.3)$$

where

$$a = \frac{a_i^1 + a_j^2}{2} \qquad (3.4)$$

$$\mu = \frac{\mu_i^1 + \mu_j^2}{2} / C$$

And C in Equation 3.4 is defined as follows:

$$\sum_{j=1}^{m} \sum_{i=1}^{n} \left(\frac{\mu_i^1 + \mu_j^2}{2}\right) \qquad (3.5)$$

when $\sum_{i=1}^{n} \mu_i^1 = 1$, and $\sum_{j=1}^{n} \mu_j^2 = 1$.

$$\sum_{j=1}^{m} \sum_{i=1}^{n} \left(\frac{\mu_i^1 + \mu_j^2}{2}\right) + \sum_{j=1}^{m} \left(\frac{\mu_c^1 + \mu_j^2}{2}\right) \qquad (3.6)$$

when $\sum_{i=1}^{n} \mu_i^1 < 1$, and $\sum_{j=1}^{n} \mu_j^2 = 1$.

$$\sum_{j=1}^{m} \sum_{i=1}^{n} \left(\frac{\mu_i^1 + \mu_j^2}{2}\right) + \sum_{j=1}^{m} \left(\frac{\mu_i^1 + \mu_c^2}{2}\right) \qquad (3.7)$$

when $\sum_{i=1}^{n} \mu_i^1 > 1$, and $\sum_{j=1}^{n} \mu_j^2 = 1$.

$$\sum_{j=1}^{m} \sum_{i=1}^{n} \left(\frac{\mu_i^1 + \mu_j^2}{2}\right) + \sum_{j=1}^{m} \left(\frac{\mu_c^1 + \mu_j^2}{2}\right) + \sum_{j=1}^{m} \left(\frac{\mu_i^1 + \mu_c^2}{2}\right) + \frac{\mu_c^1 + \mu_c^2}{2} \qquad (3.8)$$

when $\sum_{i=1}^{n} \mu_i^1 < 1$, and $\sum_{j=1}^{n} \mu_j^2 < 1$.

where $\mu_c^1 = 1 - \sum_{i=1}^{n} \mu_i^1$ and $\mu_c^2 = 1 - \sum_{i=1}^{n} \mu_j^2$.

It should be added that, similar to D-S theory, when the number of observations is increased to 3 or more, the denominator is also changed accordingly.

Definition three: (Aggregation of D numbers), supposing that $D = \{(a_1, \mu_1), (a_2, \mu_2), \ldots, (a_n, \mu_n)\}$ is a D number, the aggregation procedure of D numbers can be derived as Equation 3.9:

$$I(D) = \sum_{i=1}^{n} a_i \mu_i \quad (3.9)$$

3.2.3.2. The procedure of experts' judgment and BWM

The employed procedure of the experts' judgment to estimate the probability of root events and safety barriers have four different steps which are as follows (i) Employing a heterogeneous group of multiple independent experts, (ii) Providing a quality expert profile and expert weighting which have considerable effects on the final results, (iii) Collecting the subjective experts' opinions, and (iv) Aggregating experts' opinions. The details of each expert are provided as follows.

Step one: Employing a group of experts

In the present study, A heterogeneous group of experts having different backgrounds and expertise was employed to independently express their individual opinions in a democratic decision-making style environment. To reduce any ambiguity as well as increase the consistency of experts' opinions in the elicitation procedure, the provided opinions from participants were checked to see whether they required further modification or not.

Step two: Providing quality expert profiles and expert weightings

Estimating a high realistic importance weight for the employed group of experts is an important task. In the present study, the BWM proposed by Rezaei (2015), as a new and powerful multi-criteria decision-making approach to estimate the subjective weights of criteria/alternatives in the typical decision-making problems, was used to obtain the importance weight of the employed experts. Accordingly, in the beginning, the best (i.e. most profitable, most advantageous) and the worst (i.e. least profitable, least advantageous) criteria were regarded by an assessor. The considered criteria were judged according to the best and worst criteria. Afterward, a maximum/minimum objective function was created to calculate the optimum importance weights of criteria. The importance of weight for each expert for other criteria was estimated employing the same process. The BWM was applied to obtain the importance weight of each expert using the following steps:

(i) Identifying the best or the most important criterion and the worst or the least important criterion.

The best criterion C_B and the worst criterion C_W have to be derived using decision-makers from the identified n criterion.

(ii) Computing the preference of the best criterion over the other criteria.

In this step, decision-makers express their opinions about the best criterion over other criteria using the nine-scale provided in Table 3.1, and the vector of best to other (BO) is defined as $C_{BO}^{k}, k = 1,2,3, \dots, l$ which was computed by using Equation 3.10:

$$C_{BO}^{k} = (C_{B1}^{k}, C_{B2}^{k}, \dots, C_{Bn}^{k}) \tag{3.10}$$

where C_{Bj}^{k} is the opinion of an expert on the C_B compared to the C_j, and $C_{BB} = 1$.

Let us assume that the importance weight of l decision-makers is equal. Therefore, l best to others' vectors can be further aggregated into single best to others' vector $C_{BO} = (C_{B1}, C_{B2}, \dots, C_{Bn})$ using Equation 3.11:

$$C_{Bj} = \frac{C_{Bj}^{k}}{l}\ , j = 1,2, .., n \quad (3.11)$$

Table 3. 1 The nine-scale of comparison

Scale	Descriptions
1	C_i has equivalence important C_j
3	C_i has slightly more important than C_j
5	C_i has obviously more important than C_j
7	C_i has strongly more important than C_j
9	C_i has extremely more important than C_j
2, 4, 6, and 8	Mean value of the aforementioned preference opinions

(iii) Computing the preference of the other criteria over the worst criterion.

Similarly, l other to worst (OW) vectors $C_{OW}, k = 1, 2, 3, \dots, l$ is computed by being compared to the other criteria over the worst criterion utilizing the nine - scale (Table 4.1) by Equation 3.12:

$$C_{OW}^{k} = (C_{1W}^{k}, C_{2W}^{k}, \dots, C_{nW}^{k}) \quad (3.12)$$

where C_{jW}^{k} is the opinion of an expert on the C_j compared with the C_W, and $C_{WW} = 1$.

Therefore, l others to worsts' vectors can be further aggregated into a single worst to others' vector $C_{OW} = (C_{1W}, C_{2W}, \dots, C_{nW})$ by applying Equation 3.13:

$$C_{jW} = \frac{C_{jW}^{k}}{l}\ , j = 1,2, .., n \quad (3.13)$$

(iv) Calculate the optimal weights of criteria.

In the BWM, the ratio of $\frac{W_B}{W_j}$ and $\frac{W_j}{W_W}$ followed by $\frac{W_B}{W_j} = C_{Bj}$, and $\frac{W_j}{W_W} = C_{jW}$. To satisfy the aforementioned conditions, a solution by maximizing the value of $\left|\frac{W_B}{W_j} - C_{Bj}\right|$ and minimizing the value of $\left|C_{jW} - \frac{w_j}{w_W}\right|$ should be derived. Accordingly, the following optimization model was employed to estimate the optimal criteria weight:

Model 1:

$$\min \max \left\{ \left|\frac{w_B}{w_j} - C_{Bj}\right| , \left|C_{jW} - \frac{w_j}{w_W}\right| \right\}$$

Subject to.

$$\sum_{j=1}^{n} w_j = 1$$

$$w_j \geq 0 , j = 1,2, \dots n.$$

Model 1 can be reintegrated into model 2:

$$\min \xi$$

Subject to.

$$\left|\frac{w_B}{w_j} - C_{Bj}\right| \leq \xi$$

$$\left|C_{jW} - \frac{w_j}{w_W}\right| \leq \xi$$

$$\sum_{j=1}^{n} w_j = 1$$

$$w_j \geq 0 , j = 1,2, \dots n.$$

The optimal weights of criteria were obtained by solving Model 2 and denoted as follows: $w^* = (w_1^*, w_2^*, \dots, w_n^*)$.

(v) Compute the consistency of the obtained results from decision-makers.

To compute the value of consistency, first, it is necessary to derive the consistency ratio (CR) using Equation (3.14) [31]:

$$CR = \frac{\xi^*}{CI} \tag{3.14}$$

where CR is the consistency index regarding the maximum value of ξ based on Table 3.2. The smaller value of CR shows better consistency. In the current study, the condition $CR \leq 0.1$ was considered to accept the weights of criteria.

Table 3. 2 Consistency index (CI)

C_{BW}	CI
1	0.00
2	0.44
3	1.00
4	1.63
5	2.30
6	3.00
7	3.73
8	4.47
9	5.23

Step three: Collecting subjective opinions

The group of experts expressed their individual opinions to derive the probability of each event. In cases with a lack of data and insufficient information, subjective opinions are collected from a group of experts. The estimation of results was provided as intuitionistic fuzzy numbers (IFNs). Afterward, the IFNs were converted to D numbers, and subsequently, the combination rule of D numbers was used to elicit group opinions. The employed linguistic terms and their IFNs are provided in the appendix (section 2) [32].

Step four: Aggregating experts' opinions

Based on their quality profile, the group of experts employed may have different opinions. Hence, it is necessary to aggregate multiple experts' opinions to reach a consensus. Once all the IFNs were derived from expert evaluations, D number theory was employed to elicit group opinions. All the expert opinions were aggregated into the crisp value considering their importance weight based on their background information provided by Equation (3.15).

$$A^{\text{agg}} = \sum_{i=1}^{n} \omega_n^* a_i \mu_i \tag{3.15}$$

where A is the aggregated opinions obtained from experts and ω is the importance weight of experts, and a_i and μ_i are the first and second components of D numbers, respectively.

It should be noted that in the original Equation of D numbers theory (Eq. 9), the importance weight of experts was ignored, whereas as a new contribution of this study Equation 9 was modified into Equation 15. Once the aggregated opinions are obtained from the employed expert, the possibility can be converted into the probability by Equation 3.16.

$$P = \begin{cases} 1/10^K & , CP \neq 0 \\ 0 & , CP = 0 \end{cases} \quad , \quad K = \left[\left(\frac{1}{CP} - 1\right)\right]^{1/3} \times 2.301 \tag{3.16}$$

where *P* is the probability of the desired events (i.e., root events, safety barriers), and *CP* (crisp probability) denotes the confidence degree of membership (crisp possibility) obtained from Equation 3.15.

3.2.4. Dynamic Bayesian Network (DBN) (Step 4)

3.2.4.1. Dynamic modelling of hydrogen release probability (HRP) and system reliability

The prior obtained probabilities were defined as failure probabilities of the root events and safety barriers in the Bow time-based model to develop a DBN model. A detailed description of mapping BT to DBN can be found in the works of [33]. A DBN is a long-established extension of static BN with additional algorithms, and it is a well-known tool to model the time series phenomena due to its modeling of the dynamic relationships of variables. To recall briefly DBN, it is characterized to be a set $(A_1 \colon A_{\rightarrow})$ where A_1 show a BN which presents the prior $\mathrm{P}(Z_1)$, and $A_{\rightarrow}$ shows a two-time series temporal network, which defines $\mathrm{P}(Z_t|Z_{t-1})$ using a directed acyclic graph as follows [34]:

$$\mathrm{P}(Z_t|Z_{t-1}) = \prod_{i=1}^{N} P\left(Z_t^i \middle| Pa(Z_t^i)\right) \tag{3.17}$$

where Z_t^i is the i'th node at time t, can be an element of $X_t, Y_t\ or\ U_t$ and Pa(Z_t^i) is the parent of Z_t^i in the network.

After the first time slice, each nod has a conditional probability table (CPT), which defines $P\left(Z_t^i \middle| Pa(Z_t^i)\right)$, and the function of the joint probability density for time t=1 to N is presented as:

$$\mathrm{P}(Z_{1=T}) = \prod_{t=1}^{T} \prod_{i=1}^{N} P\left(Z_t^i \middle| Pa(Z_t^i)\right) \tag{3.18}$$

To present the dynamic features of the developed model, the dynamic occurrence probability of the hydrogen release scenario and the reliability of the hydrogen generation system within 52 weeks were modeled using the DBN model. To establish CPT between two-time slices, the probability of failure in the current state (t) is considered 1 when failure happens in the previous state (t-1), while the probability of failure in the current state is $1 - e^{-\lambda T}$ when failure does not take place in the previous state. It is assumed that failures follow a constant failure rate (λ) distribution that has an exponential distribution function [35,36]. In this case, the reliability of the system is $e^{-\lambda T}$. It is noteworthy that different applications, for instance, effectiveness of safety interventions, and the effect of different pieces of evidence (observations) over a period can be investigated using the model.

3.2.4.2. Deductive and Abductive reasoning

This section attempts to address some existing limitations of the conventional risk analysis methods of hydrogen infrastructures using Bayes' theorem. Therefore, the model was utilized to illustrate inferences; predictive modeling (*Deductive reasoning)* and updating the risk profile under uncertainty (*Abductive* reasoning). In other words, deductive reasoning (forward analysis) is a predictive analysis under uncertainty to estimate the prior occurrence probability of the top event, while abductive reasoning (backward analysis), as a unique feature of BN, is a logical inference that begins by obtains evidence or a set of evidence, and next looks to determine the simplest and most probable explanation for the evidence [37].

3.2.4.3. Critical analysis

Applying only prior or posterior probabilities to determine the factors that contribute the most is highly probable to result in incorrect findings. Hence, in the current work, the ratio of variation (RoV) of probability, which developed recently as a precise important measure for sensitivity analysis in Bayesian assessment of system safety, was utilized to identify the most contributing root events to the occurrence of the hydrogen release. The RoV of each root event is estimated as follows [38].

$$Rov(X_i) = \frac{\pi(\mathrm{X_i}) - \theta(\mathrm{X_i})}{\theta(\mathrm{X_i})} \tag{3.19}$$

where $\pi(\mathrm{X_i})$ and $\theta(\mathrm{X_i})$ denote the posterior and prior failure probabilities, respectively, of $\mathrm{X_i}$.

3.2.4.4. Predictive modelling of safety barriers and consequences

The predictive safety barrier modeling is mainly conducted based on the SHIPP methodology which is a systematic approach to model the safety barrier thereby predicting and preventing future accidents in the chemical process industry [39,40]. To calculate the number of abnormal events in the next time interval y_{t+1}, given the observed data, a predictive model was utilized based on Eq. (3.20) [40];

$$p((y_{t+1}|date) = \frac{{\lambda_p}^{y_{t+1}}\, e^{\lambda p}}{y_{t+1}!} \tag{3.20}$$

where *data* = ($y_1, y_2, y_3 \ldots y_t$) is the number of abnormal event data in the time t, λ_p is the updated rate of abnormal events as calculated via Eq. (3.21):

$$\lambda_p = E\left[\frac{\lambda}{data}\right] = \frac{\alpha+\sum_{i=n}^{n} y_n}{\beta+n} \tag{3.21}$$

where $\sum_{i=n}^{n} y_n$ is the total number of abnormal events in the time interval n, and α and β are gamma distribution parameters of λ which are taken as 0.01.

By applying the updating mechanism, the posterior failure probability was estimated using Bayes' theorem [41] as presented in Eq. (3.22):

$$p\left(\frac{y_i}{data}\right) = \frac{p\left(\frac{data}{y_i}\right)p(y_i)}{\sum p\left(\frac{data}{y_i}\right)p(y_i)} \tag{3.22}$$

where $p\left(\frac{y_i}{data}\right)$ indicates the posterior failure probability, $p(y_i)$ is the prior probability of y_i, $p\left(\frac{data}{y_i}\right)$ is the likelihood failure probability extracted from abnormal event data from the plant, and *data* is the new observation from the plant. The likelihood failure probability of each safety barrier can be estimated according to Eq. (3.23 and 3.24):

$$p\left(\frac{y_i}{data}\right) = \frac{N_{F,i}}{N_{F,i}+N_{S,i}} \tag{3.23}$$

$$N_{F,i} = \sum_{k>i} N_{C,k} \ and \ k > i, i = 1,2,3,4 \ and \ K = 1,2,3,4,5 \tag{3.24}$$

where $N_{c,k}$ is the number of abnormal events of consequence kth level, $N_{S,i}$ and $N_{F,i}$ are the number of successes and failures for the ith barrier.

3.3. The application of the model

3.3.1. Establish the Context (Description of hydrogen generation plant)

To present the utilization of the proposed methodology, a real case study was conducted on a hydrogen generation plant by alkaline water electrolysis in a combined-cycle power plant. In the studied plant, electrolysis employed electricity to break water into hydrogen and oxygen, is a successful alternative for hydrogen generation from renewable resources. This reaction happens in an electrolysis cell, and it consists of an anode and a cathode separated by an electrolyte. The alkaline electrolyzers used an electrolyte such as sodium or potassium hydroxide, to convey the hydroxide ions (OH^-) from the cathode to the anode while hydrogen was produced on the latter side. This process lead to zero greenhouse gas emissions and the purity of generated hydrogen is very high (> 99.999%). For some usages, such as polymer electrolyte membrane fuel cells that require ultra-pure hydrogen, electrolysis may currently be the only available means to produce hydrogen that can meet this demand [42]. Fig. 3.2 illustrates the main equipment of the studied hydrogen plant, both structurally and functionally.

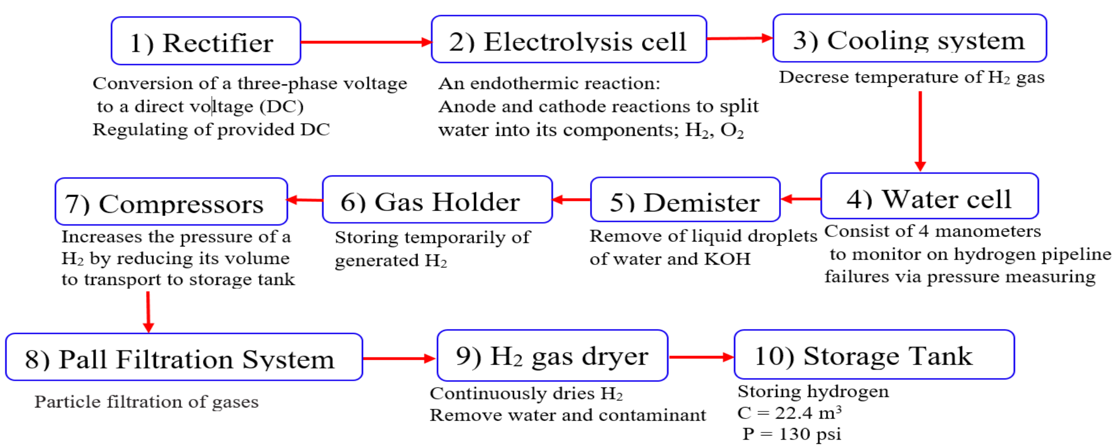

Figure 3. 2 A block diagram of hydrogen generation plant by alkaline water electrolysis.

3.3.2. Causation Factor Modeling

The results of causation factor modeling of hydrogen release scenarios in the three sections (i.e., chemical, mechanical, and storage sections) are shown in Fig. 3.3a, b, c., while Fig. 3.4. illustrates the entire scenario of the studied plant. Applying the Bow tie logic as well as employing well-rounded engineers with different professional backgrounds to perform the causality modeling revealed that a wide range of contributory factors (Fig. 3.3, Table 3.3) was at the root of hydrogen release. These influential latent factors can be classified as, 1) from individuals (i.e., poor training, lack of risk awareness) to organizational factors (i.e., maintenance issues, resource management), 2) from operational (i.e., overpressure, overcurrent) to mechanical failures (i.e., electrolytic corrosions, rectifier malfunctions), and 3) from job difficulties (i.e., workload, shift work) to external events (i.e., natural hazards). A holistic causality modeling in risk analysis studies was rarely observed however, identifying all latent failures is vital to effectively developing both preventive and mitigating safety measures. This finding helps to extend probabilistic safety analysis modeling frameworks to include the effect of human and organizational factors, as more fundamental and latent causes of accident occurrence, along with operational and mechanical failures which are more observable causes. Moreover, modeling of common-mode failures (CMF) and their dependency on using BN improve the transparency and accuracy of causation analysis of accident scenarios (Fig. 3.3). For instance, X_{24} (lack of on-time preventive maintenance (PM) of temperature indicators (not temperature sensor) in chemical sections) contributed to the intermediate events of IE16, IE 19, IE21, and IE22 (Fig 3.3a).

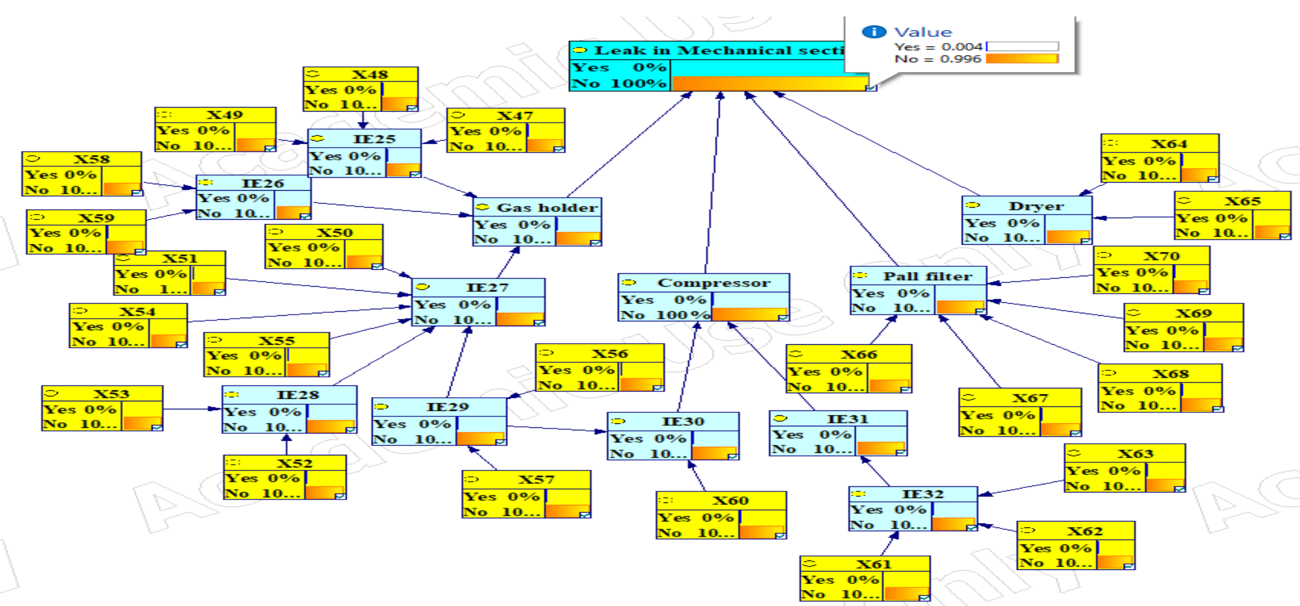

Figure 3. 3a Causality modeling of hydrogen release in the chemical section of the plant

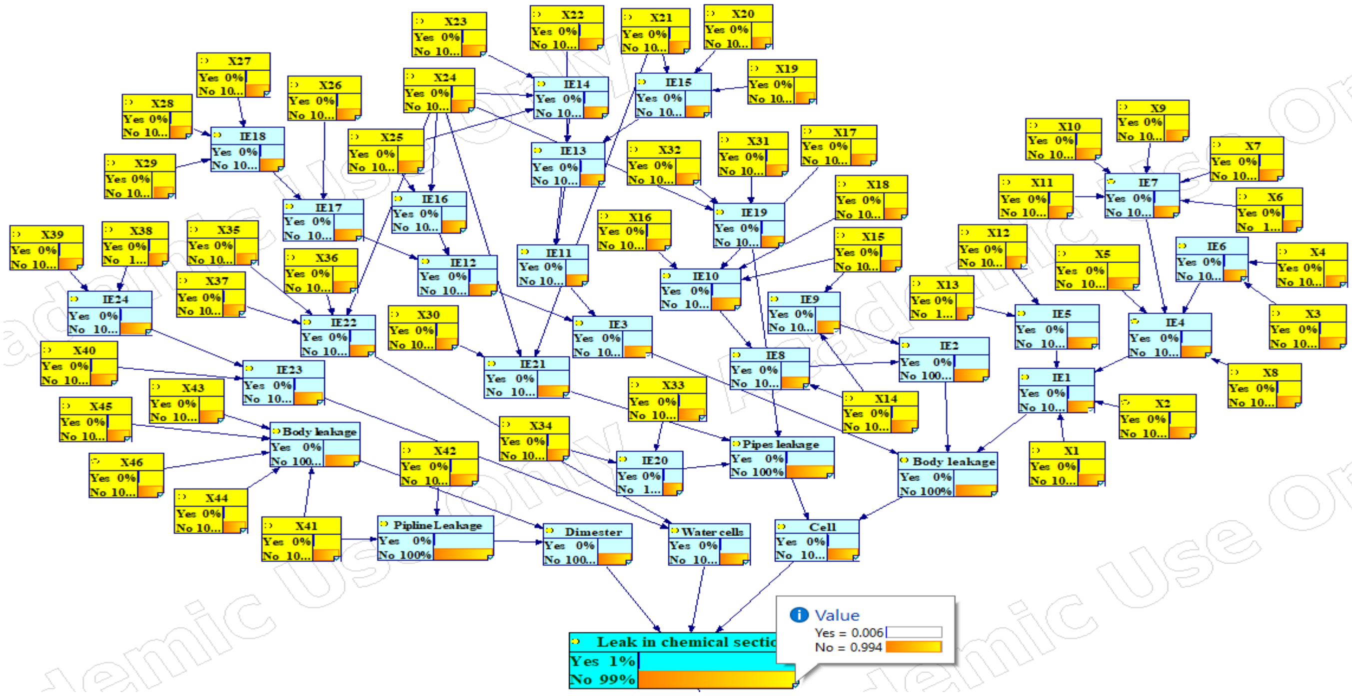

Figure.3.3b. Causality modeling of hydrogen release in the mechanical section of the plant

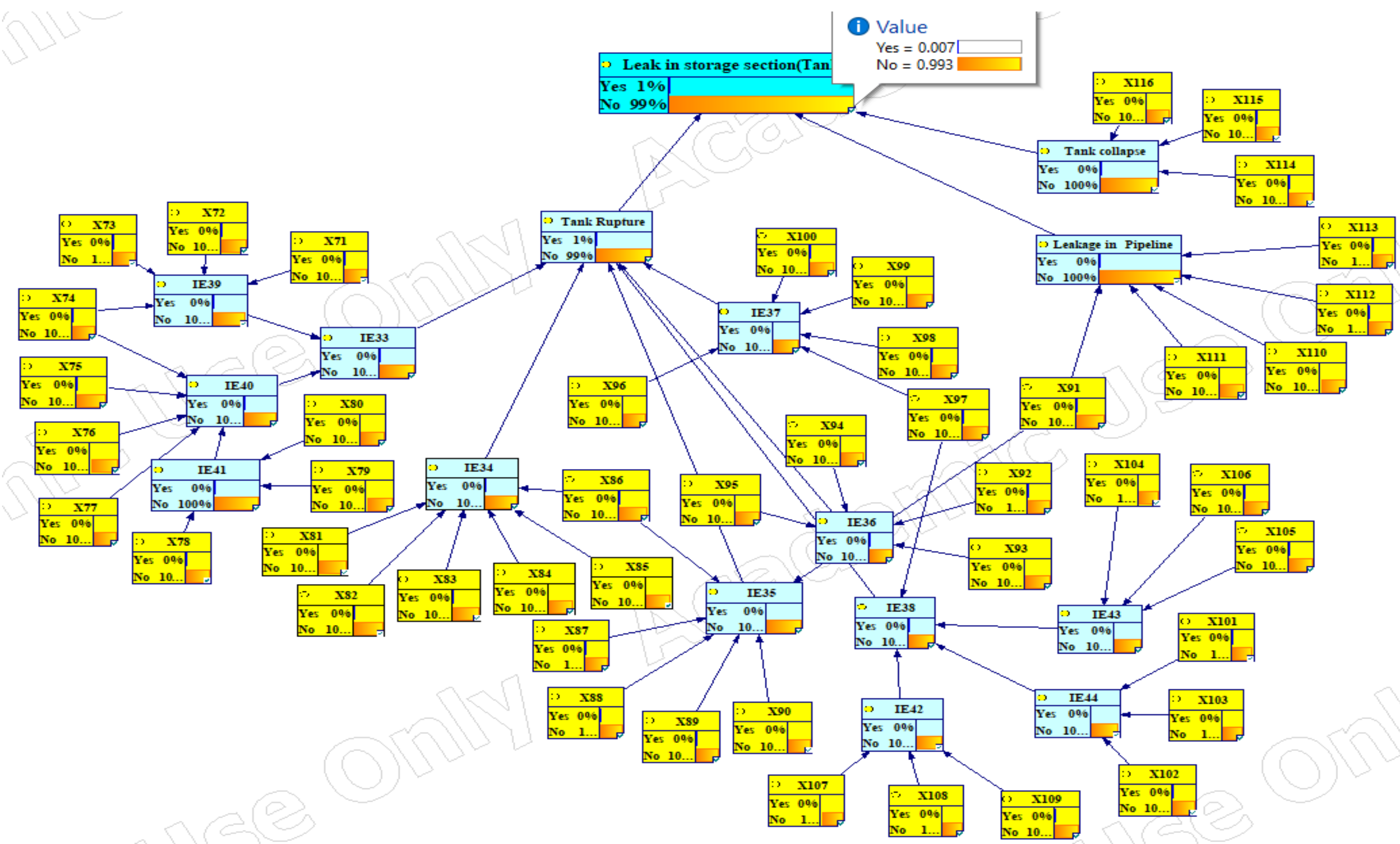

Figure.3.3c. Causality modeling of hydrogen release in the storage section of the plant

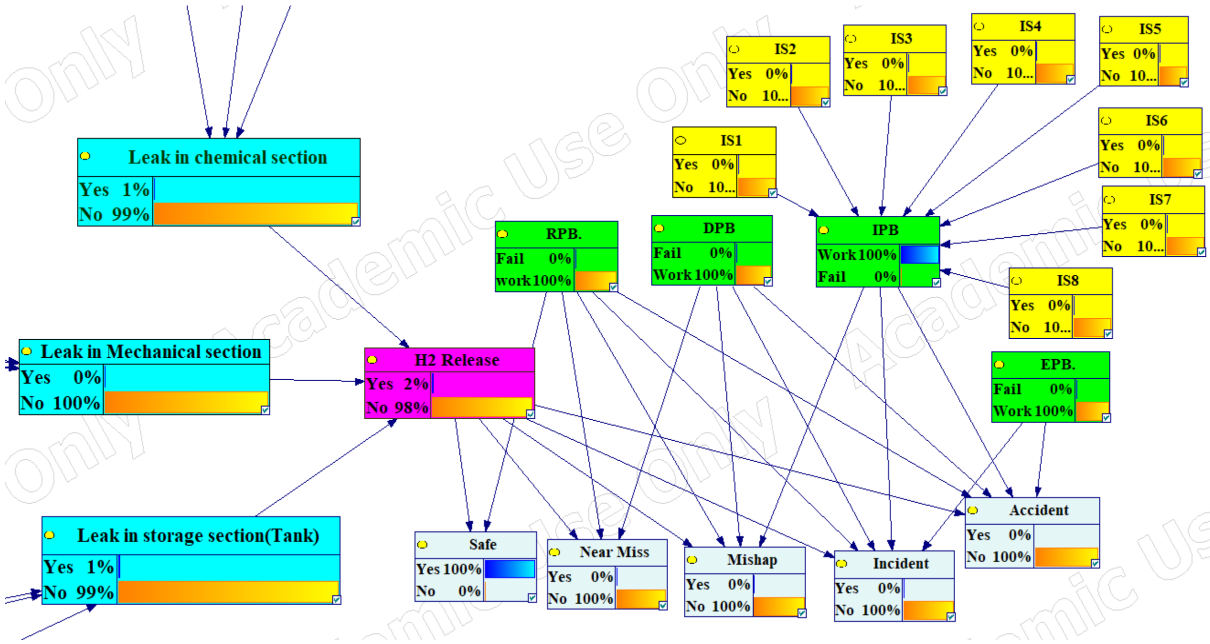

Figure 3. 4 Causality modeling of the cause-effect model of the hydrogen release accident scenario

The hydrogen release probability is estimated at 0.017 (Fig 3.4), which indicates a high value. This is due to system degradation and numerous contributing factors to the accident scenario. Tables 3.3a, b, and c provide the identified root events, a description thereof, and symbols in the three sections (i.e., chemical, mechanical, and storage) of the studied plants. However, for a better understanding of the model's applicability, the intermediate events and their descriptions are presented in the appendix (section 3). Causality modeling revealed that at least 116 root causes contributed to hydrogen release in the alkaline water electrolysis plant. Each of the two chemical and storage sections is involved equally in the number of contributing events (46 events), while 24 root events were identified in the mechanical section that caused hydrogen release.

Table 3. 3a Subsections, symbols, and root events of the chemical section in the studied plant

Section, subsection	Symbol	root event	Subsection	Symbol	Root event
*1. **Chemical section***					
1.1. Cell release	X1	Electrolytic corrosion	*1.2. Pipeline cell release*	X24	Lack of on-time PM of temperature indicators
	X2	Lack of cathodic protection		X25	Ignorance of useful life
	X3	Lack of maintenance by the manufacturer		X26	Inadequate technical knowledge
	X4	Unavailable technical information		X27	Inadequate training about power system
	X5	Lack of thickness measurement		X28	Operator distraction
	X6	Poor risks awareness/perception		X29	Being multitask/job
	X7	Inadequate safety training		X30	Equipment exhaustion
	X8	Failure in thickness testing		X31	High H_2 temperature
	X9	Inadequate budget		X32	Overuse of hose
	X10	Shortage of labor		X33	Increasing H_2 production
	X11	Heavy workload due to power production		X34	Hydrogen over-accumulation by sediments
	X12	Overvoltage by failure in Rectifier		X35	The entrance of KOH and H_2O to pipeline
	X13	Increase KOH density	*1.3. Water cell*	X36	Lack of timely change of pipes
	X14	H_2O sediment		X37	Decarbonated water of cooling system
	X15	Move out KOH from cells		X38	Inadequate injection of methyl orange
	X16	Water box function error		X39	Failure in manometers
	X17	The entrance of KOH to pipeline		X40	Operator failure in checking manometer
	X18	Overcurrent by rectifier	*1.4. Demister*	X41	Exhaustion of junctions.
	X19	Not checking cells temperature		X42	Loosening of junctions.
	X20	Lack of a permanent presence operator		X43	Failure of thickness testing
	X21	Operator failure (e.g., memory failure)		X44	Failure in the cooling system (cooler)
	X22	The closed water circulation path		X45	Corrosion with H_2O and KOH
	X23	Calibration failure		X46	Failure in cell functions

Table 3. 3b Subsections, symbols, and root events of the mechanical section in the studied plant

Section, subsection	Symbol	Root event	Subsection	Symbol	Root event
2. Mechanical section	X47	Decarbonated water in gas holder	*2.1. Compressors*	X59	Adjusting sensors and indicators failure
2.1. Gas Holder	X48	Aging	*2.2. H_2 gas dryer*	X60	Flaw communication of compressor and rectifier
	X49	Pure water existence in the gas holder		X61	Rectifier's malfunction
	X50	Clogged the outlet pipe		X62	Operator failure in rectifier operations
	X51	The flaw in minimum level sensor		X63	Pressure gage error
	X52	Compressor shut down	*2.3. Pall filter*	X64	Poor junctions
	X53	The flaw in compressor activator sensor		X65	Loose bolts
	X54	Being closed of venting pipe		X66	Filter saturation
	X55	The flaw in maximum level sensor		X67	Flaws in filter replacement process
	X56	Connection failure to the rectifier		X68	Poor filtration
	X57	Failure in sensor		X69	Lack of timely filter replacement
	X58	Failure in temperature indicator		X70	Blocking filter membranes

Table 3.3c. Subsections, symbols, and root events of the storage section in the studied plant

Section, subsection	*Symbol*	Root event	Subsection	*Symbol*	Root event
3. Storage section	X71	The flaw in Anti-corrosion layer		X94	Shear stress
	X72	Failure in cathodic protection		X95	Heat fatigue
	X73	Entrancing of H_2O into the tank		X96	Lack of sheltering
	X74	Failure in inrepairment and maintenance	*3.5. Temperature fluctuations*	X97	Inlet gas temperature higher than normal
	X75	Poor inspection program		X98	Overheating of the frozen pipelines
3.1. Tank Body Corrosion	X76	Erosion		X99	Hot work in adjacent
	X77	Poor detection of corrosion		X100	Direct sunlight
	X78	Freezing water		X101	Remaining close relief valve
	X79	Water collecting in pits by snow and rain		X102	Inadequate capacity of the relief valve
	X80	Heavy snow and rain		X103	Failure in PSV adjusting and repairment
	X81	Vehicle impact		X104	Poor repairment and maintenance
	X82	Aircraft/Helicopter impact	*3.6. Overpressure*	X105	Lack of operator's attention during work
3.2. Tank rupture due to the external event	X83	Earthquake		X106	System viruses by a terrorist attack
	X84	Heavy storms		X107	Sediment formation
	X85	Flood		X108	H_2 Freezing
	X86	Terrorist attack		X109	Harsh weather
	X87	Ignoring safety distance for H2 tank		X110	Poor maintenance
3.2. *Crash heavy objects*	X88	The flaw in contractors' safety regulation	*3.7. Leakage in Pipeline*	X111	Pipe Corrosion
	X89	Falling equipment and machines during PM		X112	Increasing pressure
	X90	Falling trees		X113	Freezing H_2O and H_2O sediment
	X91	Third-party sabotage		X114	Induced vacuum
3.4. Mechanical fatigue	X92	Tangential stress	3.8. *Tank collapse*	X115	Excessive outlet flow
	X93	Axial stress		X116	Loading stopped

3.3.3. Probability Elicitation under Epistemic Uncertainty

The four experts were asked to express their opinions on the linguistic terms to estimate the possible occurrence of root events and safety barriers. According to the literature and the present study conditions, several criteria including job field, experience, age, and education level were considered. For easy reading and understanding of the model application, the experts' profiles are presented in the appendix (section 3), while the corresponding decision weights of experts are represented in Table 3.4.

Table 3. 4 Importance weight of experts based on criteria

Criteria		$\mathfrak{C}\#1$	$\mathfrak{C}\#2$	$\mathfrak{C}\#3$	$\mathfrak{C}\#4$	Final weight
Weight of criteria		0.234	0.57	0.141	0.055	
Experts	E1	0.155	0.086	0.143	0.228	0.118
	E2	0.094	0.603	0.143	0.497	0.413
	E3	0.129	0.172	0.143	0.171	0.158
	E4	0.622	0.138	0.571	0.104	0.310

The following four different criteria were employed to evaluate the quality profile of the decision-makers: job field ($\mathfrak{C}\#1$), experience ($\mathfrak{C}\#2$), education level ($\mathfrak{C}\#3$), and age ($\mathfrak{C}\#4$). The optimal weights of the main criteria were derived as model 3 and are provided in Table 3.5.

Table 3. 5 The optimal importance weight of criteria

BWM	Main criteria of decision-makers			
	$\mathfrak{C}\#1$	$\mathfrak{C}\#2$	$\mathfrak{C}\#3$	$\mathfrak{C}\#4$
Best ($\mathfrak{C}\#2$)	3	1	5	8
Worst ($\mathfrak{C}\#4$)	6	8	5	1
Optimal weights	0.234	0.570	0.141	0.055
Reliability score (RS)	0.130			

Note: RS illustrates to what extent the results are reliable, the closer the RS to zero is the better.

The optimal weight of the main criteria was calculated for each expert. To reach this, adopting model 2, the optimal weight of the main criteria was derived as model 4 (appendix, section 3) and provided in Table 3.6.

Table 3. 6 The optimal importance weight of experts based on experience criterion

	decision-makers (employed experts)			
BWM	E#1	E#2	E#3	E#4
Best (E#2)	6	1	4	5
Worst (E#1)	1	7	3	2
Optimal weights	0.086	0.603	0.172	0.138
Reliability score (RS)	0.086			

Note: RS (reliability score) illustrates to what extent the results are reliable, the closer the RS to zero is the better.

Similar to the experience criterion, presented in the appendix (Section 3), the optimal importance weight of all the employed experts in terms of education level, job field, and age was calculated. Accordingly, the final importance weight of decision-makers as $\omega_{E\#1}$, $\omega_{E\#2}$, $\omega_{E\#2}$ and $\omega_{E\#3}$ with consideration of all criteria fall to 0.118, 0.413, 0.158, and 0.310, respectively.

Therefore, BWM, as a new and powerful MCDM technique, can remedy some uncertainties raised from the application of input data (i.e., prior profanities) in risk analysis studies. The main reason for this capability is that BWM applied a systematic and structured mechanism to perform a pairwise comparison of the decision criteria compared to other available MCDM methods which provided substantially better results in evaluation criteria (i.e., consistency ratio, minimum violation, total deviation, and conformity). This merit leads to not only more reliable and consistent results but also avoids false or unrealistic criteria weights [27]. In addition, a consistency ratio was used to check the reliability of the comparisons and final outputs. This is the first work to present this matter in safety and risk studies of the hydrogen economy.

In the next step, after collecting all experts' opinions (appendix, section 2), D number theory was employed to elicit group opinions, and the obtained possibility and prior probability in terms of D numbers are provided in Table 3.7. To simplify the calculation details, root event X7 (Inadequate safety training) was considered as an example to present the calculations (see the section 4 in the appendix)

Table 3. 7 Possibility and the prior marginal probability of the root events and safety barriers in terms of D numbers

No.	Possibility	Probability	No	Possibility	Probability	No	Possibility	Probability
X1	0.1519	8.27E-05	X44	0.2361	3.95E-04	X87	0.1947	2.03E-04
X2	0.1561	9.16E-05	X45	0.1845	1.67E-04	X88	0.1783	1.48E-04
X3	0.1344	5.23E-05	X46	0.1985	2.17E-04	X89	0.1909	1.89E-04
X4	0.2047	2.41E-04	X47	0.1112	2.51E-05	X90	0.1785	1.49E-04
X5	0.1560	9.13E-05	X48	0.1551	8.94E-05	X91	0.1892	1.83E-04
X6	0.1442	6.82E-05	X49	0.2182	3.01E-04	X92	0.1818	1.59E-04
X7	0.1517	8.23E-05	X50	0.1954	2.05E-04	X93	0.1818	1.59E-04
X8	0.1399	6.08E-05	X51	0.1791	1.51E-04	X94	0.1823	1.60E-04
X9	0.1236	3.79E-05	X52	0.1320	4.89E-05	X95	0.1840	1.66E-04
X10	0.2246	3.33E-04	X53	0.1579	9.54E-05	X96	0.1503	7.97E-05
X11	0.1988	2.18E-04	X54	0.1815	1.58E-04	X97	0.1897	1.85E-04
X12	0.2044	2.40E-04	X55	0.2040	2.38E-04	X98	0.1677	1.19E-04
X13	0.1006	1.67E-05	X56	0.1877	1.78E-04	X99	0.1512	8.13E-05
X14	0.1814	1.58E-04	X57	0.2008	2.26E-04	X100	0.1206	3.46E-05
X15	0.1472	7.36E-05	X58	0.1641	1.10E-04	X101	0.1627	1.07E-04
X16	0.1456	7.08E-05	X59	0.1657	1.14E-04	X102	0.1818	1.59E-04
X17	0.1759	1.41E-04	X60	0.2008	2.26E-04	X103	0.2108	2.67E-04
X18	0.1791	1.51E-04	X61	0.1675	1.18E-04	X104	0.2266	3.43E-04
X19	0.1807	1.55E-04	X62	0.1610	1.02E-04	X105	0.1932	1.97E-04
X20	0.0958	1.37E-05	X63	0.2171	2.96E-04	X106	0.1664	1.16E-04
X21	0.1462	7.19E-05	X64	0.1541	8.73E-05	X107	0.1969	2.11E-04
X22	0.2281	3.51E-04	X65	0.1620	1.05E-04	X108	0.1327	4.98E-05
X23	0.1757	1.41E-04	X66	0.2083	2.57E-04	X109	0.1634	1.08E-04
X24	0.2298	3.60E-04	X67	0.1874	1.77E-04	X110	0.2127	2.76E-04
X25	0.1427	6.56E-05	X68	0.1698	1.24E-04	X111	0.1571	9.36E-05
X26	0.1896	1.85E-04	X69	0.2032	2.35E-04	X112	0.1759	1.41E-04
X27	0.1605	1.01E-04	X70	0.1802	1.54E-04	X113	0.1842	1.66E-04
X28	0.1752	1.39E-04	X71	0.1752	1.39E-04	X114	0.1419	6.43E-05
X29	0.1206	3.46E-05	X72	0.1383	5.83E-05	X115	0.2051	2.43E-04
X30	0.1577	9.49E-05	X73	0.1857	1.71E-04	X116	0.2213	3.16E-04
X31	0.1823	1.60E-04	X74	0.1722	1.31E-04	Safety barriers		
X32	0.0552	1.17E-06	X75	0.1868	1.75E-04	RPB	0.2306	3.64E-04
X33	0.1446	6.90E-05	X76	0.1957	2.06E-04	DPB	0.2416	4.27E-04
X34	0.1665	1.16E-04	X77	0.1969	2.11E-04	IPB	0.1755	1.18E-03
X35	0.1573	9.41E-05	X78	0.2036	2.37E-04	EPB	0.1763	1.42E-04
X36	0.1843	1.67E-04	X79	0.1545	8.81E-05	IS1	0.1720	1.30E-04
X37	0.1030	1.85E-05	X80	0.1651	1.12E-04	IS2	0.2300	3.61E-04
X38	0.1913	1.90E-04	X81	0.1815	1.58E-04	IS3	0.2058	2.46E-04
X39	0.1788	1.50E-04	X82	0.1079	2.22E-05	IS4	0.1634	1.08E-04
X40	0.2329	3.77E-04	X83	0.1873	1.77E-04	IS5	0.1636	1.09E-04
X41	0.1674	1.18E-04	X84	0.1799	1.53E-04	IS6	0.1499	7.88E-05
X42	0.1909	1.89E-04	X85	0.1350	5.33E-05	IS7	0.1512	8.13E-05
X43	0.1615	1.04E-04	X86	0.1134	2.71E-05	IS8	0.1456	7.08E-05

IS, Ignition source; IS1, Hot surfaces; IS2, Static sparks; IS3, Hot work; IS4, Stray current; IS5, Electrical apparatus sparks; IS6, Open fires; IS7, Lightning sparks; IS8, Impact sparks.

As a result, the uncertain information regarding the prior occurrence probabilities was modeled by reasoning and synthetization of information implemented by the D numbers combination rule. The applied D numbers theory inherits the advantage of Dempster-Shafer theory and strengthens its capability of uncertainty modeling. Xiao, (2019) indicated DNT provides an excellent performance to copy with arisen uncertainties from imprecision, fuzziness, and incompleteness in subjective judgment, and it is a more reliable and effective expression of uncertain information. The main reason to prove its unique ability to represent and tackle the uncertainty is that it has no restrictions where the sets on the frame of discernment must be mutually exclusive and collectively exhaustive, and the sum of total focal elements of the basic probability assignment must be equal to one [28,43].

3.3.4. Dynamic Bayesian Network

3.3.4.1. Dynamic hydrogen release probability modeling and system reliability

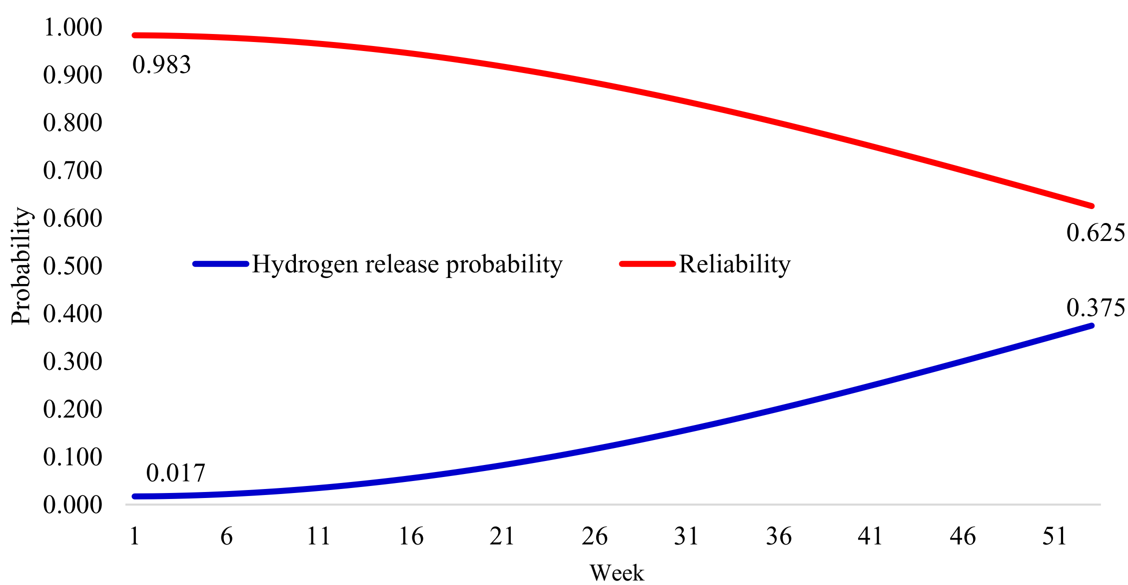

Figure 3. 5 Dynamic modeling of hydrogen release probability and the system reliability using DBN

The dynamic probability of the hydrogen release scenario and the hydrogen generation system's reliability within 52 weeks are shown in Fig. 3.5 using DBN. As shown in the results, the probability increases significantly from 0.017 to 0.375 in the 52nd week. Moreover, the reliability of the studied plant decreases substantially from 0.983 to 0.625 in the last week. In other words, hydrogen generation system's reliability declines 36.42% in the next year, which means the system degrades dramatically during the time interval. As a result, a catastrophic accident will most likely happen soon if the system safety does not improve fundamentally. Hence, given the results of the root events that contribute the most (criticality analysis) to the accident scenarios occurrence, implementing preventive safety measures can improve the system's safety and reliability.

3.3.4.2. Deductive and Abductive reasoning

The results of deductive (prior probability) and abductive (posterior probability) reasoning for the hydrogen release accident scenario and hydrogen release from the three main sections (e.g., chemical, mechanical, and storage) are presented in Table 3.8. The abductive reasoning through the developed model (Fig.3.3 and 3.4) showed the prior occurrence probability for the hydrogen release accident scenario was 1.71E-02, which is considerably high. Moreover, the results illustrated that both the prior and posterior occurrence probability of hydrogen release in the storage section was higher than in the other sections. It is noteworthy that the posterior failure probabilities in the three sections were obtained as $P(Section_i = fail|\, Hydrogen\, accident\, release\ =\ yes)$. In other words, the state of the hydrogen accident release scenario was assigned as Yes (Occurrence probability = 1) to update the failure probabilities of root events.

Table 3. 8 Hydrogen loss scenario and corresponding probabilities

Scenarios description	Prior	Posterior	RoV	Criticality
Hydrogen release accident scenario (HRAS)	1.71E-02	1	-	-
Chemical section release (CSR)	6.44E-03	3.76E-01	5.74E+01	3
Mechanical section release (MSR)	3.81E-03	2.23E-01	5.74E+01	1
Storage section release (SSR)	6.97E-03	4.07E-01	5.74E+01	2

Table 3.9 demonstrates the five possible final consequences which can result from the hydrogen release according to the functions (work or failure) of the safety barriers. Applying an abductive inference on the developed model to predict the prior occurrence probability of the consequences indicates that the result of a safe state was more probable than other events because of the lower failure probability of the release prevention barriers. In other words, the events with high occurrence probabilities have less severe consequences, whereas the events with more severe outcomes have lower occurrence probabilities.

Table 3. 9 Consequences, their description, and corresponding prior probability

Consequence	Description	Prior probability
Safe	Normal state	1.71E-02
Near miss	No injury	6.23E-06
Mishap	Minor impact on property, human and environment	2.66E-09
Incident	Considerable loss or harm	3.16E-12
Accident	Fatality or fatalities	4.49E-16

3.3.4.3. Critical Analysis

One of the most critical steps in developing a risk management plan is to understand the nature of the root events that contribute most often to the occurrence of accident scenarios. With this information, safety measures and strategies to mitigate and prevent similar accident scenarios can be developed. This should be done by applying a precise approach to accurately specify the identified root events. The findings demonstrated latent events *third party sabotage* as X91, *heavy workload due to power generation* as X11, *excessive outlet flow* as X15, *lack of on-time repairs,* *and maintenance* as X104 had the contributed most frequently to the occurrence of the accident scenario. Therefore, the plant's risk management plan should consider mitigating these root events as the top priority. Furthermore, as can be seen from Table 3.8, the critical analysis of hydrogen release indicated that the criticality of the mechanical section was higher than other sections based on RoV (Table 3.8). However, it is noteworthy that according to both prior and posterior probability, this section had the lowest criticality. Hence, relying on merely prior or posterior probability may lead to incorrect results in sensitivity analysis in Bayesian safety assessment. This issue is discussed fully and enough evidence to deal with that using a new importance measure named RoV is proposed in [38].

3.3.4.4. Predictive modeling of safety barriers and consequences

Tables 4.10 and 4.11 provide information about the cumulative number of abnormal events within each severity level (e.g., safe, near miss, mishap, incident, and accident) for the year 2019. This data was derived from the hazard analysis process, and likelihood failure probability for safety barriers over 12 months, respectively. For simplification, the likelihood failure probability of RPB for the first month (0.6000), as an example, calculated based on Eq. (3.21 and 3.22) as $\frac{3+2+1}{4+3+2+1} = 0.6000$ (Table 3.11).

Table 3. 10 Cumulative number of abnormal events over12 months

Month	Safe	Near miss	Mishap	Incident	Accident
1	4	3	2	1	0
2	8	9	3	1	0
3	13	15	5	2	0
4	30	45	16	9	1
5	35	60	21	11	1
6	36	75	22	12	1
7	48	80	23	13	1
8	52	88	25	14	1
9	55	95	25	16	2
10	56	101	27	16	2
11	59	108	28	18	2
12	61	111	28	19	3

Table 3. 11 Likelihood failure probability for safety barriers

Month	RPB	DPB	IPB	EPB
1	6.00E-01	5.00E-01	3.33E-01	0.00E+00
2	6.19E-01	3.08E-01	2.50E-01	0.00E+00
3	6.29E-01	3.18E-01	2.86E-01	0.00E+00
4	7.03E-01	3.66E-01	3.85E-01	1.00E-01
5	7.27E-01	3.55E-01	3.64E-01	8.33E-02
6	7.53E-01	3.18E-01	3.71E-01	7.69E-02
7	7.09E-01	3.16E-01	3.78E-01	7.14E-02
8	7.11E-01	3.13E-01	3.75E-01	6.67E-02
9	7.15E-01	3.12E-01	4.19E-01	1.11E-01
10	7.23E-01	3.08E-01	4.00E-01	1.11E-01
11	7.26E-01	3.08E-01	4.17E-01	1.00E-01
12	7.25E-01	3.11E-01	4.40E-01	1.43E-01

The capacity for predictive modeling is a unique feature of the proposed model. The ability to anticipate future risk levels is a momentous issue in the risk management of dynamic systems where safety barriers may degrade over the time. In these contexts, having posterior failure probability distribution of safety barriers plays a significant role in improving the system's safety, and as a result, preventing potential major accidents. The predictive probability of the observed abnormal event for the next time interval for the given data was calculated using Eq. 3.18 and 3.19. Accordingly, λ_p is the posterior rate of abnormal events (Eq. (3.19)) which was 17.91, and the occurrence probability of an abnormal event (Eq. 3.18) is equal to 0.0522. In other words, there is a 50.22% chance that an abnormal event will occur in the next time interval in the studied plants.

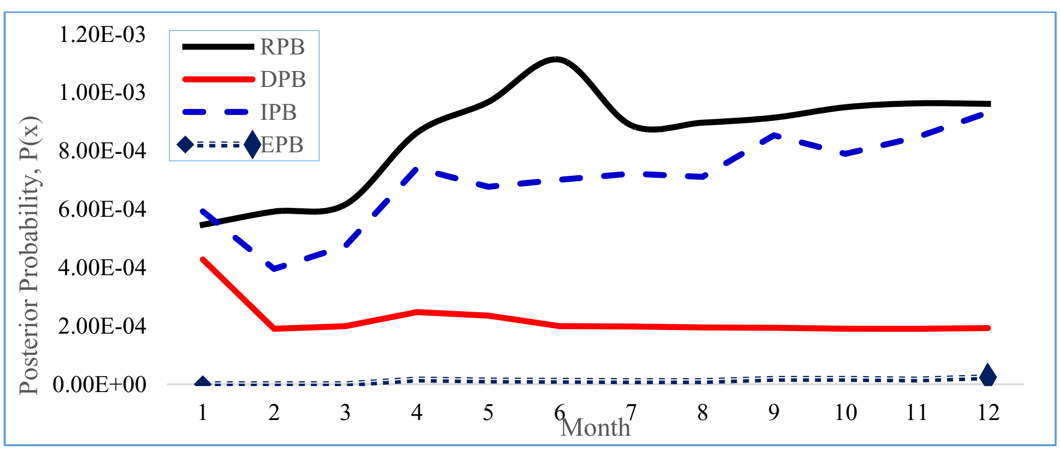

Figure 3. 6 Updated probability of failure distribution of safety barriers for 12 months.

Posterior (updated) failure probability estimation of safety barriers for 12 months is illustrated in Fig.3.6 The updated probability can be calculated using Bayes' Equation (Eq. 3.22) through utilizing prior probability (Table 3.9) and likelihood failure probabilities (Table 3.11). The degradation of safety barriers over the time frame has been confirmed by Bayesian posterior probability values (Fig.3.6). The findings depicted a dramatic surge in the failure probability of RPB and IPB in the period. This issue is significant enough to result in the lose hydrogen, as a more flammable vapor, and then meet an ignition to start a devastating fire or explosion.

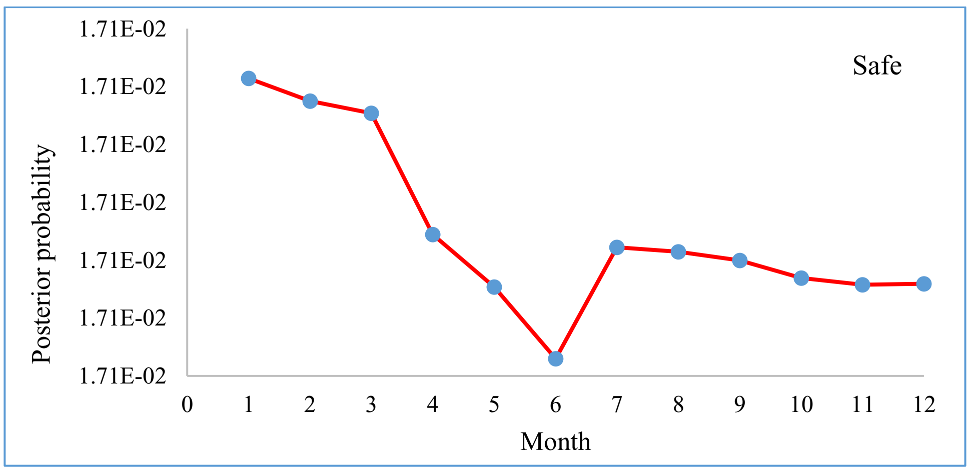

Figure 3. 7a Posterior probability distribution of consequence occurrence of safe events over 12 months.

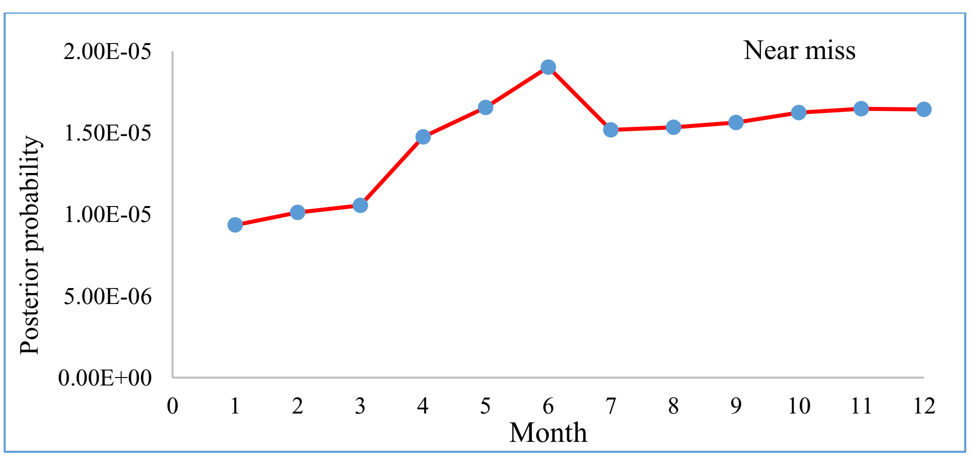

Figure 3.7b. Posterior probability distribution of consequence occurrence of near miss events over 12 months.

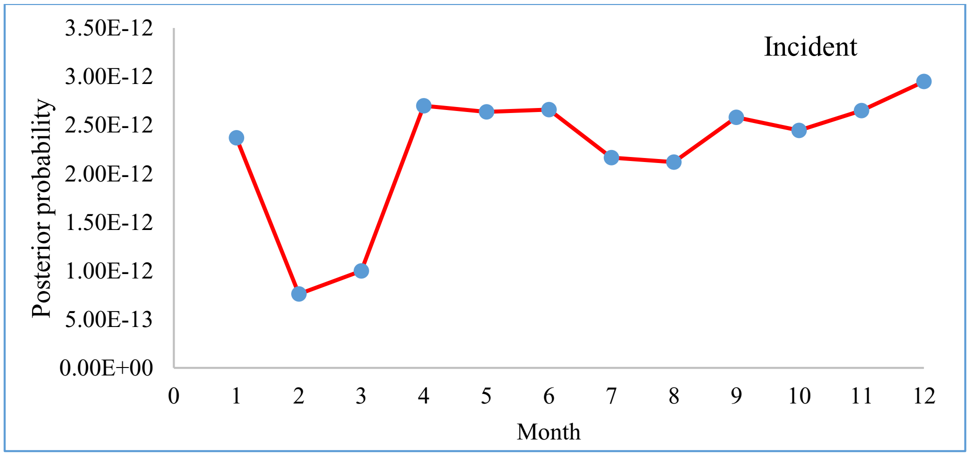

Figure 3.7c. Posterior probability distribution of consequence occurrence of incident events over 12 months.

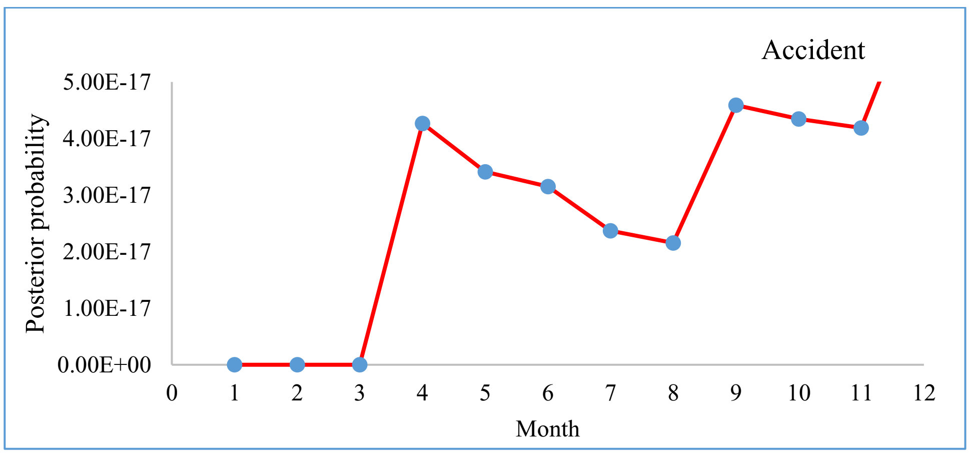

Figure. 3.7d. Posterior probability distribution of consequence occurrence of accident events over 12 months.

The historical data presented in Table 3.10 have considered as assumptions to develop the Fig. 3.7 The posterior occurrence probabilities of five severity levels (consequences) were estimated after the calculation of posterior failure probabilities of safety barriers (Fig.3.7a, b, c, and d). The findings illustrate that the occurrence probability of consequences increased drastically for 12 months as new information was applied to the analysis. As can be seen in the results, the prior probability of a safe state has a very high probability of occurrence (P=0.99, Table 4.8). However, as times change, the safe state posterior probability declines significantly, from 0.99 to 0.017, becoming fifty-eight times lower than the previous amount (Fig. 3.7a). This result proves that substantial degradation begins over time on the system safety, and consequently, because of this issue, the posterior occurrence probabilities of near misses, mishaps, incidents, and accidents are increased considerably (Fig. 3.7 b, c, and d). The posterior occurrence probabilities of the accident as the most catastrophic consequence escalated dramatically, increasing six-fold from 4.49E-16 (Table 4.8) to 6.99E-17 (Fig. 4.7d).

3.3.5. Discussion on the Comparison of the Models

This section is dedicated to presenting a brief comparison of the eleven safety and risk models applied recently on hydrogen infrastructures. Seven features that are very important in dynamic risk management of the critical systems were selected to compare the models. It is noteworthy that this section presents a comparison in dynamic risk management perspectives and the assignment of less credit to some models does not mean that they suffer from great disadvantages, or it has not have any superiority/application in risk studies. In general, most of the proposed models are unable to derive benefits from these essential dynamic traits. This deficit highlights that the novel and recent dynamic methods are not employed commonly in hydrogen safety and risk studies. This issue was confirmed in another study conducted recently to review state-of-the-art technologies and risk and reliability analysis of hydrogen storage and delivery [14].

One of the most vital issues in safety and risk models is their capability to deal with uncertainty. This issue is made more challenging by the lack of data and valid, well-specified models available for emerging technologies in hydrogen production, storage, and transportation. More specifically speaking, epistemic (subjective) uncertainty is increased by a lack of knowledge and can be addressed when enough information becomes available.

Table 3. 12 Taxonomy of the recent risk and safety models of hydrogen infrastructures (i.e., Production Plants, Refueling Stations, Storage and Transportation)

Model	Methodology	Deal with Uncertainty		Reasoning		Dynamic	Probability Elicitation	PPM	Criticality RCA*	Dependency Modeling
		Aleatory	Epistemic	Abductive	Deductive					
Kim et al., (2011)	Qualitative FTA and FMEA, Risk index									
Haugom and Friis-Hansen, (2011)	Qualitative BN, ETA, Risk Matrix				✓					
Lins and De Almeida, (2012)	ETA, Equiprobable Interval Method, Probit Models		✓		✓		✓			
Al-shanini et al., (2014)	SHIPP methodology	✓		✓	✓			✓		
Mohammadfam and Zarei, (2015)	HAZOP, PRA, ETA, PHAST, MTL-STD-882, F–N curve		✓		✓					
Duan et al., (2016)	Fuzzy probability, BN, AHP, Risk Matrix	✓	✓				✓			
Skjold et al., (2017)	HyRAM, CFD	✓			✓					
Groth and Hecht, (2017)	HyRAM Programs	✓			✓					
Chang et al., (2019)	DBN	✓		✓	✓	✓		✓	✓	
Shi et al., (2020)	BRANN, PHAST	✓						✓		
The Present Model	DNT, BWM, SHIPP, BT, DBN	✓	✓	✓	✓	✓	✓	✓	✓	✓

*RCA; Root Cause Analysis, PPM; Probabilistic Predictive Modeling

In the context of the incompleteness of reliability data (i.e., failure rate) and inconsistencies between the applied model and the system model, the DNT along with expert judgment and BWM are more suitable to tackle this epistemic uncertainty in failure probability elicitation compared to other popular approaches in particular evidence theory (Dempster–Shafer theory) and analytic hierarchy process (AHP).

In comparison with the conventional risk analysis models applied to hydrogen infrastructures (Table 3.12), the developed dynamic risk model provided strong modeling of complex stochastic processes. This capability is because of using Direct Acyclic Graph, modeling common cause failures and dependency among root events, applying conditional probability table instead of deterministic gates (i.e., AND, OR), employing exact inference algorithms, and updating the occurrence probability. These abilities not only provide constructive information for decision-makers but significantly, also address aleatory uncertainty. Aleatoric uncertainty refers to the data's inherent randomness that cannot be explained away. Some of these features were demonstrated in a model developed by Chang et al., (2019) and also Shi et al., (2020) demonstrated that BRANN can reduce the scenario-related parametric uncertainty by 97% in fire and explosion risk analysis of hydrogen refueling stations. Further, when new knowledge or evidence of the studied system becomes available, a risk analyst can model and explain the new situation of the system by employing the deductive reasoning (i.e., probability updating) of the developed model. Continuing this work over a life cycle of the system leads to the development of a tailored model and as a result, both data and knowledge, and aleatory uncertainty can be reduced naturally.

In the present model, criticality analysis of root causes to recognize the most contributing significant factors in occurrence accident scenarios was conducted using RoV of probabilities which provide more precise results [38,48]. Another positive aspect of the proposed model is the ability to perform predictive modeling. Having incomplete knowledge regarding the safety barriers' performance when a critical system fails, and hazardous consequences trends, increase our uncertainty in effectively designing safety mitigating measures. To address this important issue, SHIPP methodology integrated into the model to provide dynamic predictive modeling of safety barriers and consequences over the desired time interval. The model provides a prediction based on posterior failure rate data that has lower uncertainty compared to a prediction based on prior data because the model is worked according to Poisson distribution with the posterior rate of abnormal events [40]. Further, predictive modeling of safety barriers deviations is worthwhile in developing risk-based preventive maintenance programs, hence it can be contributed to improving system reliability, minimizing demand failures, and profitability of the operation.

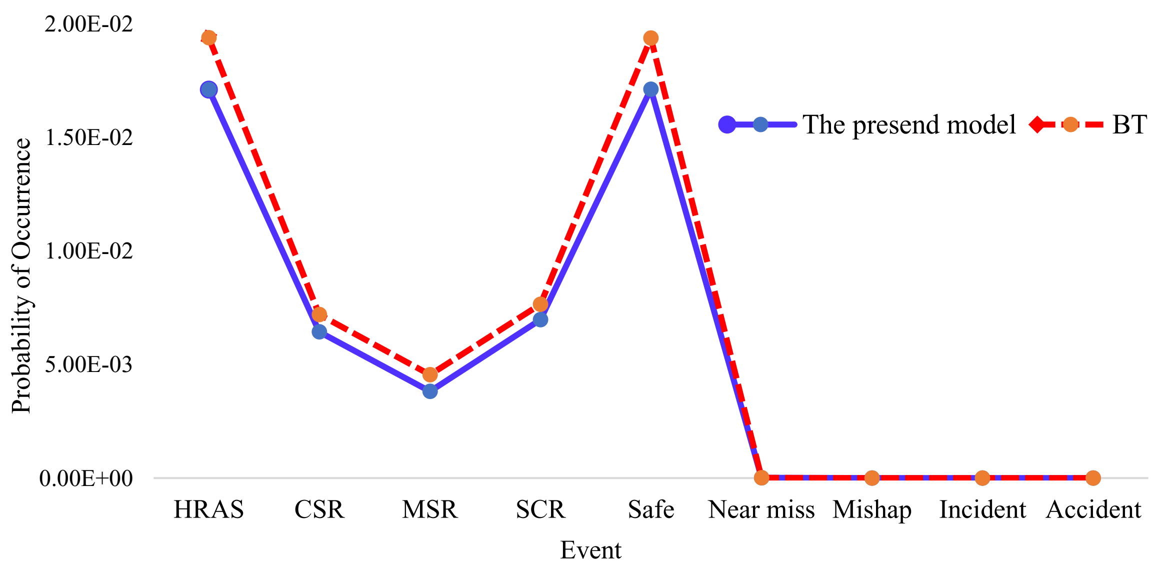

Figure 3. 8 Benchmarking some results of the proposed model with Bow tie (BT) model

It is difficult to find a model or a standard approach that can be used to benchmark all the numerical results of the proposed model against it. However, to better understand, some results of the developed model were compared with the Bow tie model as one of the most popular and acceptable probabilistic safety analysis models. The results of both models were compared in predictive reasoning to estimate the prior occurrence probability of the hydrogen release accident scenario (HRAS), chemical section release (CSR), mechanical section release (MSR), storage section release (SSR) accompanied by possible consequences (i.e., safe, near miss) of hydrogen release. As can be seen from the findings there is a substantial correlation between the results of two models (Fig. 4.8). Using CPT instead of deterministic gates (AND, OR), which used in BT model, as well as considering conditional dependencies among nodes and common mode failures, and inference algorithm in the proposed model are the main reasons why there is a little difference between the two model results.

3.4. Conclusion

Safety is one of the most critical challenges for the sustainable development of the hydrogen economy. Reaching the vision of using hydrogen as a low-carbon fuel source to phase out conventional fossil fuels and limit global warming, requires researchers to establish strong and novel safety assessment models to provide more effective safety measures. In considering such weighty matters, the present study aimed to develop an improved dynamic approach to safety modeling. This was done by integrating the D number theory, best-worst method, and SHIPP methodology into the DBN for the safety assessment of hydrogen infrastructure under uncertainty. To present the capabilities and practicality of the proposed model to perform a dynamic risk analysis, a real case study was conducted on a hydrogen production process in a power plant. The main conclusions of the present study are as follows:

- The model provides a dynamic and holistic cause-consequences modeling of the hydrogen loss accident scenario, which presents the accident profile from root causes to final consequences. This modeling revealed and incorporated a wide range of contributing latent factors both from individual to organization failures and from operational to mechanical as well as natural hazards into a probabilistic risk analysis which were ignored in the most previous models.

- A hybrid and improved algorithm containing DNT and BWM, as the latest and more reliable MCDM technique, was employed to substantially deal with epistemic uncertainty in input data (i.e., prior probabilities). This is the first that study presented an attempt to integrate this algorithm into DBN, as a well-known probabilistic safety analysis method, in safety and risk studies. This effort leads to addressing the potential uncertainties and subsequently, more realistic results and effective final decision
- Identifying a wide range of latent failures and precisely prioritizing them which contributed the most to the occurrence of the accident scenario using the RoV of probabilities was another positive aspect of the model.
- Simulation and predictive modeling of the posterior failure probability distribution of safety barriers, consequences, hydrogen release probability, and system reliability can tackle uncertainty in the safety and risk preventive and mitigative decisions.

Although integrating DNT and BWM into DBN provides great advantages and capabilities in a unique model, it may have some limitations and some attempts should be made address them. For instance, a powerful consequence modeling under uncertainty may be needed in risk analysis of some critical infrastructures, this concern was outside the scope of the present model due to the huge complexity it would impose on the proposed model. Moreover, integrating a dynamic influence diagram into the model to explore the effects of the most contributing root events in decreasing the hydrogen release probability and dealing with uncertainty in decision-making could be investigated in future studies. Finally, we call for further investigation especially using experimental data to explore and evaluate the proposed model's applications and validity in various hydrogen operations in the future studies

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Appendix:

Section 1: The Number Theory advantages

Considering the merits of D-S theory, D Numbers Theory also has the following advantages:

(i) D numbers theory has a robust and powerful hypothesis compared to D-S theory, which is that all elements in the frame of decrements must be mutually exclusive. It simply means that the hypothesis is a complex task to be satisfied in evaluations of the linguistic terms, which are based on fuzzy expressions like “high”, “moderate”, and “low”. Therefore, D numbers theory, using a non-exclusive hypothesis in the framework of evaluation will be much more reliable (Fig. 3.9)

(ii) D numbers can deal with the incompleteness information in the evaluation procedure. In D-S theory, a basic belief assignment must be made with completeness restrictions, which simply means that the summation of all focal elements should be equal to 1. That is, the experts’ judgment may be insufficient in some situations. Accordingly, the evaluation is merely based on partial information, which D numbers and D-S theory can obtain incomplete basic belief assignments. In this view, D number theory has much more applicable.

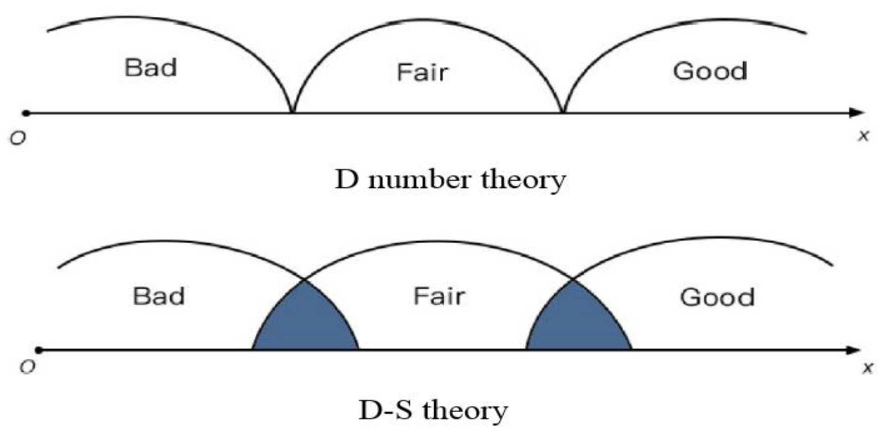

Figure 3. 9 The structure of D-S and D number theory [222] .

Section 2: linguistic terms, their IFNs, experts’ profiles and their judgments

The utilized linguistic terms and their intuitionistic fuzzy numbers (IFNs) are provided in Table 4.13.

Table 3. 13 Rating for the possibility of each event

Qualitative terms	IFNs
Extremely low (EL)	(0.10,0.90)
Very low (VL)	(0.25,0.70)
Low (L)	(0.30,0.60)
Fairly low (FL)	(0.40,0.50)
Medium (M)	(0.50,0.50)
Fairly high (FH)	(0.60,0.30)
High (H)	(0.70,0.20)
Very high (VH)	(0.75,0.20)
Extremely high (EH)	(0.90,0.10)

The employed experts' profiles:

Table 3. 14 Experts' profile

No	Job field	Experience (years)	Education level	Age
Expert 1 (E#1)	Health, Safety, and Environment (Head)	3	BSc	35
Expert 2 (E#2)	Maintenance engineering (Head)	12	BSc	38
Expert 3 (E#3)	Instrumentation engineering (Technician)	5	BSc	32
Expert 4 (E#4)	Process engineering (Supervisor)	4	MSc	29

The employed experts' judgments:

Table 3. 15 Recognized root events and their corresponding possibility in the qualitative (linguistic) terms

No.	Expert opinion				No.	Expert opinion				No.	Expert opinion			
	E#1	E#2	E#3	E#4		E#1	E#2	E#3	E#4		E#1	E#2	E#3	E#4
X1	FH	VH	H	VH	X44	FL	M	FL	M	X87	VL	L	H	M
X2	VL	H	VL	M	X45	H	VH	L	M	X88	VL	FL	FH	VH
X3	VL	H	L	L	X46	FL	H	M	M	X89	L	L	M	L
X4	M	M	FH	H	X47	VH	EH	FH	EH	X90	VL	FH	VL	L
X5	M	H	H	VH	X48	FH	VH	FH	H	X91	VL	FL	FL	VL
X6	VH	H	H	VH	X49	FH	M	FL	FL	X92	M	L	H	FH
X7	FL	H	VH	VH	X50	FL	M	EL	VL	X93	M	L	H	FH
X8	L	H	EH	VH	X51	FH	FH	VL	FH	X94	FL	L	FH	FH
X9	FL	H	EH	EH	X52	H	H	EL	H	X95	M	FL	FH	H
X10	M	M	EH	M	X53	H	H	VL	FH	X96	FH	VH	VH	H
X11	FL	M	L	H	X54	FL	FH	VL	L	X97	H	FL	L	FL
X12	M	H	M	M	X55	FL	FH	L	M	X98	M	FL	VL	EL
X13	L	EL	EL	EL	X56	FL	FH	VL	FL	X99	L	L	VL	EL
X14	L	L	VH	FL	X57	L	FH	VL	M	X100	H	VH	EH	EH
X15	H	VH	H	VH	X58	L	FH	EL	VL	X101	L	FH	VH	H
X16	H	VH	VH	H	X59	FH	FH	EL	FH	X102	M	FH	H	FH
X17	FL	L	H	FH	X60	FH	FH	VL	M	X103	M	M	H	FH
X18	L	L	VL	L	X61	FH	FH	L	H	X104	FL	M	H	M
X19	FL	L	L	VL	X62	H	FH	EL	FH	X105	FH	M	H	VH
X20	H	EH	EH	EH	X63	M	M	L	FH	X106	EL	VL	VL	L
X21	H	H	FH	H	X64	FH	H	FL	H	X107	H	L	FH	M
X22	M	M	M	L	X65	FH	H	M	H	X108	FL	EL	FH	H
X23	H	M	L	L	X66	H	FL	FL	M	X109	L	H	FH	FH
X24	FH	M	VL	M	X67	FH	FL	VL	FH	X110	L	FH	M	M
X25	VH	H	VH	H	X68	FL	FH	L	H	X111	FH	H	H	FH
X26	M	L	VH	FL	X69	FL	FH	VL	M	X112	FL	FH	H	FH
X27	FL	VH	L	VH	X70	FH	FL	EL	FL	X113	FL	FL	H	FH
X28	H	FH	L	FH	X71	H	L	FH	FH	X114	L	EL	VL	L
X29	H	VH	EH	EH	X72	FH	FH	M	M	X115	FL	VL	FL	M
X30	VH	VH	H	FH	X73	VH	FH	FL	FL	X116	M	FL	FL	M
X31	FL	L	L	FH	X74	VH	FL	FH	H	SB1	FH	M	L	M
X32	FL	L	FL	L	X75	M	FH	M	H	SB2	FH	M	M	M
X33	L	H	H	H	X76	VH	FL	M	FH	SB3	M	FL	L	L
X34	FH	H	FL	FH	X77	H	FH	FH	M	SB4	L	VL	VL	VL
X35	H	H	M	H	X78	M	FH	H	M	SB5	L	VL	FH	VL
X36	L	H	VL	M	X79	M	H	VH	H	SB6	L	FH	H	VL
X37	H	VL	EH	H	X80	FL	FH	VH	H	SB7	VL	M	L	M
X38	M	FH	FL	FH	X81	FL	L	VL	FH	SB8	M	FL	FL	FL
X39	M	FH	L	VH	X82	VL	EL	H	EL	SB9	L	H	L	L
X40	FL	M	FH	M	X83	L	VL	M	VL	SB10	VL	L	EL	VL
X41	L	VH	H	FL	X84	L	FH	L	L	SB11	FH	VL	L	EL
X42	FH	FH	M	L	X85	EL	L	H	EL	SB12	L	L	VL	EL
X43	M	H	VL	VH	X86	VL	EL	VL	EL	SB13	L	L	H	EL

EH	VH	H	FH	M	FL	L	VL	EL

Section 3: Intermediate events and their descriptions of the accident scenario

Table 3. 16 Intermediate events of the accident scenario in the studied plant

Symbol	Description	Symbol	Description
1) Chemical section			
Leak from cell		IE24	Pressure indication error
Body leak			
IE1	Corrosion	**2) Mechanical section**	
IE2	Overpressure	***Gas holder***	
IE3	Over temperature	IE25	Body corrosion
IE4	Failure in repair and maintenance	IE26	Increase H_2 temperature
IE5	Pouring of KOH on cells body	IE27	Overpressure and increase H_2 volume
IE6	Ignorance of useful time	IE28	Failure in compressor function
IE7	Failure in operator tasks	IE29	Rectifier malfunction
IE8	Blockage vent pipelines (O_2, H_2O, KOH)	***Compressor***	
IE9	Blockage in H_2 pipe	IE30	Deactivate compressor
IE10	KOH sediment	IE31	The flaw in the outlet pipe
IE11	Cells function error	IE32	High pressure in H_2
IE12	Rectifier malfunction	**3) Chemical section**	
IE13	Cooling system function error	IE33	Body Corrosion
IE14	The flaw in temperature indicator	IE34	Tank rupture due to the external event
IE15	Operator ignorance to start cooling systems	IE35	Crash heavy objects
IE16	Failure in ammeter	IE36	Mechanical fatigue
IE17	Exceeding correct by the operator	IE37	Temperature fluctuations
IE18	Ignoring of cells temperature	IE38	Increase Pressure
Pipeline leak		IE39	Internal corrosion
IE19	Hose rupture	IE40	External corrosion
IE20	Pipeline overpressure	IE41	Environmental Factors
IE21	Loose fasteners and fittings	IE42	Clogged outlet pipe
Water cells		IE43	Failure in tank pressure indicator
IE22	Corrosion of water cell pipes	IE44	Failure in pressure safety valve
IE23	Failure in manometers section		

Section 4: The optimal weights for the main criteria and each expert

Using model 2 (BWM-based), the optimal weights of the main criteria were derived as model 3 as follows.

Model 3:

min ζ^*

Subject to:

$|\omega^*_{\mathfrak{C}\#2} - 3 \cdot \omega^*_{\mathfrak{C}\#1}| \leq \zeta^*, |\omega^*_{\mathfrak{C}\#2} - 5 \cdot \omega^*_{\mathfrak{C}\#3}| \leq \zeta^*, |\omega^*_{\mathfrak{C}\#2} - 8 \cdot \omega^*_{\mathfrak{C}\#4}| \leq \zeta^*,$

$|\omega^*_{\mathfrak{C}\#1} - 6 \cdot \omega^*_{\mathfrak{C}\#4}| \leq \zeta^*, |\omega^*_{\mathfrak{C}\#2} - 8 \cdot \omega^*_{\mathfrak{C}\#4}| \leq \zeta^*, |\omega^*_{\mathfrak{C}\#3} - 5 \cdot \omega^*_{\mathfrak{C}\#4}| \leq \zeta^*$,

$\omega^*_{\mathfrak{C}\#1} + \omega^*_{\mathfrak{C}\#2} + \omega^*_{\mathfrak{C}\#3} + \omega^*_{\mathfrak{C}\#4} = 1$,

$\omega^*_{\mathfrak{C}\#1}, \omega^*_{\mathfrak{C}\#2}, \omega^*_{\mathfrak{C}\#3}$, and $\omega^*_{\mathfrak{C}\#4} \geq 0$.

To estimate the optimum experts' importance weight, the experience criterion has been taken as an instance. Adopting model 2, the optimal weight of the main criteria was derived as model 4 as follows:

Model 4:

$\min \ \zeta^{\mathfrak{C}\#2}$

Subject to:

$\left|\omega^{\mathfrak{C}\#2}_{E\#2} - 6 \cdot \omega^{\mathfrak{C}\#2}_{E\#1}\right| \leq \zeta^{\mathfrak{C}\#1}, \left|\omega^{\mathfrak{C}\#2}_{E\#2} - 4 \cdot \omega^{\mathfrak{C}\#2}_{E\#3}\right| \leq \zeta^{\mathfrak{C}\#2}, \left|\omega^{\mathfrak{C}\#2}_{E\#2} - 5 \cdot \omega^{\mathfrak{C}\#2}_{E\#4}\right| \leq \zeta^{\mathfrak{C}\#2}$

$\left|\omega^{\mathfrak{C}\#2}_{E\#2} - 7 \cdot \omega^{\mathfrak{C}\#2}_{E\#1}\right| \leq \zeta^{\mathfrak{C}\#2}, \left|\omega^{\mathfrak{C}\#2}_{E\#3} - 3 \cdot \omega^{\mathfrak{C}\#2}_{E\#1}\right| \leq \zeta^{\mathfrak{C}\#2}, \left|\omega^{\mathfrak{C}\#2}_{E\#4} - 2 \cdot \omega^{\mathfrak{C}\#2}_{E\#1}\right| \leq \zeta^{\mathfrak{C}\#2}$

$\omega^{\mathfrak{C}\#2}_{E\#1} + \omega^{\mathfrak{C}\#2}_{E\#2} + \omega^{\mathfrak{C}\#2}_{E\#3} + \omega^{\mathfrak{C}\#2}_{E\#4} = 1$,

$\omega^{\mathfrak{C}\#2}_{E\#1}, \omega^{\mathfrak{C}\#2}_{E\#2}, \omega^{\mathfrak{C}\#2}_{E\#3}$, and $\omega^{\mathfrak{C}\#2}_{E\#4} \geq 0$.

Section 5: Example for D Number theory for prior probability calculation

To simplify, take X7 (Inadequate safety training) as an example. With considering definition of D numbers explained in section 1.2, the linguistic terms, given by four experts, fall into "FL", "H", "VH", and "VH" categories. The integrated D numbers theory was attained as follows using Equations 3.13-3.14;

$A^{\text{agg}} = (0.118 \times 0.4 \times 0.5) + (0.413 \times 0.7 \times 0.2) + (0.158 \times 0.75 \times 0.2) + (0.310 \times 0.75 \times 0.2) = 0.1517$

Accordingly, the possibility of X7 can be transferred into the probability using Equation 3.16 as:

$$P = 1/10^{\left[\left(\frac{1}{0.1517}-1\right)\right]^{1/3}} \times 2.301 = 8.2341E - 05$$

CHAPTER 4

A dynamic human-factor risk model to analyze safety in sociotechnical systems

Preface

A version of this chapter has been published in ***Process Safety and Environmental Protection 164 (2022): 479-498****. I am the primary author along with the Co-authors, Faisal Khan, and Rouzbeh Abbassi. I developed a dynamic human-factor risk model to analyze safety in sociotechnical systems. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' and peer review feedback. Co-author Faisal Khan helped in the concept development, design of methodology, reviewing, and revising the manuscript. Co-author Rouzbeh Abbassi provided fundamental assistance in validating, reviewing, and correcting the model and results. The co-authors also contributed to the review and revision of the manuscript.*

Abstract

The performance of sociotechnical elements varies owing to a wide range of endogenous and exogenous influencing factors. These are called uncoupled variability as per Safety-II. The uncoupled variability has drawn rare attention, despite its vital importance in major accidents analysis as per Safety-I and Safety-II paradigms. Accordingly, Subsequently, Dempster - Shafer Evidence theory is employed to elicit knowledge under epistemic uncertainty. The proposed causation model is integrated into Dynamic Bayesian Networks to support decision-making under aleatory uncertainty. Finally, a criticality matrix is developed to evaluate the performance of the system functions to support decision-making. The proposed model is built considering the advanced canonical probabilistic approaches (e.g., Noisy Max and Leaky models) that address the critical challenges of incomplete and imprecise data. The proposed dynamic model would help

better understand, analyze, and improve the safety performance of complex sociotechnical systems.

Keywords: System safety; Performance variability; Functional resonance analysis; Performance shaping factors; Human-organization factors.

4.1. Introduction

The sociotechnical systems (STSs) (e.g., oil and gas, healthcare, aviation, manufacturing, construction, power industry, and automotive) indicate complex operational processes composed of interactive and dependent social elements, organizational and human activities. These systems are mainly attributed to dynamic complexity, relative ignorance, interactable and non-linear operations [1,2]. However, traditionally established safety and risk analysis models and techniques mainly rely on four main assumptions: a) a system can be fully decomposed into clear elements and accordingly events into individual acts, b) elements have functioned in a bimodal manner; either works or fail (Fig. 5.1), c) the sequence of events have preestablished and firmed as examined by selected representation and finally d) event combinations are linear either straightforward or complex and orderly [2,3]. While these assumptions may be partially true for technological systems, it is highly arguable to apply for STSs neither for risk assessment nor for accident analysis perspective [4,5].

It should be noted that several techniques are proposed to analyze a system's functions and model the industrial processes, such as Structured Analysis and Design Technique (SADT) [6], Function Analysis System Technique (FAST) [7], Multilevel Flow Modeling (MFM) [8], Analysis of Consequences of Human Unreliability (ACIH) [9] and Functional Resonance Analysis Method

(FRAM) [2]. The first three methods use to mainly develop a graphical representation illustrating functions of systems (e.g., project, product, or process) and existing logical relationships among them. ACIH uses diagrammatic notation and textual presentation to analyze the functional and technical context of the system, focused on human unreliability and associated consequences.

Safety I often defined as *freedom from unacceptable risk* and assume that things go wrong due to the failure of system components (e.g., human error, mechanical failure, managerial failure) [10]. Accordingly, the cause-consequence relationship is established by identifying and quantifying relationships, and safety can be improved either by preventing causes or mitigating consequences. In contrast, Safety II presumes safety as the ability to succeed under varying conditions and focuses on both windows as ‘few things as possible go wrong’ to ensuring that ‘as many things as possible go right’, with the primary focus on the latter perspective [11]. People are considered as a resource required to obtain safety, not as a source of error or hazards. According to Safety-II thinking, everyday performance variability yields the necessary adaptations in response to actual variabilities, which is why things go right [10]. According to a proactive approach, this thinking perspective constantly tries to monitor and predict events and developments. Compared to Safety I, this thinking method needs different techniques and models to identify and manage performance variability. The resilience paradigm comes from Safety I and Safety II. A system is resilient if it can adjust its functioning before, during, or after any disturbances and opportunities and keep safe operations under expected and unexpected conditions [12,13].

As a safety paradigm, Resilience engineering proposed an approach that begins by identifying and describing characteristic functions and focuses on improving the system's ability to monitor, learn, anticipate, and respond [14]. This approach has been proposed by Hollnagel (2012) named Functional Resonance Analysis Method (FRAM) [2]. In line with improving the system from a learning perspective, Vanderhaegen et al. have presented an outstanding possibility to design systems capable of learning using human error. They proposed an approach called the Benefit/Cost/Deficit (BCD) model [15] and validated it using the neural network and case-based reasoning systems. They applied it for car driving to reveal benefits, costs, and deficits considering performance criteria (e.g., safety, action opportunity, driver comfort, and time spent). They also suggested integrating the probability theory into BCD and learning from organizational factors to improve the prediction systems. This is in line with some parts of the present study, where various organizational factors included in the proposed Taxonomy and advanced probabilistic model are utilized to predict performance variability.

However, FRAM has rapidly risen in popularity and is considered in the present study for the following reasons. First, this method primarily focuses on system safety and human factors analysis, especially in sociotechnical systems. Second, FRAM acknowledged how it is possible to do safety analyses without decomposing systems into components and without being dependent on the notion of causality, which is important in Safety II. Third, FRAM provides a much stronger intellectual background, the principles, mechanisms, and a deep understanding of performance variabilities of each system's function and the entire system. This is particularly important for uncoupled performance variability as the primary concern in the present study and system safety. Fourth, the previous studies have proved a capability and necessity for integrating probability theory and Bayesian Network into FRAM to characterize uncertainty and address issues related to the qualitative nature of this method. Finally, considering the mentioned attitudes of STSs, and the superiorities of FRAM, the authors believed this method could better address the research questions of the present study.

Three different mechanisms result in performance (output) variability in STSs based on FRAM, as shown in Fig. 5.1. The first type is internal or endogenous variability, which means deviation in normal performance can be a product of the variability of the function itself, while variability because of the influence of the working environment, the actual situation in which function is performed, is called external or exogenous variability. The third one is named functional upstream-downstream coupling, which means variability of the downstream function can be affected by the output of the upstream function either in damping or amplifying states (Fig. 4.1) [2]. In this study, we called the first and second types of variabilities *uncoupled performance variability*. Function representation and variability propagation process are represented in Fig . 4.1. Accordingly, the hexagon demonstrates a FRAM function graphically, where each corner or vertex represents an aspect (e.g., Input, Time, Control, Precondition, Resource, and Output).

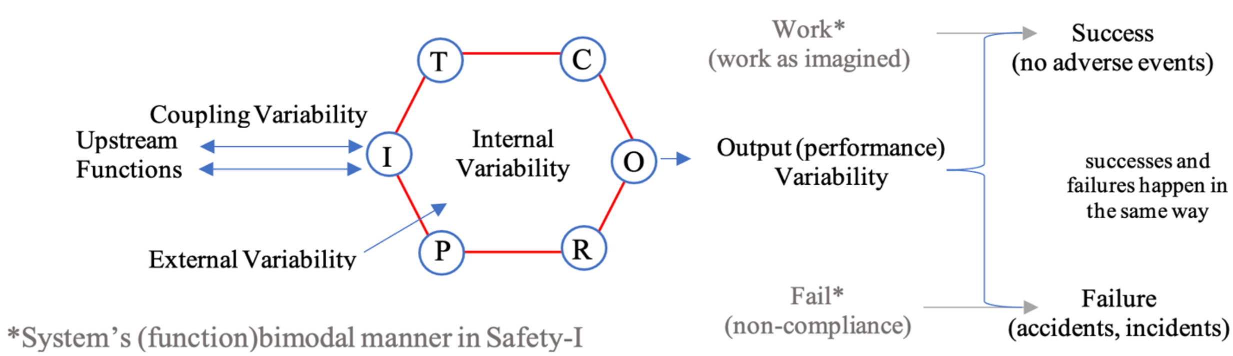

Figure 4. 1 Function representation and variability propagation process

To enhance this new safety paradigm, some researchers made their efforts to implement the FRAM in safety, risk, and accident applications in different domains, for instance, healthcare [16], aviation [17], construction [18], and oil and gas [19]. These applications highlighted the superiority of FRAM for analyzing risks and managing safety in modeling complex systems [20] and the possibility of demonstrating how systems work [21], and presenting a deeper understanding of STSs [22]. The other groups improved the FRAM primarily to deal with its qualitative nature as one of the main drawbacks. To this end, integrating FRAM into Monte Carlo simulations [20,23], proposing rules for variability propagation and aggregation [24], integrating the Accident Causation Analysis and Taxonomy (ACAT) into FRAM [25], combining fuzzy logic into FRAM [26], proposing simple aggregation rules [27], integrating FRAM into machine learning [28] and data-driven techniques [29] and integrating FRAM with fuzzy CREAM to semi-quantitatively visualize the safety of sociotechnical systems [30] have been the most interest of the researchers. However, like other systemic approaches, FRAM is still primarily qualitative. More studies are required to provide comparative analysis results for risk scenarios to support making risk-based decisions in a rigorous approach [31]. It is highlighted that more specific quantification and handling of the quantitative aspects of variabilities are needed [24]. The abovementioned research mainly focused on presenting new quantification techniques for only coupled variability, while no systematic investigation has been paid to analyze probabilistically uncoupled performance variability caused by internal and external variability shaping factors (VSFs). It is believed that there will, of course, always be cases in STS where the variability magnitude of a single function (activity) is enough that adverse outcomes (e.g., accident, incident) would be unavoidable [32]. This is vital that a system be able to monitor, learn, anticipate, and respond to critical variabilities arising from internal and external variability of functions.

Therefore, the present study aimed to address the below essential concerns mainly associated with uncoupled variability modeling, which subsequently can be a new extension in FRAM and system safety performance in STSs. We use the term "performance variability" in the rest of this work and mean only uncoupled performance variability of the system's functions and system understudy for the sake of readability. Accordingly, this work attempt to answer the following research questions:

1. Which internal and external factors are associated with the performance variabilities of human, organizational, and technical functions in STSs?
2. How can we predict the probability of performance variability and deal with its uncertainty?
3. How can we model and quantify the intra effects (coupled dependencies) among VSFs?
4. How can we update the prior probability distributions given the new evidence?
5. How can dampen the critical variability in a risk-based decision-making process?

4.2. Methodology

This section explains the proposed holistic taxonomy of VSFs based on different FRAM-driven functions and sociotechnical design hierarchy (e.g., individual, task, Human-Machine Interface (HMI), plant, organization, and culture). Dempster- Shafer Evidence theory (DSET) and Monte Carlo simulation methods, along with their integration into Dynamic Bayesian networks (DBNs) are employed to deal with critical challenges in knowledge engineering. This is a new hybrid approach used in the functional resonance analysis domain for probabilistic modeling of performance (uncoupled) variability under uncertainty. A new procedure is also developed to capture the inter-dependencies among VSFs in Bayesian Network modeling. Finally, a criticality matrix is proposed to evaluate the performance variability using a risk-based perspective to firmly support the decision-making process in damping the critical variabilities before leading to major system disruption. The proposed model is illustrated step by step in Fig 4.2. As can be seen, overall, the proposed model contains four main steps considered to achieve the specific objectives by employing the proposed techniques sequentially.

4.2.1. Developing a holistic taxonomy of variability shaping factors (VSFs)

The first step of the developed methodology is characterizing the system functions, which means identifying the functions (activities) necessary in everyday work to achieve the system's purpose. This should be proceeded to fully detail how activities are performed instead of as an overall task or operation. These functions constitute the FRAM model. This study used common approaches [2], such as hierarchical task analysis (HTA), interactive interviews, and direct observation. We also examined the system's technical and process descriptions to characterize the system's functions of interest.

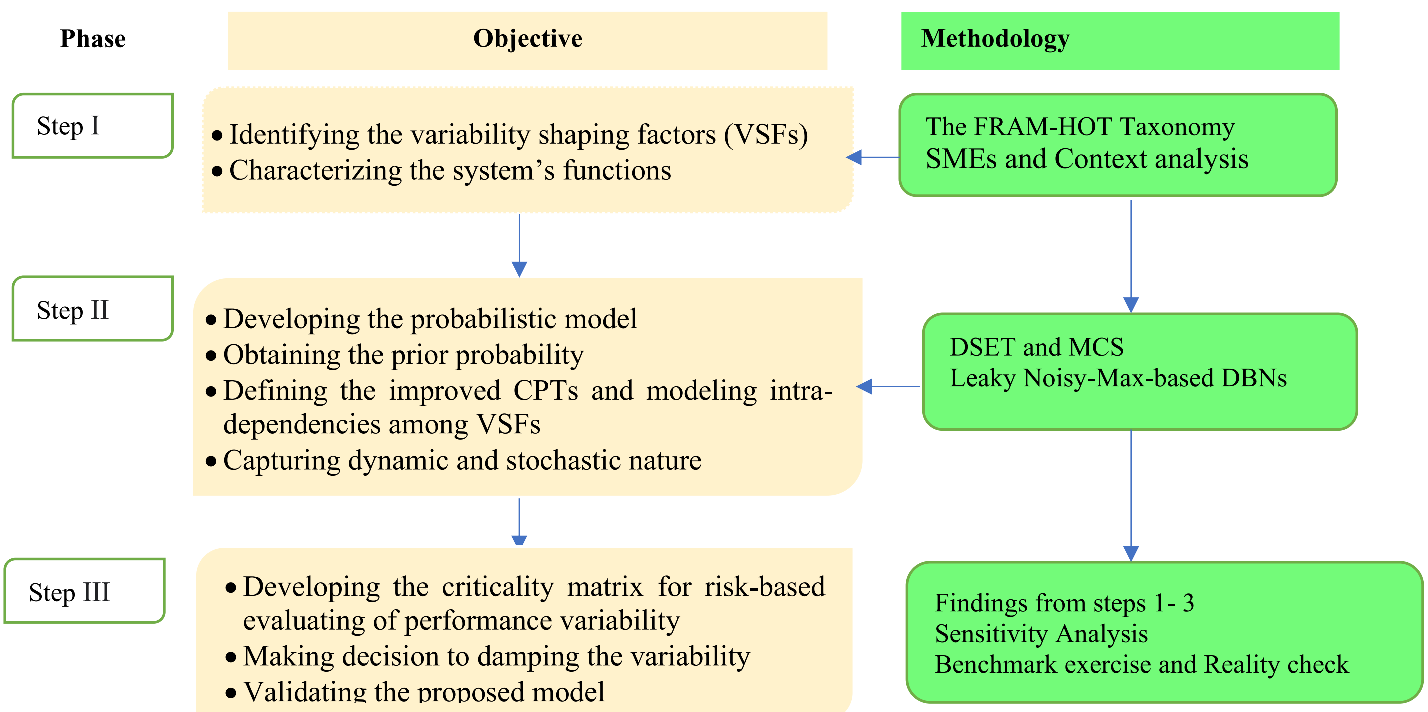

Figure 4. 2 The framework of the proposed model

Performance shaping (influencing/enforcing) factors (PSFs) are rooted in Safety-I from at least the age of human reliability analysis (HRA), where they have been considered the primary source of performance variability in terms of human error occurrence [33,34]. To this end, human error probability (HEP) is mainly estimated by multiplying the nominal value of human error occurrence by the accumulative effects of various PSFs in HRA methods. Assigning proper factors, associated numerical values for their effects, and importance level (weight) have been of utmost interest and challenges for HRA practitioners [33,34]. Several taxonomies and hierarchies (e.g., factors, sub-factors, and indicators) of PSF have been proposed mainly in nuclear power plants, such as emergency tasks, advanced main control rooms, and extreme external hazards listed [33]. We carefully examined more than four hundred influencing factors on performance from fifteen different PSF taxonomies. They have frequently been utilized in human reliability methods such as the Technique for human error rate prediction (THERP), Success likelihood index method (SLIM), Human error assessment and reduction technique (HEART), Cognitive reliability and error analysis method (CREAM), Information, decision, and action in crew context (IDAC), A technique for human error analysis (ATHEANA), Standardized plant analysis risk-human reliability analysis (SPAR-H), Analysis of consequences of human unreliability (ACIH), and Bellami's, and Gerdes' taxonomies, from 1983-2007, along with the latest scientific achievements such as [35,36]. However, they mainly focused on specific concerns such as cognitive or behavior failures in human functions, while organization and technology functions were missed [35]. Moreover, some of them suffer from overlapping or ambiguity [36], and missing factors arise from the new advancements (e.g., Industry 4.0), such as digitalization factors [37]. Accordingly, it is hard to apply them from a sociotechnical perspective [35]. Hence, in this study, a holistic VSFs taxonomy for STSs considering the FRAM paradigm, sociotechnical design hierarchy (e.g., individual, task, HMI, plant, organization, culture), and the concept of human-center design is developed. Therefore, this taxonomy is intended to consider all aspects of STSs together and can be used to examine influencing VSFs in a wide range of complex systems.

4.2.2. Developing the advanced probabilistic model under uncertainty

The performance (output) variability of functions is often evaluated or observed based on two manifestations (phenotypes) named *Time* (e.g., too early, on time, too late, and not at all) and *Precise* (e.g., precise, acceptable, imprecise, and wrong). A function may often be conducted in a timely manner, but it can be performed too early or too late due to dynamic variability [20]. This is also true for the function's output, how much is precise in dynamic working circumstances. In this sense adopting discrete probability distribution can better define and evaluate the performance variability of different functions and how likely various VSFs vary functions' performance in a real case under uncertainty [2,23]. Assessing human and organizational performance variability is required to use SMEs' judgments and then define the probability of variability. However, SMEs themselves are blamed for subjectivity and variability, which come from their different heuristic reasoning and uncertainty due to partial ignorance [31,38]. Hence, numerous STSs can't define a precise measurement from experiments or when information is extracted from expert elicitation [39]. To solve this limitation, we first employed the Dempster - Shafer Evidence theory (DSET) to combine multi-SMEs' knowledge to obtain prior information about the likelihood (prior probability) of VSFs and then the Monte Carlo Simulation (MCS) method to characterize uncertainty in the probability of performance variability modeling. These results also make a bridge to precisely construct the Bayesian network model of influence diagram regarding the VSFs. This hybrid probabilistic approach is proposed to precisely predict the probability of performance variability and deal effectively with its uncertainty which is the second research question in the present study. The details of this section are discussed in the following subsections.

4.2.3. Dempster - Shafer Evidence theory (DSET)

The DSET is used to elicit knowledge of SMEs regarding the prior probability distribution of performance variability and address the epistemic and aleatory uncertainty. It includes three vital functions as the basic probability assignment function (bpa or m), the Belief function (Bel), and the Plausibility function (Pl). The axioms of the bpa are characterized by three equations in Eq. 5.1. As mentioned, the bpa illustrated by m, allocates assigning of the power set to the interval from 0 to 1, where its value for null set is 0 and accumulative of its value for all subsets of the power set would be 1. The m(A)) means the bpa for a specific set A and indicates the proportion of all available and relevant evidence to support that a specific element of X (the universal set) exists in set A, but in no special subset of A [40]. Furthermore, any further evidence on the subsets of A is demonstrated by another bpa, i.e., B, m(B) means the bpa for the subset B.

$$m: P(X) \rightarrow [0,1], \quad m(\emptyset) = 0, \qquad \sum_{A \in P(X)} m(A) = 1 \tag{1}$$

where P (X) means the power set of X, $\emptyset$ is the null set, and A is a set in the power set ($A \in P(X)$) [47].

The orthogonal sum combination rule aggregates multiple SMEs' knowledge based on each degree of belief. Considering there are N SMEs' knowledge, The DSET combination rule is used as depicted in Eq. 5.2.

$$m_{1-n} = m_1 \oplus m_2 \ldots \oplus m_n \tag{5.2}$$

In the next step of using the DSET combination rule, the normalization process ignores all conflicting evidence and develops an agreement among the multiple knowledge sources by using normalizing factors equaled to $1 - k$. It is noteworthy that K indicates the basic probability mass associated with the degree of conflict between SMEs. K denotes bpa related to the conflict. This is obtained by summing the products of the bpa's of all sets where the intersection is null. This rule is commutative associative but not idempotent or continuous. Considering that SME's (knowledge sources) are independent, a conjunctive operation (AND) is used in the combination rule. For instance, the joint $m_{13}(A)$ by aggregation of three sets of evidence (e.g., $m_1(B), m_2(C)\ and\ m_3(D)$) which are obtained from three independent sources (e.g., SMEs), for the same event, is estimated using Eq. 5.3.

$$m_{13}(A) = \frac{\sum_{B\cap C\cap D=A} m_1(B)m_2(C)m_3(D)}{1-k} \quad , when\ A \neq \emptyset. \quad m_{13}(\emptyset) = 0 \quad (5.3)$$

$$where\ K = \sum_{B\cap C\cap D=\emptyset} m_1(B)m_2(C)m_3(D) \quad (5.4)$$

An interval's lower (Belief) and upper bounds (Plausibility) are obtained from the bpa. In the conventional sense, the precise probability of performance variability of interest (e.g., VSF or function) falls within the interval, effectively addressing the parameter (data) uncertainty. As presented in Eqs. (5.5 and 5.6), the Belief function presents the summation of all bpa's associated with the proper subsets (E) of the set of interest (X), while the Plausibility function provides the sum of all bpa's concerning of the sets € intersect the set of interest (X).

$$Bel\ (X) = \sum_{E|E\subseteq X} \prod_{1\le i\le n} m_i(E_i) \quad (5.5)$$

$$\mathrm{Pl(X)} = \sum_{E|E\cap X\neq\emptyset} \prod_{1\le i\le n} m_i(E_i) = 1 - \mathrm{Bel}\ (\bar{X}), \qquad \mathrm{Bel}\ (\bar{X}) = \sum_{E|E\subseteq\bar{X}} \prod_{1\le i\le n} m_i(E_i) \quad (5.6)$$

where $\bar{X}$ denots the complement of X, which means Belief is driven by the fact that all bpa should sum to 1.

It is often independently treated the PSFs' effect in many HRA methods and studies [41,42], while psychology and human factors engineering are acknowledged that there is a relationship between various influencing factors which amplify the influence of each other [41]. Accordingly, we proposed a practical guideline (Table 5.1) to revise better the estimated probability of VSFs considering their inter-relationship to reflect their effect on the performance variability of different functions. We defined the five levels from zero to complete dependency (influence) and took advantage of the dependency modeling framework proposed by the Standardized Plant Analysis Risk (SPAR) HRA (SPAR-H) Method [43]to revise the initial probability of the studied factors as per each level as shown in Table 4.1. Then the liner opinion pool as an appealing approach is used to aggregate the probability distributions [51] which are obtained from SMEs as Eq. (5.7).

$$\mathrm{P}_{agg} = \sum_{i=1}^{n} W_i \mathrm{RP}_{VSF_i} \tag{5.7}$$

In which n is the number of SMEs, RP_{VSF_i} is the revised probability for VSF_i, is estimated based on the dependency level expressed by expert i, while W_i denotes the weight of SMEs based on their profile quality which is the sum to one. This is to practically yield an answer for the second research question regarding quantifying the intra-effects (coupled dependencies) among VSFs. This process updates the prior probability (PP) of the factor of interest according to the dependency level.

Table 4. 1 Obtaining the inter-dependency effect among the variability shaping factors (VSFs)

Dependency level	Description	Revised probability (RV) of VSF_j
Complete (C)	It is certainly that VFS_i dramatically increase the influence of VFS_j over the function of interest.	$\mathrm{RP}_{VSF_j} = \frac{(1+\mathrm{PP}_{VSF_i})}{5} + \mathrm{PP}_{VSF_j}$
High (H)	It is highly likely that VFS_i increase the influence of VFS_j over the function of interest.	$\mathrm{RP}_{VSF_j} = \frac{(1+\mathrm{PP}_{VSF_i})}{10} + \mathrm{PP}_{VSF_j}$
Moderate (M)	It is moderately likely that VFS_i increase the influence of VFS_j over the function of interest.	$\mathrm{RP}_{VSF_j} = \frac{(1+\mathrm{PP}_{VSF_i})}{20} + \mathrm{PP}_{VSF_j}$
Low (L)	It is somewhat likely that VFS_i increase the influence of VFS_j over the function of interest.	$\mathrm{RP}_{\mathrm{VSF}_j} = \frac{(1+\mathrm{PP}_{VSF_i})}{30} + \mathrm{PP}_{VSF_j}$
Zero (Z)	There is not any evidence that VFS_i increase the influence of VFS_j over the function of interest.	$\mathrm{RP}_{VSF_j} = \mathrm{PP}_{VSF_j}$

5.2.1. Leaky Noisy-Max structure-based DBNs modeling

Bayesian Networks (BNs) can be represented as (G, θ), is one of the most popular models to effectively model probabilistic subjects that demonstrates as a set of random variables (nodes) and their associated conditional dependencies by directed acyclic graph (DAG) indicated by G. A G is a pair (V, E), where V is a finite, non-empty set whose elements are the nodes and V called directed edges (arcs) and if $(x, y) \in E$, it means there is an arc from *x* to *y,* and *y* is conditionally dependent on *x (logical relationship between nodes)*. θ represents a CPT that indicates the quantitative causality between nodes in DAG. The superiority of BNs mainly comes from its flexible structure, probabilistic reasoning engine, capability to capture different types of data (e.g., fuzzy, crisp, imprecise) [44], and dynamic nature of systems that able BN to be a popular method for modeling safety and risk in complex systems [45]. Considering $V = \{VSF_1, VSF_2, \dots, VSF_n, Time, Percise\}$ with n VSFs (e.g., complexity, fatigue, and procedure) and two performance variability phenotypes (e.g., Time and Precise) presents a set of nodes or random variables which illustrate a probabilistic causation model of the function of interest as simply shown in Fig. 4.3. After estimating the prior probability distribution of VSFs (root nodes), using DSET, and conditional probability distribution of intermediate nodes (e.g., Time and Precision in Fig. 5.3), the joint probability distribution of a set of variables can be therefore defined as a product of the conditional probability of each variable given the associated values of the parent variables as demonstrated as Eq. 5.8.

$$P(V) = P(VSF_1, VSF_2, \dots, VSF_n, Time, Percise) = \prod_{i=1}^{n} P\big(X_i \big| P_a(X_i)\big) \tag{5.8}$$

where $P_a(X_i)$ denotes the parent set of variables X_i $(e.g. VSF_1, VSF_2, \ldots, VSF_n, Time, Percise)$, accordingly the probability of X_i is estimated as:

$$P(X_i) = \sum_{\frac{V}{X_i}} P(V) \tag{5.9}$$

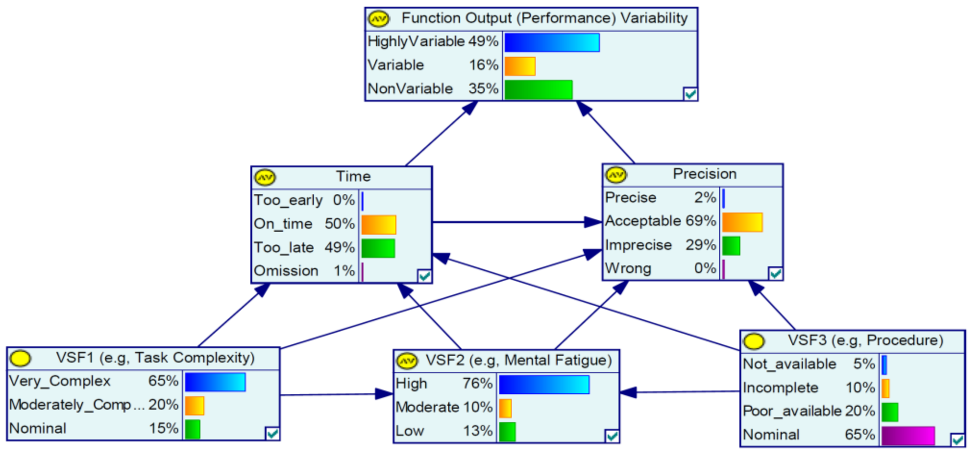

Figure 4. 3 A simple Bayesian probabilistic influence model of a hypothetical function output variability

One of the main challenges in BN modeling is defining conditional probability tables (CPTs) because their elements grow exponentially with increasing the parent nodes. As an example, when a node has five or ten parents with a binary state, the user must specify $2^5 = 32$ and $2^{10} = 1014$ parameters, respectively, while if its parent has three stats, it increased dramatically to 243 (for five parents) and 59049 (for ten parents) parameters, which is often impossible in most real complex systems. Likewise, computations to update BNs by message propagation increase exponentially, making a substantially cumbersome inference. Canonical probabilistic models, such as Noisy-MAX/OR, Noisy-MIN/AND, and Noisy Adder gate, were introduced to deal with this issue. These models are not only valuable tools for reducing the computation by the independence that they model implicitly but also for knowledge engineering that makes users easily construct and solve the complex causation models [46]. These models were introduced by Pearl (1988) [47] for binary nodes, and then by Henrion (1989) [48] was extended for binary leaky Noisy-OR gates, while the multi-valued Noisy-OR gates were developed independently by Diez (1993) [49] and Srinivas (1993) [50]. In this study, the Noisy-Max and Leaky Noisy-Max gates models have been integrated into BNs modeling to capture internal and non-linear logical relations between parents and their child nodes and deal with CPT's computation issues that arise from the exponential growth of parent numbers. It is noteworthy that these gates are a proper generalization of conventional (Leak) Noisy (OR)-gates which can be applied for multi-state (n-ary) variables [51]. It is assumed that parents can independently affect their child's nodes. Using this BN modeling technique, considering a child node is affected by its parents independently of one another (disjunctive interaction), the overall influence of all parents on a child node is obtained using Eq. 5.10 [52].

$$\mathrm{P}\left(X \middle| P_a(X)\right) = 1 - \prod_{i \in pa(X)} \left(1 - P_{X_i}\right) \tag{5.10}$$

where P_{X_i} denotes the probability of X given that its ith parent is present, and the rest are absent, which can be represented as Eq. 5.11. and estimated by Eq. 5.12.

$$P_{X_i} = P\left(X = Present \middle| \overline{Pa_1(X_i)}, \overline{Pa_2(X_i)}, \dots, Pa_j(X_i), \overline{Pa_{j+1}(X_i)}, \dots, \overline{Pa_n(X_i)}\right) \tag{5.11}$$

$$P_{X_i} = \frac{P(X|Pa_i) - P\left(X\middle|\overline{Pa_i}\right)}{1 - P\left(X\middle|\overline{Pa_i}\right)} \tag{5.12}$$

The real operation of STSs is influenced by numerous direct and indirect (latent) factors, and even using powerful probabilistic models such as BN doesn't result in completely modeling due to the limited number of nodes. This issue also arises from failing to model all influencing variables and their interactions, or SMEs may miss to identify them and do not deem it appropriate to build up a finer representation for the system [51]. It is often vital to include the cause of variabilities (e.g., common causes of failure) in reliability modeling that define the system to fail even in the presence of components up [51]. Hence, to address this drawback, have precise safety analysis, and deal with uncertainty in quantifying the causality model, we employed Leaky Noisy-OR gate, which represents all the unknown influencing factors affecting the set of V, in BN modeling. Moreover, this gate is also useful when the variable X has a primary occurrence probability regardless of its parents. The functions' performance in the FRAM model can vary in terms of time and precision even if any VSFs do not influence their outcome. Accordingly, if the initial (background) probability of variability, P_{leak} is considered an independent parent in time and precise nodes regardless of VSFs, the conditional probability of child node X, considering its parents and its prior probability, is estimated by Eq. 5.13. It should be noted that although the leak probability can be estimated from simulation and database, in most practical applications is elicited from SMEs knowledge [52,58]. In this case, to obtain it from the knowledge engineer, the question would be, "what is the probability that variable X_i results in Y if all other potential parents (causes) of Y not exist (e.g., absent)?

$$\mathrm{P}\left(X \middle| P_a(X)\right) = 1 - \left[(1 - P_{leak}) \prod_{i \in P_a(X)} (1 - P_i)\right] \tag{5.13}$$

In which $\mathrm{P_{Leak}} = \left(\mathrm{X = Present} \middle| \overline{P_{a1}(X_i)}, \overline{P_{a2}(X_i)}, \dots, \overline{P_{aj}(X_i)}, \overline{P_{aj+1}(X_i)}, \dots, \overline{P_{an}(X_i)},\ P_{aL}(X_i)\right)$,

$P_{aL}(X_i)$ denotes independent parent and $0 \leq \mathrm{P_{Leak}} \geq 1$

In the noisy Max, each W_i (e.g., Time and Precision) indicates that the value of Y (e.g., Performance variability) is affected by F_i (e.g., $\mathrm{VSF}_i, \dots, \mathrm{VSF}_n$). The obtained value produced by the individual $\mathrm{F}_i s$ is $\mathrm{y} = \mathrm{f}_{MAX}(z)$. Hence, Y and W_{iS} must share the same domain. Each W_i denots that F_i have raised the value of Y to a certain amount, and its actual value is the maximum of the $W_i s$. It should be noted that the capital letters (e.g., $W_i, \dots, W_n$) is used to denote the variables, while their value is presented by the lower-case letters (e.g., $w_i, \dots, w_n$). It is noteworthy that this Noisy MAX model only needs that Y is considered as an ordinal variable and doesn't force any conditions on the domains of $F_i s$ or on the values of the $p_y^{f_i} s$, which means the probability of each value (f_i) of the random variable F_i influences of the value of (y) of Y. To obtain the CPT of the Noisy MAX, it first obtained $P(Y \leq y|f)$ for all y's values and all configurations of f using Eq. (5.13), and then considered that $f_{MAX}(z) = \max(z_1, \dots, z_n)$, which implies that $f_{MAX}(z) \leq y$ if and only if $w_i \leq y$ for all i. Accordingly, Eq. (14-18) is used to complete the CPTs.

$$P(y|f) = \sum_{w|f(w)=y} \prod_i P(w_i|f_i) \tag{5.14}$$

$$P(Y \leq y|f) = \sum_{w|f_{MAX}(w)\leq y} \prod_i P(w_i|f_i) = \sum_{w_1 \leq y} \dots \sum_{w_n \leq y} \prod_i P(w_i|f_i) = \prod_i \left(\sum_{w_i \leq y} P(w_i|f_i)\right) \tag{5.15}$$

If we consider accumulative parameters as Eq. (5.14) and then it becomes as Eq. (5.16)

$$P(W_i = y|f_i) = \sum_{w_i \leq y} P(w_i|f_i) \tag{5.16}$$

$$P(Y \leq y|f) = \prod_i \sum_{w_i \leq y} P(w_i|f_i) \tag{5.17}$$

Finally, each value of the corresponding CPT would be estimated using Eq. (5.18).

$$P(y|F) = \begin{cases} P(Y \leq y|F) - P(Y \leq y-1|F) & for\ y \neq y_{min} \\ P(Y \leq y|F) & for\ y = y_{min} \end{cases} \tag{5.18}$$

We estimate the prior probability for each VSFs using DST, and the prior probability of each state of performance phenotypes (e.g., Time and Precision) applying Bayesian modeling so far. We then can use the deductive reasoning of BNs to predict the probability distribution of performance variability, which results in an accurate estimation [53]. Given the Time and Precision with four multi sates, each function performance has 16 states under stochastic combination, as illustrated in Table 5.2. We defined a procedure to capture the various integration of performance manifestations' states considering the three levels for function performance variability as Highly Variable (HV), Variable (V), and Non-Variable (NV) as presented in Table 4.2. It should be noted that when the combination of Time (e.g., Too early) and Precision (e.g., Precise) results in (low or high) dampening in performance quality, we considered as Non-Variability in the function's performance.

Table 4. 2 Function performance states based on the stochastic combination of performance phenotypes

State	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Time	TE	TE	TE	TE	OT	OT	OT	OT	TL	TL	TL	TL	NA	NA	NA	NA
Precision	P	A	IP	W	P	A	IP	W	P	A	IP	W	P	A	IP	W
PV	NV	NV	V	HV	NV	NV	V	HV	V	V	HV	HV	HV	HV	HV	HV

TE; Too Early, OT; On Time, TL; Too Late, NA; Note at all. P; Precise, A; Acceptable, IP; Imprecise, W; Wrong. PV; Performance Variability, NV=Non-Variability, V; Variable, H; Highly Variable

We defined the scores 3, 2, and 1, respectively, for Highly Variable, Variable Non-Variability states of performance variability and then derived the mean and standard deviation values for the predicted output variability. After that, we conducted MCS to characterize the uncertainty. We assumed the normal probability distribution for performance variability [23] and obtained the mean and standard deviation. It is a prevalent approach for estimating the information regarding the distributions, which also considers the model uncertainty [54]. Accordingly, we used MCS as a sophisticated sampling method for generating a sequence of random variables based on the predicted expected values. This advantage allows the algorithms to narrow in on the parameter value approximated from the distribution, even with many random variables, and precisely deal with the uncertainty. This study assigned a normal distribution for performance variability, its phonotypes, and related parameters (e.g., leak probability), which is frequently used for system performance and its parameters [10,24].

Identifying the most contributing (critical) factors to performance variability is vital for safety and resilience application in complex systems [13]. However, deciding on only prior or posterior probabilities to identify critical components will likely lead to inaccurate results [55]. Hence, we employed a Bayesian network-driven importance measure for system safety named Ratio of variation (RV), which denotes the normalized difference of the posterior and prior probability of variable of interest and can be used in dynamic BN inference [44,56].

$$RoV\ (VSF_i) = \frac{P(VSF_i|Function\ Performance) - PP(VSF_i)}{PP(VSF_i)} \tag{5.19}$$

where $\mathrm{PP(VSF_i)}$ stands for the prior probability of variability shaping factor i in the probabilistic model using BN and $\mathrm{P(VSF_i|Function\ Performance = highly\ variable)}$ denotes posterior (updated) probability of $\mathrm{VSF_i}$ given that the associated function performance is instantiated to its new evidence or state of interest (e.g., highly variable). This diagnostic inference of the model helps capture the new field or experiment information to update the model and address the model uncertainty.

As it is mentioned in the literature review, the previous studies considered performance variability as a static property of the system. It is an oversimplified assumption for complex systems when interacting with human, organizational, technological, and environmental factors. To capture the dynamic nature of performance variability in complex systems, we utilized the Dynamic Bayesian network (DBN), which is frequently employed to model temporal changes in risk and reliability studies. DBN is generally used to determine the temporal probability of a random variable (e.g., VSFs, time, precision, and performance variability), as illustrated in Eq. (5.20). Moreover, we will illustrate how we can update the prior distributions given the new evidence, covering the fourth research question.

$$P\ (Z_t|Z_{t-1}) = \prod_{i=1}^{N} P\left(Z_t^i \middle| \pi(Z_t^i), \pi(Z_{t-1}^i)\right) \tag{5.20}$$

where, Z_t^i is the random variable at time t, $\pi(Z_t^i)$ is the parent nodes of Z_t^i at time t and $\pi(Z_{t-1}^i)$ is the parent nodes in time t-1.

It is noteworthy that conventional BNs can only capture conditional dependency mainly arising from common-cause failures due to its limitation in cyclic modeling, while DBNs can also model dependency based on mutual cause-effect relationships among VSFs. Moreover, DBN can effectively be utilized to capture the influence of safety countermeasures to dampen the system's critical variabilities and failure analysis, considering the potential degradation of influencing factors of interest over time.

4.2.4. Proposing the criticality matrix

Supporting the decision-making process requires a framework for evaluating the performance variability to dampen the critical ones. This section develops a criticality matrix with two dimensions of estimated severity and probability of variability due to VSFs. First, we designed a score scale for the probability of variability levels as high (score = 3), moderate (score 2), and lower (score = 1) based on their importance from the safety and risk engineering perspective. Consequently, given the mean (expected value) of the discreet probability distribution and the criticality magnitude of each function, it will be placed in one of the Low (I), Tolerable (II), and High (III) levels as presented in Fig. 4.4. Table 4.3 represents how should be done at and considered each criticality level, in Safety-II perspective, concerning an individual or collective approximate adjustments necessary for everyday work and preventing adverse outcomes from having sustainable and resilience systems. The proposed variability matrix is expected to pave a practical and straightforward way to dampen the critical variability in a risk-based decision-making perspective, defined as the current study's last research question.

	Probability of Variability (expected value)		
Magnitude level	Non-Variable	Variable	High-Variable
Major	II	III	III
Moderate	I	II	III
Marginal	I	I	II

Figure 4. 4 A matrix used to evaluate the criticality level of performance variability

Table 4. 3 Criticality level of performance variability and descriptions.

Criticality level	Description
III	Adverse outcome is inevitable, and dampening must be done before function (activity) begins.
II	Function variability should be carefully monitored and being under control.
I	This can be considered as an asset since it emerges from approximate adjustments which is necessary for everyday work.

4.2.5. The model validation

Model validation plays a vital role in this methodology since it provides a sensible confidence value regarding the model's findings. Four approaches for pragmatically validating a risk analysis including a complete benchmark exercise, partial benchmark exercise, reality check, and independent peer-review are recommended. This research utilized a partial benchmark exercise, a mix of a reality check and independent peer-review (SMEs), and sensitivity analysis in Bayesian networks to validate the proposed model. As per the author's understanding, it is hard to benchmark the model entirely. Hence, we compare the study's findings with some parts of similar research results conducted in human reliability/factor analysis.

Moreover, the findings are examined with the experiences and safety data of the understudied field and SMEs' knowledge. Finally, we used two types of sensitivity analysis that are most popular in probability parameters of Bayesian Networks to evaluate the model's effectiveness and accuracy. We used the GeNIe 3.0 Academic (http://www.bayesfusion.com) for Bayesian Network modeling. This program used an algorithm developed by [57] to conduct the sensitivity analysis in Bayesian networks. This algorithm efficiently obtains a full set of derivatives of the updated (posterior) probability distributions (e.g., VSFs) considered a set of target nodes (e.g., Performance variability or its phenotypes) over each of the numerical parameters of the proposed probabilistic model. These derivatives denote the importance of precision of the model's quantitative parameters for estimating the posterior probability distributions of the targets. Accordingly, the nodes contain essential parameters to estimate the posterior probability distributions of the target nodes, which can be specified in the Bayesian Network modeling. After that, we examine the accuracy of these results during the independent peer-review and consistency check with the other model results. Moreover, we performed another sensitivity analysis to partially validate the model considering the three principles, which must therefore be satisfied as follows [58]:

Principle 1: A relative increase or decrease in the posterior probability distribution of the child nodes (e.g., VSFs) should certainly observe by a slight change in the prior probability of each associated parent.

Principle 2: Considering the prior probability distribution of each parent, its impact magnitude on the child node probability should keep consistent.

Principle 3: The overall impact magnitudes of the mix of the probability variations from Z attributes (evidence) on the values should be consistently higher than the one from the set of $Z-R$ ($R \in Z$) attributes (sub-evidence).

4.3. Case study description: Maintenance operation in oil and gas facilities

This section is devoted to illustrating the practicability of the developed model for uncoupled variability modeling of system performance. A maintenance operation cycle that includes pre- and post-maintenance activities is considered for testing the model. Although it can be identical in most industries, we tend to focus on it in the oil and gas facilities in the South Pars Gas Complex (SPGC) which is located in Pars Special Economic Energy Zone, Asaluyeh, Bushehr Province, Iran (Fig. 5.5). This energy source is the world's second-largest natural gas reservoir and contains offshore and onshore facilities. Its operation involves fourteen gas refineries, more than ten offshore platforms, 100 wells and 500 km pipelines, and twelve petrochemical plants. It is frequently acknowledged that maintenance activities give rise to numerous human and technology failures that result in catastrophic accidents [33]. Moreover, a considerable portion of the budget (e.g., more than $300 billion in the USA) is annually spent on these operations [33]. Given a wide range of VSFs (e.g., harsh environments, poorly written maintenance procedures, poor work layout, complex maintenance tasks, crew characteristics, logistics) impact on safety and risk of maintenance in critical sectors, it can be a suitable application for serving the purpose of the present study.

(a) A part of gas refineries (b) A petrochemical plant

Figure 4. 5 The Studied area, Pars Special Economic Energy Zone, an example of chemical processing plants (a, b)

4.4. The proposed model application (Result and discussion)

4.4.1. Characterizing the system's functions

As per the methodology, the system's functions should be first studied, constituting the FRAM model of maintenance operation in everyday work. The human-oriented functions of the studied maintenance operation are demonstrated in Table 4.4, while the organization and technology-oriented ones are presented in Table 4.5. Overall, thirty-one functions directly associated with the maintenance operation are identified. Nineteen functions are human-oriented activities, while organization and technology are associated with five and seven functions.

Since the FRAM deals with what happens or what has happened or is likely to happen rather than with what is or was assumed to happen, the functions referred to activities rather than

to tasks in the present research. The FRAM uses the term 'function' as in the goals-means relation, where a function indicates the means that are necessary to achieve a goal. More generally, a function refers to the activities or set of activities that are required to produce a particular outcome. A function describes what people, individually or collectively, have to do to achieve a specific aim. A function can also refer to what an organization does. A function can finally refer to what a technological system does either by itself (an automated function) or in collaboration with one or more humans (an interactive function or co-agency) [2].

Table 4. 4 The human-oriented functions of the studied maintenance operation

No.	Function	Description
1	Assessing maintenance needs and orders	Preventive or corrective maintenances (e.g., planned or unplanned) is issued as an order or need by maintenance and its subdepartments (e.g., mechanical, machinery, electrical, instrument and maintenance service)
2	Approving maintenance order	The committee members from the operation, safety and firefighting, maintenance, production, and planning departments are discussed the submitted orders.
3	Planning and referring the work to the crew group	The method (production and planning) department assigns the operation department as owner and changes the work order to work. Then the work is referred to the applicant department or unit.
4	Applying for the permit to work (PTW)	After preparing the work order, the required equipment diagnose and tags use by the hardware and software platforms. The responsibilities are defined and the PTW is referred to the operation department.
5	Assessing risks and developing emergency response planning (ERP)	After hazard identification and evaluating their risk level, safety countermeasures are all in place before pre-maintenance. On-site supervisors issued the Toolbox Risk Identification Card (TRIC) attached to the PTW order. The ERP committee is developed the required action plan.
6	Determining and certifying require isolations and preparation	After examining all lines, their pressure, vent, bleeds, and close, lock, and tag isolation valves, the most appropriate isolation approach is determined. Obtain certificates and keys, assign lockout boxes, and deliver the keys to supervisors. Review the related work orders to ensure no operational conflict or other work.
7	Knowledge management	Holding a safety talk to learn from past on-site and offsite incidents and holding safety toolbox meetings (TBM) to build a learning organizational safety culture and reinforce the safety standard and procedures.
8	Performing chemical process isolation	All affected equipment and pipelines are isolated from main chemical process lines by bypassing the feeds into other pipeline pathways. Finally, the process isolation certificate is attached to the PTW sheet.

9	Depressurizing, draining, and purging	All affected pipelines and equipment are depressurized and cleaned to ensure they are ready for safe maintenance. Inert materials (nitrogen or steam) are used to provide a free hydrocarbon gas environment.
10	Performing mechanically and electrically isolation	Blinding or blanking, disconnecting, and misaligning all affected lines and performing lockout and tag-out procedures for all energy sources. Finally, these isolations certificate is attached to the PTW sheet.
11	Performing pressure and isolation leak test	Performing the hydrostatic (water) or pneumatic (air or inert gas) pressure tests to identify the potential leak points and ensure the system is fully isolated.
12	Applying for maintenance inhibition	Isolating and deactivating All gas detectors, fire and gas systems, fire and smoke detectors, and sensors.
13	Preforming gas and oxygen testing	Employing a gas analyzer to measure flammable gases by a certified person and toxic and oxygen concentrations by the HSE department before, during, and at the end of work.
14	Confirm PTW and monitor its validity	Reviewing all requirements must by area authority, supervisor (permit issuer), and HSE to ensure meet them and not exist any cross-reference, approving PTW and place it on board and worksite. If the work must continue beyond the allowed period, PTW is closed, and a new one is prepared.
15	Performing maintenance	Carry out maintenance of the equipment as per scheduled and approved program.
16	Reassembling the components	Checking all lines and equipment for obstruction and removing mechanical and electrical isolation (lock and tags) to open valves and connect lines.
17	Preparing for start-up and conducting the pressure tests	Returning all lockout keys and certificates, giving back worksite authority to area authority, and document reinstatement by supervisor. Opening the valve and reinstate to perform test pressure, then removing air from lines and open valves and test for the leak to ensure equipment are placed in their safe conditions.
18	Conducting the Pre-Startup Safety Review (PSSR) and running operation	Employing the PSSR procedure by the committee to make sure all safety requirements are in place properly. Finally, running the system to begin the normal operation if there is not any non-compliance.
19	Monitoring the Simultaneous Operations (SIMOPS) limitations	Ensuring the safety of operations and more coordination when maintenance and production are performed simultaneously.

Table 4. 5 The organization and technology-oriented functions of the studied maintenance operation

F N	Function	Description
20*	Establishing and holding the crew training programs	All crew members must generally receive training programs regarding the standard operation procedures, HSE risks, effective communication, emergency response management based on their responsibilities and authority. Some staff must be continuously trained with technical courses and get certified.
21	Providing the required hardware (e.g., tools, instruments, and programs), software (e.g., SOP, PFD, P&ID), legal support)	The necessary equipment (e.g., proper gas tester, PPE, LOTO, isolators) and software are available to conduct activities safely. Maintenance contractors' safety and financial requirements are clearly reflected and confirmed in official documents by the site leader.
22	Establishing the Radar system to improve the spirit of team working, mutual communication, and safety culture	The organization should clarify team roles and provide a solid culture to communicate openly and effectively, trust and support each other, appreciate the ideas diversity, high engagement level, and create strong team spirit among and between both contractor and site leader crew members
23	Managing human resources	Competent crew members from maintenance contractors to site leaders hired, trained, and certified based on the required standard procedures considering the operation, maintenance, and safety requirements. Contractors are asked to provide a proper organization chart and a competent maintenance crew.

24	Protection of environmental programs	Critical systems and packages are available to ensure pollution by hydrocarbons (e.g., sewage, solid disposal, flow monitoring) are protected.
25**	Pressure and leak test system	These devices measure the pressure and specify any leakage in the area of interest.
26	Gas analyzer and leak tester	The related device measures the concentration of gases of interest.
27	Depressurizing, draining, and purging system	This system reduces the operational pressure and cleans the component for safe maintenance.
28	Isolation systems (flange, gaskets, stud bolts, valves)	This system safely separates the operation zones from the components under maintenance.
29	Lockout and Tagout system	This system prevents any energy sources from unsafe start-up during maintenance.
30	Portable Fire and Gas detection packages	Replacement for disabled Fire and Gas Detection system in maintenance areas
31	Escape, Evacuation and Rescue (EER) Facilities	Ensure the availability of escape, evacuation, and rescue apparatus based on emergency response procedure and plan

* Organization and ** technology-oriented functions

4.4.2. FRAM-driven HOT Taxonomy of VSFs for STSs

Considering the function types in the FRAM model, sociotechnical design hierarchical (e.g., individual, task, HMI, plant, organization, culture), and the concept of human-center design, a holistic taxonomy of VSFs for STSs is proposed (Table 4.6). The authors prepared a template (e.g., the checklist) to obtain the data systematically and identify which VSFs influence each function. After reviewing extensive literature on performance-shaping factors concerning safety I and II, the authors developed the initial taxonomy of VSFs for STSs. After that, it was shared with thirteen subject matter experts (SMEs) in the studied field (Pars Special Economic Energy Zone) to capture field experiences and two full academic professors with great experience in both studied operation and research methodology. The field SMEs participated in various departments such as operation, maintenance, management, health, safety, and environment. Through several interactive meetings, they were first provided with detailed information regarding the research methodology and objectives. After collecting their knowledge and feedback on the revised ones, 25 new influencing factors were added, some factors were merged or removed, and finally, the novel FRAM-driven

HOT taxonomy was developed. It contains 80 contributing factors to human factions, 26 organization functions, and 16 technology functions. It was developed in line with the FRAM paradigm, sociotechnical design hierarchy (e.g., individual, task, HMI, plant, organization, culture), and human-center design concept. Therefore, this taxonomy captures all aspects of STSs and subsequently provides a deep understanding of complex system elements, their interaction, and their influence on system performance systems. This importance can substantially improve the designing of technical systems, business processes, organizational structures, and human operations [59]. This attempt addresses the research question: which internal and external factors are associated with the uncoupled variabilities of human, organization, and technical functions in everyday work?

Table 4. 6 A holistic FRAM-driven HOT (human-organization- technology) Taxonomy of VSFs for STSs

Function category	VSFs category	VSFs sub-groups	Variability Shaping Factors (VSFs) and their ordinal coding
Human	Human-driven factors	Physical condition	Physical Fatigue, Physical abilities, Age, Gender; (VFS#1-4)
		Physiological and Phycological factors	Problem-solving style, Morale, Motivation, (Safety)Attitude, Situational awareness, Vigilance, Cognitive bias, Emotional arousal (Stress), Self-confidence, Perception and appraisal, Mental Fatigue, Circadian rhythm (disorders); (VFS#5-16)
		Memorized information	Working and intermediate memory, Long-term memory, Experience and knowledge, Skills, Information uncertainty; (VFS#17-21)
	Task-driven factors	Task type and cognition	Observation, Diagnostic, Monitoring, Planning, Execution (e.g., Construction, Operational, Maintenance, Commissioning or Decommissioning); (VFS#22-26)
		Task attribute	Task mode (Parallel task and dependent task), Shift working, Task scheduling (Time of day and task duration) Task urgency (Available task time), Task complexity, Task risks, Task novelty, Task workload (Manual labor strength and Cognitive resource demand), Task consequence (e.g., Financial); (VFS#23-35)
	Organization-driven factors	Strategy-oriented factors	Safety measures program, Perceived safety culture/climate, Safety incentive; (VFS#36-38)
		Strategy-oriented factors	Resources management (workforce, procedures, tools availability and quality), Goal substitution, Organisational double-binds (e.g., safety and productivity conflicts), Perceived organizational support, External demands to quality and quantity; (VFS#37-43)
		Management-oriented factors	Training program, Staffing and scheduling management, Monitoring teamwork, Monitoring work conditions, Monitoring skills and competencies, Monitoring procedures; (VFS#44-49)
	Technology-driven factors	Human-machine interface (HMI)	Digitalization level, Controller layout and availability, Indicator layout, Displayer availability, Warning light, Alarm sound systems; (VFS#45-55)
		Technical system State	Operating parameter (State, Change rate and number of parameter anomalies), Number of abnormal operating phenomena, Ambiguity in system response; (VFS#56-58)

	Environment-driven factors	Harsh environment	Temperature, Humidity, Air pressure, Noise, Vibration, Lighting, Toxic gas, Dust and fume, Wind speed, Radiation, Natural hazards (e.g., Rainfall); (VFS#59-69)
	Team-driven factors		Cohesiveness, Coordination, Communication, Composition (crew arrangement and structure), Leadership, Team roles and responsibility, Team norms; (VFS#70-76)
	Social-driven factors		Expectations to oneself or colleagues, Compliance with the group working standard, Social norms, Religious beliefs; (VFS#77-80)
Organization	Strategy-driven factors		Authority gradient, Organizational safety culture, Organizational trust, Goal substitution, Simultaneous goals, Organizational vision, Strategy and goals, Organizational structure and practices, Organisational double-binds; (VFS#1-9)
	Knowledge management factors		Performance feedback process, Communication effectiveness, management of change, Organisational learning, Organizational memory, Resource availability, Operating environment; (VFS#10-16)
	External factors		External demands to quality and quantity, Customer demand/expectation, Natural disasters, Sanction; (VFS#17-20)
	National factors		Physical/legislative/business environment, National culture, Regulatory scrutiny, Regulatory environment, Commercial resource; Religious beliefs; (VFS#21-26)
Technology	Safety-oriented factors		Failure or malfunction detection systems, Reliability and availability, Inspection's methods and intervals, Warranty and supply management, Resilience, Inherent safety design, Redundancy (Standby or Active), Management of change, Maintenance policies; (VFS#1-9)
	Operation-oriented factors		Physical (harsh) environment, Operator characteristics, process or operational conditions, Operating procedures; (VFS#10-13)
	Mechanical degradation-oriented factors		Wear and tear conditions, Corrosion and erosion, Mechanical degradation/integrity, Inner workings and Damage mechanisms (rate and severity), Equipment or device age (aging); (VFS#14-18)

4.4.3. Integrating DSET into DBNs results

This section provides the probability-oriented findings for the variability of functions' performance (output) using DSET and their integration into a Dynamic Bayesian network while efficiently addressing the main challenges in handling uncertainty. It should be noted that there have not been any direct questions or interviews to obtain data. Experts already involved through previous steps (e.g., 4.1. Characterizing the system's functions and 4.2 FRAM-driven HOT Taxonomy of VSFs for STSs) learned and obtained information regarding the research methodology. The employed SMEs are first asked to express their knowledge on how likely function’s performance *X* varied [Yes] and not [No] varied by VSF *Z* using the developed Survey in Excel. In this sense, they defined the probability of performance variability between 0 to 1 for each function considering the proposed VSFs. After that, the knowledge of SMEs is aggregated and then yields to interval estimation of variability for each function using the DSET. To illustrate the computation process,

Table 4.7 represents the details and results for obtaining probability distribution of variability for performance function "*F#8 = Performing chemical process isolation*" stem from a VSF called "*N#59 "Ambient temperature*" as an instance. We used the Basic Probability Assignment function (bpa or m), the Belief function (Bel), and the Plausibility function (Pl), which respectively estimate the most likely, min, and max values. This deals with fuzziness uncertainties in knowledge elicitation, while probability distributions are used to characterize the stochastic uncertainty caused by the randomness of variables, lack of knowledge, and potential biases among SMEs [60,61].

Regarding critical challenges in knowledge engineering, dissonance engineering pave the way to treat dissonance [62]. Cognitive dissonance means an incoherence between cognitions, such as between elements of knowledge or between knowledge sets. It can happen when something sounds incorrect, i.e., it will be, is, maybe or was not correct, and be explained as gaps or conflicts between the individual or collective knowledge [63]. Erroneous affordances and contradictory knowledge are two salient types of dissonance in human reliability and risk analysis [62,64]. The dissonance discovery and control include the dissonances' influence evaluation, accepting or refusing dissonances, reinforcing the frames of reference, and subsequently improving the system resilience. We want to draw readers' attention to this important subject in knowledge acquisition, and dealing with it seems to be beyond the present study. We would like to refer interested scholars to the primary literature, where more explanations and practical cases can be easily found [62–65].

Table 4. 7 The prior probability distribution of performance variability for F#8 "*Performing chemical process isolation*" caused by variability shaping factor N#59 "*Ambient temperature*"

	{Yes}	{No}	{Yes, No}		
m_1(Ex#1)	0.40	0.50	0.10		
m_2(Ex#1)	0.30	0.62	0.08		
m_3(Ex#1)	0.45	0.44	0.11		
Sets No.	m_1	m_2	m_3	Sets (A)	Probability
1	{Yes}	{Yes}	{Yes}	{Yes}	0.0540
2	{Yes}	{Yes}	{Yes, No}	{Yes}	0.0132
3	{Yes}	{Yes, No}	{Yes}	{Yes}	0.0144
4	{Yes, No}	{Yes}	{Yes}	{Yes}	0.0135
5	{Yes}	{Yes, No}	{Yes, No}	{Yes}	0.0035
6	{Yes, No}	{Yes}	{Yes, No}	{Yes}	0.0033
7	{Yes, No}	{Yes, No}	{Yes}	{Yes}	0.0036
8	{No}	{No}	{No}	[No]	0.1364
9	{No}	{No}	{Yes, No}	{No}	0.0341
10	{No}	{Yes, No}	{No}	{No}	0.0176
11	{Yes, No}	{No}	{No}	{No}	0.0273
12	{No}	{Yes, No}	{Yes, No}	{No}	0.0044
13	{Yes, No}	{No}	{Yes, No}	{No}	0.0068
14	{Yes, No}	{Yes, No}	{No}	{No}	0.0035
15	{Yes}	{Yes}	{No}	{Ø}	0.0528
16	{Yes}	{No}	{Yes}	{Ø}	0.1116
17	{No}	{Yes}	{Yes}	{Ø}	0.0675
18	{Yes}	{No}	{No}	{Ø}	0.1091
19	{No}	{Yes}	{No}	{Ø}	0.0660
20	{No}	{No}	{Yes}	{Ø}	0.1395
21	{Yes}	{No}	{Yes, No}	{Ø}	0.0273
22	{Yes}	{Yes, No}	{No}	{Ø}	0.0141
23	{Yes, No}	{Yes}	{No}	{Ø}	0.0132
24	{No}	{Yes}	{Yes, No}	{Ø}	0.0165
25	{No}	{Yes, No}	{Yes}	{Ø}	0.0180
26	[Yes, No]	{No}	{Yes}	{Ø}	0.0279
27	{Yes, No}	{Yes, No}	{Yes, No}	{Yes, No}	0.0009
$K = \sum_{B \cap C \cap D = \emptyset} m_1(B) m_2(C) m_3(D) = 0.3566$					$\sum_{A \in P(X)} m(A) = 1$
			{Yes}	**{No}**	**{Yes, No}**
$\boldsymbol{m_{13}}(A = \{Yes\}, \{NO\} and \{Yes, No\}) = \frac{\sum_{B \cap C \cap D = A} m_1(B) m_2(C) m_3(D)}{1-K}$			0.3136	0.6838	0.0026
$\boldsymbol{Bel}\ (X) = \sum_{E \mid E \subseteq X} m(E)$			0.1055	0.2301	0.0009
$\mathbf{Pl}(\mathrm{X}) = \sum_{E \mid E \cap X \neq \emptyset} m(E) = 1 - \mathrm{Bel}\ (\bar{X})$			0.7699	0.8945	0.6644

The DSET's findings were assigned as a prior probability distribution of VSFs, as parent nodes, in the Bayesian Network's causality model. We used the proposed causation model to take unique advantages of the Bayesian Network, especially conducting precise predictive and diagnostic inferences, updating the model given new evidence, modeling dependencies among VSFs, and addressing the model uncertainty. We developed the causality model of performance variability for all proposed functions. As an example, the probabilistic causation model for Function #18 (Conducting the Pre-Startup Safety Review (PSSR) and run operation) is demonstrated in Fig 4.5. The advanced canonical models (e.g., Leaky Noisy-Max) were utilized to solve the CPTs associated with the child nodes (e.g., human factors, organization factors). Table 4.8 (Part A) presents the CPT computation process of the child node related to VSF#15 (Mental Fatigue), considering Function #18 as an instance. Furthermore, the detailed calculation process is shown in Part (B) Table 4.8, considering VSF#15 (Sate= High) and VSF#12 (Emotional arousal (Stress), Sate= High), while the knowledge of three experts is used to obtain the inter-dependency effect among these two factors. We used the proposed procedure to capture inter-dependency among contributing factors and then liner opinion pool, as an appealing approach, to aggregate the probability distributions as presented in Table 4.8.

We also used the Leaky Noisy-OR gate to capture the inter-dependency effects that arise from explicitly unknown factors or SMEs' ignorance about the VSFs interactions. This helps to deal with the aleatory uncertainty caused by incompleteness or ignorance. Leap probability obeys the Gaussian probability density [66] and the confidence level was considered 99% and 95% (e.g., in this CPT), that is PL = 0.04 (VSFs state = High), and 0.01 (VSFs state= Moderate). Accordingly, the value of leak probability in Table 5.8 reflects the sum of the initial (prior) probability of VSF15 and the probability associated with explicitly unknown factors or SMEs' ignorance about the VSFs interactions. As can be seen from Table 4.8, the synergism effect of the six VSFs resulted in a probability increase from 0.0602 to 0.1212 for VSF15 (Mental Fatigue), which denotes dependency among Mental Fatigue and those contributing factors performing the *Pre-Startup Safety Review*

(PSSR) and run operation function *(#18*). We found that modeling all possible dependencies among variables leads to too cumbersome computations and difficulties running the Bayesian Network model, especially in performing predictive and diagnostic reasoning. Accordingly, we only present the dependencies among variables in Fig. 4.6, where all three SMEs believed the dependency level is equal to or greater than *Moderate* among VSFs. However, we assumed that considering the confidence level (95%) and leak probability in the probabilistic model addressed this issue and did not affect the results accordingly. Moreover, the model served for knowledge engineering associated with the causality mechanisms that exist or emerge among VSFs by capturing both dependency and conditional independency among VSFs and performance manifestations (phenotypes). The conditional independencies come from the Markov chin condition, which means a node is independent of its non-descendants given its known parents.

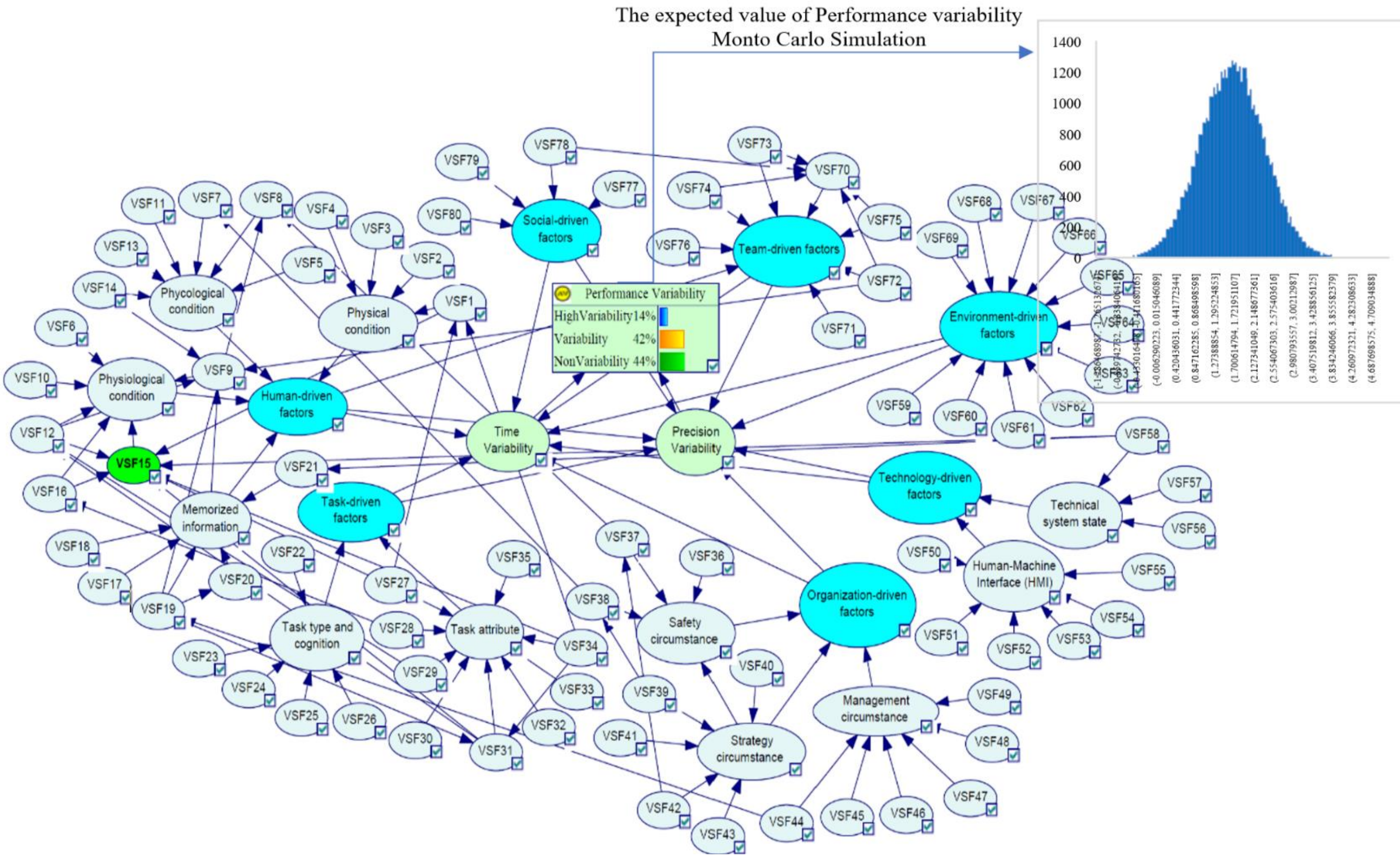

Figure 4. 6 The probabilistic causation model for performance variability of Function#18 (*Conducting the Pre-Startup Safety Review (PSSR) and run operation*)

Table 4. 8 The CPT computation for VSF#15 (Mental Fatigue) considering Function #18 (Conducting the PSSR and run operation)

Part (A)		VSF1			VSF12			VSF16			VSF27		
		High	Moderate	Low	High	Moderate	Low	High	Moderate	Low	High	Moderate	Low
VSF15	PP	0.0373	0.0002	0.9625	0.0102	0.0004	0.9893	0.0118	0.0003	0.9879	0.0452	0.0001	0.9546
High	0.0602	0.1121	0.1102	0	0.1460	0.1452	0	0.1053	0.1048	0	0.1072	0.1052	0
Moderate	0.0012	0.0531	0.0513	0	0.0870	0.0862	0	0.0463	0.0458	0	0.0482	0.0462	0
Low	0.9385	0.8348	0.8385	1	0.7670	0.7686	1	0.8484	0.8494	1	0.8446	0.8486	1

		VSF31			VSF34			VSF58				
		High	Moderate	Low	High	Moderate	Low	High	Moderate	Low		
VSF15	PP	0.0208	0.0003	0.9789	0.0460	0.0010	0.9530	0.0168	0.00004	0.9831	Leak	**RP$_{VSF15}$**
High	0.0602	0.1455	0.1438	0	0.1490	0.1452	0	0.0941	0.0936	0	0.1002	**0.1212**
Moderate	0.0012	0.0865	0.0848	0	0.0901	0.0862	0	0.0351	0.0346	0	0.0112	**0.0216**
Low	0.9385	0.7680	0.7714	1	0.7609	0.7686	1	0.8708	0.8718	1	0.8886	**0.8571**

Part (B)

Example for the CPT estimation				Dependency level (DL)			Weight of SME			
VSF15	PP	VSF12	PP	Ex#1	Ex#2	Ex#3	Ex#1	Ex#2	Ex#3	Confidence level= 95% (in this CPT)
High	0.0602	High	0.0102	High	High	Moderate	0.3688	0.3292	0.3020	

$$\text{DL} = \text{High}, \quad \text{RP}_{VSF_{15}} = \frac{\left(1+\text{PP}_{VSF_{12}}\right)}{10} + \text{PP}_{VSF_{15}} == \frac{(1+0.0102)}{10} + 0.0602 = 0.1612$$

$$\text{DL} = \text{Modearte}, \quad \text{RP}_{VSF_j} = \frac{\left(1+\text{PP}_{VSF_{12}}\right)}{20} + \text{PP}_{VSF_{15}} = \frac{(1+0.0102)}{20} + 0.0602 = 0.1107$$

$$\text{P}_{agg} = \sum_{i=1}^{n} W_i \text{RP}_{VSF_i} = \sum_{i=1}^{3} (0.3688 \times 0.1612)(0.3292 \times 0.1612)(0.3020 \times 0.1107) = \mathbf{0.1460}$$

Leak probability for VSF15=High
= 0.0602+0.04= 0.1002

Leak probability for VSF15=Medium
= 0.0012+0.01=0.0112

After defining the CPTs, Bayesian network inferences can be performed. We defined three levels from Highly Variable (HV), Variable to Non-Variable for performance variability considering the combination of performance phenotypes' states (Time= Too Early, On Time, Too Late, Note at all and Precision= Precise, Acceptable, Imprecise, Wrong) for each function. Deductive reasoning is employed to predict performance variability's probability distribution, which results in an accurate estimation. Table 5.9 presents the findings of the probability distribution of variability for output (performance) for all maintenance functions and their ranking based on criticality in performance variation. We first derived the mean and standard deviation values for the corresponding scores based on the predicted output variability and conducted Monto Carlo Simulation to characterize the uncertainty accordingly. We assumed the normal probability distribution for performance variability [23,67] and obtained the mean and standard deviation, as shown in Table 5.9, by performing the 100,000 iterations using the Excel program. As demonstrated, functions include #F9 (*Depressurizing, draining and purging*), F#17 (*Preparing for start-up and conducting the pressure tests*), and F10 (*Performing mechanically and electrically isolation*) introduced the highest variability, respectively, among the Human-oriented functions. In comparison, F#21(*Providing the required hardware, software, and legal support*) from Organization and F#27 (*Depressurizing, draining, and purging system*) from Technology-oriented functions have the most critical variability from a probabilistic perspective.

Table 4. 9 Probability distribution of variability for functions output (performance) in maintenance operation

Rank	Function	Variability Level (State)			Corresponding Sores			Mean	SD	Uncertainty	
		HV	V	N-V	3	2	1			LB	UP
1	F9	0.2091	0.5681	0.2228	0.6273	1.1362	0.2228	1.9871	0.6570	1.3301	2.6440
2	F17	0.1815	0.5331	0.2854	0.5445	1.0662	0.2854	1.8921	0.6754	1.2186	2.5657
3	F10	0.1681	0.5192	0.3127	0.5043	1.0384	0.3127	1.8565	0.6782	1.1774	2.5356
4	F4	0.1521	0.4661	0.3818	0.4563	0.9322	0.3818	1.7672	0.6936	1.0704	2.4640
5	F18	0.1382	0.4227	0.4391	0.4147	0.8454	0.4391	1.6993	0.6941	1.0247	2.4127
6	F15	0.1301	0.4261	0.4438	0.3903	0.8522	0.4438	1.6864	0.6976	1.0013	2.3967
7	F6	0.1267	0.4091	0.4642	0.3801	0.8182	0.4642	1.6627	0.6906	0.9720	2.3534
8	F5	0.1206	0.3931	0.4863	0.3618	0.7862	0.4863	1.6345	0.6879	0.9469	2.3221
9	F14	0.1131	0.3481	0.5388	0.3393	0.6962	0.5388	1.5744	0.6861	0.8885	2.2603
10	F19	0.1099	0.2821	0.6080	0.3297	0.5642	0.6080	1.5021	0.6854	0.8166	2.1876
11	F8	0.1021	0.2684	0.6295	0.3063	0.5368	0.6295	1.4225	0.6734	0.7493	2.0957
12	F11	0.0921	0.2372	0.6707	0.2763	0.4744	0.6707	1.4215	0.6542	0.7672	2.0758
13	F16	0.0791	0.1891	0.7318	0.2373	0.3782	0.7318	1.3472	0.6204	0.7268	1.9676
14	F13	0.0531	0.1641	0.7828	0.1593	0.3282	0.7828	1.2704	0.5509	0.7197	1.8211
15	F12	0.0481	0.1276	0.8243	0.1443	0.2552	0.8243	1.2237	0.5195	0.7041	1.7433
16	F7	0.0201	0.1008	0.8791	0.0603	0.2016	0.8791	1.1409	0.4016	1.0094	1.8124
17	F1	0.0161	0.0961	0.8878	0.0483	0.1922	0.8878	1.1284	0.3795	0.7493	1.5075
18	F2	0.0105	0.061	0.9285	0.0315	0.1220	0.9285	1.0790	0.3103	0.7687	1.3893
19	F3	0.0053	0.0378	0.9569	0.0159	0.0756	0.9569	1.0486	0.2380	0.8107	1.2865
1	F21	0.1176	0.2567	0.6257	0.3528	0.5134	0.626	1.4921	0.6965	0.7956	2.1886
2	F22	0.1062	0.2392	0.6546	0.3186	0.4784	0.655	1.4514	0.6783	0.7733	2.1295
3	F23	0.0776	0.2165	0.7059	0.2328	0.433	0.706	1.3719	0.6235	0.7484	1.9954
4	F20	0.0348	0.1107	0.8545	0.1044	0.2214	0.855	1.1801	0.4663	0.7138	1.6464
5	F24	0.0218	0.0937	0.8845	0.0654	0.1874	0.885	1.1375	0.4026	0.7349	1.5401
1	F27	0.1336	0.3647	0.5017	0.4008	0.7294	0.502	1.6317	0.7070	0.9293	2.3341
2	F28	0.1252	0.3029	0.5719	0.3756	0.6058	0.572	1.5330	0.7054	0.8279	2.2381
3	F25	0.1195	0.2374	0.6431	0.3585	0.4748	0.643	1.4766	0.6989	0.7777	2.1755
4	F29	0.1032	0.1946	0.7022	0.3096	0.3892	0.702	1.4012	0.6683	0.7332	2.0692
5	F26	0.0676	0.1234	0.809	0.2028	0.2468	0.809	1.2588	0.5718	0.5070	2.0106
6	F30	0.0539	0.1021	0.844	0.1617	0.2042	0.844	1.2098	0.5231	0.6868	1.7328
7	F31	0.0367	0.0996	0.8637	0.1101	0.1992	0.864	1.1732	0.4653	0.7079	1.6385

HV= Highly Variable, V= Variable, N = Non-Variable, LB= Lower Bound, UB= Upper Bound

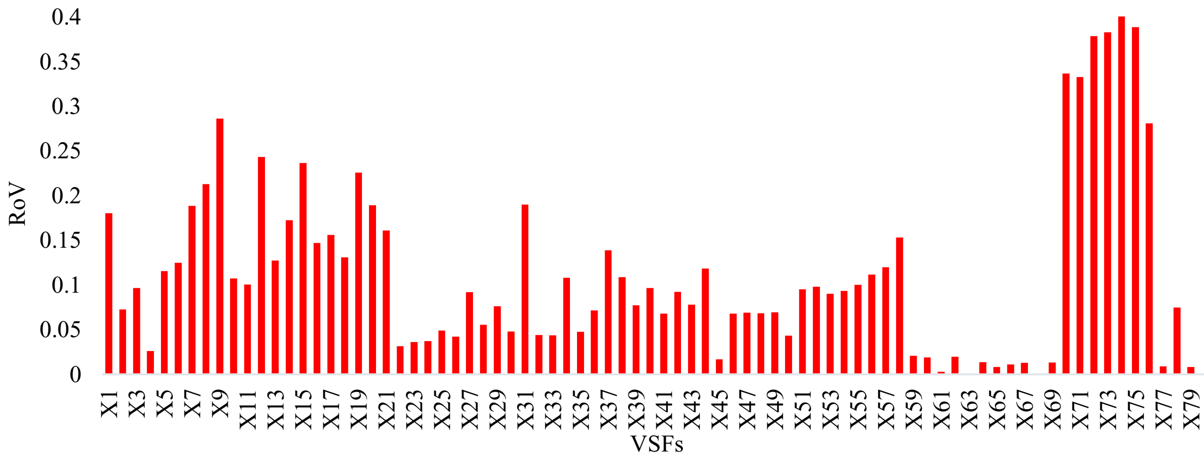

Figure 4. 7 Criticality analysis of variability shaping factors (VSFs) using Ratio of Variation (RoV) of the probabilities (F#18)

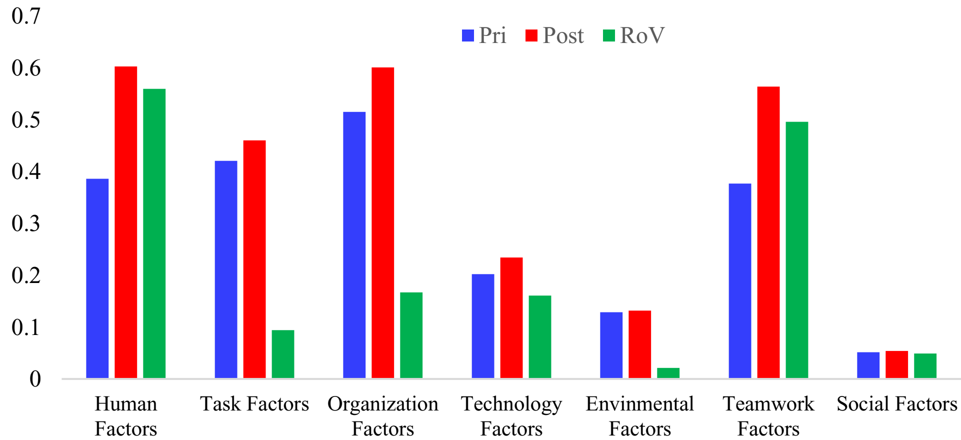

Figure 4. 8 Comparison of posterior, prior, and Ratio of Variation (RoV) of the probabilities for F#18

One of the unique capabilities of the proposed model is evidence (belief) propagation to update the model findings and subsequently threaten uncertainty using backward inferences. Fig 4.7. illustrates the Ratio of Variation (RoV) of the probabilities of the VSFs related to function F#18 (*Conducting the Pre-Startup Safety Review (PSSR) and run operation*) as an example. Moreover, the prior, posterior, and RoV of the main category of influencing factors probabilities are presented in Fig 5.6. The posterior (updated) probability distribution was obtained given $\mathrm{P}(\mathrm{X_i}\ (e.g., Human, Organization, \ldots Social\ factor)|\text{Function Performance} = highly\ variable)$. Considering the normalized probability using the RoV as a Bayesian Network-oriented importance measure [55,56] it is revealed that Teamwork and Human-driven factors respectively contributed most to probabilistic performance (output) variation. In contrast, Environmental and Social factors imposed the least effect on performance variability in F#18. Give the results of Table 4.9 and Fig 4.8 as an example. The proposed model paves the way for making the right decision to prioritize which function effectively, the main element of the sociotechnical system (e.g., human, organization, task, technology), and VSFs give rise to most likely variability in system performance. Accordingly, they should be dampened first as the critical safety investment factors to improve system resilience and safety.

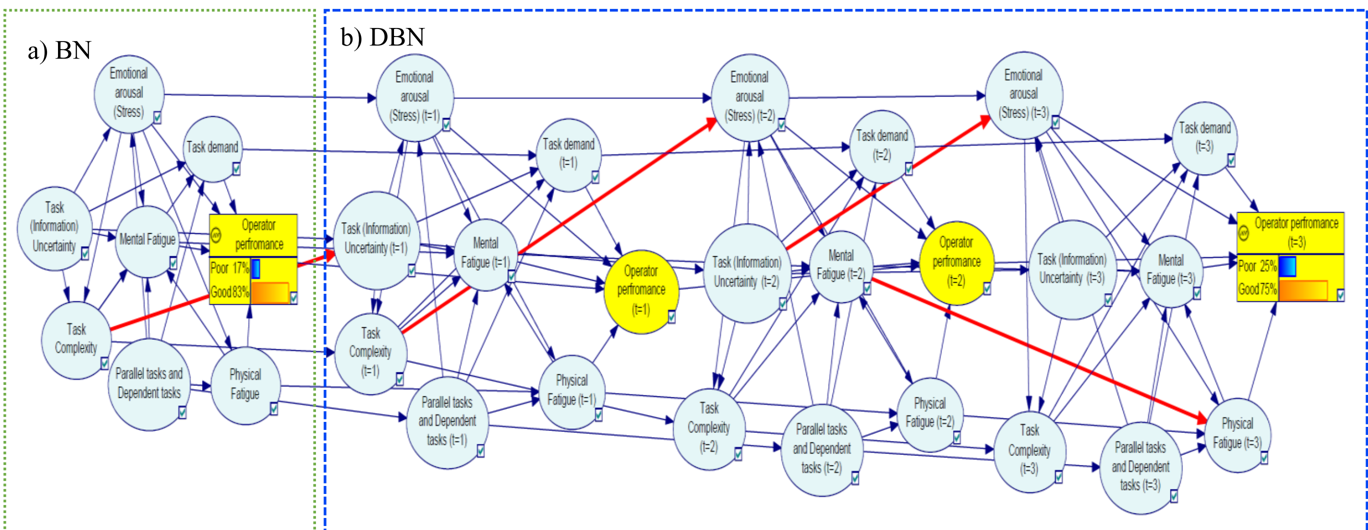

Figure 4. 9 Unrolled dynamic mutual cause-effect dependencies modeling using DBN

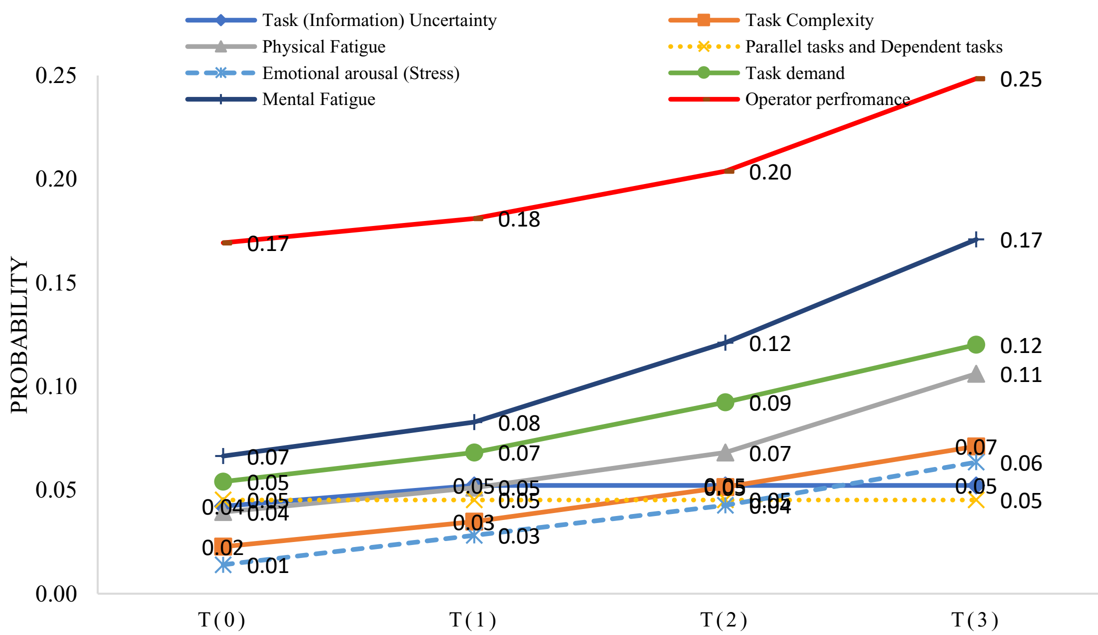

Figure 4. 10 The results of dynamic mutual dependencies modeling using DBN

Conventional BNs can only capture conditional dependency mainly arising from common-cause failures due to its limitation in cyclic modeling, while DBN can also model dependency stemming from mutual cause-effect relationships among VSFs. Therefore, we employed DBN to address this issue, impacting the results of predictive inference in BNs. For the sake of exemplifying and better illustration, we chose a part of the presented model in Fig. 5.6 and assumed the below circumstances:

- *Operator performance* is influenced by *Mental Fatigue, Physical Fatigue, Stress, and Task demand*, while each of them is impacted by contributing factors such as *Task Complexity, Task (Information) Uncertainty, Parallel and Dependent tasks,* as presented in Fig 5.8(a).
- It is assumed that there are mutual cause-effect dependencies between *Task Complexity and Task (Information) Uncertainty, Task Complexity and Stress, Task (Information)*

Uncertainty and Stress, and finally, between Mental Fatigue and Physical Fatigue. They are specified by the red-directed arc in Fig 5.9(b) and captured by DBN modeling.

- We considered binary states as High (Poor) or Low (Good) for studied variables and three intervals of time to illustrate the model, as demonstrated in Fig 4.9. It should be noted that prior probabilities obtained for Function#18 are considered in BN.

DBN can effectively deal with the temporal dependencies modeling. As can be seen from Fig 5.10, the probability of poor performance of the operator during the conducting Function#18 increased from 0.17 (BN in Fig 5.9(a)) to 0.25 (DBN in Fig 4.9(b)) when potential mutual relationships among influencing factors are captured. Moreover, for other factors such as Mental Fatigue, the probability of Mental Fatigue = high rose from 0.07 to 0.17.

It is argued that safety (I, II, and III) and anticipation of function outcomes cannot be meaningfully defined and interpreted without addressing risk and using risk sciences [3,12,68]. Accordingly, safety cannot be meaningfully defined, assessed, and managed without considering risk [12]. Hence, we wanted to treat performance variability using contemporary risk science where considerations are given to uncertainty [12,69]. In this sense, we focused on the probability aspect of performance variability in the present study considering its importance and necessity to address current issues, especially uncertainty characterization in this matter. Moreover, it is frequently acknowledged that a function may often be conducted in a timely manner, but it can be performed too early or too late due to dynamic variability [20]. This is also true for function's output, how much is precise in dynamic working circumstances. In this sense adopting discrete probability distribution can better define and evaluate the performance variability of different functions, and how likely various VSFs vary functions' performance in a real case under uncertainty [2,23]. Finally, the probabilistic model's findings yield to development of the criticality matrix (section

2.3.), which strongly supports the decision-making process to precisely identify safety-critical investment factors and functions and, as a result, effectively damping critical variabilities. It paves a way to relax the difficulties in dampening the critical performance resonance in a rational risk-based approach.

We agree that a qualitative model is easier to build and more understandable. However, the qualitative nature of the model and subsequently their inability to support the decision-making process in a rigor and quantitative manner are frequently highlighted in the literature [20,23,24,69,70]. More studies are required to provide comparative analysis results for risk scenarios to support making risk-based decisions in a rigorous approach [31]. Accordingly, this study has been designed to serve this purpose by developing an extension of FRAM.

4.4.4. The risk-based criticality matrix

We also proposed a tailored criticality matrix to evaluate the performance variability of the system's functions in a risk-based decision-making process, as illustrated in Fig 5.11. It results in a more reasonable and accurate procedure for dampening the critical variabilities by capturing both the magnitude and probability of critical variations under uncertainty instead of merely variability likelihood. It should be noted that the SMEs have been asked to determine the magnitude of performance variability of each function considering the maintenance process and operational circumstances in the studied plants. It may vary in other processing plants with different conditions and operational requirements. We will explore estimating variability magnitude in another study, which seems to be beyond this part of the study scope, and would like to focus on probabilistic modeling of performance variability in this study. As can be seen, the Functions F#4 and F#6 that have highly variable (critical) performance fell in Tolerable Risk level (II) and subsequently do not impose serious risk as high-risk level (III) functions such as F#9 and F#10. It should be noted that boundaries among the probability and magnitude levels are defined considering the South Pars Gas Complex (SPGS) requirements where highly dense and critical infrastructures from gas refineries, petrochemical plants, and pipelines to residential areas are intertwined with each other. However, the proposed matrix has the flexibility to define or extend based on user requirements to serve a system of interest.

	Probability of Variability (expected value)		
Magnitude	Non-Variable ≤1.30	Variable 1.30 -1.55	High-Variable ≥1.55
Major	II F#20	III F#22, F#25	III F#18, F#15, F#27, F#28
Moderate	I F#26, F#30 F#31	II F#16, F#19 F#23	III F#9, F#10, F#5, F#17
Marginal	I F#1, F#2, F#3 F#7, F#13, F#12, F#24	I F#8, F#11 F#21, F#29	II F#4, F#6, F#14

Figure 4. 11 A criticality matrix for a risk-based evaluation of the performance variability

Functions that fall in level III impose a serious adverse outcome, and dampening must be done before function (activity) begins to have a resilient system, while functions in level II should be carefully monitored and controlled before jumping into a higher risk level. However, as per the Safety-II principle, variability in level I, which includes around half of the functions in this study, can be considered an asset since it emerges from approximate adjustments necessary for everyday work. As a result, this study specified in a rigorous manner which functions should be given the highest priority in defining safety countermeasures to dampen the variability of their output before leading to major accidents in maintenance operations.

4.4.5. Validation of the results

We used several approaches to validate the proposed model and its findings. First, the results were shared with five independent SMEs to check their consistency considering the field (SPGC) experiences and expert knowledge. They approved the study findings, especially ranking functions concerning their variability magnitude, probability, and criticality level. We also reviewed the accident investigations [71] issued concerning the major accidents in the Iranian chemical plants from 2007 to 2022. Most of the high-risk functions in the present research have been recognized as severe failures that significantly contributed to catastrophic accidents. To explain, considering the Bouali Sina Petrochemical Plant fire (2016), the largest fire in Iran's petrochemical industry to date with up to $200 million in financial loss, failures in functions including F#18, F#15, F#28, F#10 and F#17 are among the leading causes of this catastrophic accident [72].

Moreover, the partial benchmark exercise is also used to validate the results, although it is hard to find a similar study. Noroozi et al., (2013) employed the Success Likelihood Index Method (SLIM) to analyze human error in maintenance activities. This study revealed that human error most likely occurred during depressurizing lines (2.9E 01), performing mechanical isolation (1.09E 01), and assessing the risk of activity (6.5E 02) which is respectively reflected in F#9, F#10, and F#5 as the highly critical functions in the present study. Hence, our study aligns with Noroozi's research in this perspective, although the applied methodology differs in some aspects. [74] employed Graph Theory to quantify the human error in maintenance activities that model the identified factors and their interactions/interrelationships in terms of human error digraph. [75] used the three most common HRA techniques, including HEART, SPAR-HR, and BN, to obtain human error probabilities and evaluate obtained findings' consistency in maintenance. They found that the results of the three techniques are similar and consistent. However, both studies focus on only human-oriented activities, while successful pre-and post- maintenance activities require intensive technological and organizational involvement. Ignoring such essential functions also lead to a lack of understanding of the contributing factors and mechanisms. This can lead to severe failures in organizational operations as the leading line and technology operations as the fundamental line in complex system's maintenances. However, the present research delivered an in-depth insight into those functions and their influencing factors under uncertainty. Noroozi et al. (2013) applied an interval approach for uncertainty propagation as the only previous research that considered this issue. However, we utilized the DSET, DBN, and MCS, which are the most effective approaches to dealing with uncertainty in knowledge engineering. Furthermore, we employed an interval-valued set to propagate uncertainty in the quantifying process.

Finally, we conducted a sensitivity analysis to validate the proposed probabilistic model and parameter used in Bayesian network modeling. As shown in Table 5.10, the results satisfied the three axioms explained in the methodology part. To illustrate, when the probability of VSF#56 (Operating parameter (State, change rate, and the number of parameter anomalies) = high) is assigned to be 0.1, the expected value of the function (F#18) performance variability is increased to 1.7008 ± 0.6979 from initial (prior) values as 1.6991± 0.6977. Based on this change, if the probability of VSF#57 (number of abnormal operating phenomena = high) is assigned to be 0.1, the expected value of the function (F#18) performance variability is increased to 1.70366 ± 0.6981. Then if the probability of VSF#58 (Ambiguity in system response = high) is also assigned to be 0.1, the expected value of performance variability is increased to 1.7070 ± 0.6984. Accordingly, the variation of function performance satisfies the three axioms and can be used to validate the developed model partially. Furthermore, an increase in the posterior probability of function performance variability (state= Highly variable) increased the posterior probability of the main category of contributing factors (e.g., human, organization, and social factors).

Table 4. 10 Sensitivity analysis results in partial validation of the proposed model (Function#18)

Scenario	VSFs and probability	Variability level	Posterior Probability	Function Performance Variability (Mean ± SD)
Prior Probabilities	VSF#56(state=High, P=0.0588)	High Variability	0.1382	1.6991± 0.6977
	VSF#57(state=High, P=0.0266)	Variability	0.4227	
	VSF#58(state=High, P=0.0168)	Non-Variability	0.4391	
Posterior one VSFs	VSF#56(state=High, P=0.1)	High Variability	0.1387	1.7008 ± 0.6979
	VSF#57(state=High, P=0.0266)	Variability	0.4235	
	VSF#58(state=High, P=0.0168)	Non-Variability	0.4379	
Posterior two VSFs	VSF#56(state=High, P=0.1)	High Variability	0.1394	1.70366 ± 0.6981
	VSF#57(state=High, P=0.1)	Variability	0.4248	
	VSF#58(state=High, P=0.0168)	Non-Variability	0.4358	
Posterior three VSFs	VSF#56(state=High, P=0.1)	High Variability	0.1403	1.7070 ± 0.6984
	VSF#57(state=High, P=0.1)	Variability	0.4263	
	VSF#58(state=High, P=0.1)	Non-Variability	0.4333	

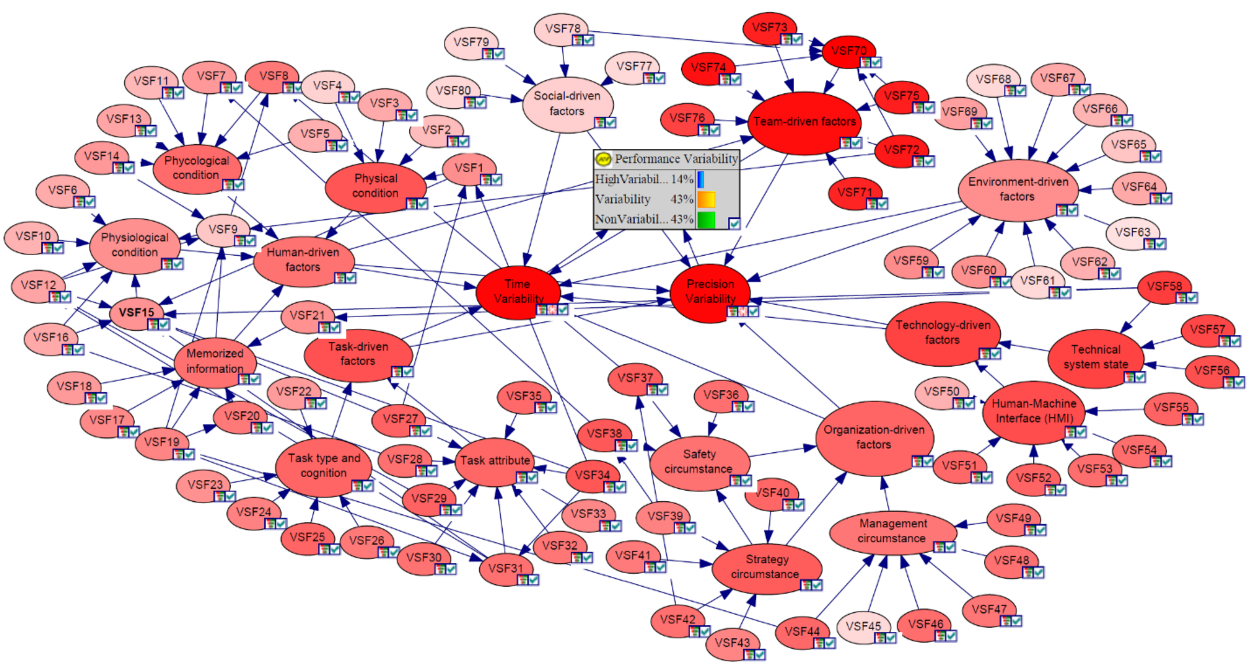

Figure 4. 12 The model sensitivity analysis targeted performance variability phototypes nodes (Time and Precision)

The model sensitivity analysis was conducted for Bayesian Network modeling using a module available in GeNIe 3.0 Academic (http://www.bayesfusion.com). The employed algorithm [57] efficiently obtained a complete set of derivatives of the updated (posterior) probability distributions of all VSFs) considered the performance variability phenotypes (Time and Precision) as a set of target nodes over each of the numerical parameters of the proposed probabilistic model. These derivatives denoted the importance of precision of the model quantitative parameters for estimating the posterior probability distributions of the targets. Accordingly, the nodes of all VSFs in the Bayesian Network model that contains important parameters to estimate posterior probability distributions of the target nodes are specified based on their contribution. Fig 4.12 illustrates the model sensitivity analysis results for Function#18 as an example. The nodes (VSFs) with the highest red color intensity mean the most important factors, while less intensity indicates the less importance of the corresponding factors. For example, as can be seen from Fig 5.11, the social factors (VSFs#77-80) introduced the least and teamworking factors (VSF#71-76) the most contributing factor in Time and Precision during conducting the Pre-Startup Safety Review (PSSR) and run operation (F#18). This is true for the rest of the nodes, and SMEs confirm these results.

4.4.6. Future applications of the proposed model

The present research focused on a proactive perspective to predict system performance variability and explore critical safety investment factors. Although we proposed a risk-based decision-making process to improve system safety, the developed model can also be used for risk assessment. Furthermore, the proposed model can also be employed as a reactive approach to retrospectively analyze and investigate accident scenarios to reveal the most contributing factors in accident occurrence and system's weakness from a sociotechnical perspective. Furthermore, we will seek human reliability analysis using the proposed approach in future research.

4.5. Conclusions

The safety performance of sociotechnical systems and their main elements (e.g., human, technology, organization) critically varied due to numerous contributing endogenous and exogenous influencing factors. This variability is called uncoupled variability, leading to catastrophic accidents with far-reaching consequences in critical systems from the chemical industry to healthcare. This research first introduced a dynamic hybrid model based on advanced techniques to illustrate how uncoupled performance variability can be rigorously modeled. The proposed model builds upon findings in Safety-II, especially from a functional safety perspective, and performance variability arises from endogenous and exogenous factors in complex systems. The real case study illustrated the capability and effectiveness of the proposed approach to model performance variability associated with system resilience and safety in complex systems. The model captured various (inter) dependencies, and uncertainties (e.g., stochastic and fuzziness) and addressed the main challenges in knowledge acquisition and engineering in this domain. The results of the present study would be a full complement of existing knowledge regarding coupled variability. In the previous studies, the decision to dampen the critical variabilities has been made just based on coupled variability, which stems from upstream functions. Moreover, this approach hindered and excluded some optimal safety countermeasures to dampen criticality. Accordingly, capturing uncoupled and coupled variabilities yields a deep understanding and more practical and versatile countermeasures to improve system safety and resilience cost-effectively. Given the application, the main contributions of the proposed model are as follows:

- The proposed VSFs Taxonomy filled the gaps in the current performance shaping factors taxonomies, and it ties in closely with sociotechnical system engineering.

- The DSE theory differently addressed subjective uncertainty arising from insufficient data and vagueness in the knowledge elicitation process, which is crucial in dealing with human and organizational-oriented factors.
- The proposed probabilistic model and mathematical procedures established a prefund causality model which could integrate sociotechnical systems elements, address computations challenges related to CPTs, and characterize randomness and incompleteness uncertainties.
- The proposed DBNs model is a non-linear performance variability causation model aiming to trace thoroughly interconnected accident causal factors, conduct forward and backward inferences, update model parameters and outcomes extensively used in the advanced system safety and reliability assessment.
- The risk-based criticality matrix strongly supports the decision-making process to precisely identify safety-critical investment factors and functions and, as a result, effectively damping critical variabilities. It paves a way to relax the difficulties in dampening the critical performance resonance in a rational risk-based approach.
- The proposed model can be applied for both proactive (e.g., safety performance and risk assessment) and reactive safety assessment (e.g., accident analysis) and can capture all aspects of STSs. Accordingly, it provides a deep understanding of complex system elements, their interaction, and their influence on system safety and resilience performance.

It should be noted that the present research has also had some limitations, which should be considered in its applications and improved in future research. There are some challenges, such as potential conflicts and dissonance in the knowledge engineering process, which might affect the findings of this study. We would like to focus on proposing a holistic approach to model uncoupled performance variability in a risk-based manner, and there was no room to address these concerns in the present study. Moreover, we used DSET to elicit expert knowledge to determine prior probability distributions, while more research should be conducted to compare and validate the knowledge acquisition process. To illustrate, the employed experts had almost the same professional profile (e.g., work experience, education, and position). Accordingly, we assumed the same importance level for their beliefs. Second, some detailed techniques might better quantify the potential dependencies among VSFs, while we intended to present a simple and practical approach. The main reason behind this decision was to avoid increasing the model complexity and intensely focus on the present research concerns. Several methods such as Analytic network process (ANP), Analytic hierarchy process (AHP) and Decision making trial and evaluation laboratory (DEMATEL), and Cognitive map (CM) and their extensions have been regularly employed to consider potential dependencies in safety probabilistic analysis [34,76]. The proposed model is tested based on SME's knowledge, while simulation or historical data should be assigned to illustrate and improve the model's compatibility and weakness. This provides the possibility to compare and assess the robustness of the results. Finally, employing mirror effect-based and reinforced learning systems to manage variability can be an academic opportunity to be investigated in future studies.

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CHAPTER 5

An advanced Approach to the System Safety in Sociotechnical Systems

Preface

A version of this chapter has been submitted in ***Safety Science****. I am the primary author along with the Co-authors, Faisal Khan, and Rouzbeh Abbassi. I developed a framework for the System Safety Assessment using Performance Shaping Factors in Complex Systems. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' and peer review feedback. Co-author Faisal Khan helped in the concept development, design of methodology, reviewing, and revising the manuscript. Co-author Rouzbeh Abbassi provided fundamental assistance in validating, reviewing, and correcting the model and results. The co-authors also contributed to the review and revision of the manuscript.*

Abstract

The safety performance of complex systems and their main components (e.g., human, organization, and technology) vary due to numerous performance shaping factors (PSFs). However, previous research mainly focused on studying limited PSFs related to human functions, while organization and technology functions have often been ignored. This paper proposed a systematic approach to identify PSFs and quantify their importance level and influence on the performance of sociotechnical systems' functions. To this end, we first developed a holistic PSFs Taxonomy based on sociotechnical systems design and then employed novel Interval-Valued Spherical Fuzzy Sets (IVSFS) and Best Worst Method to quantify the importance of performance. We tested the proposed model's capability on maintenance operations in the chemical process plants and compared the model with the previous research considering fourteen criteria. The findings revealed the approach's effectiveness in dealing with epistemic uncertainty, vagueness, and fuzziness in the knowledge acquisition process. It revealed the critical safety investment

factors among different sociotechnical elements and contributing factors to maintenance operations. This helps to effectively allocate safety countermeasures to improve resilience and system safety performance.

Keywords: Operational safety; Performance variability; Functional resonance analysis; Performance shaping factors.

5.1. Introduction

Complex systems such as oil and gas facilities contain numerous operational and organizational processes that must handle interactive and dependent social elements, organizational and human activities. These systems are mainly attributed to interactable, non-linear, and relative ignorance of dynamic complex operations [1,2]. Ignorance is a fact of sociotechnical systems (STSs) because it is impossible to fully explain their parameters in space or time and the whole behavior of the systems. This stems from uncertainty about the future, oversimplification in representative models of STS, illusory comprehension, and lack of imagination [2]. Dynamic complexity introduces a circumstance where effect and cause are subtle and effects over time of interventions are not easy to notice. Interactable systems are elaborate with many details, prone to substantial change, partly incomprehensible, heterogeneous, and possibly irregular. In other words, the interactable system is highly problematic or impossible to follow and understand how to function. Moreover, its performance is irregular and cannot be specified in detail, and it is not rational to decompose it [2–4].

In contrast, it is acknowledged that entirely possible to describe a system in a different approach, mainly from how it functions perspective instead of what the elements (parts) are and how they are architecturally assembled [4]. Accordingly, a group of coupled or mutually dependent functions constitute the system and can be understood by a complete description of their functions. In this sense, what seems to be indispensable are the performance of functions and entire systems, the variability of function performance, and whether the functional outcomes are acceptable or lead to undesirable events. As a result, understanding to what extent and how the system's performance varies can effectively support decision-making process in safety and resilience engineering [5]. Accordingly, there is a necessity to shift from "human error" to "human and system performance variability (resonance)" during the risk and safety assessment in STSs [2]. It is believed that conventional methods cannot understand risks associated with performance variability [6,7]. As a result, it is vital to move toward the system methods to deal with the risk-driven issues in STSs [7,8].

Resilience engineering proposed an approach called the Functional Resonance Analysis Method (FRAM) [2], which is more compatible with the characteristics of complex sociotechnical systems [9]. This popular method begins by identifying and describing characteristic functions and focuses on improving the system's ability to monitor, learn, anticipate, and respond [3]. This is necessary for complex systems that a system can monitor, learn, anticipate, and respond to critical variabilities arising from internal and external variability of functions. It is believed that there will, of course, always be cases in STS where the variability magnitude of a single function (activity) is enough that adverse outcomes (e.g., accident, incident) would be unavoidable [10].

However, a rare attempt has been made to systemically identify various endogenous and exogenous factors contributing to the performance resonance of complex systems. Even popular human reliability or human factors analysis techniques, such as SLIM, HEART, CREAM, SPAR-H, HFACS, and STAMP, only examined a few limited operator performance shaping factors

(PSFs), even though complex system's performance may critically vary due to numerous human, organizational, environmental, and social factors. Therefore, the present study aims to propose a systematic approach to entirely explore PSFs, their optimal importance, and the extent to which PSFs contribute to critical system performance. Moreover, the model deal with all kinds of sociotechnical system functions (e.g., human, organization, and technology) and paw a practical way to precisely identify safety investment elements in a system-based hierarchical structure (e.g., PSFs level, PSFs sub-groups, PSFs category, system function level). In the rest of the paper, the proposed methodology is first explained, then it procced with the model application's findings and discussion, and finally main conclusions.

5.2. Methodology

This section presents a holistic taxonomy of PSFs based on different FRAM-driven functions and sociotechnical design hierarchy (e.g., individual, task, Human-Machine Interface (HMI), plant, organization, culture). Then, a novel Interval-Valued Spherical Fuzzy Sets (IVSFS) is explained, which is employed to quantify the magnitude of performance variability arising from the influence of PSFs. The Best Worst Method is employed to obtain the importance level of PSFs in each system function, and finally, an Overall Variability Index (OVI) is proposed, which yields to rank of the system functions based on their criticality level.

5.2.1. Propose a taxonomy of performance shaping factors (PSFs) for complex systems

Several taxonomies and hierarchies (e.g., factors, sub-factors, and indicators) of human PSFs have been proposed mainly in nuclear power plants [11]. However, they suffer some important drawbacks, including a) They fail to introduce influencing factors on organization and technology functions, despite their importance in system failure [12], b) Those focus on human performance, only concerned about specific aspect on human performance (e.g., cognitive or behavior failures), c) Most taxonomies missed factors arise from the new advancements (e.g., Industry 4.0), such as digitalization factors [13], d) a limited set of PSFs on human functions (often nine factors) are considered in the previous studies [14], while human performance is affected by a wide range of endogenous and exogenous factors. As a result, they fail to model safety performance from sociotechnical perspective [12]. Accordingly, a new PSFs taxonomy for STSs considering the FRAM paradigm, sociotechnical design hierarchy (e.g., individual, task, HMI, plant, organization, culture), and the concept of human-center design is developed. Therefore, this taxonomy is intended to consider all aspects of STSs together and can be used to examine influencing PSFs in a wide range of complex systems. It is expected that using this model provides a better understanding of complex system elements, their interaction, and their influence on system performance. This importance can substantially improve the designing of technical systems, business processes, organizational structures, and human operations [15].

5.2.2. A novel Interval-Valued Spherical Fuzzy Sets (IVSFS)

Assessing to what extent the performance of different functions is affected by various PSFs is a multi-criteria decision-making process under uncertainty while dealing with it is a prominent issue in safety management. Supporting decision-making requires numerical values that reach exact values is impossible in many actual conditions. This is owing to the diverse nature of influencing factors, uncertainty, and fuzziness of the practical decision-making environment, and the lack of information [16,17]. It is argued that human functions experience substantial variability in terms of both frequency and magnitude, while organizational functions vary with low frequency but high severity [2]. Accordingly, these issues become vital and sensitive when modeling human or organizational factors has to be considered [18,19]. To overcome this challenge and apply a rigorous approach, fuzzy set theory achieved the most popularity in many scientific domains, from health care to engineering [20,21]. In this sense, Zadeh (1965) defined the fuzzy set, which only quantifies the membership degree but excludes the non-membership, on this basis, several extensions of fuzzy sets (e.g., Intuitionistic, Neutrosophic, Hesitant, Pythagorean, Picture fuzzy sets) have been successfully introduced [22]. Recently, Kutlu Gündo˘ gdu and Kahraman (2019) proposed a novel fuzzy set named three-dimensional spherical fuzzy set (SFS) to address the limitations encountered in the previous extensions and deal with more widely uncertain information, vagueness originate from the human judgments, ambiguity in the decision-making process and clarify hesitancy of decision makers' judgments [23]. A geometric illustration of Intuitionistic (IFS), Pythagorean (PFS), Neutrosophic sets (NS), and SFS is presented in Fig. 5.1. As can be seen, using this novel sets decision-makers able to define their hesitancies independently to decide with a larger three-dimensional domain (Fig. 5.1) through a linguistic evaluation scale according to the IVSFSs presented in Table 5.1 [24]. Therefore, SFSs are among the most important and underlying concepts to accommodate more uncertainties than existing fuzzy set structures. In SFSs, while the squared sum of three parameters (e.g., membership, non-membership, and hesitancy) is between 0 and 1, each of them can be independently estimated from 0 and 1. The shape of this new fuzzy sets is the outcome of these two conditions. These novel sets enable decision-makers to independently define their degree of hesitancy ($\gamma_{\widetilde{A_S}}(z), Eq. 1$) to decide environment with a larger domain. The superiority of the SFSs comes from collecting the scientifically accepted advantages of other fuzzy sets extensions (e.g., PFS and NS in a unique theory), while not including the criticized aspect of the neutrosophic theory, i.e., a sum of μ, v, and π larger than 1 and the criticized aspect of PFS theory, i.e., disregarding an independent hesitancy [22–24].

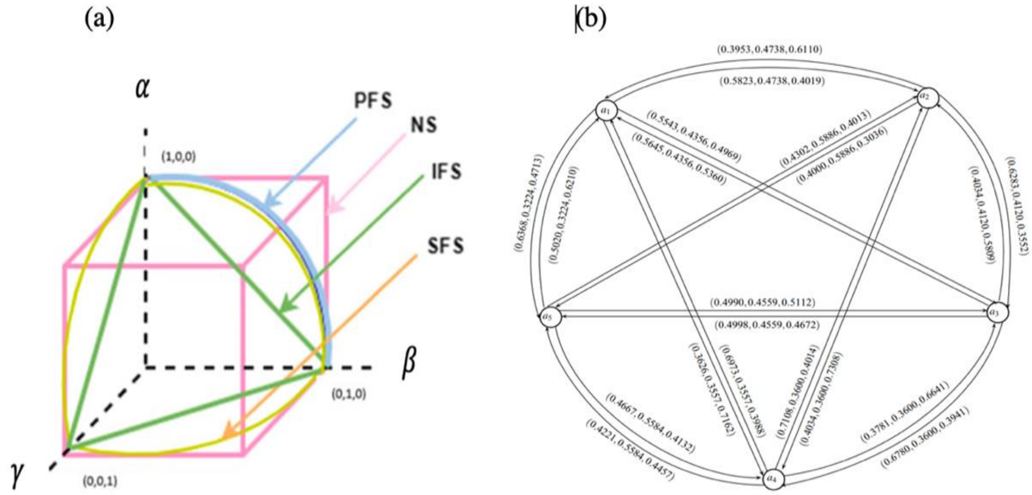

Figure 5. 1 (a) A geometric illustration of IFS, PFS, NS, and SFS, (b) Spherical fuzzy digraphs for five experts [23].

More details about the advantages of SFS are available and referred to primary literature [22] to narrow down the main concerns of the present study (performance variability in STSs). Moreover, we used the interval-valued spherical fuzzy sets to effectively characterize the potential uncertainty associated with the expert elicitation process [23]. Accordingly, the following sections allocate to define IVSFS, arithmetic operations, aggregation, and defuzzification operations.

Definition 1: Considering SFSs $\widetilde{A_S}$ of the discourse universe of Z is indicated by Eq. (6.1).

$$\widetilde{A_S} = \left\{z, \left(\alpha_{\widetilde{A_S}}(z), \beta_{\widetilde{A_S}}(z), \gamma_{\widetilde{A_S}}(z)\right) \middle| z \in Z\right\} \tag{6.1}$$

where for each z, the values $(\alpha_{\widetilde{A_S}}(z), \beta_{\widetilde{A_S}}(z)\ and\ \gamma_{\widetilde{A_S}}(z)$ indicate the degree of membership, non-membership, and hesitancy of z to $\ddot{\mathcal{A}}^{\sim}$, respectively, and associated principles are as follows:

$$\alpha_{\widetilde{A_S}}: Z \to [0,1], \qquad \beta_{\widetilde{A_S}}: Z \to [0,1], \qquad \gamma_{\widetilde{A_S}}: Z \to [0,1],$$

and

$$0 \leq \alpha^2{}_{\widetilde{A_S}}(z) + \beta^2{}_{\widetilde{A_S}}(z) + \gamma^2{}_{\widetilde{A_S}}(z) \leq 1 \qquad \forall_z \in Z \tag{6.2}$$

Definition 2: Considering the IVSFSs $\widetilde{A_S}$ of the discourse universe of Z is specified by Eq. (6.3).

$$\widetilde{A_S} = \left\{ z, \left(\left[\alpha^L{}_{\widetilde{A_S}}(z), \alpha^U{}_{\widetilde{A_S}}(z) \right], \left[\beta^L{}_{\widetilde{A_S}}(z), \beta^U{}_{\widetilde{A_S}}(z) \right], \left[\gamma^L{}_{\widetilde{A_S}}(z), \gamma^U{}_{\widetilde{A_S}}(z) \right] \right) \middle| z \in Z \right\} \tag{6.3}$$

where $0 \le \alpha^L{}_{\widetilde{A_S}}(z) \le \alpha^U{}_{\widetilde{A_S}}(z) \le 1,\ 0 \le \beta^L{}_{\widetilde{A_S}}(z) \le \beta^U{}_{\widetilde{A_S}}(z) \le 1$

and

$$0 \le \left(\alpha^U{}_{\widetilde{A_S}}(z) \right)^2 + \left(\beta^U{}_{\widetilde{A_S}}(z) \right)^2 + \left(\gamma^U{}_{\widetilde{A_S}}(z) \right)^2 \le 1$$

For each z ∈ Z, L and U are the lower and upper degrees of membership ($\alpha_{\widetilde{A_S}}(z)$), non-membership ($\beta_{\widetilde{A_S}}(z)$) and hesitancy ($\gamma_{\widetilde{A_S}}(z)$) of z to $\widetilde{A_S}$ presented in Table 5.1 based on corresponding linguistic terms and fuzzy numbers. The intervals α^U and β^L demonstrate the degree of belongingness and non-belongingness of z , respectively, while γ^2 denotes the hesitancy degree of element z in the universe independently from the two former elements.

Table 5. 1 Linguistic evaluation scales and their interval-valued spherical fuzzy sets

Linguistic terms	Score	Interval-valued $[a, b], [c, d], [e, f]$
Absolutely more influence/important/probably (AMI)	9	[0.85, 0.95], [0.10, 0.15], [0.05, 0.15]
Very high influence/ important/ probably (VHI)	8	[0.75, 0.85], [0.15, 0.20], [0.15, 0.20]
High influence/ important/ probably (HI)	7	[0.65, 0.75], [0.20, 0.25], [0.20, 0.25]
Slightly more influence/ important/ probably (SMI)	6	[0.55, 0.65], [0.25, 0.30], [0.25, 0.30]
Slightly low influence/ important/ probably (SLI)	5	[0.50, 0.55], [0.45, 0.55], [0.30, 0.40]
Low influence/ important/ probably (LI)	4	[0.25, 0.30], [0.55, 0.65], [0.25, 0.30]
Very low influence/ important/ probably (VLI)	3	[0.20, 0.25], [0.65, 0.75], [0.20, 0.25]
Absolutely low influence/ important/ probably (ALI)	2	[0.15, 0.20], [0.75, 0.85], [0.15, 0.20]
No influence/ equal important / probably (NI)	1	[0.10, 0.15], [0.85,0.95], [0.05, 0.15]

Definition 3: The aggregation of fuzzy sets using a novel Interval-valued Spherical Weighted Arithmetic Mean (IVSWAM). Considering $\tilde{\alpha}_j = \langle [a_j, b_j], [c_j, d_j], [e_j, f_j] \rangle$ is an IVFSS and weighted arithmetic Mean of n sets concerning weight (w_j), which means the decision maker's weight (importance level), who express their opinion in linguistic evaluation scale (terms) as Table 5.2, $w_j = (w_1, w_2, \dots, w_n);\ w_j \in [0,1]$, and $\sum_{j=1}^{n} w_j = 1$, IVSWAM is specified as:

$$\mathrm{IVSWAM}(\tilde{\alpha}_1, \tilde{\alpha}_2, \dots, \tilde{\alpha}_n) = \sum_{j=1}^{n} w_j . \tilde{\alpha}_j =$$

$$\left\{\begin{array}{c} \left[\left(1-\prod_{j=1}^{n}\left(1-{a_j}^2\right)^{w_j}\right)^{\frac{1}{2}}, \left(1-\prod_{j=1}^{n}\left(1-{b_j}^2\right)^{w_j}\right)^{\frac{1}{2}}\right], \left[\prod_{j=1}^{n} {c_j}^{w_j}, \prod_{j=1}^{n} {d_j}^{w_j},\right], \\ \left[\left(\prod_{j=1}^{n}\left(1-{a_j}^2\right)^{w_j} - \prod_{j=1}^{n}\left(1-{a_j}^2-{e_j}^2\right)^{w_j}\right)^{\frac{1}{2}}, \left(\prod_{j=1}^{n}\left(1-{b_j}^2\right)^{w_j} - \prod_{j=1}^{n}\left(1-{b_j}^2-{f_j}^2\right)^{w_j}\right)^{\frac{1}{2}}\right] \end{array}\right\} \quad (6.4)$$

For the sake of simplifying, we represent the lower and upper values of membership degree with *a* and *b*, non-membership ($\beta_{\widetilde{A_S}}$) with *c* and *d*, while hesitancy ($\gamma_{\widetilde{A_S}}$) with *e* and *f*. It is important to clarify that the IVSWAM aggregates experts' opinions regarding both the weight and influence of internal and external factors. In other words, first assigned experts are asked to express their belief regarding how much various factors can vary functions performance, and then how important they are considering the real working circumstances. The optimal weights (W_j) of heterogeneous group decision-makers (j=1, 2,…, n) is calculated based on their profile quality characterizing factors considering professional position (PP), experience time (ET), education (E) and age (A) (Table 5.2) [40]. To this end, we employed a new robust and popular approach named the Best-Worst Method (BWM), which is proposed to solve multi-criteria decision-making (MCDM) problems [25], and Eq. (6.5) [26].

$$\mathrm{OW_j} = \frac{\sum_{i=1}^{4} Obtained\ score_i \times OWC_i}{\sum_{SMEs=1}^{6}\sum_{i=1}^{4} Obtained\ score_i \times OWC_i} \quad (6.5)$$

where OW_j is the optimal weight of employed subject matter experts (j=1, 2…, 6) who have received a score based on their characteristics in each criterion (e.g., experience, education) using Table 5.2. OWC_i denotes the optimal weight of criteria (i=1,.., 4) obtained using BWM.

Table 5. 2 Weighting score of heterogeneous group decision-makers [27]

Criteria	Classification	Score	Criteria	Classification	Score
Professional position	Academician	5	Education level	PhD	5
	Operation manager	4		Master	4
	Engineer	3		Bachelor	3
	Technician	2		Diploma	2
	Worker	1		School level	1
Experience time (year)	≥26	5	Age (year)	≥50	4
	16 - 25	4		40-49	3
	11 - 15	3		30-39	2
	6 – 10	2		< 30	1
	≤5	1			

Definition 3: The score function used for the defuzzification of IVSFS number $\tilde{a}$ is calculated as Eq. 6.6, while the accuracy function is defined as Eq. 6.7.

$$Score\ (\tilde{a}) = S(\tilde{a}) = \frac{a^2 + b^2 - c^2 - d^2 - \left(\frac{e}{2}\right)^2 - \left(\frac{f}{2}\right)^2}{2} \qquad (6.6)$$

where Score $(\tilde{a}) = \mathrm{S}(\tilde{a}) \in [-1, +1]$. It is noteworthy that the greater $\tilde{a}$ results in the larger $\mathrm{S}(\tilde{a})$. Especially, when $\tilde{a} = \{[1,1], [0,0], [0,0]\}$ then $S(\tilde{a}) = 1$, while $\tilde{a}$ is the smallest spherical fuzzy set number, $\tilde{a} = \{[0,0], [1,1], [0,0]\}$, then $S(\tilde{a}) = -1$.

$$\text{Accuracy } (\tilde{a}) = H(\tilde{a}) = \frac{a^2 + b^2 + c^2 + d^2 + e^2 + f^2}{2} \qquad (6.7)$$

In which $H(\tilde{a}) \in [0, 1]$, and $\tilde{a}_1 < \tilde{a}_2$ if and only if $S(\tilde{a}_1) < S(\tilde{a}_2)\ or\ S(\tilde{a}_1) = S(\tilde{a}_2)$ and $H(\tilde{a}_1) < H(\tilde{a}_2)$.

Finally, after collecting the experts' opinions using the linguistic evaluation scale (Table 5.1) as input data and employing Eqs.6.4 and 6.6, the performance variability's magnitude of different functions due to the influence of internal and external factors is calculated. It is essential to model the accumulative influence of various PSFs in a real operating scenario. To this end, Eq. 6.8 is proposed to estimate the overall influences of factors named Overall Variability Index (OVI) as:

$$\mathrm{OVI}_x = \left(\sum_{i=1}^{n} \lambda_i w_i\right) t_f \tag{6.8}$$

where λ_i represents to what extent PSF_i (i =1, 2, …, n) influence (obtained using IVSFSs) over output (performance) variability of function x, w_i indicates the importance level (weight) of variability shaping factor i (i =1, 2, …, n) and t_F means the time fraction related to the working Time.

It should be noted that BWM was used to calculate the importance level of PSFs. The BWM utilizes an optimization model by a structured pairwise comparison to obtain the optimal weight of each PSF, and its value denotes how much the SMEs prefer the PSF_i over PSF_j. This structured technique makes the decision easier, more understandable, and most importantly, results in more consistent comparisons and subsequently more reliable results (e.g., weights, ranking). This technique contains six steps as follows [25,28]:

Step 1: Specifying the set of influencing criteria: Considering the proposed taxonomy of PSFs and SMEs' belief, the set of influencing factors over the system performance or function under study are defined.

Step 2: Defining the most important (best) and the least important (worst) factors (criteria). It is noteworthy that decision-makers don't make a comparison in this step, and they just determine the best and worst factors.

Step 3: Establish the preference of the best factor over all the reset factors using a scale from 1 (Equal importance) to 9 (Absolutely more important) according to Table 5.1. The resulting Best-to-Rest (BR) vector would be as Eq. (6.9):

$$P_B = (p_{B1}, p, \dots, p_{Bn}) \tag{6.9}$$

where P_{Bj} denotes the preference of the best factor X over the factor j (j=1,…, n).

Step 4: Establish the preference of all the factors over the worst factor using the same scale as the previous step that the results of Others-to Worst (OW) vector would be as Eq. (6.10):

$$P_w = (p_{1W}, p_{2W}, \dots, p_{nW})^T \tag{6.10}$$

where p_{jw} presents the preference of the factor j over the worst factor W

Step 5: Find the optimal weight of each factor $(W_1^*, W_2^*, \dots, W_3^*)$. The optimal weight of the factor is the one where for each pair of W_B/W_j and W_j/W_w, we have $W_B/W_j = p_{Bj}$ and $W_j/W_w = p_{jW}$. It should be found a solution where the maximum absolute differences $\left|\frac{W_B}{W_j} - p_{Bj}\right|$ and $\left|\frac{W_j}{W_W} - p_{jW}\right|$ for all j would be minimized to meet these conditions for all j. Given the non-negativity and sum conditions for the estimated weights, the optimization model is formulated as follows Eq. (6.11) (Model 1):

$$min \max_j \left\{ \left| \frac{W_B}{W_j} - p_{Bj} \right|, \left| \frac{W_j}{W_W} - p_{jW} \right| \right\}$$

Subject to $\sum_{j=1}^{n} W_j = 1,\ W_j \geq 0$, for all j. (11, Model 1)

The optimal weight of factors is obtained by converting the previous model into the below linear Model 2 as Eq. (6.12):

$\min \xi$

Subject to

$$\left| \frac{W_B}{W_j} - p_{Bj} \right| \leq \xi, \text{for all } j, \quad \left| \frac{W_j}{W_W} - p_{jW} \right| \leq \xi, \text{for all } j$$

$\sum_{j=1}^{n} W_j = 1,\ W_j \geq 0$, for all j. (12, Model 2)

For any estimation of ξ, the first set of model (2) constraints by and the second set of constraints by, the solution space of the model (2) can be an intersection of $4n - 5$ linear constraints

$(2(2n-3)$ comparison constraints and one constraint for the sum of the weights). Finally, the optimal weight of the factor of interest and ξ^* can be obtained by solving the model (2).

Step 6: Consistency check: A comparison is entirely consistent when $p_{Bj} \times p_{jW} = p_{BW}$ (the preference of the best factor over the worst factor) for all j. However, it may happen for some j not to be fully consistent that can be measured the consistency level using a robust index called consistency ratio (CR) using Eq. (6.13).

$$Consistency\ ratio\ (CR) = \frac{\xi^*}{Consitensy\ Index} \qquad (6.13)$$

where $CR \in [0,1]$ and the lower CR means that the comparisons are more consistent and subsequently yield more reliable results. Moreover, given the number of criteria and maximum value of pairwise comparison, a threshold value for CR is presented that can be considered to find the acceptable level. The maximum value of the consistency index for various estimations of p_{BW} is presented in Table 5.3.

Table 5. 3 Consistency index (CI) for different values of p_{BW}

p_{BW}	1	2	3	4	5	6	7	8	9
CI (max ξ)	0.00	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

It is acknowledged that working time impacts human performance resonance, so as time continues, operators' performance often varies negatively in complex systems [43,44]. It is believed that human function has the highest reliability, lowest performance variability in the first hour of the processing shift, and lowest reliability, highest performance variability at the eighth hour of a regular working shift [29]. We define different multipliers according to the working Time (WT) for a regular shift duration (T = 8 hr) as WT ≤ 2 hr, time fraction $t_f = 1$, for $2 <$ WT ≤ 4 hr, $t_f = 2$, for $4 <$ WT ≤ 6 hr, $t_f = 3$, and as WT > 6 hr, $t_f = 4$. It should be noted that for specific functions (e.g., technology and organization), their performance is not substantially affected by the working Time, time fraction, t_F, can be ignored in estimating the overall variability of function performance. This section is defined to precisely answer the to what extent do internal and external factors are associated with the performance variabilities of human, organizational, and technical functions?

5.3. Result and Discussion

5.3.1. Cases study: Maintenance operation in oil and gas facilities

A maintenance operation cycle containing both pre-and post-maintenance activities is considered for testing the model's capability and effectiveness. Although it is often undifferentiated in most industries, we would like to concentrate on it in the chemical processing facilities in the South Pars Gas Complex (SPGC) located in Pars Special Economic Energy Zone, Asaluyeh, Bushehr Province, Iran. This energy source is identified as the world's second-largest natural gas reservoir and contains both offshore and onshore facilities. Its operation involves fourteen gas refineries, twelve petrochemical complexes, more than ten offshore platforms, 100 wells and 500 km pipelines. It is frequently recognized that human, technological and organizational failures in maintenance operations of critical systems, such as general and civil aviation, nuclear power and oil and gas, lead to catastrophic accidents [11,14]. Some of these disasters include Three Mile Island, Piper Alpha, Bhopal, American Airlines Flight 191, Japan Airlines Flight 123, Clapham Junction rail crash. Moreover, a considerable portion of the budget (e.g., more than $300 billion in the USA) is annually allocated to these operations [11]. This maintenance operation is considered a sociotechnical system as many crews from different departments (e.g., operation, safety, and environment, maintenance, human resources, logistics) are individually and collectively involved. Moreover, organizational (production, stakeholders, market) and technology concerns are inextricably intertwined with human functions in maintenance of such large critical processing plants. Given a wide range of PSFs (e.g., harsh environments, poorly written maintenance procedures, poor work layout, complex maintenance tasks crew characteristic, logistics), impact on safety and risk of maintenance in the critical sectors, it can be a suitable application for serving the purpose of the present study.

5.3.2. Characterizing the system's functions

The system's functions should be first studied, which constitutes the FRAM model of maintenance operation in everyday work. To this end, the maintenance operations' functions were identified, revised, and described considering everyday maintenance work (work as done, not as imagined) by actively participating fifteen experts from the operation, maintenance, management, safety, and environment departments. The human-oriented functions of the studied maintenance operation are demonstrated in Table 5.4, while the organization and technology-oriented ones are presented in Tables 5.5 and 5.6. Overall, thirty-one functions directly associated with the maintenance operation are identified. Nineteen functions are human-oriented activities, while organization and technology are associated with five and seven functions. This step yields a deep understanding of different individual and team activities in the maintenance operation.

Table 5. 4 The human-oriented functions of the studied maintenance operation

No.	Function	Description
1	Assessing maintenance needs and orders	Issuing the preventive or corrective maintenances (e.g., planned or unplanned) as an order or need by the maintenance department or its subdivisions (e.g., mechanical, machinery, instrument)
2	Approving maintenance order	Assessing the orders by committee members from the operation, safety and firefighting, maintenance and sub-units (e.g., Instrument, Electricity), production, and planning departments.
3	Planning the work and referring to working crew	After approving orders, details and resources of work as materials, maintenance sub-department responsible for, human force, timetable, etc., are defined and then referred to the working crew.

4	Applying for the permit to work (PTW)	Using the PTW procedure, the required equipment diagnoses and tags. After specifying responsibilities, the PTW is referred to the operation department.
5	Assessing potential risks and developing emergency response planning (ERP)	Identifying HSE hazards, analyzing their risks, and ensuring the recommended safety measures are all in place. The Toolbox Risk Identification Card (TRIC) is issued by supervisors on-site and attached to the PTW order. If it needs to develop an ERP, it is in place by the ERP committee.
6	Determining and certifying require isolations and preparation	Identifying the most appropriate isolation approach and checking all lines, their pressure, vent, bleeds, and close, lock and tag isolation valves. Obtaining required certificates and keys and assigning lockout box and delivering the keys to supervisors. Review the related work orders to ensure no operational conflict or other work.
7	Knowledge management	Holding a safety talk to learn from past on-site and offsite incidents and holding safety toolbox meetings (TBM) to build a learning organizational safety culture and reinforce the safety standard and procedures.
8	Performing chemical process isolation	All affected equipment and pipelines are isolated from main chemical process lines by bypassing the feeds into other pipelines pathways. Finally, the process isolation certificate is attached to the PTW sheet.
9	Depressurizing, draining, and purging	All affected pipelines and equipment are depressurized and cleaned to ensure they are ready for safe maintenance. Inert materials (nitrogen or steam) are used to provide a free hydrocarbon gas environment (LFL&LEL= 0).
10	Performing mechanically and electrically isolation	Blinding or blanking, disconnecting, and misaligning all affected lines and performing lockout and tag out procedures for all energy sources. Finally, these isolations certificate is attached to the PTW sheet.
11	Performing pressure and isolation leak test	Performing the hydrostatic (water) or pneumatic (air or inert gas) pressure tests to identify the potential leak points and ensure the system is fully isolated.
12	Applying for maintenance inhibition	Isolating and deactivating All gas detectors, fire and gas systems, fire and smoke detectors, and sensors.
13	Preforming gas and oxygen testing	Employing a gas analyzer to measure flammable gases by a certified person and toxic and oxygen concentrations by the HSE department before, during, and at the end of work.
14	Confirm PTW and monitor its validity	Reviewing all requirements must by area authority, supervisor (permit issuer), and HSE to ensure meet them and not exist any cross reference, approving PTW and place it on board and worksite. If the work must continue beyond the allowed period, PTW is closed, and a new one is prepared.
15	Performing the required maintenance	Carry out maintenance of the equipment (e.g., pump, compressor) as per scheduled and approved program.
16	Reassembling the components	Checking all lines and equipment for obstruction and removing mechanical and electrical isolation (lock and tags) to open valves and connect lines.
17	Preparing for start-up and conducting the pressure tests	Returning all lockout keys and certificates, giving back worksite authority to area authority, and document reinstatement by supervisor. Opening the valve and reinstate to perform test pressure, then removing air from lines and open valves and test for the leak to ensure equipment are placed in their safe conditions.
18	Conducting the Pre-Startup Safety Review and running operation	Employing the PSSR procedure by the committee to make sure all safety requirements are in place properly. Finally, running the system to begin the normal operation if there is not any non-compliance.
19	Monitoring the Simultaneous Operations (SIMOPS) limitations	Ensuring the safety of operations and more coordination when maintenance and production are performed simultaneously.

Table 5. 5 The organization-oriented functions of the studied maintenance operation

F N	Function	Description
20*	Establishing and holding the crew training programs	All crew members must generally receive training programs regarding the standard operation procedures, HSE risks, effective communication, emergency response management based on their responsibilities and authority. Some staff must be continuously trained with technical courses and get certified.

21	Providing the required hardware (e.g., tools, instruments, and programs), software (e.g., SOP, PFD, P&ID), legal support)	The necessary equipment (e.g., proper gas tester, PPE, LOTO, isolators) and software are available to conduct activities safely. Maintenance contractors' safety and financial requirements are clearly reflected and confirmed in official documents by the site leader.
22	Establishing the Radar system to improve the spirit of team working, mutual communication, and safety culture	The organization should clarify team roles and provide a solid culture to communicate openly and effectively, trust and support each other, appreciate the ideas diversity, high engagement level, and strong team spirit among and between both contractor and site leader crew members
23	Managing human resources	Competent crew members from maintenance contractors to site leaders hired, trained, and certified based on the required standard procedures considering the operation, maintenance and safety requirements. Contractors are asked to provide a proper organization chart and a competent maintenance crew.
24	Protection of environmental programs	Critical systems and packages are available to ensure pollution by hydrocarbons (e.g., sewage, solid disposal, flow monitoring) are protected.

Table 5. 6 The technology-oriented functions of the studied maintenance operation

F N	Function	Description
25	Pressure and leak test system	These devices measure the pressure and specify any leakage in the area of interest.
26	Gas analyzer and leak tester	The related device measures the concentration of gases of interest.
27	Depressurizing, draining, and purging system	This system reduces the operational pressure and cleans the component for safe maintenance.
28	Isolation systems (flange, gaskets, stud bolts, valves)	This system safely separates the operation zones from the components under maintenance.
29	Lockout and Tagout system	This system prevents any energy sources from unsafe start-up during maintenance.
30	Portable Fire and Gas detection packages	Replacement for disabled Fire and Gas Detection System in maintenance areas
31	Escape, Evacuation and Rescue (EER) Facilities	Ensure the availability of escape, evacuation and rescue apparatus based on emergency response procedure and plan

5.3.3. Performance shaping factors (PSFs) Taxonomy results

After systematically analyzing the literature, the first taxonomy draft has been shared with thirteen safety practitioners from different academia and industry background. They were first provided with detailed information regarding the research methodology and objectives through several interactive meetings. After collecting their knowledge and feedback and thoroughly discussing in several meetings, 25 new influencing factors were added, some factors merged or removed, and finally, the holistic FRAM-driven HOT (Human-Organization-Technology) taxonomy was developed. It contains 80 contributing factors to human factions, 26 organization functions, and 16 technology functions. It was developed in line with the FRAM paradigm, sociotechnical design hierarchy (e.g., individual, task, HMI, plant, organization, culture), and human-center design concept. Therefore, this taxonomy manages to capture all aspects of STSs and subsequently provides a deep understanding of complex system elements, their interaction, and their influence on system performance. It is expected that using this model provides a better understanding of complex system elements, their interaction, and their influence on system performance. This importance can substantially improve the designing of technical systems, business processes, organizational structures, and human operations [15]. Considering the function types in the FRAM model, a novel taxonomy of PSFs is proposed in Tables 5.7-5.9.

Table 5. 7 Taxonomy of Human Performance Shaping Factors (PSFs) in Sociotechnical Systems

PSFs category	PSFs sub-groups	Performance Shaping Factors (PSFs) and their ordinal coding
Human-driven factors	Physical condition	Physical Fatigue, Physical abilities, Age, Gender; (PFS#1-4)
	Physiological and Phycological factors	Problem-solving style, Morale, Motivation, Safety attitude, Situational awareness, Vigilance, Cognitive bias, Emotional arousal (Stress), Self-confidence, Perception and appraisal, Mental Fatigue, Circadian rhythm (disorders); (PFS#5-16)
	Memorized information	Working and intermediate memory, Long-term memory, Experience and knowledge, Skills, Information uncertainty; (PFS#17-21)
Task-driven factors	Task type and cognition	Observation, Diagnostic, Monitoring, Planning, Execution (e.g., Construction, Operational, Maintenance, Commissioning or Decommissioning); (PFS#22-26)
	Task attribute	Task mode (Parallel task and dependent task), Shift working, Task scheduling (Time of day and task duration), Task urgency (Available task time), Task complexity, Task risks, Task novelty, Task workload (Manual labor strength and Cognitive resource demand), Task consequence (e.g., Financial); (PFS#23-35)
Organization-driven factors	Strategy-oriented factors	Safety measures program, Perceived safety culture/climate, Safety incentive; (PFS#36-38)
	Strategy-oriented factors	Resources management (workforce, procedures, tools availability and quality), Goal substitution, Organisational double-binds (e.g., safety and productivity conflicts), Perceived organizational support, External demands to quality and quantity; (PFS#37-43)
	Management-oriented factors	Training program, Staffing and scheduling management, Monitoring teamwork, Monitoring work conditions, Monitoring skills and competencies, Monitoring procedures; (PFS#44-49)
Technology-driven factors	Human-machine interface (HMI)	Digitalization level, Controller layout and availability, Indicator layout, Displayer availability, Warning light, Alarm sound systems; (PFS#45-55)
	Technical system State	Operating parameter (State, Change rate and number of parameter anomalies), Number of abnormal operating phenomena, Ambiguity in system response; (PFS#56-58)
Environment-driven factors		Temperature, Humidity, Air pressure, Noise, Vibration, Lighting, Toxic gas, Dust and fume, Wind speed, Radiation, Natural hazards (e.g., Rainfall); (PFS#59-69)
Team-driven factors		Cohesiveness, Coordination, Communication, Composition (crew arrangement and structure), Leadership, Team roles and responsibility, Team norms; (PFS#70-76)
Social-driven factors		Expectations to oneself or colleagues, Compliance with the group working standard, Social norms, Religious beliefs; (PFS#77-80)

Table 5. 8 Taxonomy of Organization Performance Variability Shaping Factors (PSFs) in Sociotechnical Systems

PSFs sub-groups	Performance Shaping Factors (PSFs) and their ordinal coding
Strategy-driven factors	Authority gradient, Organizational safety culture, Organizational trust, Goal substitution, Simultaneous goals, Organizational vision, Strategy and goals, Organizational structure and practices, Organisational double-binds; (PFS#1-9)
Knowledge management factors	Performance feedback process, Communication effectiveness, Management of Change, Organisational learning, Organizational memory, Resource availability, Operating environment; (PFS#10-16)
External factors	External demands to quality and quantity, Customer demand/expectation, Natural disasters, Sanctions; (PFS#17-20)
National factors	Physical/legislative/business environment, National culture, Regulatory scrutiny, Regulatory environment, Commercial resource; Religious beliefs; (PFS#21-26)

Table 5. 9 Taxonomy of Technology Performance Shaping Factors (PSFs) in Sociotechnical Systems

PSFs sub-groups	Performance Shaping Factors (PSFs) and their ordinal coding
Safety-oriented factors	Failure or malfunction detection systems, Reliability and availability, Inspection's methods and intervals, Warranty and supply management, Resilience, Inherent safety design, Redundancy (Standby or Active), Management of Change, Maintenance policies; (PFS#1-9)
Operation-oriented factors	Physical (harsh) environment, Operator characteristics, process or operational conditions, Operating procedures; (PFS#10-13)
Mechanical degradation-oriented factors	Wear and tear conditions, Corrosion and erosion, Mechanical degradation/integrity, Inner workings, and Damage mechanisms (rate and severity), equipment or device age (aging); (PFS#14-18)

5.3.4. The novel Interval-Valued Spherical Fuzzy Sets (IVSFS) results

This section presents the employed IVSFS for effective knowledge acquisition concerning the magnitude of performance. Table 5.10 illustrates the SMEs profile, optimal weight of considered criteria to estimate each experts' importance level using the Best-Worst Method, and weighting score of heterogeneous decision-makers group. After aggregating the experts' judgment, the Score Function was employed for the defuzzification process. Considering the taxonomy, including 80 PSFs for nineteen human-driven functions, 26 PSFs for five organizational, and 18 PSFs for seven technology-driven functions, it is tough to demonstrate the entire computation process related to all PSFs overall functions. To illustrate the estimating process of the knowledge acquisition for performance variability magnitude using IVSFS, let's consider "*Monitoring procedures*" as PSF 50 over the ninth human function, "*Depressurizing, draining and purging*" as an instance (Table 5.11).

Table 5. 10 The employed subject matter experts (SMEs) and their profile characteristics and optimal weight of expert (OWE)

Ex. No	Company	Position (Cr#1)	Age (Cr#2)	Experience (Cr#3)	Education (Cr#4)	
Exp #1	Gas refinery	Safety Engineer	36	11	M.Sc.	
Exp #2	Gas refinery	Department Head	48	18	Ph.D.	
Exp #3	Offshore platform	Safety Supervisor	33	10	Ph.D.	
Exp #4	Petrochemical	Department Head	40	15	M.Sc.	
Exp #5	Academic	Department Head	42	15	Ph.D.	
Ex. No		Cr#1	Cr#2	Cr#3	Cr#4	OWE
Exp #1		0.4342	0.1579	1.4605	1.1579	0.1703
Exp #2		0.7237	0.2368	1.9474	1.4474	0.2310
Exp #3		0.4342	0.1579	1.4605	1.4474	0.1856
Exp #4		0.5789	0.2368	1.9474	1.1579	0.2080
Exp #5		0.7237	0.2368	1.4605	1.4474	0.2052
Optimal weight of criteria		0.1447	0.0789	0.4868	0.2895	Consistency ratio (CR) = 0.0921

Table 5. 11 The computation process of estimating the performance variability magnitude for the "*Depressurizing, draining and purging*" function cased by "*Monitoring procedures*"

Ex. No	OWE	Linguistic terms	The corresponding IVSFS
Ex#1	0.1703	Slightly low influence	[0.50, 0.55], [0.45, 0.55], [0.30, 0.40]
Ex#2	0.2310	Slightly more influence	[0.55, 0.65], [0.25, 0.30], [0.25, 0.30]
Ex#3	0.1856	Very high influence	[0.75, 0.85], [0.15, 0.20], [0.15, 0.20]
Ex#4	0.2080	Absolutely more influence	[0.85, 0.95], [0.10, 0.15], [0.05, 0.15]
Ex#5	0.2052	Very high influence	[0.75, 0.85], [0.15, 0.20], [0.15, 0.20]

SMEs' judgment aggregation

$$\mathrm{IVSWAM}(\tilde{\alpha}_1, \tilde{\alpha}_2, \ldots, \tilde{\alpha}_5) = \sum_{j=1}^{5} w_j . \tilde{\alpha}_j$$

$$\left[\begin{array}{l} \left(1 - \prod_{j=1}^{5} (1-0.50^2)^{0.1703}\,(1-0.55^2)^{0.2310}(1-0.75^2)^{0.1856}(1-0.85^2)^{0.2080}(1-0.75^2)^{0.2052}\right)^{\frac{1}{2}}, \\ \left(1 - \prod_{j=1}^{5} (1-0.55^2)^{0.1703}\,(1-0.65^2)^{0.2310}(1-0.85^2)^{0.1856}(1-0.95^2)^{0.2080}(1-0.85^2)^{0.2052}\right)^{\frac{1}{2}} \end{array}\right],$$

$$\left[\prod_{j=1}^{5} 0.45^{0.1703} 0.25^{0.2310} 0.15^{0.1856} 0.10^{0.2080} 0.15^{0.1703}, \prod_{j=1}^{5} 0.55^{0.1703} 0.30^{0.2310} 0.20^{0.1856} 0.15^{0.2080} 0.20^{0.2052}\right]$$

$$\left[\begin{array}{l} \left(\begin{array}{l} \prod_{j=1}^{5} (1-0.50^2)^{0.1703}(1-0.55^2)^{0.2310}(1-0.75^2)^{0.1856}(1-0.85^2)^{0.2080}(1-0.75^2)^{0.2052} \\ - \prod_{j=1}^{5} (1-0.50^2-0.30^2)^{0.1703}\,(1-0.55^2-0.25^2)^{0.1856}(1-0.75^2-0.15^2)^{0.2018}(1-0.85^2-0.05^2)^{0.2080}(1-0.75^2 - \end{array}\right. \\ \left(\begin{array}{l} \prod_{j=1}^{5} (1-0.55^2)^{0.1703}(1-0.65^2)^{0.2310}(1-0.85^2)^{0.1856}(1-0.95^2)^{0.2080}(1-0.85^2)^{0.2052} \\ - \prod_{j=1}^{5} (1-0.55^2-0.40^2)^{0.1703}\,(1-0.65^2-0.30^2)^{0.2310}(1-0.85^2-0.20^2)^{0.1856}(1-0.95^2-0.15^2)^{0.2080}(1-0.85^2 - \end{array}\right. \end{array}\right.$$

$$= [0.71, 0.83], [0.19, 0.25], [0.18, 0.24]$$

Score function (SF)

$$Score\ (\tilde{a}) = \frac{0.71^2 + 0.83^2 - 0.19^2 - 0.25^2 - \left(\frac{0.18}{2}\right)^2 - \left(\frac{0.24}{2}\right)^2}{2} = 0.5368$$

Modified Score

$$= \frac{(0.5368+1)}{2} = 0.7684$$

Accuracy function

$$\text{Accuracy } (\tilde{a}) = H(\tilde{a}) = \frac{0.71^2 + 0.83^2 + 0.19^2 + 0.25^2 + 0.18^2 + 0.24^2}{2} = 0.6888$$

Finally, the accumulative influence of various PSFs called the OVI was estimated for all developed human, organization, and technology functions. It is essential to note that various influencing factors introduce a different level of importance in real operation scenarios, which should be considered when their influence on performance variability is aggregated. We utilized the BWM as a popular optimization model to obtain the optimal weight of each PSFs using a structured pairwise comparison. The BWM developer recommended that when the number of criteria is more than nine, a clustering approach facilitates the computation and comparison process as well as leads to reliable results. The proposed PSFs taxonomy used a structural approach (e.g., FRAM paradigm, sociotechnical design hierarchical) for clustering the factors in each PSFs sub-groups. Accordingly, we use this clustering perspective for specifying each cluster. To illustrate, considering the human faction, we first used the PSFs category to define seven sets from human-driven factors to social-driven factors. Then PSFs sub-groups are utilized to specify small clusters for the sub-groups that contained more than nine PSFs. As instance, the human-driven factors category was classified into three sub-groups a) physical condition, b) physiological and phycological factors and c) memorized information. Finally, the best (most important) and worst (least important) factors in each PSFs category, groups (sets), and sub-groups were determined. This helps SMEs make a pairwise comparison among the main sets and sub-sets of PSFs and reach a deeper analysis and understanding of factors' impact. After employing the BWM, multiply the weight obtained for each criterion belonging to each sub-set by the weight of the whole sub-set resulting in the overall optimal weight (OOW) of the criteria. Note that the sum of the total weights of all criteria should be 1.0. It should be mentioned that the results reflect the employed SMEs' knowledge, studied field data, and practical and theoretical findings regarding the PSFs and may differ in other research with different operational and cultural circumstances. Table 5.12 demonstrates the summarized computation process, as an instance, for PSFs *Physical Fatigue, Physical abilities, Age and Gender,* which are associated with PSFs sub-groups of *Physical condition* from the PSFs category of *Human-driven factors.* Considering that maintenance operations, as done every day in the studied field, require actively involving skilled personnel from various departments and backgrounds such as operation, safety, environment, maintenance and instrument and electricity from both owner and contractor. Accordingly, teamwork-driven factors directly play a vital role in establishing successful maintenance. However, social factors seem to influence less at performance variability of maintenance functions. Accordingly, these two PSFs categories received the highest and lowest importance level. The lower Consistency ratio (CR) $\in [0,1]$ means the more consistent the comparisons and subsequently more reliable results that its value was acceptable for all comparisons in the present research. The overall optimal weight (descending sequence) of all PSFs associated with the FRAM-driven HOT (human-organization-technology) Taxonomy is presented in Fig. 5.2-5.4.

Table 5. 12 Overall importance level estimating for PSFs in sub-groups "Physical condition" and main group "Human-driven factors."

PSFs category						
Human-driven factors	Task-driven factors	Organization-driven factors	Technology-driven factors	Team-driven factors	Social-driven factors	Environment-driven factors
0.1898	0.1604	0.2203	0.0398	0.2501	0.0298	0.1098
$\sum_{l=1}^{7} 0.1898 + 0.1604 + 0.2203 + 0.0398 + 0.2501 + 0.0298 + 0.1098 = 1$, Consistency ratio (CR) = 0.0731						
PSFs sub-groups	Optimal weight	PSFs	Optimal weight	OOW		NOOW
Physical condition	0.0833	Physical Fatigue	0.4808	=0.1898×0.0833×0.4808=0.0076		0.0076
Physiological and Phycological factors	0.5833	Physical abilities	0.1538	=0.1898×0.0833×0.1538= 0.0024		0.0024
Memorized information	0.3333	Age	0.3077	=0.1898×0.0833×0.3077= 0.0049		0.0067
$\sum_{l=1}^{3} 0.0833 + 0.5833 + 0.3333 = 1$		Gender	0.0577	=0.1898×0.0833×0.0577= 0.0009		0.0013
		$\sum_{l=1}^{4} 0.4808 + 0.1538 + 0.3077 + 0.0577 = 1$, Consistency ratio (CR)= 0.0655				
Consistency ratio (CR) = 0.0833		OOW = Overall Optimal Weight, NOOW = Normalized Overall Optimal Weight				

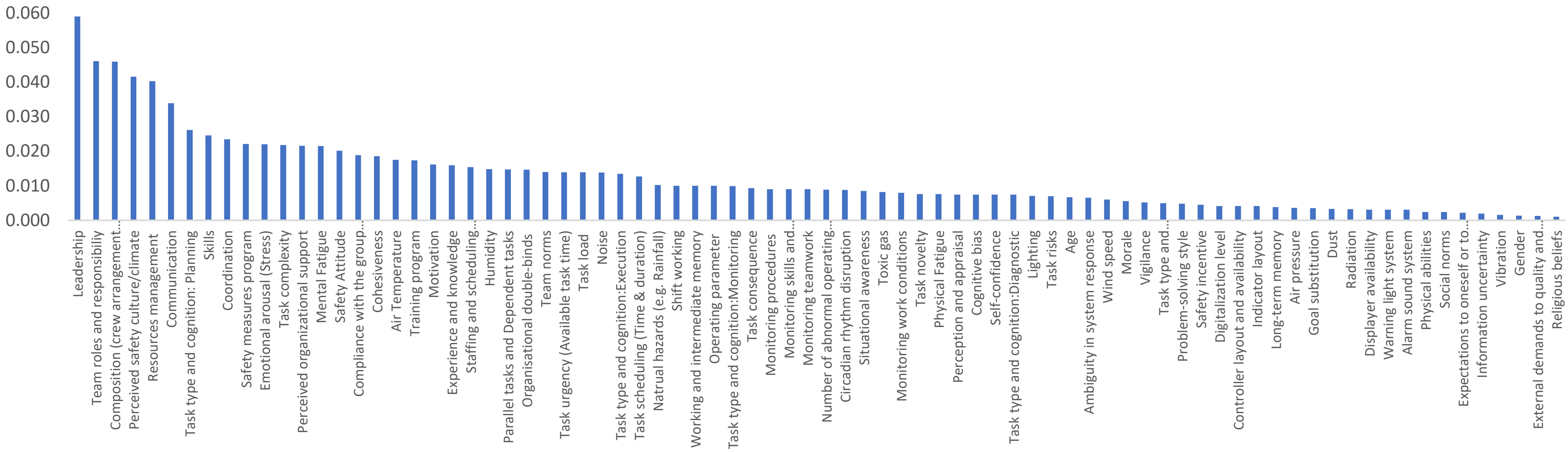

Figure 5. 2 The overall optimal importance level of human performance shaping factors

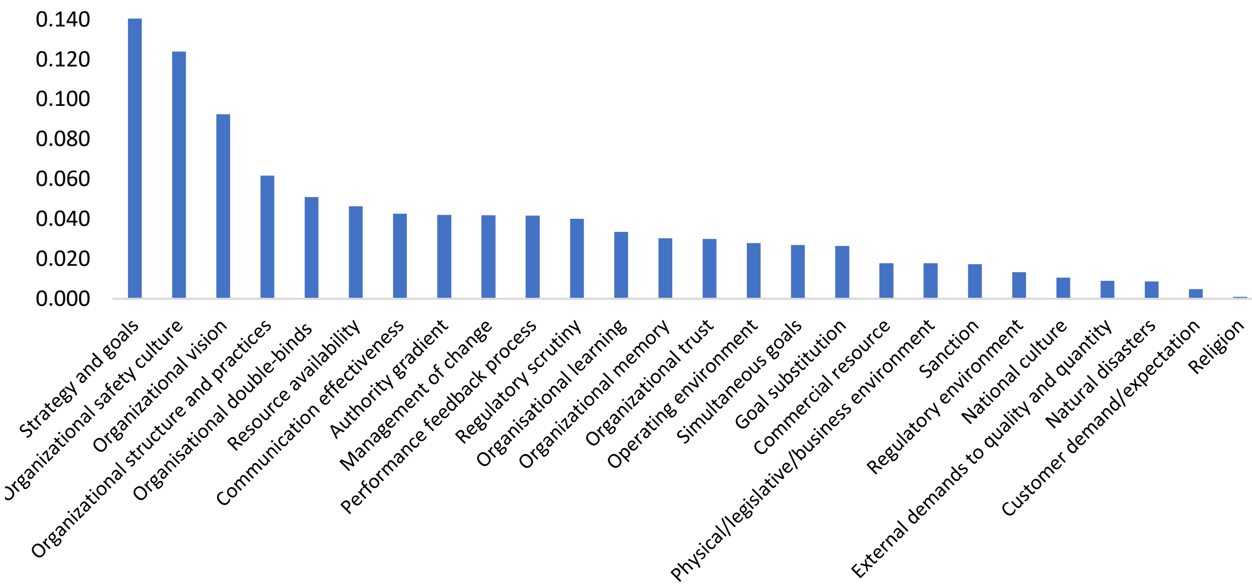

Figure 5. 3 The overall optimal importance level of organization performance shaping factors

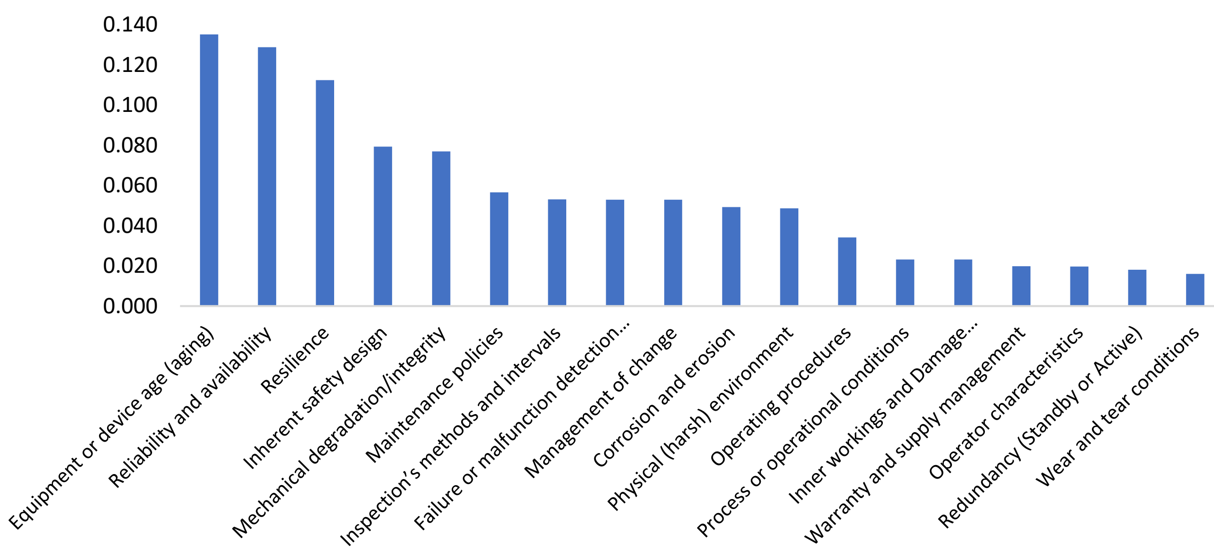

Figure 5. 4 The overall optimal importance level of technology performance shaping factors

Finally, after aggregating the experts' knowledge and obtaining the importance level of PSFs, it is important to model the accumulative influence of various PSFs on the developed functions in a real operating scenario. To this end, Eq. 6.8 is proposed to estimate the overall influences of factors named OVI. In this research, the value of λ_i is equal to the modified Score obtained by Score

Function. We excluded the parameter of Time (t_F) in obtaining the overall variability because functions are performed in non-sequential order and by different crews. We believed that working time does not considerably impact human performance variability as functions do not follow a fixed time manner in the studied plants. However, if the same operators perform the activities in a sequential working time, t_F should include to capture the working time on operator performance variability.

Let's consider the first technology function named "*Pressure and leak test system"* to illustrate the quantification process of OVI. Its performance is influenced by 18 factors presented in Table 5.13. As can be seen from the results, OVI is obtained at 0.6449 for this function which is considered high considering $\text{OVI}_x \in [0,1]$ in such a safety-critical operation.

Table 5. 13 The overall variability index (OVI) estimation for Function "*Pressure and leak test system (F_{25})"*

No.	Performance shaping factors (PSFs)	Normalized overall optimal weight (w_i)	The modified Score (λ_i)	$\lambda_i w_i$
PSF1	Physical (harsh) environment	0.0487	0.6798	0.0331
PSF2	Operator characteristics	0.0197	0.5587	0.0110
PSF3	Maintenance policies	0.0567	0.6507	0.0369
PSF4	Inspection’s methods and intervals	0.0530	0.6317	0.0335
PSF5	Warranty and supply management	0.0199	0.5421	0.0108
PSF6	Reliability and availability	0.1289	0.6685	0.0862
PSF7	Inner workings and Damage mechanisms	0.0231	0.5573	0.0129
PSF8	Wear and tear conditions	0.0160	0.5866	0.0094
PSF9	Mechanical degradation/integrity	0.0769	0.6042	0.0465
PSF10	Corrosion and erosion	0.0493	0.7459	0.0368
PSF11	Management of change	0.0529	0.6770	0.0358
PSF12	Resilience	0.1124	0.7401	0.0832
PSF13	Inherent safety design	0.0793	0.7232	0.0573
PSF14	Redundancy (Standby or Active)	0.0181	0.6460	0.0117
PSF15	Process or operational conditions	0.0232	0.7504	0.0174
PSF16	Equipment or device age (aging)	0.1351	0.6914	0.0934
PSF17	Operating procedures	0.0342	0.7046	0.0241
PSF18	Failure or malfunction detection systems	0.0526	0.7253	0.0384
		$\sum_{i=1}^{18} w_i = 1$	$\text{OVI}_{F_{25}} = \sum_{i=1}^{18} \lambda_i w_i = \mathbf{0.6449}$	

The performance variability magnitude findings for the developed functions (human (N=19), organization (N=5), and technology (N=7)) are presented in Table 5.14. The Interval-valued Spherical Weighted Arithmetic Mean (IVSWAM) presents the aggregated knowledge of five SMEs and considerably addresses the epistemic uncertainty and bias in the knowledge elicitation process. The OVI also captured the importance level of PSFs (N= 124), which are 80 factors for human functions, 26 and 18 factors for organization and technology functions, respectively. The findings revealed the criticality ranking of functions' variability in each category. Accordingly, the highest performance variability of human functions is respectively associated with F#18 (*Conducting the Pre-Startup Safety Review (PSSR) and run operation,* OVI=0.5947), F#15 (*Performing the required maintenance,* OVI=0.5829), and F#9 (*Depressurizing, draining, and purging*, OVI=0.5782). Furthermore, critical variability for organizational functions is associated with F#22 (*Establishing the Radar system to improve the spirit of team working, mutual communication and safety culture*, OVI=0.6996) and F#20 (*Establishing and holding the crew training programs*, OVI=0.6737), while for technology function is contributed by F#27 (*Depressurizing, draining, and purging system*, OVI=0.6807) and F#25 (*Pressure and leak test system*, OVI=0.6781), respectively. The percentage of total human errors which have caused system failure is significantly higher in maintenance operations than in the assembly, and installation, and operational errors in the system life cycle [30]. This indicates the seriousness of safety concerns in maintenance activities closely intertwined with complex operations and interactions among different departments.

Table 5. 14 The ranking of maintenance functions using IVSWAM, OVI

Function	IVSWAM*	OVI**	Rank	Function	IVSFAM	OVI	Rank
Human							
F1	38.1379	0.5367	11	F18	43.5903	0.5947	1
F2	32.3418	0.5367	12	F19	43.1018	0.5730	5
F3	33.2104	0.4530	19	**Organization**			
F4	37.2812	0.4998	17	F20	15.9191	0.6737	2
F5	41.6207	0.5635	7	F21	14.8249	0.6275	4
F6	36.4654	0.4910	18	F22	16.8923	0.6996	1
F7	39.2180	0.5246	15	F23	15.8309	0.6572	3
F8	40.8271	0.5375	10	F24	15.6833	0.6230	5
F9	44.1555	0.5782	3	**Technology**			
F10	42.6572	0.5620	8	F25	11.8835	0.6781	2
F11	40.8175	0.5331	13	F26	11.7444	0.6628	5
F12	38.1999	0.5077	16	F27	12.1378	0.6807	1
F13	41.9230	0.5417	9	F28	12.1082	0.6756	3
F14	39.2202	0.5291	14	F29	10.8107	0.6228	7
F15	43.4942	0.5829	2	F30	11.6936	0.6629	4
F16	42.0252	0.5647	6	F31	11.4248	0.6560	6
F17	42.5486	0.5760	4				

*Interval-valued Spherical Weighted Arithmetic Mean, **Overall Variability Index

It should be noted that the results of performance magnitude are in line with the studied field experiences and confirmed by all SMEs, which proves the capability of the proposed model to precisely quantify the performance variability's magnitude and deal with the epistemic uncertainties that arise from fuzziness, vagueness, and lack of knowledge. Furthermore, using the interval values can better characterize the potential variation of findings and result in accurate findings in fuzzy mathematics which effectively addresses the aleatory uncertainty in the magnitude of functions' performance variability [18]. In SFSs, the sum of the square of membership, non-membership, and hesitation degrees is less than or equal to 1. This entirely copes with stress on SMEs to give preference values without any limitation based on their knowledge, despite the other fuzzy sets [22,23]. Moreover, hesitancy degree indicates ignorance or indeterminacy stems from insufficient or lack of information. Accordingly, it is crucial to be independently and explicitly expressed and measured regardless of membership and non-membership degree [22]. Hence, the employed sets in the present research can accurately reveal the SMEs' judgments and are more efficient in knowledge engineering to capture uncertainty, vagueness, and imprecision as key challenges existing in this domain.

As mentioned above, the performance variability magnitude of each maintenance function caused by PSFs has been investigated so far. However, exploring which contributing factors most vary the performance of the entire maintenance process would effectively assign safety countermeasures to dampen critical variabilities before they lead to system disruption. We pointed out those factors using two approaches using Eq (6.14) to estimate the Optimal Total Influence (OTI) and Total Influence (TI) of each PSFs on the maintenance process system. The former indicates the overall influence of each PSFs over the entire maintenance system considering its optimal importance level (weight), while the latter reflects the overall influence of each PSF without capturing its importance level.

$$\mathrm{OTI}_{PVSF_i} = \left(\sum_{j=1}^{n} \mathrm{V}_{i,j}\, W_i\right), \quad \mathrm{TI}_{PVSF_i} = \left(\sum_{j=1}^{n} \mathrm{V}_{i,j}\right) \tag{6.14}$$

OTI_{PVSF_i} denotes the Optimal Total Influence of PSF_i (i=80 for human-oriented functions, i=26 for organization-oriented functions and i=16 for technology-oriented functions). $\mathrm{V}_{i,j}$ indicates the variability level imposed by $PVSF_i$ over function j (n_j=19 for human, n_j=5 for organization and n_j=7 for technology). W_i represent optimal importance level of PSF_i is obtained using Best Worst Method and illustrated in Fig. 5.2-5.4. TI_{PVSF_i} stand for total influence of PSF_i by ignoring its importance level.

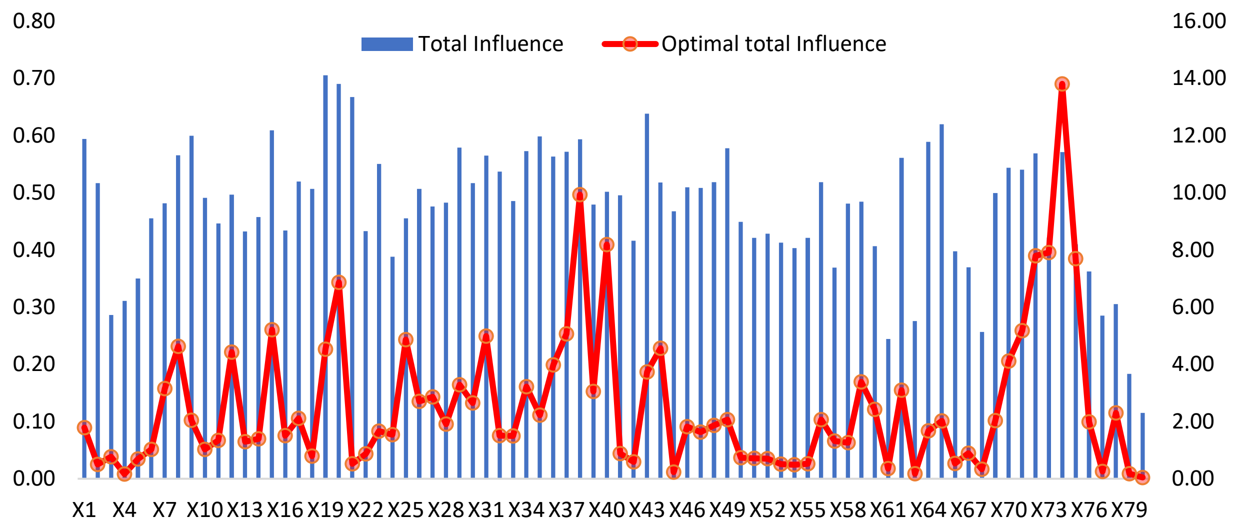

Figure 5. 5 The influence of PSFs on human-oriented functions of maintenance operation

Fig 5.5 illustrates the extent to which PSFs contributed to human performance most in the entire process of maintenance operations, considering or ignoring their importance level. This accumulated influence of each PSFs on nineteen human-oriented functions of pre- and post-maintenance activities. The findings revealed that PSF_{19} (*Experience and knowledge*, TI=14.10), PSF_{20} (*Skills*, TI=13.81) and PSF_{21} (*Information uncertainty*, TI=13.34) have the highest impact on human performance. This means that human-driven factors contributed to most among the PSFs category (e.g., human, task, organization, team, environment, and social). However, when it changes to capturing the importance level of each PSFs, PSF_{74} (*Leadership*, OTI=0.69), PSF_{74}(*Perceived safety culture/climate*, OTI=0.50), PSF_{40}(*Resources management*, OTI=0.41) are leading factors in performance variability. This implies that human-driven factors are direct, while team- and organization-driven factors are indirect(latent) components of sociotechnical systems that cause performance resonance.

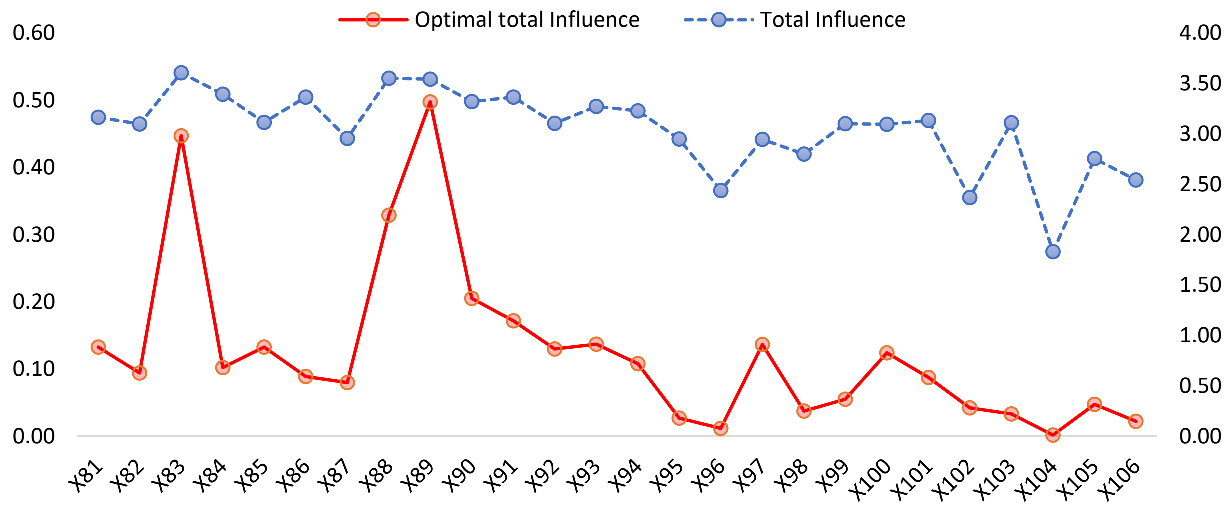

Figure 5. 6 The influence of PSFs on organization functions of maintenance operation

The contribution of PSFs to the performance of organizational functions is presented in Fig 5.6 As can be seen, PSF_{83} (*Organizational safety culture*, TI=3.61), PSF_{88} (*Organizational vision*, TI=3.55), PSF_{89} (*Strategy and goals*, TI=3.54) are leading among the studied factors. However, considering the importance level of PSFs, there is a prominent difference among the organizational-driven factors, which are respectively led by PSF_{89} (OTI=0.50), PSF_{83} (OTI=0.45) and PSF_{88} (OTI=3.55). Hence, these three factors have been recognized as significant sources of variability (resonance) in organizational performance and should be the main priority in safety intervention programs.

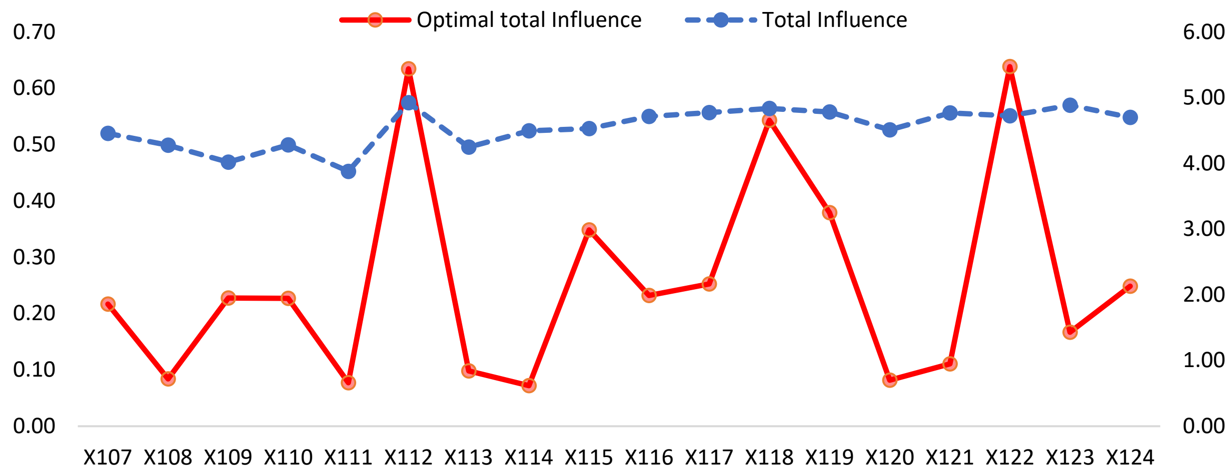

Figure 5. 7 The influence of PSFs on technology functions of maintenance operation

Technology-driven failures have always been highlighted as prevalent sources of system failure in process safety and risk engineering [31]. However, a few systemic investigations have been conducted to reveal which factors contribute most to technical disruptions in the system safety domain. This research analyzed the impact of eighteen responsible elements for the technology-driven failures from a process safety and risk perspective. As can be noticed from Fig 5.7, there is a slight difference among studied factors to the varying performance of technological functions, although PSF_{112} (*Reliability and availability*, TI=4.92), PSF_{123} (*Operating procedures*, TI=4.88) and PSF_{118} (*Resilience*, TI=4.84) have a higher impact. Nevertheless, capturing the importance level of PSFs, PSF_{122} (*Equipment or device age (aging),* OTI=0.64 and PSF_{112} (OTI=0.63) remarkably determine the performance of technological functions. These results are consistent with the fact that most processing plants in the studied area end up their useful life. The obtained importance level of contributing factors mainly reflects their importance in the studied oil and gas plants concerning their safety, operational, technical, and organizational requirements and circumstances. However, the Total Influence (TI) findings of PSFs may be more practical than those that reflect OTI in a wide range of complex systems. Overall, the findings indicate safety investment factors in each category of sociotechnical systems' functions (i.e., human, organizational, and technological), subcategories, and factor levels. Accordingly, the proposed approach entirely supports the decision-making process to dampen critical variability effectively.

5.3.5. Comparison with the previous research

Comparing the proposed model with similar research is one of the most common and practical approaches to illustrate the model's superiority. We found six studies focused on analyzing PSFs, human factors, and reliability in maintenance tasks in various industrial domains. We considered fourteen important factors to compare the present research to the previous ones, as presented in Table 5.15. As can be seen, the previous investigations only focus on human-oriented activities, while successful pre- and post- activities of maintenance required intensive technological and organizational involvement. Ignoring such essential functions also lead to a lack of understanding of contributing factors and mechanisms, which can cause severe failures in organizational operation as leading line and technology operations as the fundamental line in complex system maintenance. However, the present research delivered an in-depth insight into those functions and their influencing factors under uncertainty.

System safety performance assessment often requires subject matter experts' knowledge acquisition which entails handling epistemic uncertainty, vagueness, and fuzziness in the decision-making environment. Moreover, quantifying system performance should also address objective uncertainty in the computation process and yield reasonable numerical results. Noroozi et al. (2013) applied an interval approach for uncertainty propagation, the only previous research that considered this issue. However, we utilized the latest extensions of fuzzy set theory as one of the most effective approaches to deal with epistemic uncertainty in knowledge engineering.

Furthermore, we employed an interval-valued set to propagate uncertainty in the quantifying process.

In safety management, identifying safety critical investment factors is a core part of designing effective countermeasures to prevent or mitigate system failures. However, previous research in maintenance activities has not paid attention to this concern. In contrast, the present study reveals critical functions and PSFs that paw a way to proactively support decision-making in safety management.

However, it should be noted that employing a probabilistic approach to analyze system performance is beyond the present study's scope, and it is acknowledged that human functions experience the most likely and organizational functions the least likely performance resonance [3,4,10]. Numerous human reliability methods have been frequently used to analyze human performance probabilistically. Furthermore, modeling dependencies among PSFs is another important concern in system performance assessment. This study proposed 124 PSFs over 19 functions, and potential modeling dependency dramatically increases this study's complexity. Hence, we preferred not to deal with these concerns in the present research to address other vital objectives deeply. Several methods such as Analytic Network Process (ANP), Analytic Hierarchy Process (AHP) and Decision making trial and evaluation laboratory (DEMATEL), and Cognitive Map (CM) and their extensions have been regularly employed to consider potential dependencies in safety probabilistic analysis [18,33].

Table 5. 15 Maintenance studies concerning safety, human factor, and reliability in complex systems

Studies Features	[34]	[35]	[36]	[37]	[38]	[32]	This study
Human Functions	✓	✓				✓	✓
Organizational Functions							✓
Technological Functions							✓
Identification of PSFs			✓	✓			✓
Importance level of PSFs	✓		✓			✓	✓
Dependency among PSFs			✓				-
Handling subjective uncertainty							✓
Handling objective uncertainty						✓	✓
PSFs' criticality analysis			✓				✓
Functions' criticality analysis						✓	✓
Quantitative results	✓	✓			✓	✓	✓
Probabilistic analysis	✓	✓				✓	-
Studied PSFs (H, T, M, TM, E, O, S*)	Selective (H,T,TM,O)	Selective (H,T,TM,O	Selective (H,T,M,TM,E)	All	H & O	Selective (H,T,E)	All
Number of studied PSF	9	9	38	34		12	124

*Human (H), Task (T), Machin (M), Teamwork (TM), Environmental (E), Organizational (O), Social (S)

5.4. Conclusions

The safety performance of sociotechnical systems and their main elements (e.g., human, technology, organization) critically varied due to numerous contributing endogenous and exogenous factors. This paper first introduced a model to identify system safety performance shaping factors and then rigorously quantified safety performance affected by various endogenous and exogenous factors considering sociotechnical system design under uncertainty. The proposed PSFs Taxonomy is a forward step to fill the gaps remaining in existing PSFs taxonomies, and it ties in closely with sociotechnical system engineering. The applied novel three-dimensional spherical information sets differently addressed fuzziness, vagueness, and subjective uncertainty in the knowledge acquisition process, which is one of the key challenges in system safety and human-organizational factor analysis. The model captured the optimal importance level of contributing factors in system safety performance analysis and proposed variability indices. Quantifying these indices yielded to clearly specify safety investment elements in system hierarchies from factor level to three types of system functions. This provides a deep understanding of complex system elements, their interaction, and their influence on system safety performance and paws a rational way to effectively dampen critical performance resonance based on different human, organizational, and technological functions before the system fails. Comparing the present research with the previous studies pointed out new aspects of the proposed model in the safety assessment of maintenance operations. Although we tested the model capabilities in a proactive assessment, it can also be utilized in reactive approaches such as accidents investigation and analysis. Furthermore, the model has potential application to assess resilience engineering because a signification relationship between PSFs and system resilience, especially in industrial maintenance departments, has been reported.

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CHAPTER 6

How have artificial intelligence and expert systems contributed to human reliability and factor analysis in complex systems?

Preface

A version of this chapter has been presented in ***the 2022 Mary Kay O'Connor Safety and Risk Conference. Texas A&M University, Oct 2022*** *and published in Process Safety and Environmental Protection (2023), 171 736-750. I am the primary author along with the Co-authors, Faisal Khan, and Rouzbeh Abbassi. I developed a systematic review and analysis of artificial intelligence and expert systems contributions to human reliability and factor analysis in complex systems. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' and peer review feedback. Co-author Faisal Khan helped in the concept development, design of methodology, reviewing, and revising of the manuscript. Co-author Rouzbeh Abbassi provided fundamental assistance in reviewing and correcting results. The co-authors also contributed to the review and revision of the manuscript.*

Abstract

Human reliability and factors analysis (HR&FA) have been thoroughly explored from various aspects (e.g., engineering, psychology, physiology, and ergonomics) in critical systems. Accordingly, numerous conventional techniques have been developed and applied to improve system safety from the human perspective. However, emerging socio-technical systems, industry 4.0, and artificial intelligence reveal these methods' incapability and the necessity for developing state-of-the-art intelligent approaches. Hence, this work is designed to demonstrate how artificial intelligence and expert systems have contributed to HR&FA, focusing on machine and deep learning, and knowledge/data-driven modeling approaches. The systematic review primarily investigated the applications, contributions, challenges, and research gaps in HR&FA using those intelligent approaches. We analyzed seven vital elements of HR&FA to illustrate these contributions. Furthermore, this work highlighted some important myths, misapplications, and critical concerns that should be addressed using these advanced approaches. This research yields detailed insights into HR&FA using artificial intelligence and expert systems.

Keywords: Human error; Human reliability; Human Performance; Human factors; Artificial intelligence; Expert systems.

6.1. Introduction

Human reliability and factors analysis (HR&FA) play an essential role in the entire life cycle of complex systems to develop and maintain sustainable and resilient operations. These factors significantly contributed to design, construction, normal operation, maintenance, emergency preparedness, and decommissioning. In addition, a careful examination of the catastrophic accidents from Bhopal (1984), and the Deepwater Horizon oil spill (2010) has shown that human factors have played a leading role in their occurrence. The retrospective analysis also shows that human factors, individually or collectively, are recognized as dominant contributing factors in all complex systems' accidents (e.g., process industries (>80%), nuclear power plants (≈90%), and marine operations (75% to 96%)) [1]. Therefore, numerous human factors, reliability techniques, and models have been developed to identify, analyze, and prevent human-oriented failures. They significantly improved our understanding of human behavior and error mechanisms and enhanced system safety and resilience in socio-technical systems. However, there are still some crucial challenges in establishing conventional techniques because of either insufficient classified data or emerging extensive databases (e.g., accidents data), subjective uncertainty and bias, emerging new performance shaping factors (PSFs) associated with Industry 4.0, industrial internet of things (IIoT), and increasing complex system's attributes (e.g., dynamic complexity, relative ignorance, interactable and non-linear operations) [2]. Artificial intelligence models (e.g., machine learning, deep learning, data-driven) and fuzzy expert systems have been increasingly considered as a proper response to address most of those issues. They have proved the proficient approach in classification, knowledge acquisition, reasoning, and diagnosis of complex problems, which are of utmost importance in human factors and reliability analysis.

Moreover, knowledge acquisition through domain experts and historical or observed data are still the main resources to establish successful human reliability and human factors analysis in numerous domains. However, using them systematically requires employing fuzzy expert systems and artificial intelligence models. Several genuine attempts have been made in this direction, but a systematic review with a primary focus on their applications, contributions, challenges, myths and misconceptions, and research gaps in human reliability and human factors analysis have not been observed yet. Hence, it is hard to ascertain how those models and systems have contributed to human factors and reliability analysis, despite their numerous applications and conducted systematic reviews in different domains (e.g., healthcare, autonomous systems, computer sciences) and other safety concerns (e.g., engineering risk assessment [3]).

Accordingly, this research was designed to fill this scientific gap by synthesizing stat-of-the-art achievements. This research aims to explore the contribution of artificial intelligence and fuzzy expert system considering seven major concerns in human factors and reliability analysis, including a) Quantifying human error probability, b) Quantifying the influence of PSFs, c) Modeling human behavior and factors, d) Integrating human factors into risk assessment, e) Learning from Accidents, f) Critical analysis and finally, g) uncertainty analysis. We also want to focus primarily on the process industry and compare this sector with other complex domains, considering the HR&FA literature using artificial intelligence and fuzzy expert systems. The rest of the paper is as follows. The methodology is presented in Section 2, while the results and discussion of artificial intelligence and fuzzy expert systems are thoroughly presented in Section 4. The final section is devoted to key findings of the present results.

6.2. Methodology

This systematic research reviewed HR&FA literature associated with artificial intelligence and fuzzy expert systems in Scopus databases from 1978 to 2022. After selecting the appropriate keywords and combining them with the Boolean operators, we performed advanced searches. We found 64 primary records related to artificial intelligence and 650 in fuzzy expert systems. After scrutinizing the collected documents, 56 (artificial intelligence) and 502 (fuzzy expert systems) literature are reviewed during this research. We focused on their application in HR&FA in complex industrial systems.

6.3. Results and Discussion

6.3.1. Intellectual structure of knowledge using Bibliometric data analysis

A bibliometric survey in the Scopus database shows 56 documents using artificial intelligence and 502 documents using fuzzy expert system to investigate HR&FA from 1978 to 2022, May. The trend and type of publications for each domain are presented in Fig.6.1. The content analysis indicates that conference proceedings (48%) and then journal articles (43%) are the most common literature for the fuzzy expert system, while it is apposite by artificial intelligence, where journal papers are significantly dominant (58.50%). Overall, both domains drew increasing attention over the period, while the fuzzy expert system employed earlier rose substantially after 2008. One of the main reasons for this increase might be the capability and practicality of fuzzy expert systems in handling primary challenges in HR&FA, such as data scarcity, subjective uncertainty, and incomplete information in tacit knowledge elicitation. Tacit knowledge is related to emotions, beliefs, intuition, understanding, experiences, and expertise of domain experts. Knowledge is the key to success and competitive advantage for most organizations. Multi-granularity linguistic term sets help identify and create knowledge of domain experts, and fuzzy set theory paves a way to transfer tacit knowledge to explicit ones and handle potential challenges [4,5].

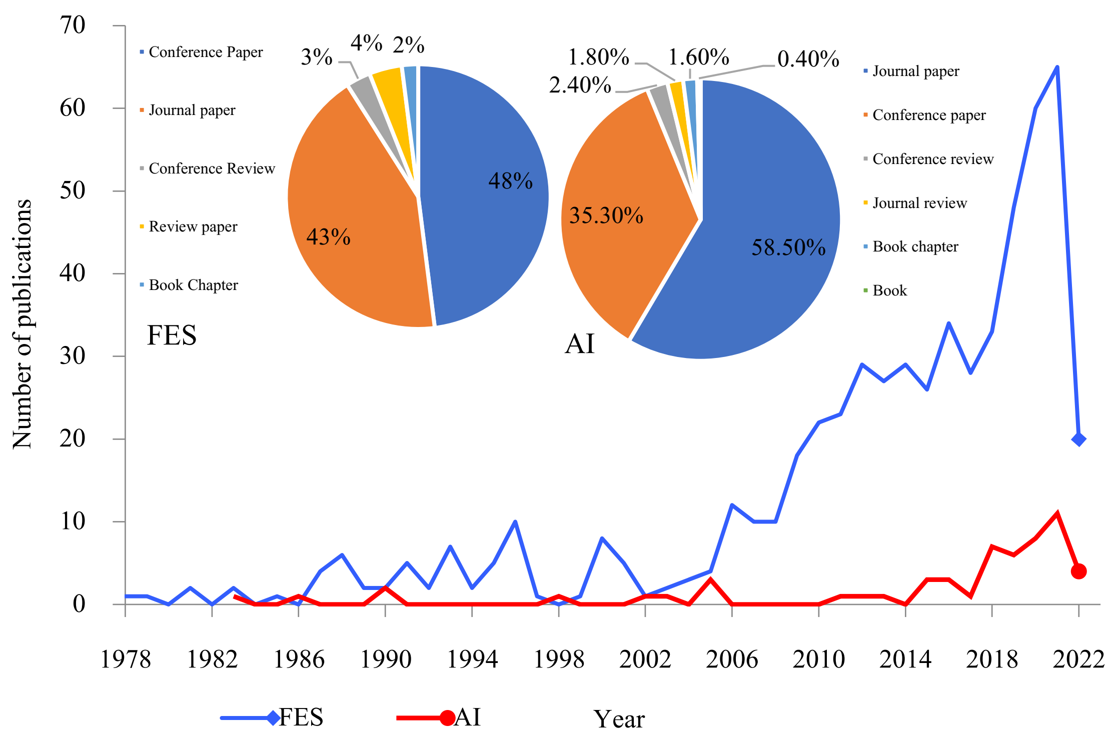


Figure 6. 1 The time trend and content presentation of fuzzy expert systems (FES) and artificial intelligence (AI) in human reliability and factors analysis (Scopus database since 1978)

6.3.2. Contribution of artificial intelligence in HR&FA

Modeling human factors and predicting human performance are among the main concerns that have been studied using artificial intelligence techniques in recent years. Researchers use historical, observational, and simulation data or subject matter experts' knowledge to feed various artificial intelligence techniques. Deep learning is one of the subsections of artificial intelligence. It is the science of extracting patterns and knowledge from a raw data set generated in an organization, community, or any other set. In the past, when the amount of data generated was minimal, many managers could grasp the concepts behind them by taking a simple look and manually separating the data. Nevertheless, when we are faced with a considerable amount of data, this is practically impossible, and the limited power of any human being will not be responsible for analyzing this data and extracting its patterns. Different intelligent algorithms can categorize, analyze, and extract concepts embedded in accident data and support making informed decisions. In other words, in today's management world, intuition has no place in decision-making, and managers should make appropriate decisions based on the data extracted in each case. Several kinds of research have been conducted to explore such capabilities of the machine and deep learning in HR&FA, which will be thoroughly discussed in the following section with a focus on human error prediction, human factors analysis, accidents learning (textual and numerical data) and finally critical analysis of artificial intelligence literature in HR&FA.

6.3.2.1. Human error prediction

Several researchers argued that predicting human error using machine learning techniques is more accurate than statistical techniques. Ouache et al. (2022) introduced evidence reasoning (ER) and a machine learning-based framework to analyze human error-induced firs in residential buildings.

ER is used to assess potential human error factors pessimistically by focusing on critical risk levels. They also used classification-based machine learning to examine fire accident data, select potential factors, train models, and assess fire effects. They considered decision trees, discriminate analysis, support vector machines, nearest neighbors, ensemble classification, and Bayesian's artificial neural network (ANN) to classify, quantify, and predict human error factors. Their findings showed that Bayesian's ANN model has the highest accuracy and efficiency in predicting and classifying human error factors among the models used.

Data-driven models have been drawn to increasing popularity to deal with issues associated with insufficient data and parameter and model uncertainties in recent years. Moreover, they help develop a causality model to demonstrate how various contributing factors threaten human reliability or shape operators' performance quantitatively, while it has been solely explored using bivariate statistical analysis and historical data. Model construction and parameterization in data-free modeling techniques mainly depend on experts' knowledge [6], which usually introduces uncertainty and bias. In contrast, data-driven methods assign empirical data to direct the search-based learning algorithms with objective results. In this sense, Liao et al. (2018) proposed a data-driven influence model (DDIM) to explore the relationship between occupational environment and human error (e.g., wrong sequence). They used the cognitive reliability and error analysis method (CREAM) to collect prior knowledge to develop a knowledge-combined structured learning algorithm in the Bayesian network structure. However, they made several assumptions, ignored parameter learning and estimation, excluded cognitive factors that suffer from lack of data and various human error modes, and the causal relationships' relative importance to focus on proposing a data-driven influence model.

In a different context, Hu et al. (2015) proposed a dynamic data-driven model to predict operator error using advances in neurophysiologic sensors. In their study, a human operator connected to three devices of commercial alarm sensors grade-B, shimmer, and an eye-tracking sensor while doing a computer-based Stroop test. The proposed dynamic system model employed Principal Components Analysis and the Least Squares Complex Exponential methods to analyze the collected raw data. Their findings show that under stressful conditions, the obtained model can mathematically capture mental states to predict human error [7].

Empirical data on human reliability is still inadequate to understand the connections between human errors and their contributing factors. Advanced probabilistic methods like Bayesian networks are employed to relax this issue and capture uncertainty and imprecise data. However, defining the conditional probability tables, the core part of those methods requires factual data, which is often unavailable. This issue is often addressed by making assumptions and experts' intuition and experiences which create an unjustified sense of confidence in the findings [8]. To tackle this drawback, a data-driven human reliability analysis model based on the credal networks and interval probabilities is developed to model imprecision empirical data [8]. The proposed model presents the possibility of defining and quantifying the influence of PSFs over the nominal probability of human error in an invariable and unbiased manner without relying on domain experts' knowledge.

6.3.2.2. Human factor analysis

Human factor analysis is one of the most challenging domains in safety and ergonomics sciences which has rapidly risen in popularity in recent decades. It has been analyzed using conventional and tailored techniques such as HFACS or statistical analysis employing historical accident data. It pays a way to support decision-making in various practical approaches such as preventing similar accidents, improving operator and system performance, and designing and optimizing the system or task of interest. It is acknowledged that conventional methods introduced a substantial lack of versatility as model structures and categories might not be applicable in different applications. Moreover, the predefined categories and contributing factors taxonomy might alter or constrain the investigations' findings. Finally, quantifying the psychological factors often suffer from subjective uncertainty, bias, and insufficient information, which significantly relies on expert experiences and understanding. Furthermore, statistical analysis requires enough and consistent human factor data collection [9]. However, data-driven approaches have been considered as a potential response to address these drawbacks in human factor analysis. To illustrates, [9] proposed a data-driven model to reveal the leading human factors in maritime accidents. They included 94 human factors that contributed to 91 accidents used to develop a data-driven model to predict nine accidents type (e.g., Grounding, Capsizing, Collision) based on contributing factors. They utilized Ensemble and Kernel methods which used learning algorithms in optimal linear or non-linear combinations to reach better predictive performance in a binary decision tree (i.e., presence or absence of each human factor in occurrence of each accident type). After that, they employed Random Forests (RF) and Multiclass -Support Vector Machine with Boolean Kernels (MSVM-BK) to rank the most influencing factors.

Although this model seems less costly, more accurate, practical, and versatile than HFACS, it still requires substantial examinations to perform an unbiased estimator of the generalization error, model error, and predictions. Furthermore, the employed algorithms considered a Boolean manner, influence or not influence of human factors over accident occurrence, and ignored the interaction and dependencies among factors which are far away from the accident characterization defined by system accident models [10]. One of the main challenges in data learning is the optimal selection of hyperparameters used in all learning algorithms to develop model structures (e.g., conceptual or causation) [11]. The resampling methods are among the effective ones where the main dataset is resampled many times, either by replacing or not, to create training, validation, and test independent datasets. Moreover, statistical relevance, enough human factor data, and consistent data collection procedure with data-driven approaches to accurately link the data with accident reports are highly demanded to improve the data-driven model's performance in human factor analysis.

In applying data mining and machine learning to explore human factors, Madeira et al. (2021) proposed a hybrid intelligent model to identify and classify primary human factors that caused aviation incidents using aviation incident reports as descriptive text data. They first proposed an HFACS-ML framework to address the challenges of inconsistency between databased reports and standard HFACS structure. In this research, a text pre-processing and Natural Language Processing (NLP) pipeline are used for the feature extraction, allowing assigned computers to efficiently read and drive numerical vector projections from the accident causes reports. After that, semi-supervised Label Spreading (LS) and supervised Support Vector Machine (SVM) techniques are utilized to model data, while Random search and Bayesian optimization methods are employed to analyze hyper-parameters and the model performance improvement. They used Micro F1 score to measure the proposed model performance. Their findings show that the semi-monitored LS algorithm provides more accurate findings with small data sets. On the other hand, the supervised SVM is more reliable for larger and uniform datasets. It was also found that the Bayesian optimization utility, when properly adjusted, gives a better result for finding near-optimal meta-parameter combinations over non-convex objective functions. This investigation shed some light on understanding such intelligent techniques' capabilities to achieve desirable performance in human factors analysis [12]. However, further research requires deeply interpreting the proposed model's performance in capturing larger sets of both labeled and unlabelled data. Nonrandom selection methods such as Active Learning, which prioritizes the labeling of uncertain points, should be employed and compared in constructing labeled data sets. Furthermore, a concrete and sound performance prediction model entails intensely dealing with redundancy and noise in feature selection analysis.

Some researchers integrated intelligent techniques to improve the proposed model's predictive outcomes. In this line, Yu et al. (2018) combined Fuzzy C-Means clustering (FCM) into Backpropagation neural networks (BPNN) to propose a human factor accident prediction model for improving flight safety through accident prevention. FCM is derived from K-means and uses the fuzzy theory concept to improve clustering accuracy using flight accident data. Despite the K-means, it allows every data member to be a member of different groups wherein subordination degrees were different. BPNN employed the gradient descent method to minimize error functions and derive delta rules which diminish the gaps between the estimated and actual output. They compared predictive accuracy indices such as Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) in the two prediction groups using FCM-BPN and FCM lonely. The findings demonstrated that the MAE and MAPE scores improved using FCM-BPN [13]. However, further research to include more human factors into the model and compare it with the other predictive models requires assessing the quality of results.

MacKinnon et al. (2020) studied machine learning and human factors analysis in maritime navigation. Their findings provided two key points. First, deep machine learning requires significant data. Unlike the automotive industry, it is challenging to obtain on-site data. Simulation technologies may bridge this gap; however, this approach may eliminate natural behaviors.

Second, artificial intelligence and automation come from different technology providers. Given the developed algorithm, monitoring and regulating these technologies and their use in navigation may be necessary. Moreover, Fan et al. (2020) incorporated human factors in the risk assessment of maritime accidents using the data-driven Bayesian network. They attributed the reason for using this method to the ability to determine the dependency between different factors using the limited data available and the higher accuracy of calculations in the Bayesian network compared to classical approaches such as fault tree and event tree due to considering the nonlinear relationships. Data-driven algorithms also can deal with the exponential increase of computation burden in defining the conditional probability tables, which is the core and hardest element in Bayesian network modeling.

6.3.2.3. Accidents learning (textual and numerical data)

Learning from accidents is still considered for improving the system safety and resilience. However, capturing data on new major accidents and updating the already proposed accident models are cumbersome because it requires much time to digest detailed reports. In this sense, it is asserted that machine learning techniques already developed and trained with previous accident data can promptly recognize the most relevant features and then dynamically update the developed accident causation model [14]. In this regard, Morais et al. (2019) employed a machine learning tool to update Bayesian network probabilities by scanning new reports without traditional work's time-consuming and costly approach. They first used the Cognitive reliability and error analysis method (CREAM) taxonomy to develop a human error model and mapped identified organizational, technological, and individual factors into the Bayesian Network model. The proposed approach was based on text recognition and text classification, integrated into a support vector machine for text classification as per a predefined classification to develop a "virtual risk expert". The proposed model trained up with US National Transportation Safety Board (NTSB), for aviation accidents and the U.S. Chemical Safety and Hazard Investigation Board (CSB) for chemical accidents. The model accuracy increases from 85% (trained only by NTSB data) to 91% when capturing information from both databases. The results showed that human factors become apparent when the model is taught using data from the chemical industry and not only from aviation, which indicates the importance of interdisciplinary knowledge transfer. This study indicates the possibility of the real-time updating of the model parameters (e.g., human error), and it is essential to reveal the leading causes of accidents.

Furthermore, safety incident reports are often recorded in textual format with different structures and taxonomies. Systematic analysis of them always hinders by allocating huge resources (e.g., time, trained workforce, cost) and is considered a time-consuming, error-prone, cumbersome, and bureaucratic process which leads to inconsistencies in safety assessments [7]. However, machine learning algorithms can quickly and deeply explore and learn from such rich textual data. These capabilities yield invaluable insights into the different contributing factors to human factors and reliability, the revelation of complex dependencies among factors, and categorical and predictive safety outcomes. Natural language processing (NLP), support vector machine (SVM), artificial neural network (ANN), decision tree (DT), radial basis function (RBF), and latent semantic analysis (LSA) are among the most popular techniques to serve for that purpose. This is also true for learning from numerical data like frequencies and statistical data of accidents and their influencing factors.

6.3.2.4. *Critical analysis of artificial intelligence literature in HR&FA*

This section briefly highlights some critical issues using artificial intelligence techniques. The deep analysis of these concerns is beyond the present research, and we want to bring the researcher's attention to this critical subject by exemplifying some drawbacks. Wen et al., (2022) reported six significant myths and misconceptions, with twelve subcategories frequently found in process safety research using data-driven methods. They defined myths and misconceptions as *"the application of a method or a model and the representation of data without adhering to their respective scientific norms"*. They identified that 33.6% (168 papers) of 500 collected articles hold 288 cases of those myths and misconceptions that rare attentive to data representation (163 cases), and ignore appropriate Bayesian network assumptions (55 cases) considered as the dominant ones. They also reported digit inconsistency, the inaccurate calculation of significant digits, false precision, and improper uncertainty as the most frequently observed misconceptions in data presentation. Proper choosing the hyperparameters is a core part of developing and learning the proposed model structure in machine learning and data-driven models, which highly determine the model performance. Given the Artificial neural network (ANN), as one of the most popular intelligent techniques, several vital hyper- parameters define the appropriate and accurate neural network. For example, the hidden layers' quantity and their neurons, function type for activation, dropout and learning rate, optimization algorithm and epochs, and iterations numbers. Nevertheless, Wen et al., (2022) presented that most studies have not suitably addressed these core elements using ANN in process safety investigations as researchers arbitrarily assigned two or three hyperparameter sets and accordingly reported their findings. However, this crucial concern can be simply handled by employing hyperparameter optimization algorithms like grid search and random search. Informing how well the proposed model accurately works depends on error analysis and reporting it. A survey indicated that some papers had not reported any accuracy indicators and error analysis, and numerous studies have varying error degrees in their data presentation [15].

6.3.3. Contribution of Fuzzy expert system in HR&FA

This section discusses the application of fuzzy expert systems, which work based on fuzzy logic and fuzzy set theory (FST), focusing on some essential concerns in HR&HF analysis. Most scientific endeavors to replace expert-driven human reliability analysis methods with empirical data-driven methods have failed due to significant uncertainty in human reliability databases and the incapability of conventional techniques to relax it. Despite the emerging Bayesian and credal networks and their invaluable contributions, tackling data scarcity using the tacit knowledge of domain experts is still the most prevalent and practical way[16]. Hence, this section explores how and which HR&FA concerns are improved through knowledge engineering using fuzzy expert systems.

6.3.3.1. Human error probability (HEP) prediction

HEP prediction is a core step to managing human error and improving system safety and resilience from a human performance perspective. To this end, enough numerical data should be available, while lacking human performance data is the most prevalent and crucial challenge in all industrial sectors. However, several genuine attempts have been established (e.g., databases, simulation data) to threaten these issues, and knowledge acquisition of subject matter experts (SMEs) is still considered a global and successful solution in HR&HF analysis. However, this popular approach has been strongly criticized since it purely relies on SMEs' experiences and understanding, which introduces bias, subjective uncertainty, and insufficient information. To address this challenge, FST is considered an accepted and practical response [17,18]. In this regard, numerous studies have been conducted in different industrial sectors, and unique ones are illustrated in Fig. 6.2, considering their applications and contributions. As presented in Fig 6.2, different extensions of

FST have been utilized to estimate HEP in various domains, from transportation to manufacturing plants. In essence, linguistic terms (e.g., low, high, very high) are used to elicit SMEs' knowledge regarding the parameter of interest (e.g., the generic task types (GTTs) and error-producing conditions (EPCs)) while conducting task analysis-based scenario. After that, fuzzy computations employ to aggregate SMEs' knowledge, estimate the fuzzy probability, and finally transform it into crisp HEP. Various aggregation functions such as Averaging, Conjunctive, Disjunctive, and Symmetric are available, and Weighted Arithmetic Means from Averaging class is the most popular ones in human reliability analysis. Membership functions (e.g., Triangular, Trapezoid, Sigmoidal, Gaussian) demonstrate the aggregated information. Finally, the estimative value has been assigned into employed the HRA technique (i.e., HEART, CREAM, THERP) to predict HEP. It should be noted that FST substantially also treats subjective uncertainty during the HEP process. However, using FST to estimate probability values assigned in risk and reliability analysis, several critical issues have been identified. Considering its importance, we would like to discuss these challenges in the *Critical analysis* subsection.

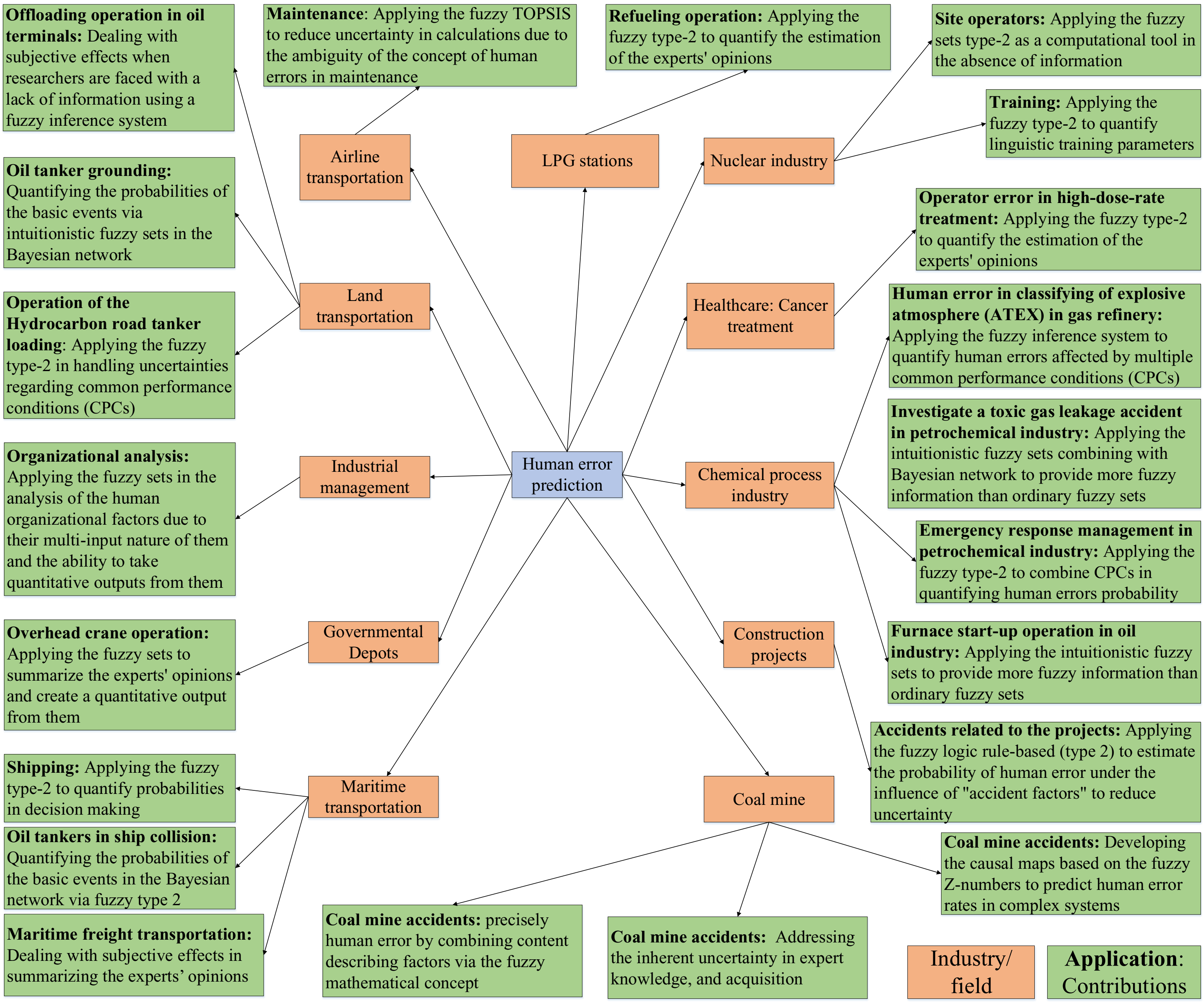


Figure 6. 2 The applications and contributions of fuzzy sets in predicting HEP in the complex system

6.3.3.2. Quantification of PSFs influence

PSFs have been consistently recognized as the most contributing element to occurring human error or shaping human performance in all human reliability analysis techniques. Accordingly, HEP is adjusted based on PSFs' influence on task-based scenarios. However, assigning a precise quantity associated with these factors, which reflects their impact and importance (weight) on operator commission, is one of the most exciting and demanding research topics [1]. These factors are associated with the organization, task design, human-system interface, environment, and individual or collectively operator attributes which such context diversity makes them more challenging in human reliability analysis. Allocating an optimal weight for the contributing characteristics is inquiring in most multi-criteria decision-making (MCDM) methods. It is a fact that various influencing factors do not have the same priority in all-natural conditions, and those values substantially can influence the outcome (e.g., over or underestimation) of the decision-making function. Hence, it is crucial to deeply pay attention to quantifying their impact and weight in estimating HEP. Experimental data can only provide information for a few sets of these factors under a specific simulation environment. Accordingly, knowledge elicitation from SMEs and relaxing their issues using FST has been the most available and practical alternative in recent decades.

FST provides rigorous mathematical computations to quantify subject-matter experts' knowledge, which we can obtain in real situations under uncertainty. Two essential quantities associated with PSFs have been frequently estimated using FST. Firstly, to what extent do these factors impact human unreliability, and then how much should be assumed importance level (weight) of their factors and assigned SMEs in human performance. The former concern is tackled by integrated linguistic terms and FST, while the latter requires integrating MCDM into FST to precisely estimate. In this sense, some researchers employed the Fuzzy Analytical Hierarchy Process (FAHP) to obtain PSFs importance level in machinery maintenance [19], oil cargo handling process [20], expert domain weight in assessing human factors of hot tapping operation in natural gas facilities [21]. They requested the experts to approximate the pairs of facets based on a fuzzy guide argument and then figured the weight of the segments by aggregating the experts' views. Other groups employed the Fuzzy Best-Worst Method (FBWM) along with fuzzy Vlse Kriterijumska Optimizacija Kompromisno Resenje (VICOR) in Shale gas fracturing [22], FBWM and HFACS to analyze human factors in chemical process accidents [23,24], a hybrid D-DEMATEL–IFISM (D number Decision Making Trial and Evaluation Laboratory- Fuzzy Interpretive Structural Modeling) method. These hybrid models provide deep insights (e.g., importance, intensity, impact, and dependencies) into leading factors affecting the occurrence of workplace accidents in micro-enterprises [25]. The fuzzy-VICOR is a suitable agent because of its capability to prioritize PSFs when faced with various inconsistent variables.

The BWM, which raise more in popularity in recent years, utilizes an optimization model by a structured pairwise comparison to obtain the optimal weight of each PSF in a more rigorous mathematical manner than AHP. FST deal with epistemic uncertainty, vagueness, and fuzziness in the knowledge acquisition process and inconsistency and conflict among knowledge sources [17].

Integrating FST into MCDM techniques paves a way to model intra-dependency among PSFs under uncertainty. It is hard to treat it using statistical tests due to insufficient data for a wide range of PSFS. This is another crucial concern in predicting HEP precisely and human performance.

Dealing with all these integrations helps develop the causality map, which is problematic in conventional HRA methods. The MCDM techniques play a considerable role in handling this crucial matter and have risen in favor in recent years. Some significant contributions and their application are presented in Fig. 6.3. Among the different methods, integrating FST into Analytic Network Process (ANP)[26,27], DEMATEL [28], Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [29], Cognitive Map [30] and their hybrid extensions (e.g., ANP-DEMATEL, ANP-TOPSIS) has been raise most popularity in different sectors. FBWM uses an optimized two-pairwise comparison with less bias, more consistency, and time efficiency than other techniques. The contributions of these studies can be discussed in two overall aspects. First, they made reasonable attempts to improve the capabilities of conventional HRA techniques (e.g., CREAM, HEART) to capture inter-dependencies among different PSFs in a cost-effective and time-saving manner. Second, employing fuzzy sets can effectively handle the inherent ambiguity, vagueness, and data scarcity encountered in the knowledge elicitation process [31]. It also significantly helps map the proposed causation model into advanced probabilistic techniques such Bayesian Network to take advantage of such powerful reasoning models (e.g., handling parameter and model uncertainty, deductive and abductive reasoning, parameter and model learning) [32]. It should be noted that fuzzy expert systems can be used to model dependence between successive actions, another type of dependency in human reliability analysis. Zhang et al., (2021) proposed a new method to assess such dependence in human reliability analysis using linguistic hesitant fuzzy information. They confirmed the dependence degree between successive actions by integrating hesitant fuzzy sets into the THERP method through an empirical healthcare dependence analysis.

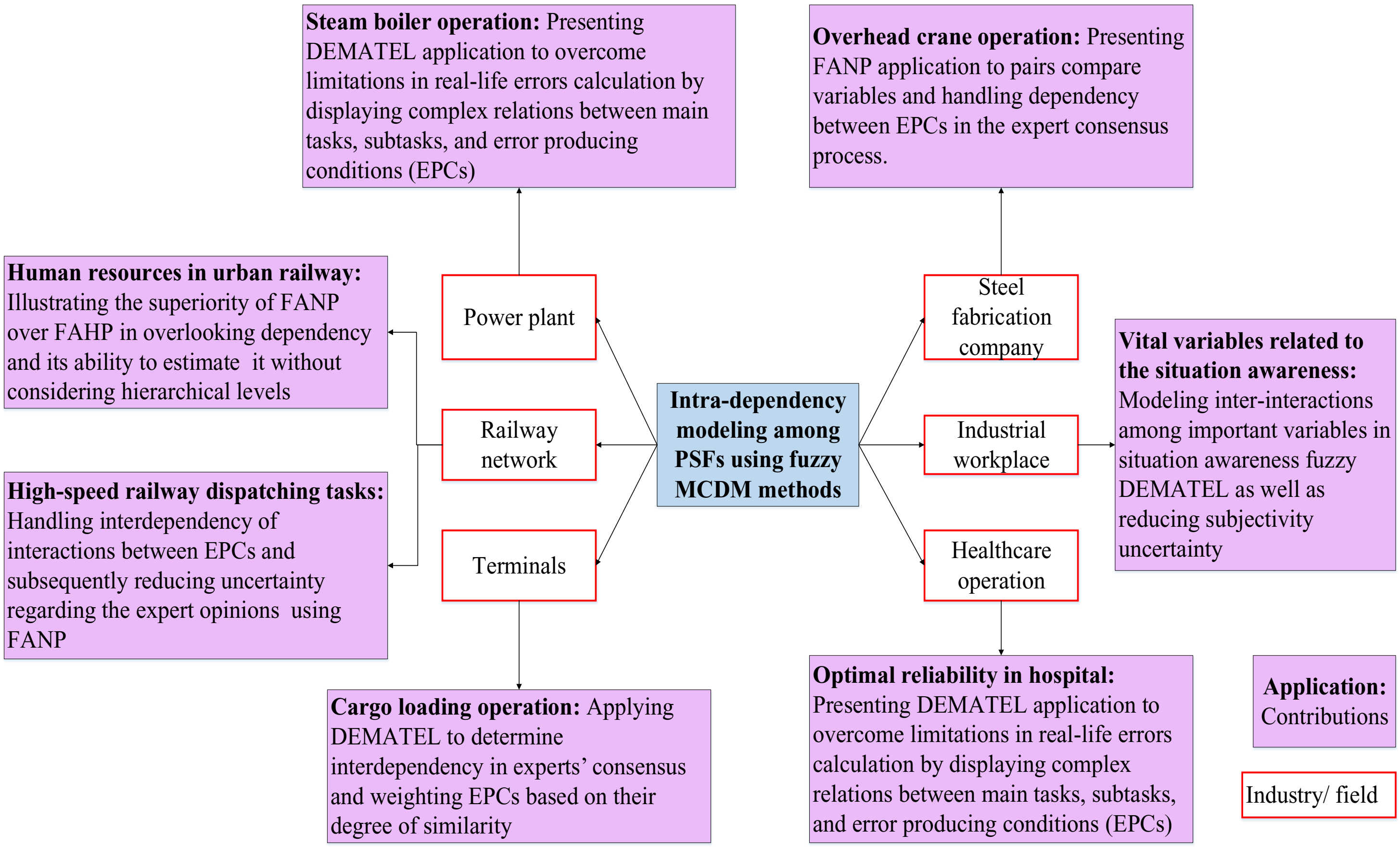


Figure 6. 3 Intra-dependency modeling among PSFs using hybrid fuzzy MCDM techniques

6.3.3.3. Integrating HEP into quantitative risk analysis

Holistic system safety analysis requires integrating human error with other dominant failures (e.g., mechanical, operational). To this end, the risk analysis model should simultaneously identify and quantify all failure modes. Fig. 6.4 illustrates how human error is incorporated into the most popular probabilistic safety analysis techniques in different sectors such as high-speed railways, process systems, and traffic operations. Fuzzy sets have been evolving with eleven extensions from the ordinary sets (Zadeh, 1967) to Spherical sets (Katlu Gondogdu, 2018) to improve their accuracy and capabilities, which is frequently acknowledged. Frequency analysis of integrating human error into probabilistic safety analysis indicates that it is mainly handled by Ordinary sets [34,35] and followed by interval Type-2 [36], Intuitionistic [37], and recently Spherical sets [2]. It also observed that those fuzzy sets were often incorporated into Fault tree analysis, Bow tie, and (dynamic) Bayesian network in descending order.

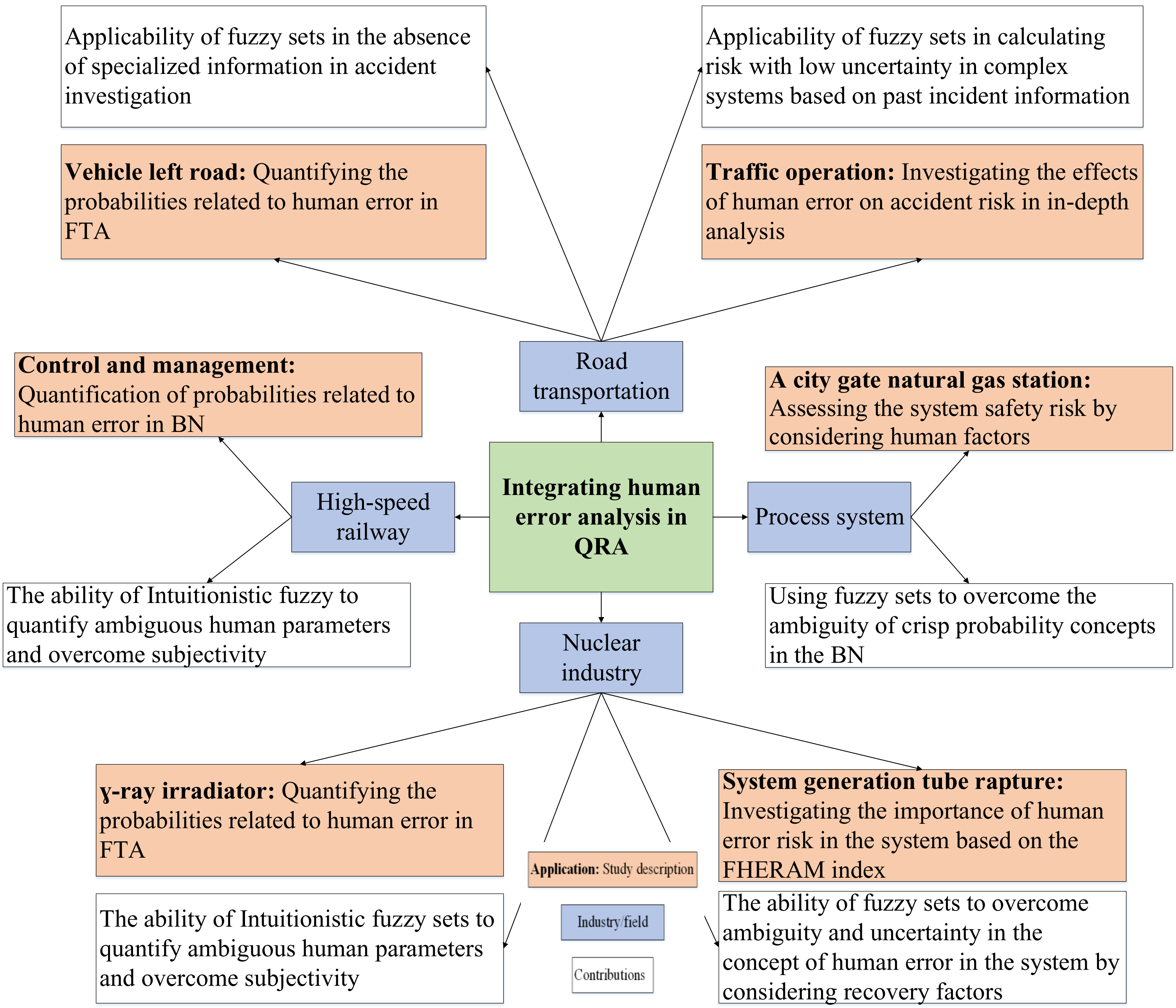
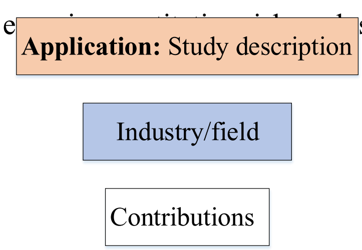


Figure 6. 4 Integrating human e[illegible]sis using fuzzy set theory



It should be noted that fuzzy inference systems are also used to propose human error risk analysis models [38]. This model was built based on fuzzy logic and IF-THEN rules which can yield more realistic results than the traditional human reliability analysis considering its capability to handle uncertainty and imprecision in the knowledge acquisition process. However, considering too numerous quantitative risk analyses with a deep focus on mechanical and process failures, integrating human error into risk analysis has drawn less attention, despite its leading role in major accidents.

6.3.3.4. Human factors analysis

Human and organizational factors (HOFs) play a vital role in safe designing, sustainable operating, and successfully managing abnormal situations in a complex system. HOFs individually or collectively contain various elements from operators to senior managers, affecting all activities at different organizational levels. Major accidents have always been rooted in issues related to HOFs. For illustration, poor maintenance, operators' error, insufficient knowledge about existing risks, poor communication, inadequate safety management, and lack of senior management's commitment to safety frequently have contributed to catastrophic accident occurrence (e.g., Bhopal disaster, Piper Alpha explosion, Deepwater Horizon oil spill, and Texas City Refinery explosion). Therefore, human factor analysis and behavior modeling is a core part of safety management in socio-technical systems. However, like human reliability elements, quantitative analysis of HOFs suffers from data scarcity which requires domain experts' knowledge and highlights the necessity of employing fuzzy expert systems to handle this challenge. In this sense, a few researchers genuinely took some forward steps. Liu et al., (2008) developed fuzzy Petri nets-based techniques to verify and validate fuzzy rules-based human behavior models in military simulation systems. They first developed a static verification of human behavior models using fuzzy rules and then a dynamic validation of human behavior models employing fuzzy Petri nets. They argued that their research addressed the drawbacks of conventional verification and validation methods for human behavior models as the proposed model is more systematic, straightforward, and comprehensible. However, further investigations are required to refine human behavior models' errors, applicability, and performance accuracy.

Recognizing human behavior is a crucial challenge in intelligent surveillance systems with various industrial applications in abnormal situations and emergency detection. Batchuluun et al., (2017) proposed a fuzzy system-based behavior recognition model by integrating both behavior prediction and recognition. They used surveillance cameras with visible light and far-infrared light to capture eleven different human behaviors (e.g., from Lying down and Standing to Punching and Running) in both daytime and nighttime. They developed a fuzzy system-based classifier of behaviors to fuse the recognized data to predict behaviors. The experimental findings have confirmed the superior accuracy and processing time compared to previous conventional techniques.

The main advantage of Intuitionistic fuzzy sets over type-1 and type-2 is utilizing Euclidean geometric operations to specify the space between non-membership and membership regarding threat consistency between experts to handle the randomness. These benefits have allowed it to deliver more precise findings. In this sense, some researchers integrated intuitionistic fuzzy sets with AHP and BWM, considering HFACS taxonomy to determine how much various human factors contributed to process accidents. They mapped the proposed model of HFACS into Fuzzy Bayesian Network to take advantage of advanced probabilistic reasoning. These studies deal with fuzziness and vagueness in quantifying human factors’ influence and subjective uncertainty in the computation process of knowledge engineering [21,24,41–43].

6.3.3.5. Critical analysis of fuzzy expert systems

Literature analysis indicates that fuzzy expert systems have been employed in estimating human error probability far more than other human behavior and factor analysis aspects. We understand that lack of data and perhaps lack of other alternatives for methodology would be the primary motivation to serve fuzzy expert systems for this purpose. However, we would like to highlight some critical concerns and call for action to find proper alternatives, despite these systems being the accepted approach to treatment domain experts' knowledge. Domain experts' knowledge acquisition in HR&FA begins by obtaining their opinions about human error probability or their modifiers, such as PSFs, using linguistic term sets. Using the corresponding fuzzy set numbers, aggregation methods are utilized to elicit the fuzzy numbers from the expressed linguistic terms. After the defuzzification process and employing related equations (e.g., Onisawa), the crisp possibility and failure probability are estimated. We classified these concerns into six groups as follows and would like to refer the interested readers to [18], where the authors are thoroughly discussed considering the page limitation of this research.

I) Various fuzzy numbers yield different and inconsistent probability values; which ones would be more accurate and reliable?

II) Various aggregation techniques result in distinct probability values, which aggregation method seems much more reliable?

III) Enforcing linguistic term sets to the domain experts would present limitations in freely stating their knowledge.

IV) We would eliminate a wide range of essential probability quantities by employing linguistic term sets and then corresponding fuzzy numbers. Any probability values less than 1.63E-05 and more than 0.078 are excluded from any available combinations of fuzzy numbers.

V) Utilizing different fuzzy numbers cannot provide a confidence level for the obtained findings.

VI) Employing each fuzzy number results in different findings in the critical ranking of contributing factors or human error modes. It not only imposes more ambiguities but also might wrongly assign safety countermeasures in the decision-making process; hence, which is more precise and reliable?

VII) The aggregated findings from domain experts' knowledge by capturing their importance level are sensitive to outliers.

Therefore, these concerns introduce important criticisms and question fuzzy set theory in human error probability estimation. Accordingly, it might be necessary to cease using it for this purpose or apply it with the most caution to avoid poor decision-making in human error management from a human reliability perspective. The new extensions of the Belief function theory [44] might be an alternative at the moment as it can deal with some of those concerns more rigorously with the possibility of quantifying uncertainty using the plausibility function.

6.3.3.6. Uncertainty treatment in knowledge engineering and input data

HR&FA is challenged with various types of uncertainties (i.e., epistemic (model uncertainty), aleatory (data uncertainty)), the same as other scientific disciplines. Uncertainty refers to how computations and estimations counter reality or the measurement of the goodness of an evaluation. Machine and deep learning models are used for making inferences and predictions subject to noise and error (2). For instance, uncertainty sources arise when training and test data are incompatible, while class overlap and incomplete, noisy, discordant, or multimodal data lead to data uncertainty [45]. Surprisingly, most artificial intelligent articles in HR&FA failed to discuss and adhere to a systematic procedure to address uncertainties or have not quantified the uncertainty. Hence, we would like to shed some light on the importance, sources, and proper techniques to threaten uncertainty in artificial intelligent systems.

At least four uncertainties are reported in different steps of deep learning, which include a) The training data selection and collection, b) The training data completeness and accuracy, c) Performance bounds and limitations of the deep learning model, and d) The model performance. Moreover, similar data-driven models present at least four overlapping challenges: The absence of theory and causality models, sensitivity to imperfect data, and computational costs [46]. Hence, it is of utmost importance that the artificial intelligence methods' reliability, efficiency, and accuracy be evaluated and uncertainty represented in a trustworthy form prior they applied in practice [47]. Epistemic uncertainty can be formulated as a probability distribution over the model parameters, while aleatory uncertainty is an inherent property of the data distribution, not a model property, and accordingly, it is not reducible [45]. Standard deep learning techniques suffer from presenting reliable information about their predictions. Bayesian deep learning (BDL) and Bayesian Neural Networks (BNNs) can deal with uncertainties associated with the model parameters as they are strongly addressed overfitting problems and can be trained using small and extensive databases. Bayesian techniques include Monte Carlo (MC) dropout, Markov chain Monte Carlo (MCMC), Variational inference (VI), Bayesian Active Learning (BAL), Bayes By Backprop (BBB), Variational autoencoders, Laplacian approximations are most common methods to quantify uncertainty in deep learning systems. Each technique has its pros and cons, and hence careful selection should be considered depending on the nature of the phenomena under study, objectives, input data requirement, computational capacity and requirement, and employed intelligent model's limitations and assumptions [45,48]. In essence, Bayesian techniques employed probability functions and Bayes' rules to quantify uncertain information and make inferences.

In machine learning, mainly supervised learning benchmarks, Neural Networks result in highly competitive accuracy but poor predictive uncertainty quantification meaning they are prone to overconfident estimations [49]. Hence, calibration and domain shift methods are suggested to quantify uncertainty in Neural Networks' applications. The former specifies the discrepancy between long-run frequencies and subjective forecasts, while the latter considers the generalization of predictive uncertainty to a domain shift that measures whether the network knows what it knows [45]. Furthermore, possibility theory, the imprecise probability theory, and the belief function theory are other approaches to quantify uncertainty, despite the lack of consensus on the best approach.

Estimating knowledge uncertainty is substantially more problematic than estimating data uncertainty. Dempster-Shafer (DS) theory utilizes belief and plausibility functions to handle uncertainty stemming from knowledge, opinions, judgments, and evidence which can yield a more realistic and flexible treatment [2,48]. Epistemic uncertainty often stems from knowledge attributes, such as lack of, insufficient, imprecision, subjectivity, and ignorance, which can be refined and eliminated in the knowledge engineering process. Moreover, other kinds have also been recognized apart from the main type of uncertainty, including vagueness (fuzziness) and ambiguity. Fuzzy set theory and linguistic term sets provide robust computation to deal with these uncertainties and epistemic as they could be represented with a fuzzy interval centered [5].

6.3.4. Bibliometrics analysis of HR&FA in chemical process systems (CPIs)

CPIs have handled inherently high-risk operations with far-reaching potential consequences. HR&FA has been considered a core element of safety management systems in designing and operating most industrial activities. Human reliability primarily begins with task-based scenario development and then proceeds with human error identification, *PSFs'* influence specification and ends by quantifying HEP in each step and entire takes. This section is designed to answer the following questions associated with the evolution of HR&FA on CPIs: (i) Who are the top contributing authors behind the citations? (ii) How much global popularity does this field possess? (iii) Which scientific records have impacted most in initiative research? (iv)Which journals draw the most attention in this domain? (v) What are the key areas? (vi) What is the industries' contribution? (vii) What are the most popular techniques to analyze HR&FA on CPIs?

Furthermore, we discussed how much artificial intelligence and fuzzy expert systems have contributed and should deserve further consideration in chemical industries.

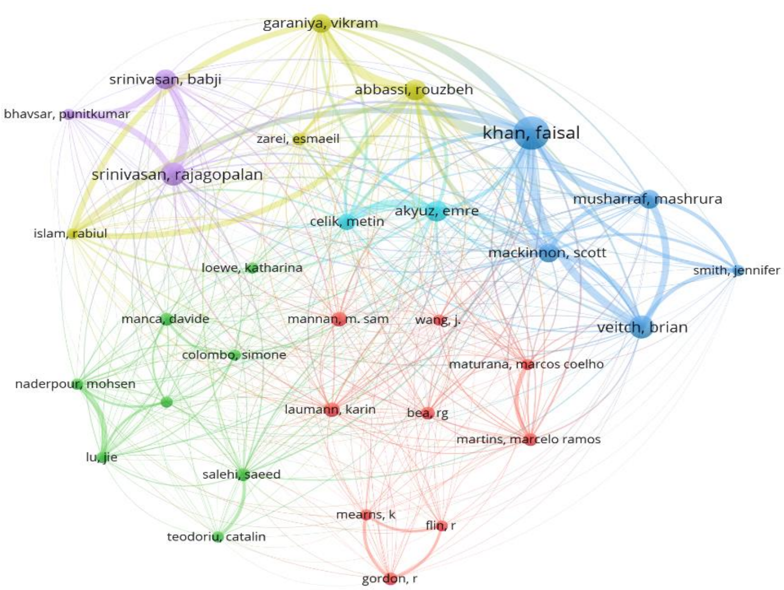


Figure 6. 5 Coupling authors

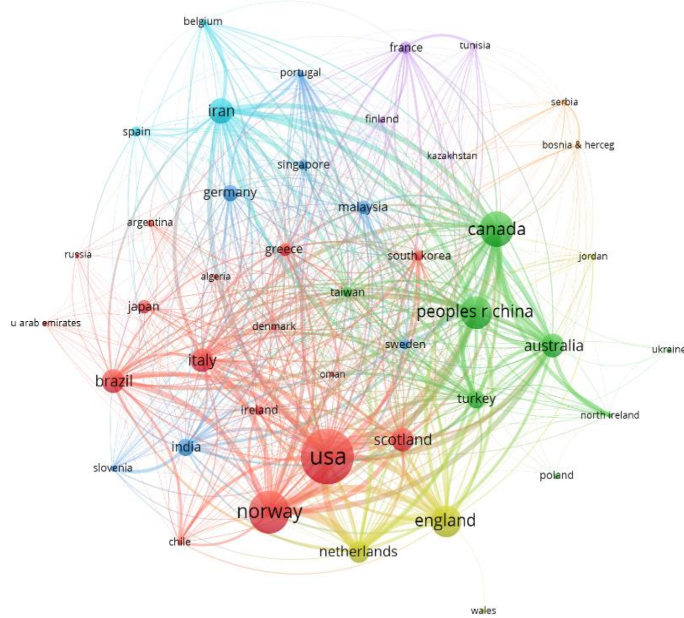


Figure 6. 6 Coupling countries

A significant increase in the number of studies in the two recent decades is found, and we analyzed around 500 documents, the highest type of journal articles (277), followed by proceedings papers (151). A uniformity measure that adopts citation analysis to build a similarity relationship among documents is considered in bibliographic couplings, such as authors coupling. It happens when two documents or authors reference a joint third work or scholar in their bibliographies. It is a manifestation that a probability those two works or researchers treat a related subject matter. Figs 6.5 and 6.6 present coupling authors and countries regarding HR&FA on CPIs. An author, number of documents, and co-citation strengths are respectively defined by each sphere, size of a sphere, and arc displays, as illustrated in Fig. 6.5. The co-citation network of notable contributors indicate five main clusters which are specified by different colors. Although Srinivasan R, Srinivasan B, and Bhavsar P formed the cluster with a minimum number of authors, Khan F. and Veitch B, MacKinnon S and Musharraf M make the strongest co-citation link. These two groups, along with Abbassi R and Akyuz E are the most vibrant researchers in this domain. It is recognized that HR&FA is a global concern, and top sex active contributors are from the USA (80, Texas A&M University), Norway (59, Norwegian University of Science and Technology and University of Stavanger), UK (57, Universities of Aberdeen and Liverpool), Canada (45, Memorial University of Newfoundland), China (39, China University of Petroleum) and Iran (28, Shiraz University of Medical Sciences). These countries, along with Australia (25, University of Tasmania), Brazil (23, University of São Paulo), Italy (23, Polytechnic University of Milan), and the Netherlands (20, TU Delft), build the most vibrant and top ten coupling countries. It can be noted that other scholars and countries worldwide have significantly impacted the aforementioned scientist and countries.

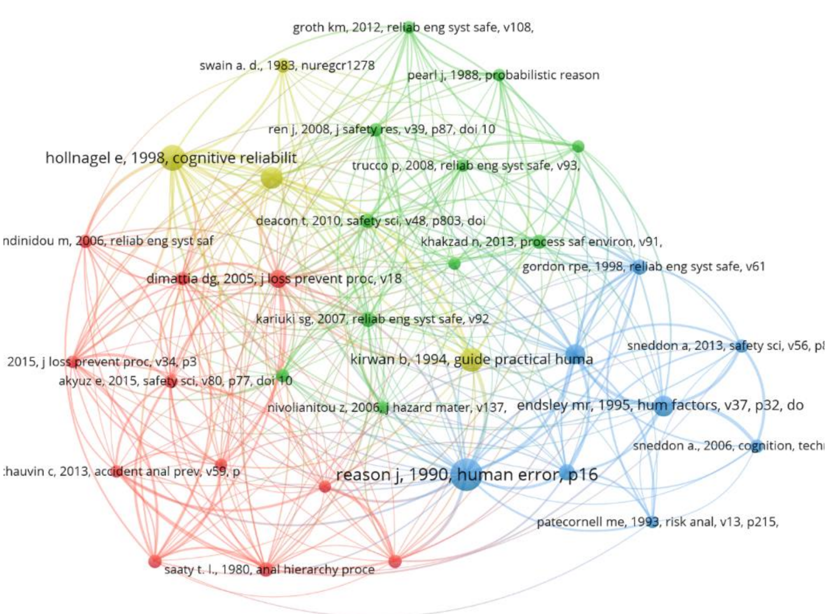


Figure 6. 7 Co-Citation references

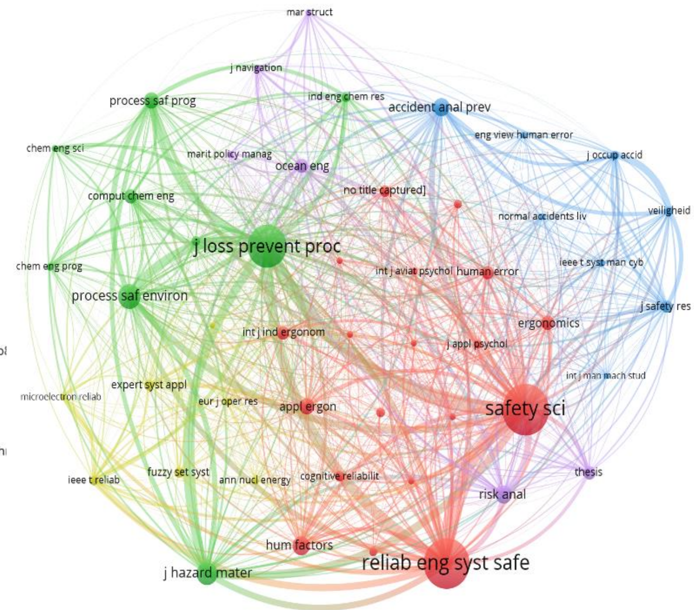


Figure 6. 8 Co-Citation sources

Fig. 6.7. illustrates the co-citation references used semantic similarity measure for documents that have been cited together by other articles. When two papers receive more co-citation, they have higher co-citation strength, meaning they are more probably semantically related. It yields a forward-looking assessment of document similarity and indicates the evolution of an academic domain. As can be seen from Fig. 6.7, there are four clusters of the references-based network of co-citation and documents of Reason, J (*Human error,1990*), Hollnagel, E (*Cognitive reliability,1998*), and Kirwan B (*Human factor, 1994*) have been substantially cited by others which means more likely are most promising documents in this field. The authors believe that three original works developed or supported numerous HR&FA techniques and models. For example, the taxonomy and concept of human error proposed by Reason, J, [50] yield significant research initiatives in human reliability and factors analysis in complex systems. The co-citation

journals are presented in Fig 6.8. Reliability Engineering & System Safety, Safety Sciences, and Loss Prevention in the Process Industries are the chief sources of documents.

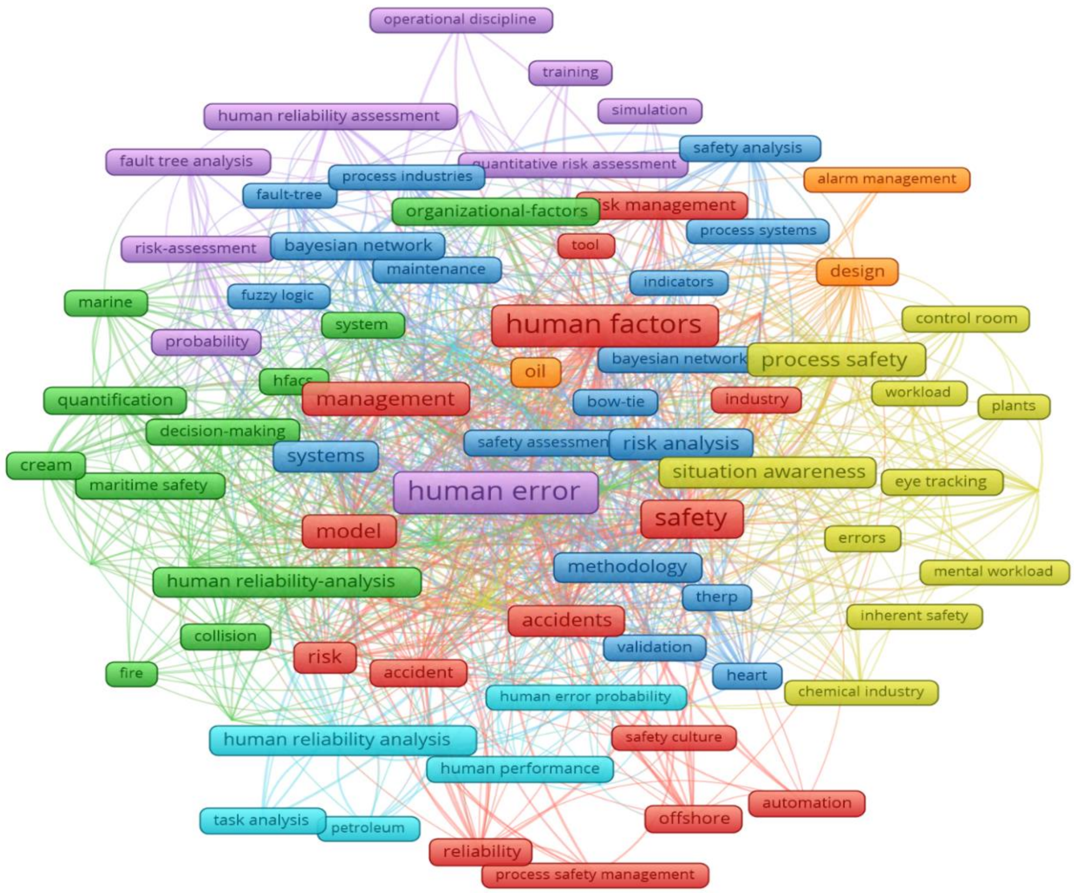


Figure 6. 9 Co-occurrence keywords

Fig. 6.9 presents the main research insights, trends, and structure of HR&FA investigated in the CPIs. As illustrated, six major clusters contain the most popular techniques, subjects, and sectors in each group. For instance, in a green research trend focused on marine, the CREAM method is frequently used for human reliability analysis and human error quantification, while HFACS is employed to analyze human-organizational factors in dominant maritime accidents such as collisions and fire. Those methods support the decision-making process in maritime safety. Another example is specified by the yellow color, where concerns like situation awareness, mental workload, and human error in control rooms of the chemical industry are investigated. Those human factors elements are inextricably intertwined with inherent safety design principles and process safety. Moreover, novel real-time monitoring approaches such as eye-tracking are used to model these vital safety concerns [51,52]. Among the probabilistic techniques, Fault tree analysis (FTA), Bow tie, and Bayesian Networks are commonly used to quantify human error probability. CREAM, Human error assessment and reduction technique (HEART), and Success Likelihood Index Method (SLIM) are the most prevalent human reliability analysis methods, while it is valid for HFACS techniques in human factor analysis on CPIs. Fuzzy logic or theory and MCDM have been frequently employed to improve conventional methods.

We surprisingly found that most of the top hundred authors have been affiliated with only academic organizations, meaning that industry contributions or joint collaborative projects between industry and academia are rare. DNV GL is the only industrial sector directly contributing to this field. Other studies reaffirmed that despite a healthy contribution from the industry, joint collaborations or industry-oriented works are rare in process safety and risk assessment [53]. We also discovered that artificial intelligence techniques have remarkably drawn less attention in HR&FA than in other scientific disciplines, despite increasing dramatically in many fields. Retrospective statistics proved that CPIs substantially prone to catastrophic accidents with far-reaching financial, human, and environmental losses. In contrast, a well-organized global accident database to record chemical process incidents has not been established [1]. If there are, the need to publicly access to those large databases from industries and agencies is highly demanded [54] as it can substantially support developing machine learning algorithms to support risk and accident analysis. This might be among the main reasons why data-driven and deep learning methods have been rarely used in CPIs, despite their meaningful capabilities in deeply analyzing accident databases, which is impossible by conventional accident analysis and statistical techniques. Furthermore, humans are still core elements in the entire life cycle of oil and gas operations and are directly involved in most high-risk activities such as control room operations, maintenance, emergency management and normal operations. Accordingly, it is the right time to establish industry partnership works to fill this crucial gap in HR&FA.

6.4. Conclusion

Knowledge acquisition through domain experts and historical or observed data are still the main resources to establish successful human reliability and human factors analysis in numerous domains. However, taking advantage of them requires employing fuzzy expert systems and artificial intelligence models. Several genuine attempts have been made in this direction, but a systematic review with a primary focus on their applications, contributions, challenges, myths, misconceptions, and research gaps in human reliability and human factors analysis have not been observed yet. Accordingly, this research was designed to fill this scientific gap by synthesizing state-of-the-art achievements. Apart from highlighting how artificial intelligence and expert systems contributed to different elements of human reliability and factor analysis, the key findings of this research and future research directions are as follows:

- Text recognition, classification, and natural language processing algorithms can digest accident report highly cost and time-effectively. They can be integrated into deep learning algorithms to update the model parameters and make new inferences. This is technically a forward step to improve learning from accidents.
- Advanced machine learning techniques can classify the various contributing factors, from big data to human error and accidents. It reveals latent dependencies and meaningful and

non-linear interactions among diverse influencing factors. This capability yields a more accurate prediction and a deep understanding of the accident causation mechanisms.

- Data-driven models can provide accident causation models with versatile applications. The main reason can be that they do not force us to follow a specific taxonomy and structure in developing causality models, which are prevalent drawbacks of conventional accident analysis techniques and models. These models can address issues related to subjective uncertainty stemming from expert knowledge acquisition. They also can be a potential response to drawbacks of statistical analysis, which requires enough and consistent human factor data collection.
- Researchers should be aware of several crucial myths and misconceptions in using artificial intelligence systems that need to be addressed in future research.
- Fuzzy expert systems and their interactions with MCDM have significantly contributed to improving the knowledge acquisition process required for human factors modeling, human error probability estimation, performance shaping factors' influence quantification, and dependency modeling.
- There might be time to be more cautious or desist from using fuzzy set theory to estimate human error probability in sociotechnical systems. This might be more sensitive when the obtained results are used to make critical decisions.
- There is a real need to establish more joint collaborative works between academics and industry to benefit the machine and deep learning techniques in the HR&FA field.

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CHAPTER 7

Summary, Contribution, Conclusions and Recommendations

7.1. Summary

This study demonstrates the novel applications of the advanced system engineering methods for dynamic risk-based system safety and human factors analysis in critical sociotechnical systems. The existing mechanistic models for system safety and human factors susceptibility assessment are not dynamically structured, unable to capture the unstable, dynamic, and non-linear interactions among contributing factors of critical sociotechnical systems and their key element' functions (e.g., human, organization, technology, and environment. Dynamic risk-based assessment techniques for system safety and human factor performance are developed to capture the significant factors' non-linear interactions; they address the knowledge gaps and aid performance management of the complex sociotechnical systems. System safety and human factor performance in sociotechnical elements varies owing to a wide range of endogenous and exogenous influencing factors. These are called uncoupled variability as per Safety-II. The uncoupled variability has drawn rare attention, despite its vital importance in major accidents analysis as per Safety-I and Safety-II paradigms. Accordingly, we proposed a novel dynamic model which can analyze both the probability and magnitude of performance variability. This research integrated system thinking into system safety and human factor performance modeling. This research also proposed a holistic VSFs taxonomy for STSs considering the FRAM paradigm, sociotechnical design hierarchy (e.g., individual, task, HMI, plant, organization, culture), and the concept of human-center design is developed. Therefore, this taxonomy is intended to consider all aspects of STSs together and can be used to examine influencing VSFs in a wide range of complex systems.

7.2. Contributions and novelty

This doctoral research's main contributions and novelties are in the area of dynamic risk-based human factor and system safety assessment of complex sociotechnical systems using advanced system engineering methods and models. The highlights of the contributions are listed below:

- A critical analysis of the state-of-the-art theoretical and empirical findings concerning HR&FA in CPIs is proposed. As the first review investigation, it is first also identified the needs, gaps, and challenges of HR&FA in CPIS. An in-depth analysis of the literature in Web of Science core collection and Scopus databases from 1975 to August 2020 is conducted. This analysis focuses on human factors in three critical elements of CPIs: maintenance operations, emergency operations, and control room operations. The analysis synthesized the theoretical and empirical findings, shed light on the strengths and shortcomings of current literature and identifying research opportunities. A comparison of HRA in CPIs is undertaken with nuclear power plants (NPPs) to better understand the current stage of research and research challenges and opportunities. Importance and necessity of a new thinking system about human reliability to take more advantages of results of new safety management paradigms is also highlighted.
- A novel dynamic model by integrating human and organizational failures into conventional failure modes (e.g., mechanical, operational, and environmental) and system barriers into system safety is developed under uncertainty for emerging complex systems. The application of the proposed model is demonstrated on a water electrolysis process. The hydrogen release scenarios are modeled using the Bow-tie technique integrated with

improved D Numbers Theory and Best-Worst Method. This helps to analyze epistemic uncertainty in the prior probabilities of the causation factors and barriers. Subsequently, a Dynamic Bayesian Network (DBN) model is developed to analyze dynamic risk and deal with aleatory uncertainty. This part of the present research presented a dynamic and holistic risk model to address some significant shortcomings of the current system safety risk analysis models in hydrogen infrastructures. The results of the case study provide a better understanding of the causal modeling of accident scenarios, associated evolving risks with uncertainty. The proposed model will serve as a useful tool for the operational safety management of the hydrogen infrastructure or other emerging complex engineering systems.

- A dynamic human-factor risk model to probabilistically analyze system safety in sociotechnical systems is developed. Accordingly, as the first attempt, this study proposes a systematic model to analyze performance variability in human, organizational, and technology-oriented functions caused by various variability shaping factors (VSFs). The model contains three main phases. First, a FRAM (Functional Resonance Analysis Method) - driven Human-Organization-Technology Taxonomy is developed. Subsequently, Dempster - Shafer Evidence theory is employed to elicit knowledge under epistemic uncertainty. The proposed causation model is integrated into Dynamic Bayesian Networks to support decision-making under aleatory uncertainty. Finally, a criticality matrix is developed to evaluate the performance of the system functions to support decision-making. The proposed model is built considering the advanced canonical probabilistic approaches (e.g., Noisy Max and Leaky models) that address the critical challenges of incomplete and imprecise data. A maintenance operation cycle that includes pre- and post-maintenance activities is considered for testing the model. The proposed dynamic model would help better understand, analyze, and improve the safety performance of complex sociotechnical systems.

- An advanced approach to assess system safety in sociotechnical systems is proposed. It proposed a systematic approach to identify PSFs, quantify their importance level and influence on the performance of complex sociotechnical systems' functions. To this end, we first developed a new holistic PSFs Taxonomy based on sociotechnical systems design and then employed novel Interval-Valued Spherical Fuzzy Sets (IVSFS) and Best Worst Method to quantify the importance of performance. We tested the proposed model's capability on maintenance operations in the chemical process plants and compared the model with the previous research considering fourteen criteria. The findings revealed the approach's effectiveness in dealing with epistemic uncertainty, vagueness, and fuzziness in the knowledge acquisition process. It revealed the critical safety investment factors among different sociotechnical elements and contributing factors to maintenance operations. This helps to effectively allocate safety countermeasures to improve resilience and system safety performance.
- Finally, we revealed how have artificial intelligence and expert systems contributed to HR&FA in complex systems. The systematic review primarily investigated the applications, contributions, challenges, and research gaps in HR&FA using those intelligent approaches such as machine and deep learning, and knowledge/data-driven techniques. We analyzed seven vital elements of HR&FA to illustrate these contributions. Furthermore, this work highlighted some important myths, misapplications, and critical

concerns that should be addressed using these advanced approaches. This research yields detailed insights into HR&FA using artificial intelligence and expert systems.

7.3. Conclusion

The significant conclusions drawn from the current research is summarized as follows:

7.3.1. Critical analysis of human reliability and factors in CPIs

This research presents the first critical analysis of human reliability and factors analysis in CPIs as a salient instance of critical sociotechnical systems. The experience with accidents in this domain shows many cases which involve complex human-machine interactions. Consequently, researchers have actively worked on enhancing process safety and risk engineering since the '70s. However, despite its importance and practical implications for improving human reliability, there has not been a review of human reliability related to processing systems. This research identified the needs, gaps, and challenges of HR&FA in three critical elements of chemical process systems, namely maintenance operations, emergency management operations, and control room operations. Moreover, the main research streams and contributions of previous studies into HRA are specified, and some novel approaches are suggested to deal with the dominant drawbacks of current HRA knowledge. The importance and necessity of a new thinking system about human reliability to take more advantage of the results of new safety management paradigms is also highlighted. Most of the studies have been focused on HEP estimation using conventional methods in maintenance activities, while they continue to be accompanied by the virtual offshore simulator and hybrid models (i.e. fuzzy theory, BN and TOPSIS) to analyze human error and develop HRA data in the emergency management sector. In contrast, some new experiments are performed to assess operator reliability and performance using cognitive functions that have not been given the attention they deserve in two previous elements of CPIs operations. Furthermore, integrating dynamic models and human cognitive and behavioral theories into conventional HRA techniques can provide a better understanding of human performance variability and reliability. A comparison of HRA in CPIs is undertaken with nuclear power plants (NPPs) to better understand the current stage of research and research challenges and opportunities.

7.3.2. Developing a novel dynamic model to analyze risk in emerging critical systems

Safety management of emerging critical and complex technologies such as hydrogen infrastructure is vital for sustainable progress especially in the hydrogen economy as global demand. Reaching the vision of using hydrogen as a low-carbon fuel source to phase out conventional fossil fuels and limit global warming, requires researchers to establish strong and novel safety assessment models to provide more effective safety measures. Accordingly, this study presented an improved dynamic and holistic risk model to address some significant shortcomings of the current hydrogen risk analysis models. This was done by integrating the improved D number theory, best-worst method, and SHIPP methodology into the DBN for the safety assessment of hydrogen infrastructure under uncertainty. The model provides a dynamic and holistic cause-consequences modeling of the hydrogen loss accident scenario, which clearly presents the accident profile from root causes to final consequences. Firstly, this modeling revealed and incorporated a wide range of contributing latent factors both from individual to organization failures and from operational to mechanical as well as natural hazards into a probabilistic risk analysis which were ignored in the most previous models. Secondly, a hybrid and improved algorithm contain DNT and BWM, as the latest and more reliable MCDM technique, was employed to substantially deal with epistemic uncertainty in input data (i.e., prior probabilities). This is the first that study presented an attempt to integrate this algorithm into DBN, as a well-known probabilistic safety analysis method, in safety and risk studies. This effort leads to addressing the potential uncertainties and subsequently, more realistic results and effective final decisions. Thirdly, it yielded predictive modeling of the posterior failure probability distribution of safety barriers, consequences, hydrogen release probability, and the system reliability can tackle uncertainty in the safety and risk preventive and mitigative decisions.

7.3.3. Proposing a novel human-factor risk model to analyze system safety performance in complex STSs

This phase of the study was intended to explore system safety and human factors beyond of Safety-I paradigm. Accordingly, we employed advanced system thinking methods to analyze human factors challenges as per Safety-II. Accordingly, as the first attempt, this study proposes a systematic model to analyze performance variability in human, organizational, and technology-oriented functions caused by various variability shaping factors (VSFs). The proposed FRAM (Functional Resonance Analysis Method) - driven Human-Organization-Technology Taxonomy filled the gap in PSFs impact on human reliability. Dempster - Shafer Evidence theory is employed to elicit knowledge under epistemic uncertainty. The proposed causation model is integrated into Dynamic Bayesian Networks to support decision-making under aleatory uncertainty. The proposed model is built considering the advanced canonical probabilistic approaches (e.g., Noisy Max and Leaky models) that address the critical challenges of incomplete and imprecise data. The proposed VSFs Taxonomy filled the gaps in the current performance shaping factors taxonomies, and it ties in closely with sociotechnical system engineering. The DSE theory differently addressed subjective uncertainty arising from insufficient data and vagueness in the knowledge elicitation process, which is crucial in dealing with human and organizational-oriented factors. Moreover, the proposed probabilistic model and mathematical procedures established a prefund causality model which could integrate sociotechnical systems elements, address computations challenges related to CPTs, and characterize randomness and incompleteness uncertainties. Furthermore, the proposed DBNs model is a non-linear performance variability causation model aiming to trace thoroughly interconnected accident causal factors, conduct forward and backward inferences, and update model parameters and outcomes extensively used in the advanced system safety and reliability assessment. The risk-based criticality matrix strongly supports the decision-making process to precisely identify safety-critical investment factors and functions and, as a result, effectively damping critical variabilities. It paves a way to relax the difficulties in dampening the critical performance resonance in a rational risk-based approach. Finally, the proposed model can be applied for both proactive (e.g., safety performance and risk assessment) and reactive safety assessment (e.g., accident analysis) and can capture all aspects of STSs. Accordingly, it provides a deep understanding of complex system elements, their interaction, and their influence on system safety and resilience performance.

7.3.4. Proposing an advanced approach to the system safety in sociotechnical systems

Th is phase of the present research aimed at proposing a systematic framework to assess system safety performance using performance shaping factors in complex sociotechnical systems. The safety performance of complex systems and their main components (e.g., human, organization, and technology) vary due to numerous performance shaping factors (PSFs). However, previous research mainly focused on studying limited PSFs related to human functions, while organization and technology functions have often been ignored. This part of the present investigation proposed a systematic approach to identify PSFs and quantify their importance level and influence on the performance of sociotechnical systems' functions. To this end, we first developed a holistic PSFs Taxonomy based on sociotechnical systems design and then employed novel Interval-Valued Spherical Fuzzy Sets (IVSFS) and Best Worst Method to quantify the importance of performance. We tested the proposed model's capability on maintenance operations in the chemical process plants and compared the model with the previous research considering fourteen criteria. The applied novel three-dimensional spherical information sets differently addressed fuzziness, vagueness, and subjective uncertainty in the knowledge acquisition process, which is one of the critical challenges in system safety and human-organizational factor analysis. The model captured the optimal importance level of contributing factors in system safety performance analysis and proposed variability indices. Quantifying these indices yielded to clearly specify safety investment elements in system hierarchies from factor level to three types of system functions. This provides a deep understanding of complex system elements, their interaction, and their influence on system safety performance and paws a rational way to effectively dampen critical performance resonance based on different human, organizational and technological functions before the system fails. Comparing the present research with the previous studies pointed out new aspects of the proposed model in the safety assessment of maintenance operations. Although we tested the model capabilities in a proactive assessment, it can also be utilized in reactive approaches such as accident investigation and analysis. Furthermore, the model has potential application to assess resilience engineering because a signification relationship between PSFs and system resilience, especially in industrial maintenance departments, has been reported. It also revealed the critical safety investment factors among different sociotechnical elements and contributing factors to maintenance operations. This helps to effectively allocate safety countermeasures to improve resilience and system safety performance.

7.3.5. Develop a systematic review of how to account artificial intelligence in human factor analysis of complex systems

Human factors analysis (HFA) has been explored from various aspects (e.g., engineering, psychology, physiology, and ergonomics). Numerous conventional techniques have been developed and applied to improve system safety from the human perspective. However, emerging socio-technical systems, industry 4.0, and the use of artificial intelligence-driven systems reveal these methods' incapability. This necessity is developing intelligent approaches that account for integrating artificial intelligence (AI) into human factors. This work reviewed the integration of artificial intelligence and expert systems into HFA. It focuses on using machine, deep learning, and knowledge/data-driven modeling approaches to HFA. The systematic review investigated the applications, contributions, challenges, and research gaps in HFA in complex systems. We analyzed seven vital elements of HFA to illustrate these concerns. This work also highlighted important myths, misapplications, and critical concerns that need to be addressed using advanced approaches. Apart from highlighting how artificial intelligence and expert systems contributed to different elements of human reliability and factor analysis, the key conclusion of this research are as follows: a) Machine learning and data-driven models help address subjective uncertainty, bias, and insufficient information stem from domain experts' experiences and understanding of human error probability prediction, b) Text recognition, classification, and processing algorithms can update the model parameters highly cost and time-effectively. They integrate them into deep learning algorithms, updating the model and making new inferences. This is technically a forward step to improve learning from accidents, c) Advanced Machine learning techniques classify the various contributing factors from big data into human error and accidents and reveal latent dependencies and meaningful and non-linear interactions among them. This capability yields a more accurate prediction and deep understanding of the accident causation mechanism, d) Data-driven models can provide accident causation models with versatile applications. The main reason can be that they do not force to follow a specific taxonomy and structure in developing causality models, which are prevalent drawbacks of conventional accident analysis techniques and models. These models can address issues related to subjective uncertainty stemming from expert knowledge acquisition. They also can be as a potential response to drawbacks of statistical analysis, which requires enough and consistent human factor data collection and finally E) Fuzzy expert systems and their interactions with MCDM have significantly contributed to improving the knowledge acquisition process regarding human factors modeling, human error probability estimation, performance shaping factors' influence quantification, and dependency modeling.

7.4. Recommendations

Based on the completed objectives, the following areas are recommended for further investigation:

- Fundamental steps should be taken to develop HE/HRA database, tailored HRA techniques, and PSFs taxonomies for oil and gas operations as well as new advancements of performance simulators and novel human reliability modeling methods. Furthermore, integrating dynamic models and human cognitive and behavioral theories into conventional HRA techniques can provide a better understanding of human performance variability and reliability. It is worth noting that the present study does not cover all potential human activities in CPIs. Important operations such as permit to work, confined space activities, shutdown and pre-startup of units and management of change are some common activities prone to human error in this industry. Exploring available investigations into these activities to deal with difficulties and to give research opportunities can be revealed in future academic efforts.

- Although integrating DNT and BWM into DBN provides great advantages and capabilities in a unique model, it may have some limitations and some attempts should be made to address them. For instance, a powerful consequence modeling under uncertainty may be needed in risk analysis of some critical infrastructures, this concern was outside the scope of the present model due to the huge complexity it would impose on the proposed model. Moreover, integrating a dynamic influence diagram into the model to explore the effects of the most contributing root events in decreasing the hydrogen release probability and dealing with uncertainty in decision-making could be investigated in future studies. Finally, we call for further investigation especially using experimental data to explore and evaluate the proposed model's applications and validity in various hydrogen operations in future studies.
- This study proposed 124 PSFs over 19 functions, and potential modeling dependency dramatically increases this study's complexity. Hence, we preferred not to deal with these concerns in the present research to address other vital objectives deeply. Several methods such as Analytic Network Process (ANP), Analytic Hierarchy Process (AHP) and Decision-making trial and evaluation laboratory (DEMATEL), and Cognitive Map (CM) and their extensions have been regularly employed to consider potential dependencies in safety probabilistic analysis.

- There might be time to be more cautious or desist from using fuzzy set theory to estimate human error probability in critical systems.
- There is a real need to establish more joint collaborative works between academics and industry to benefit the machine and deep learning techniques in the HR&FA field.