Artificial Intelligence (AI) Application in Process Safety Cumulative Risk Visualization for Petroleum Operations: Conceptual Framework

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doi: https://doi.org/10.37745/ijeats.13/vol12n13349 Published March 25, 2024

Citation: Maduabuchi E. (2024) Artificial Intelligence (AI) Application in Process Safety Cumulative Risk Visualization for Petroleum Operations: Conceptual Framework, *International Journal of Engineering and Advanced Technology Studies* 12 (1), 33-49

ABSTRACT: *One of the key challenges in preventing major process safety accidents in an operating plant is the lack of an integrated system/model that brings together the risks posed by the deficiencies / deviations on the safety critical barriers, for operational decision making. Based on this context, a model/framework was developed for assessing and visualizing the accumulation of process safety risks arising from safety critical barriers impairments in petroleum facilities in Niger-Delta Nigeria. Based on the review of the model, the need for an intelligent web-based software was identified. An exploratory study was therefore undertaken through extensive literature review and focused group participants, to develop a conceptual framework for an intelligent web-based software for process safety cumulative risk visualization. The results from the study make it evident that the conceptual framework provides a novel approach in developing an intelligent web-based software using artificial intelligence (AI) techniques, for real time visualization of process safety cumulative risk picture*.

KEYWORDS: process safety, cumulative risk assessment, artificial intelligence, major accident prevention, petroleum operations

INTRODUCTION

An event that is potentially catastrophic, involving the release/loss of containment of hazardous materials with massive health and environmental consequences [1], injuries/multiple fatalities and loss production [2] is known as a process safety accident. It is acknowledged on a global scale that there have been significant process safety mishaps in petroleum plants [3]. The absence of a system to guarantee that senior management receives sufficient risk-based information to inform operational decisions is one of the main obstacles to averting significant process safety mishaps at an operating facility. Numerous instances of judgments that were made without the benefit of a thorough risk assessment and that had disastrous results are found in accident investigation reports. According to [4], the majority of significant accident investigation reports show that the involved companies encountered many safety critical barrier impairment difficulties during the asset's operational stage, but that they either ignored the signs or handled them improperly. Prior to the incidents in the majority of these significant accidents, process safety hazards resulting from barrier impairments accumulated, but plant operators were unaware of the influence of these deviations on "cumulative risk". Prior to the majority of these significant incidents, process safety risks resulting from barrier impairments had been building [4][5]. However, plant operators were unaware of the cumulative risk impact of the deviations [6], primarily because they lacked systems for proactively monitoring and managing the facility's impaired safety critical barriers. [7] pointed out that insufficient steps were frequently taken to identify barrier limitations and stop the events from spreading. In order to lower the probability of significant accidents in petroleum operations, [8] (submitted for publication) developed a model/framework for assessment of process safety cumulative risk. The model offers petroleum industries a risk-based approach to understanding and managing safety critical deviations and using risk-based decision making to better prioritize plant maintenance, optimize work execution and improve productivity. It was acknowledged, therefore, that the framework/model is data-centric and that the necessary impairment data is spread across many systems without a single point of access. Equally, the plant's operations and maintenance interventions cause the barrier impairment data to fluctuate quickly over time and location, which means that risk levels are never static. The framework's inadequacies led to the identification of the need for intelligent web-based software that uses artificial intelligence (AI) techniques to collect barrier impairment data from many systems automatically, evaluate the data, and provide real-time representation of the cumulative risk picture. This study seeks to deliver a conceptual framework that will enable development of an intelligent web-based software for process safety cumulative risk assessment and visualization.

METHODS

The aim of this study is to develop a conceptual framework for developing an intelligent web-based software for process safety cumulative risk visualization for petroleum operations. To achieve this aim, the two objectives were pursued:

a) Conduct literature review on application of (AI) in process safety risk assessment and visualization

b) Develop a conceptual framework for AI application in process safety cumulative risk assessment and visualization web-based software for petroleum operations

The study was piloted on the research questions - (i) what are the AI techniques that can be applied in developing a web-based software for process safety cumulative risk assessment and visualization for petroleum operations and (ii) what is the unified approach / concepts in developing an intelligent web-based software for process safety cumulative risk assessment and visualization for petroleum operations using AI techniques. The following methodology was used in the study:

a) Extensive literature review was carried out to identify the AI techniques to be applied in developing an intelligent web-based software for process safety cumulative risk assessment and visualization in petroleum facilities
b) Conceptual framework was developed and validated in a workshop using an inter-disciplinary "focused group" of Process Safety and Asset Integrity professionals, Information Systems Engineers and Software Engineers.

RESULTS

Literature Review on AI Application in process safety cumulative risk assessment and visualization

AI and Techniques

Artificial intelligence (AI) "is a contemporary technological science that investigates and creates concepts, approaches, tools, and implementations to mimic, supplement, and enhance mankind's intelligence" [9]. AI simulates a variety of issues and functions relating to human intellect and cognition [10]. The trust of AI is to understand the fundamentals of human intelligence with a view to developing new types of clever machines that mimic human action or even supersede human intelligence [11]. AI is different from automation in that automation is about getting a kit either a hardware or software to do repetitive jobs automatically without human intervention whereas AI is about making machines intelligent. By design, AI seeks patterns and learns from experience which can be deployed to self-select appropriate responses in varying situations. AI is data-drive intelligent automation.

According to [10], there are five types of AI viz: (a) analytical, (b) functional, (c) interactive, (d) textual and (e) visual. Analytical AI identifies, interprets and communicates meaningful patterns of data and in the process engenders discovering of patterns, new insights, and data relationships / dependencies to drive data-driven decision-making. Functional AI is similar to analytical AI in analyzing huge quantities of data for patterns and dependencies. However, the major difference is that functional AI instead of making recommendations, execute actions. In interactive AI, automation of interactive and efficient communication is enabled. Textual analytics or natural language processing are typically covered in Textual AI and businesses can enjoy a number of functionalities including text recognition, speech-to-text conversion, machine translation, etc. Visual AI can often identify, categorize, and arrange objects in addition to creating insights from photos and videosThere are ten categories of AI techniques capable of playing a significant role in automation, intelligent, and smart computer systems.

Machine Learning

The study of computer algorithms that automate the creation of analytical models is known as machine learning (ML) [12]. ML models are frequently composed of a collection of guidelines, protocols, or complex "transfer functions" that can be applied to find intriguing patterns in data or predict behavior [13]. Predictive analytics, another name for machine learning, uses data to forecast certain unknowns in the future and is used to the resolution of numerous real-world problems. Within ML, there is supervised learning ML. This is done as part of a "task-driven strategy," which employs labeled data to train algorithms to categorize data or forecast outcomes, where certain goals are stated to be attained from a collection of inputs. Classification (predicting a label) and regression (predicting a quantity) are the two most popular supervised learning outcomes. Another is unsupervised learning. This is known as a "data-driven method," where the main objective is to extract knowledge, patterns, or structures from unlabeled data. Among the most popular unsupervised tasks include clustering, visualization, dimensionality reduction, establishing association rules, and anomaly detection. A semi-supervised learning is a hybrid of supervised and unsupervised learning techniques. To train a model, both labeled and unlabeled data are used. It might work well for enhancing model performance in situations when data needs to be automatically tagged without human assistance.

Neural Networks and Deep Learning

Deep learning (DL) is another popular AI Technique that is based on artificial neural networks (ANN) [12]. DL learns from data. Multiple hidden layers, including input and output layers, make up a typical deep neural network. DL techniques can be divided into three major categories: deep networks for supervised or discriminative learning, deep networks for unsupervised or generative learning and deep networks for hybrid learning.

Data mining, knowledge discovery and advanced analytics

The process of extracting valuable patterns and knowledge from massive volumes of data is known as data mining, knowledge discovery, and advanced analytics. It is based on four types of analytics - descriptive, diagnostic, predictive, and prescriptive analytics, which can be used to build the corresponding data-driven models. For example, analyzing historical data to have a better understanding of how a firm has changed is known as descriptive analytics. Descriptive analytics provides a solution to the query, "What happened in the past?" by providing an account of the historical data. Diagnostic analytics is more sophisticated in approach and provides solution to the query “Why did it happen?” Descriptive analytics targets the root causes of the problem [10] and provides solution to the query “What will happen in the future?” and “what action should be taken in the future”, with a view to answering the question with a high degree of confidence. In summary, historical data is used in both diagnostic and descriptive analytics to identify what occurred and why. Prescriptive and predictive analytics make use of past data to forecast future events and recommend courses of action to lessen their effects.

Rule-Based Modelling and Decision Taking

To retain and alter knowledge in order to interpret data meaningfully, rule-based modeling and decision-making are utilized [10]. A knowledge base with a list of rules is called a rule base. IF-THEN statements of the following format are typically used to write rules: IF < antecedent > THEN < consequent >. In an intelligent system intended to address complicated problems, an IF-THEN rule-based expert system model can possess the decision-making capacity of a human expert. Additionally, rule-based models can be swiftly enhanced in response to needs by adding, removing, or updating rules based on knowledge from domain experts or based on current trends. Rule-based machine learning approaches are more suited to automation and intelligence [14].

Fuzzy Logic-Based Approach

A precise logic of imprecision and approximation is known as fuzzy logic. A concept's degree of truth, sometimes referred to as its membership value or degree of membership, can vary from 0.0 to 1.0 in this natural extension of conventional logic. Conventional reasoning is limited to ideas that are either totally true (degree of truth 1.0) or totally wrong (degree of truth 0.0). The concept of partial truth, on the other hand, where the truth value might range from totally true to completely false, like 0.9 or 0.5, has been dealt with using fuzzy logic [10]. Models using fuzzy logic are capable of identifying, representing, manipulating, comprehending, and applying ambiguous and uncertain facts and information [15]. The fuzzy logic technique is favored when distinguishing qualities are not well defined and depend on human expertise and knowledge, even if machine learning models can distinguish between two (or more) object classes based on their capacity to learn from data. As a result, the system can operate with any kind of input data, even noisy, distorted, or imprecise data, as well as restricted data. In summary, fuzzy logic may draw valid conclusions in an environment characterized by imprecision, uncertainty, and incomplete facts.

Knowledge Representation, Uncertainty Reasoning, and Expert System Modeling

One of the most exciting areas of artificial intelligence research is knowledge representation, which is the study of how an intelligent agent's beliefs, intents, and judgments may be stated correctly for automated reasoning. The process of drawing conclusions, formulating predictions, or creating explanations based on what is already known is known as reasoning. A wide range of knowledge kinds, including as structural, procedural, meta-, descriptive, and heuristic knowledge, can be applied in different application domains [16].

Beyond merely putting data in a database, knowledge representation enables an intelligent computer to operate like a human by drawing on its own experiences and knowledge. Because of this, developing an intelligent system requires the use of an efficient knowledge representation technique. A knowledge-based conceptual model can be developed using a variety of knowledge representation techniques, such as logical, semantic network, frame, and production rules. A rule-base usually consists of two parts: an action and a condition, or "IF < condition > THEN < action >." Consequently, the associated rule fires after an agent verifies that the condition is met. This kind of rule-based system's main advantage is that the "condition" portion can decide which rule to apply in a particular situation. On the other hand, carrying out the problem's solutions falls under the purview of the "action" section [17].

Case-based reasoning

A paradigm in cognitive science and artificial intelligence called case-based reasoning (CBR) views reasoning as mostly memory-based. The "smart" reuse of information from cases—previously resolved problems—and its application to new, unsolved problems are the focus of CBR [18]. The inference is a technique for addressing problems that relies on how closely the current circumstance resembles previously resolved issues that have been stored in a repository. Its idea is that the solutions to two problems will be more similar, the more similar the problems are. In order to solve new problems, case-based reasoners retrieve previously saved "cases" that explain comparable past problem-solving experiences and modify their solutions to fit the needs. For example, in medical education, for instance, patient case histories and therapies are used to help diagnose and treat new patients.

Text Mining and Natural Language Processing

Similar to text analytics, text mining, often referred to as text data mining, is the process of obtaining valuable information from a range of text-based resources, including books, websites, emails, reviews, documents, comments, articles [19] and so on Text analysis includes information retrieval, pattern recognition, tagging or annotation, information extraction, lexical analysis to look into word frequency distributions, and data mining techniques like link and association analysis, visualization, and predictive analytics. To do this, text mining uses a variety of analysis methods, including natural language processing (NLP).

Visual Analytics, Computer Vision and Pattern Recognition

Another area of artificial intelligence called computer vision enables computers and systems to take action or offer suggestions based on relevant information that is extracted from digital photos, videos, and other visual inputs [20]. From an engineering perspective, its goal is to understand and mechanize tasks that the human visual system can perform. Therefore, the automatic extraction, analysis, and comprehension of pertinent information from a single image or a set of photos is what this is all about. In technical words, it means developing an algorithmic and theoretical framework to process an image at the pixel level in order to achieve autonomous visual understanding. Object recognition or classification, detection, tracking, picture restoration, feature matching, image segmentation, scene reconstruction, video motion analysis, and other related activities are typical tasks in the fields of visual analytics and computer vision [12]. Modern computer vision techniques are based on pattern recognition, which is the automatic identification of patterns and regularities in data. Frequently, pattern recognition entails classifying (supervised learning) and clustering (unsupervised learning) patterns.

Hybrid Approach, Searching, and Optimization

A "hybrid approach" combines several methods or frameworks to create an improved and novel model. Consequently, depending on the needs, a hybrid strategy combines the essential principles mentioned above. In a hybrid approach, a variety of strategies are crucial to developing a successful AI model in the field. [10].

AI Application in Petroleum Operations & Process Safety Risk Management

[21] outlined the most recent trends in developing AI-based tools and identified their effects on accelerating and de-risking processes in the industry. The upstream segment of the oil and gas industry is the most capital-intensive and presents the greatest challenges. Moreover, data, people,

and new forms of collaboration represent the primary non-technical obstacles to the widespread implementation of artificial intelligence in the petroleum business.

[22] investigated the use of sophisticated analytics and machine learning to digitize workflows in the petroleum business. In addition to doing a SWOT analysis for strategic management and technology enablement, the study covers some of the most recent advancements and practices in the field.

[23] reviewed the construction process of intelligent oil fields in domestic (China) and foreign oil and gas development companies, analyzed the issues and challenges that currently exist, and made recommendations for the development of future artificial intelligence technology in the oil and gas development industry. It also focused on the application status and development trends of artificial intelligence technology in oil and gas reservoir development, as well as the research progress of big data and artificial intelligence in oil and gas field development. According to the report, Statoil in Norway effectively lowers the risk of accidents by using artificial intelligence technology for safety monitoring and accident prevention of its offshore oil and gas rigs. Another oil company Shell significantly increases the energy efficiency and product quality of its refining equipment by using artificial intelligence technology to intelligently monitor and optimize the control of the machinery. The study also noted that the use of artificial intelligence in the field of oil and gas pipelines primarily consists of intelligent maintenance and pipeline safety monitoring. It also noted that through real-time data analysis and monitoring, comprehensive pipeline operation status monitoring can be achieved, issues can be quickly identified, and appropriate action can be taken to ensure the pipeline operates safely. The study pointed out how the Chinese research team integrated learning algorithms to create a proxy model for well control production optimization, a complex well control reservoir state prediction and production analysis model based on convolutional neural networks (CNN), a multi-sequence reservoir state analysis and production prediction model based on CNN and recurrent neural networks (RNN) under various geological conditions, and a reservoir uncertainty reduction model based on Bayesian evidence learning framework.

According to [24], AI is widely used to address significant difficulties in oilfield development, such as oilfield production, dynamic prediction, plan optimization, identification of residual oil, identification of fractures, and better oil recovery. In addition, the study weighed the benefits and drawbacks of current AI algorithms and predicted the use of AI technology in intelligent drilling, intelligent production, intelligent pipelines, and intelligent refineries in the future.

The effective integration of AI techniques in reservoir management, drilling system design and operation, and production optimization was examined and studied in a paper by [18] and the study included an updated assessment of the use of AI in service operations and application trends within the pipeline sector. The limits of AI approaches for petroleum operations were also discussed in the paper. The study found that the most well-liked and often utilized artificial intelligence (AI) techniques in the upstream petroleum operations industry are fuzzy logic and artificial neural networks. The study identified roughly 20 AI application areas in the upstream petroleum sector, all of which are associated with subsurface operations. Research was done on artificial intelligence (AI) approaches in drilling systems and operations, including well planning, drilling optimization, well integrity, troubleshooting, and more.

[25] suggested that the digital twin be implemented in the process industries using a basic systems thinking methodology. The usage of reasoning engines and the capacity to connect models and systems throughout the process and product lifecycle are feasible with a common language and ontology. The operator training simulator and its embedded dynamic models were the main topic of discussion when it came to use-cases and forms of the digital twin to enhance safety in the process industries. An overview of the potential and risks related to process safety that are connected to the use of digitalized dynamic models in the petroleum sector was provided in the study's conclusion.

[26] noted that when well-designed production facilities are put into operation, a gap occurs. Major incidents might arise from the dynamic nature of the frontline and the compartmentalized sources of knowledge about scheduled activities and vital equipment. He pointed out that an improved approach to risk management—one that is more practical, straightforward in theory, and based on real-time risk status—is being offered by an emerging category of enterprise software systems for operational risk management that aims to bridge this gap by utilizing tested risk models to support all levels of operational decision-making.

According to [27], safety can be assured in an asset by employing Real Time Data Analytics to reduce operational process safety risk and improve plant safety and integrity assurance and Real Time Web Based Dashboard can be designed to user specific actionable analytics to visualize current risk.

[28] studied a drone and artificial intelligence reconsolidated technological solution (DARTS) by integrating deep learning techniques and drone technology. By periodically gathering and evaluating picture data, DARTS is able to identify the targeted probable fundamental problems—such as misaligned pipes and deteriorating pipe support systems—that may lead to catastrophic pipeline failures and forecast how quickly those problems may manifest. According to the study's findings, DARTS can be a useful tool for decision-making in preventive pipeline maintenance, improving pipeline systems' safety and resilience.
[29] studied the use of data analytics and machine learning to uncover the most effective ways to reduce green-house gas (GHG) emissions.

Development of conceptual framework for process safety cumulative risk visualization
Mapping of the process safety cumulative risk assessment and visualization process to the relevant AI techniques were carried out in consideration of the probable sources of the barrier impairment data as shown in Table 1. Another consideration is the insights or knowledge to be extracted from the data as input into the intelligent system. The process safety cumulative risk logic rule shown

in Figure 1 and model/framework shown in Figure 2 were used for the consideration. Figure 2 shows the conceptual framework.

Table 1: Sources of Barrier Impairment Data

S/N	Description	Data Source
1.	Preventive Maintenance Deviation	Maintenance Management System
2.	Corrective Maintenance Deviation	Maintenance Management System
3.	Overrides / Inhibits	Manual Override Register
4.	Temporary changes/repairs	Manual temporary change register
5.	Down-graded integrity items	Maintenance Management System
6.	Open actions from safety audits/reviews	Action Tracking Management System
7.	Open actions from hardware barrier assessment	Action Tracking Management System

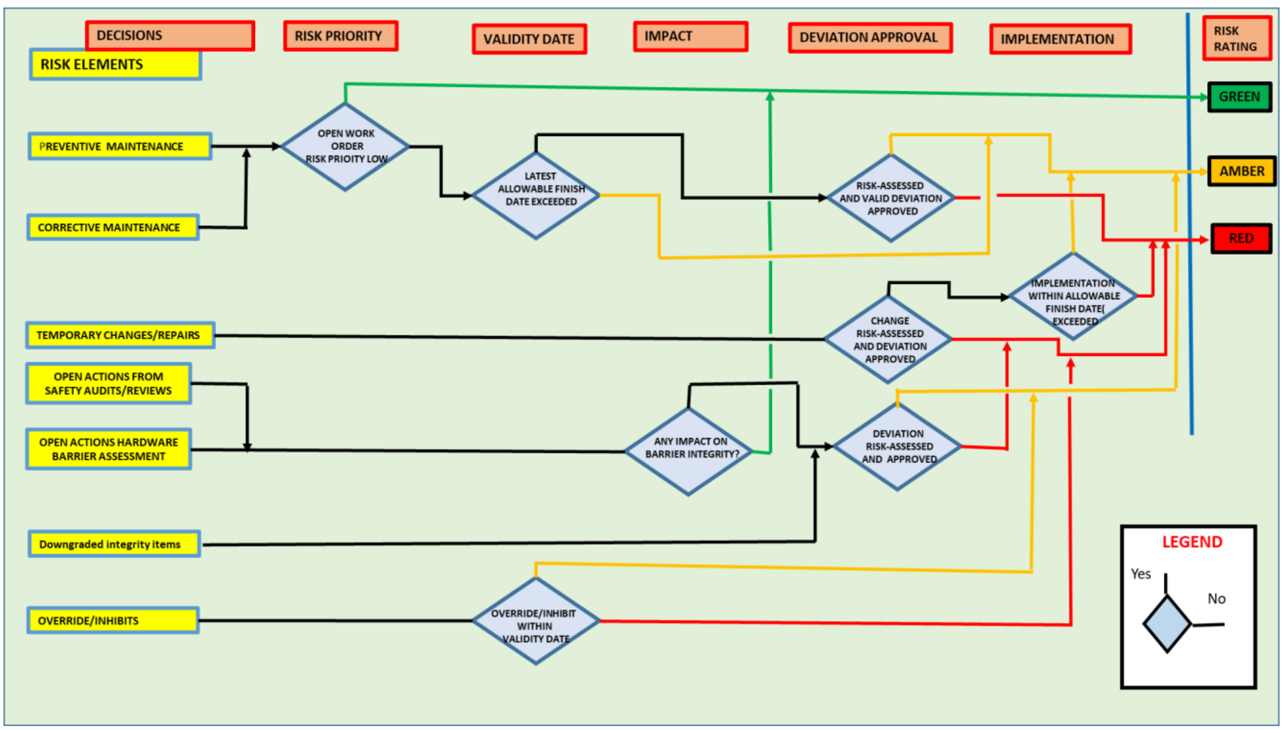

Figure 1: Logic/Rule for assessing process safety cumulative risk (adapted from [8])

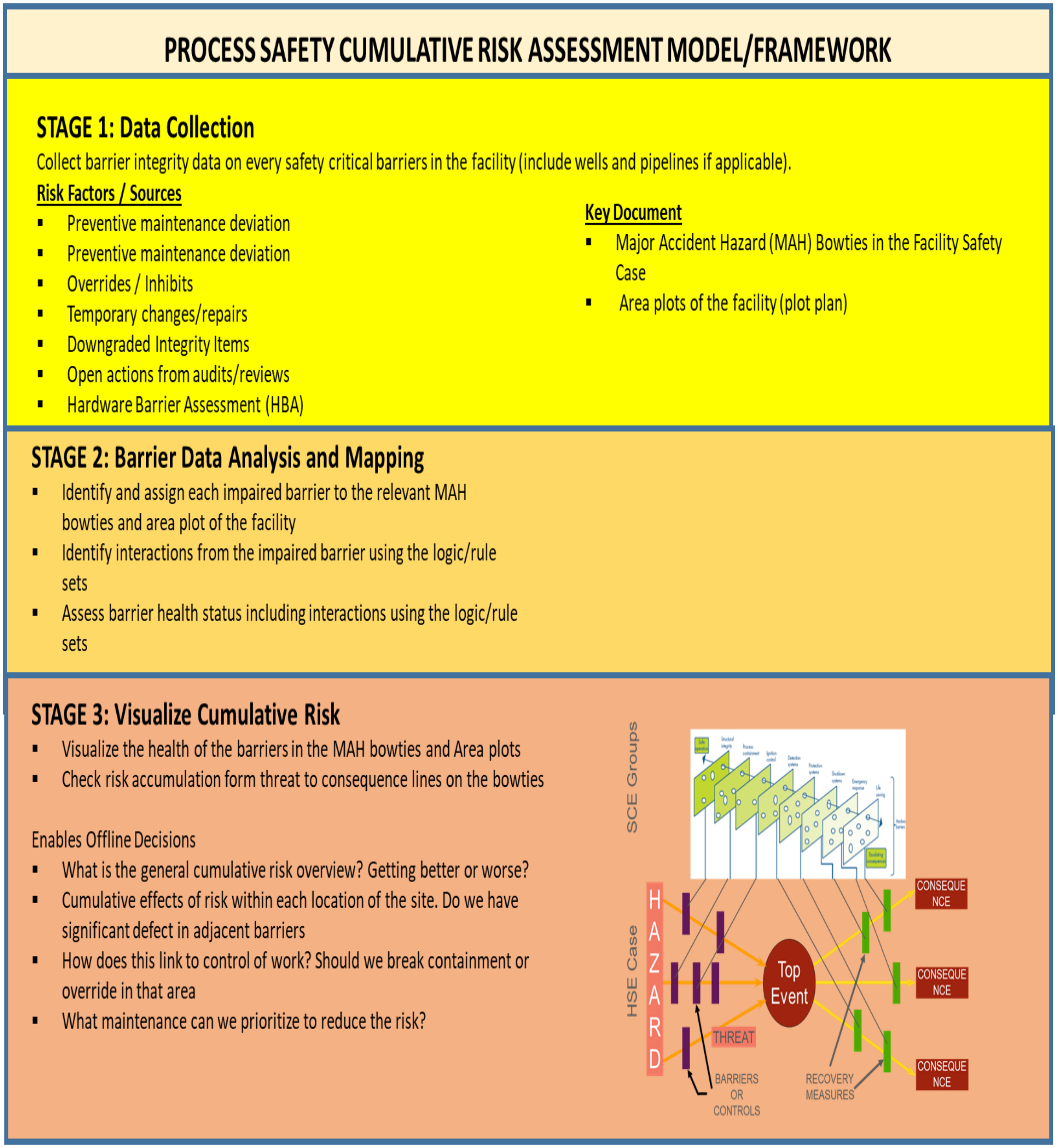

Figure 2: Process safety cumulative risk assessment model/framework (adapted from [8])

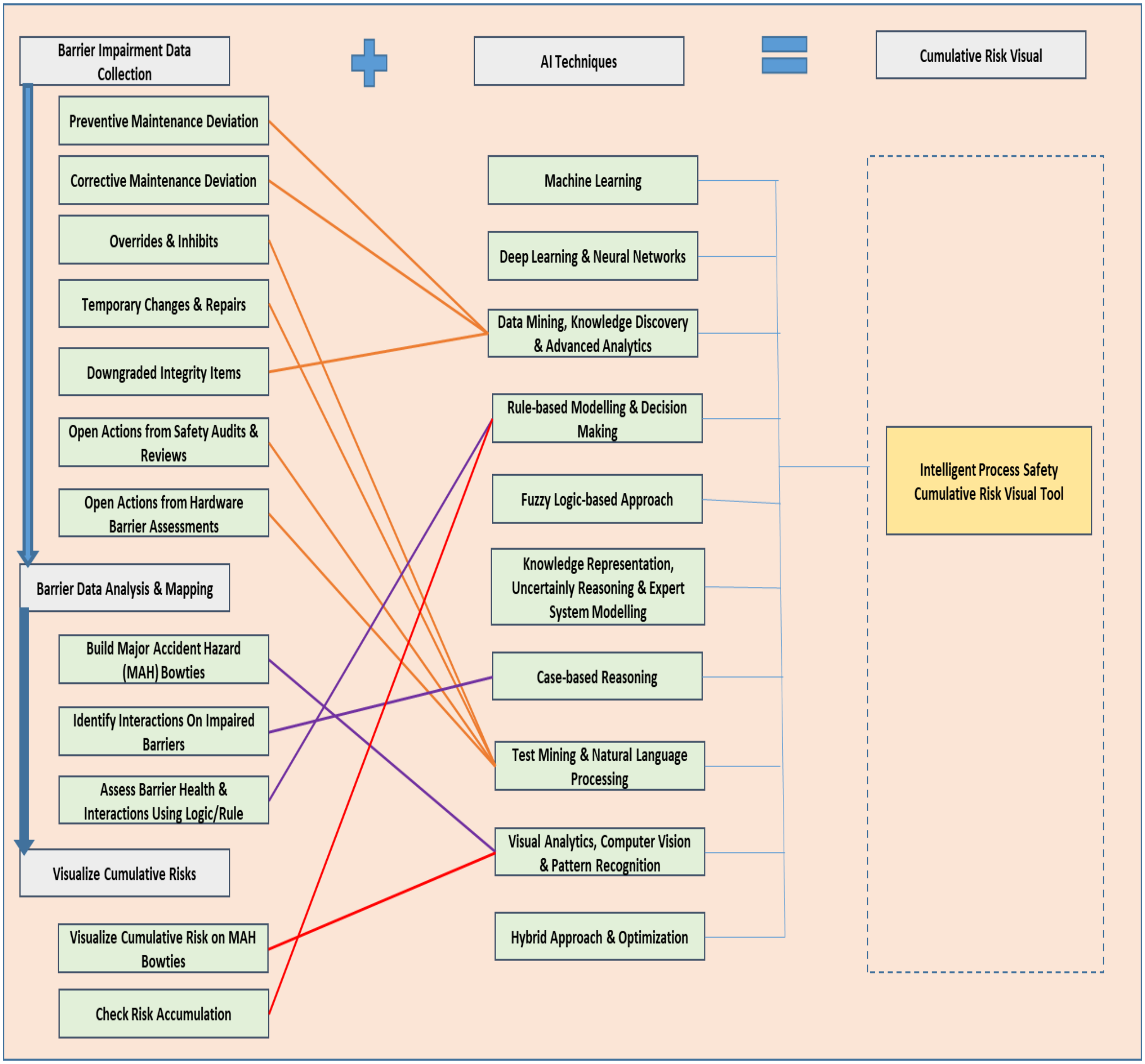

Figure 3: Conceptual Framework for Web-based Intelligent Process safety cumulative risk visual tool

DISCUSSION

Artificial intelligence (AI) is an emerging technological field with immense transformative potential and Industries are involved in intensive research efforts in the area of artificial intelligence and different AI enabled techniques. From the literatures reviewed, AI application in petroleum operations is mature especially with respect to the geological assessment, reservoir engineering, drilling, well integrity and production optimization including enhanced oil recovery. These AI applications use a diverse array of AI techniques, ranging from machine learning (ML), to artificial neural networks (ANN), fuzzy logic, data mining and hybrid systems. ANN and fuzzy logic are the most popular and widely used AI tools in subsurface works. The major threat identified in moving AI to the next level in petroleum subsurface works is to do with lack of industry collaboration in AI application. AI has also been applied in pipeline systems resilience by integrating drones technology with deep learning (DL) technique, to detect the targeted potential root problems e.g. pipes out of alignment and deterioration of pipe support system, that are capable of causing critical pipeline failures. The technique also predicts the progress of the detected problems by collecting and analyzing image data periodically, to support decision making for preventive pipeline maintenance to increase pipeline system safety and resilience.

On AI application in safety management and/or process safety management, literatures in this area are scant. There are a few literature on AI application in operational safety management and the application is limited to using AI Computer vision technique to monitor workplace and alert management on safety regulatory deviations. AI also has the potential to analyze data from various sources, including sensors and historical data, to identify patterns and predict potential safety risks (predictive analytics) which can help employers to take proactive measures to prevent accidents and injuries before they occur. AI is also applied in monitoring workers and equipment in real-time, alerting managers and workers to potential safety issues as they happen, helping the company management to prevent accidents and injuries by allowing workers to respond quickly to potential hazards.

There are many articles on the application of "digital twins" technology using AI techniques. This is mostly used in predictive maintenance in petroleum facilities and also to identify exceedance of integrity operating windows. The "twin" gathers data from the physical asset on a continuous basis and uses machine learning (ML) and predictive analytics algorithms to forecast performance in the future. Operators can anticipate possible malfunctions or breakdowns by continuously observing the operation of the equipment and comparing it to virtual counterparts. Regarding safety, operators can optimize operational procedures and prevent potential hazards by using digital twins, which model a variety of scenarios.

In summary, there is a gap in literature in the application of AI to process safety and risk assessment. On the conceptual framework for AI application in process safety cumulative risk visual, the framework has three major steps – barrier impairment data collection, barrier data analysis & mapping and visualization of cumulative risk. Each of the steps is mapped to the applicable AI techniques. For example, data for preventive maintenance deviation on any barrier resides in the Maintenance Management System (MMS) as shown in Table 1 and this will be collected by data mining AI technique. The same applies to data for corrective maintenance deviation. Data for overrides/inhibits typically resides in the manual override/inhibit register and this will be collected by text mining and natural language AI technique. On barrier data analysis and mapping, for example, building the major hazard bowties on which the barrier impairment health is mapped to computer vision AI technique while assessing the barrier health status using the logic rule is mapped to rule-based modelling AI technique. Visualization of the barrier health status is mapped to visual analytics and computer vision while checking for cumulative risk is mapped to rule-based modelling AI technique.

The focused group participants adduced that the model/framework in Figure 3 provides a clear guidance on process safety cumulative risk assessment and visualization and the model literally covered every aspect of the process safety cumulative risk assessment and visualization, related to safety critical barrier impairment. The Focused Group participants observed that for the proper application of the conceptual framework, petroleum organization need to change their safety management systems, affecting the way barriers data are gathered, possibly by opting for the use of robotic techniques. This aligns with the view of [25] that people and safety management systems aspects must be considered when embarking on a digitalization project to ensure that all of the necessary skillsets are available and that team structures and management systems are capable of delivering an acceptable outcome.

CONCLUSIONS

The aim of this study is to develop a conceptual framework for an intelligent web-based software for process safety cumulative risk visualization for petroleum operations. Extensive literature review was carried out on application of artificial intelligence (AI) and especially in process safety risk assessment and visualization. The Conceptual framework was developed and validated using a focused group of Process Safety and Asset Integrity professionals, Information Systems Engineers and Software Engineers. From the results of the study, it was evident that the conceptual framework provides a novel approach in developing an intelligent web-based software using artificial intelligence (AI) techniques, for real time visualization of process safety cumulative risk picture.

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