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A survey on artificial intelligence in nuclear emergency preparedness and response

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Nuclear energy is considered one of the safest sources of energy in the world, however there is a low probability of occurrence of a nuclearaccident that might trigger a nuclear emergency. As of December 2023, there are 413 operating nuclear power plants in 31 different countries,and although the design of these nuclear power plants is based upon the concepts of Defence in Depth with very conservative assumptions,the hazard from natural disaster, human error and non-vigilant actions might results in nuclear emergency. Since the last majornuclearaccident Fukushima Daichi in 2011, many researchers have highlighted the need for more advanced and automated system tosupport the emergency preparedness and response in optimizing the protective action strategies. In this study we introduce the concept ofapplying artificial intelligence to enhance the readiness and the response capability during nuclear emergency. Through the predictability and computational features of AI models and machine learning techniques, the EPR systems can be enhanced by improving the hazardassessment, optimizing the dose projections models, enhancing the protective actions strategies and improving the decision-making process. However, this application also presents challenges such as data reliability, cybersecurity and regulatory compliance. The results of this studyhighlight the significance of applying AI in EPR and the need for further research on this application with a particular focus on addressingthese challenges to ensure safe implementation.

KEYWORDS

artificial intelligence (AI), emergency preparedness and response (EPR), nuclear emergency, nuclear power plant (NPP), emergency planning zone (EPZ), atmospheric dispersion, prediction, protective action

1 Introduction

Nuclear power is deemed to be one of the safest sources of energy (Hussain, 2023), however, there is still a very low probability of the occurrence of a nuclear accident within the nuclear power plant (NPP) that might lead to a nuclear emergency which could impact the workers, public and environment. In the nuclear energy sector, controlled nuclear chain reactions produce heat, which is then used to generate electricity through steam turbines (Hussain, 2023). As of the end of December 2023, the worldwide operational nuclear power capacity is 371.5 GW (electric), generated by 413 nuclear reactors in 31 countries and additional 21.3 GW (electric) generated from 25 reactors which are licensed for operation but stayed in suspended operations during 2023 (IAEA, 2024b).

Furthermore, since the construction of the first reactor in 1954, the public have been concerned about the consequences of the health effects of a nuclear accident within the operated NPPs (Hussain, 2023). Although the design of these plants is based on the concept of Defense in Depth (DiD) (CNSC, 2014) with very conservative assumptions and with high safety margin, the hazards from natural disasters, errors made by humans, and non-vigilant actions might result in a nuclear accident, which will trigger a nuclear emergency.

Since the construction of the first nuclear reactor, three major nuclear accidents have occurred over the past 70 years in three different member states. The most recent was the Fukushima Daiichi accident in Japan in 2011, preceded by the Chernobyl disaster in Ukraine in 1986, and the earliest was the partial meltdown of the Three Mile Island (TMI) Unit in the United States in 1979 (Hussain, 2023). According to the International Nuclear and Radiological Event Scale (INES), only the Chernobyl and Fukushima Daiichi accidents were rated at the maximum severity level of INES 7, reflecting widespread health and environmental consequences. In contrast, the TMI accident was rated at INES level 5, as its off-site impact was limited.

During the evaluation of the effectiveness of the protective actions that were taken during the Fukushima Daiichi accident, it was identified that some of the protective actions were not optimized and were doing more harm than good (Sawano et al., 2021).

For instance, during the Fukushima Daiichi evacuation, it was reported that some of the critical patients passed away during evacuation due to lack of staff and disruption of infrastructure (Sawano et al., 2021). Therefore, poorly prepared protective response during emergencies can lead to serious impacts on vulnerable populations, thus it is fundamental to identify risks associated with nuclear emergencies and it is crucial to be well prepared for these emergencies by implementing suitable and effective protective actions.

According to Carr (2018) the limited protective actions taken during the Fukushima Daiichi and Chernobyl accidents caused numerous social problems, such as depression, anxiety, and societal problems. There is a need to use advanced methodologies, criteria, and approaches to prepare for a nuclear emergency and have contingency plans in place that will not fail during the response. For those reasons, in this present work we are proposing a novel idea for enhancing the emergency preparedness and response by implementation of advanced automated techniques that are based on Artificial Intelligence (AI) models and Machine Learning (ML) algorithms. The first part of this paper provides an overview of the AI technologies in EPR and the different machine learning techniques in emergency management. The second part highlights the existing and the potential application of AI in EPR. Subsequently the last part of this paper focus on the associated challenges with this applications, significance of this application to EPR and some future work recommendations.

2 Overview of AI technologies in EPR

Artificial Intelligence was first invented in the 1940s, however, advancement in AI capabilities has been rapidly growing since 2010 (DHS, 2024). This growth was due to the huge increase in the computational capabilities, publicly available data, novel algorithms and the increase in the number of individuals with the ability to manipulate this computational power (DHS, 2024). Recently, processing and computational capabilities have become more accessible by organizations and by individuals, which made the AI very scalable and can be applied in different applications (DHS, 2024). In this paper we are exploring the applicability and the scalability of AI in the field of nuclear emergency preparedness and response.

2.1 Nuclear emergency data source

Data sources are the key components in any artificial intelligence model as they are the main inputs to the machine learning algorithms associated with the model. The data used to train and test the AI models in the field of nuclear emergency and response are crucial to the accuracy and the reliability of the output pf these models. This data mainly comes from three different categories (Jendoubi and Asad, 2024). The first set of data comes from mathematical models and simulators based on complex physics and thermal hydraulics equations (Ejigu, 2024). Thus, mathematical modelling data can be used to train the AI-based EPR models and decision support systems. The second set of data might come from the experiments in the laboratory; nevertheless, this type of data is not always accessible and might require an elevated expenditure to perform the experiment. However, we still can use this type of data to train and test the ML algorithms used in EPR models (Ejigu, 2024). The last set of data comes from the actual operation sensors, real-time data transmission Internet of Things (IoT) sensors, aerial images, sensors on the drones, etc. This type of data serves as important inputs to the EPR models and decision support systems based on ML algorithms.

2.2 Machine learning algorithms for emergency management

ML algorithms have been around for decades however they have attained new popularity as AI has grown in prominence (Hong, 2020). The variety of ML techniques include supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning, classification, regression, decision tree, clustering, deep learning, etc., (Hong, 2020).

Few scientific works have been published regarding the ML algorithm used for nuclear emergency management. However, in the literature, several works explored the use of different ML technique to manage other type of emergency such as, earthquake or Hurricane. Given the similarity in the predictivity and the identification features of all the emergency which implies deviation of the data from the predicted trend, we are able to match the ML algorithm used to forecast and monitor other type of emergencies with the nuclear emergency.

In his paper, Xu (2017) used a clustering technique to detect patterns of abnormal activities that could potentially escalate into nuclear security events, which are events involving malicious acts, unauthorized access, or intentional disruptions that threaten the safe operation of a nuclear facility. By identifying such patterns early, machine learning (ML) algorithms can assist security and emergency teams in taking pre-emptive measures, thus enhancing overall control and situational awareness during a nuclear emergency. Similarly Yin et al. (2012) employed an Online Incremental Clustering algorithm to continuously monitor and classify unusual signals or events, supporting real-time situational awareness. In our case, we could use the same technique during nuclear emergency to enhance radiological risk awareness within the affected population in the EPZ. Another author (Harris, 2017), used Fast K-means Clustering technique to detect the incident location based the crowd sourcing patterns. In our case, we can use this technique to track and monitor the evacuation routes during the response. This is important because during nuclear emergency, people tend to escape from their homes even without any evacuation orders, which would result in traffic and the probability for vehicle accident increase under the anxiety and fear of radiation exposure, as we saw during the Three Mile Island Accident.

In paper, Martínez-Álvarez et al. (2011) used a regression technique to predict the magnitude of earthquakes by identifying correlations between seismic precursor patterns and resulting earthquake strength. Although earthquakes and radiation releases are fundamentally different phenomena, regression techniques can still be applied to model cause-effect relationships in nuclear emergencies.

In our case, regression models can be trained using historical plant data and simulated scenarios to estimate the extent of radiation levels following a release event. For example, inputs such as the size of the release, containment status, meteorological conditions, and ventilation patterns can serve as predictors for the spatial and temporal distribution of radiation. This approach does not assume that radiation behaves like seismic activity but rather leverages the same statistical principle of regression to quantify relationships between input parameters and predicted outcomes.

Likewise, Sakaki (2010) employed Support Vector Machine (SVM) to detect an emergency event and classify the emergency attributes positive and negative classes. In our case, we can take advantage of this method during the triage after a contamination event. Another author, Fersini (2016) used Bayesian-based technique to train the AI model to be able to send early warning regarding the emergency magnitudes and degree of the predicted damage.

In our case, this technique can be used to detect a sequence of events that may lead to severe nuclear accidents and provide an early warning to the operator and emergency response authorities. According to the IAEA's emergency classification system, such detection can automatically trigger a predefined emergency category (e.g., Alert, Site Area Emergency, or General Emergency), which in turn activates the corresponding protective actions.

For example, if the predicted conditions meet the criteria for a General Emergency, authorities can immediately invoke the Precautionary Action Zone (PAZ), initiate public notification, and implement urgent protective measures such as sheltering or distributing Thyroid Blocking Tablets (TBTs).

Similarly, author in Kim et al. (2014) used Multilayer Feed-Forward Network and Back Propagation technique to forecast the level of damage caused by a hurricane. In our case, this technique can be adapted to predict the level of damage resulting from combined emergencies, such as a nuclear event occurring simultaneously with a natural disaster. The model can be trained using historical data and simulated scenarios where multiple hazards overlap, such as the Fukushima Daiichi accident in 2011, where a nuclear emergency coincided with a tsunami.

Specifically, a Multilayer Feed-Forward Network with Back Propagation could take as input variables related to both the nuclear plant (e.g., reactor thermal power, coolant system status, and containment pressure) and the natural disaster (e.g., tsunami wave height, flooding level, and seismic activity). By processing these multi-hazard inputs, the network can estimate a combined damage index, which reflects the expected severity of plant degradation, off-site radiological consequences, and infrastructure impact. This adaptation allows EPR authorities to forecast worst-case outcomes for complex scenarios, enabling them to prioritize resources, pre-stage protective measures, and mitigate cascading effects before they fully develop. By forecasting the level of damage caused by the combination of events, the EPR authorities can plan and have more robust and effective protective actions to mitigate the consequences caused by this type of combined emergency. Another author in Bai et al. (2018) used Convolutional Neural.

Network (CNN) to train the AI model based on pixels images from radar Earth observation satellite in the purpose to evaluate damage level of the affected regions, the output from the AI models was instant evaluation and classification of the damaged area into the following categories "washed away", "collapsed" and "slightly damaged regions". In our case we can use this CNN technique to evaluate the contamination level after a severe nuclear accident and classify the affected area in "Highly contaminated area", "moderate contaminated area", and "slightly contaminated areas". This is very important, because during the evacuation process, it is crucial to determine the non-contaminated route to make sure the evacuation is done safely. The following Table 1 summarizes the machine learning techniques reviewed in this section.

3 AI application in EPR

In this section of this paper, we are introducing the existing and the possible application of artificial intelligence in the area of nuclear emergency and response.

3.1 Predictive modeling of nuclear security threat scenarios

Nuclear power plants face different types of threat that includes nuclear security threat, examples includes cyberattack and physical intrusion. These threats may affect the safety of the NPP operation and cause significant risks to the public (Choi, 2020), that's why it is crucial for the nuclear facilities to be well prepared for these type of attacks in order to mitigate the consequence. Artificial intelligence is a very powerful tool that can be used during the emergency preparedness phase to help with the protective action strategies for offsite and onsite response plans during a nuclear emergency that is triggered by a nuclear security event. According to DHS (2024) AI is already used by the Department of Homeland Security of the United States to predict detect, identify and mitigate the impact of the threat that is raised from nuclear security situation. Machine learning (ML) algorithms can support the simulation of various nuclear security attack scenarios—such as physical intrusion, cyber-attacks, and coordinated threats—by analyzing the outputs of simulation models rather than directly running the simulations

TABLE 1 Modern AI algorithms used in emergency management.

Emergency phase	Emergency management task	ML technique	Other emergencies application	Nuclear emergency application	Reference
Preparedness stage	Event Detection	Clustering	Detect events that are more likely to trigger an emergency	Detect and recognize the set of events related to nuclear security events	Xu (2017)
Response Phase	Situational Awareness	Online Incremental Clustering	Situational awareness	Enhance radiological risk awareness	Yin et al. (2012)
Response Phase	Crowd-sourcing	Fast K-means Clustering	Detect the incident location based on the crowd sourcing patterns	Track and monitor the evacuation routes	Harris (2017)
Preparedness Stage	Prediction	Regression	Predict magnitude of earthquakes	Predict the extent of the radiation dose	Martínez-Álvarez et al. (2011)
Response Phase	Detection/Classification	Support Vector Machine (SVM)	Detect an emergency event and classify the emergency attributes positive and negative classes	Triage after a contamination event	Sakaki (2010)
Urgent Response Phase	Crowdsourcing/Early Warning	Bayesian-based technique	Early warning regarding the emergency magnitudes and degree of the predicted damage	Detect nuclear events and send an early warning for Iodine Prophylaxis	Fersini (2016)
Preparedness Stage	Prediction	Multilayer Feed-Forward Network and Back Propagation	Forecast the level of damage caused by a hurricane	Predict the level of damage caused by a combination of a nuclear emergency and a natural disaster	Kim et al. (2014)
Response Phase	Evaluation	Convolutional Neural Network (CNN)	Evaluate damage level of the affected regions: "washed away", "collapsed" and "slightly damaged regions"	Evaluate the contamination level: "Highly contaminated area", "moderate contaminated area", and "slightly contaminated areas"	Bai et al. (2018)

(Wasil et al., 2024). In practice, the simulations themselves are typically executed using physics-based or agent-based modeling tools to generate large datasets representing system behavior under different attack conditions. ML is then applied to process and interpret these outputs, identify recurring vulnerabilities, detect anomalous patterns, and predict the likelihood of cascading failures. This approach allows security planners to focus on high-risk scenarios, prioritize protective measures, and improve the robustness of the emergency preparedness and response plan.

By running the simulation codes, the emergency planners can assess the impact of such type of attack on the nuclear power plant and they will be able to determine the extent of the emergency planning zones (EPZs) according to the simulation results from the ML algorithms. These algorithms, such as Deep Learning (DL) (Chernavskikh, 2024) hold a significance simulation and scenario reconstruction capabilities (NNSA, 2023) that can optimize the extension of the EPZs and therefore optimize the protective action and the emergency response plans onsite and offsite the plant. In his paper, NNSA (2023) states that since 1992, the National Nuclear Security Administration (NNSA) of the United States has undergone different testing for artificial intelligence integration for nuclear security purposes, to detect and identify any potential threat through prediction algorithm and simulate different nuclear security threat scenarios through and an advanced program called Advanced Simulation and Computing (ASC) program. In the same paper, NNSA (2023) affirms that in 2023, this simulation program ASC has reached unique modeling and simulation capabilities that use extensive machine learning tools allowing the simulator to mimic the nuclear security attack which high accuracy (NNSA, 2023), which will result in high accuracy in predicting the impact of this attack, thus more effective protective action planning strategy. Therefore, AI can be applied in EPR during the hazard assessment phase to address Requirement number 4.22 in the GSR-Part 7 (IAEA, 2015) to include nuclear security threat assessment in the hazard assessment, and it can simulate different nuclear security threat scenarios to assess the extension of their potential impacts on the public. The concept of applying AI in predictive modeling in nuclear security threat assessment is illustrated in Figures 1, 2.

3.2 Prediction of the atmospheric dispersion model and deposition profiles

Atmospheric dispersion models are indispensable modelling tools in projecting the consequences of the radioactive release from a severe accident at a NPP. This consequences assessment is a crucial part of the decision making process for implementation of effective protective actions to mitigate the health and societal consequences of this impact. Nuclear emergencies are different from any other emergencies because their impact is long-lasting and may continue to cause this impact through generations if justified and optimized protective actions are not implemented (Hussain, 2022). The application of artificial intelligence in plume dispersion modelling can enhance the prediction of these atmospheric models and improve the prediction of deposition profiles during the emergency preparedness phase. Machine learning algorithms such as Long Short-Term Memory (LSTM) can be used to train the dispersion models using the historical data of radioactive releases to predict future deposition patterns based on different atmospheric

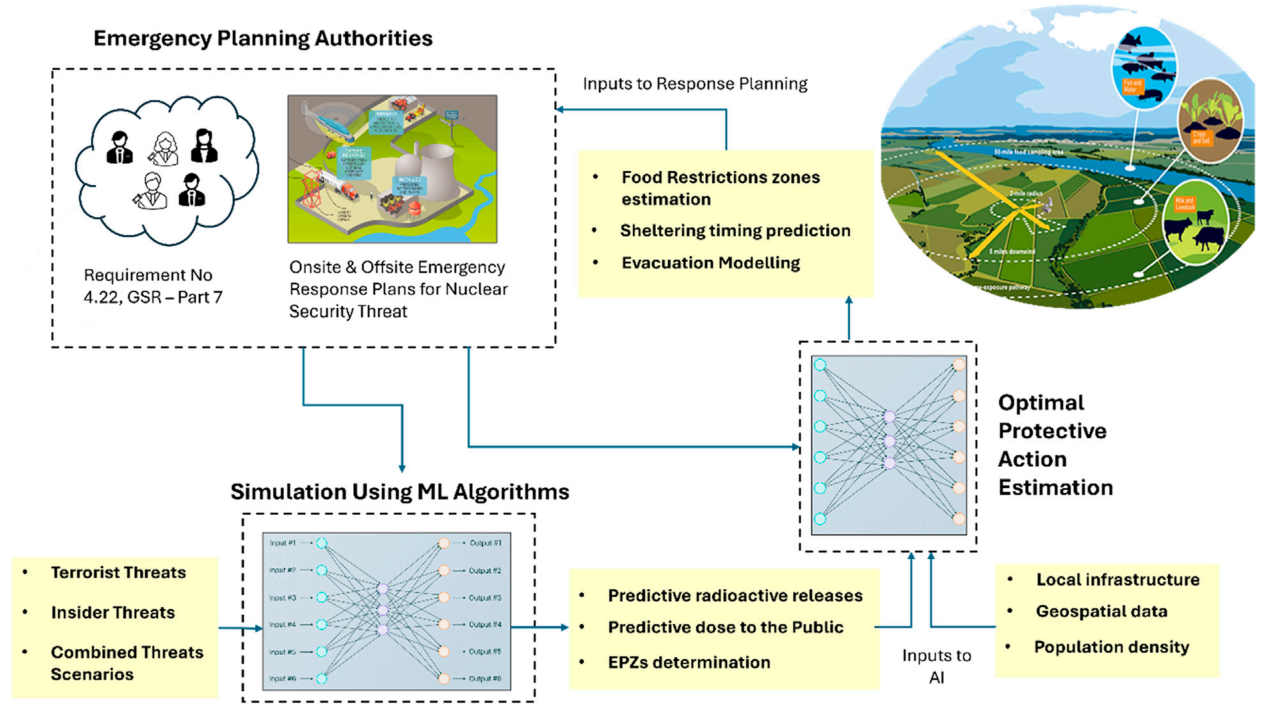

FIGURE 1
Predictive modeling of nuclear security threat scenarios.

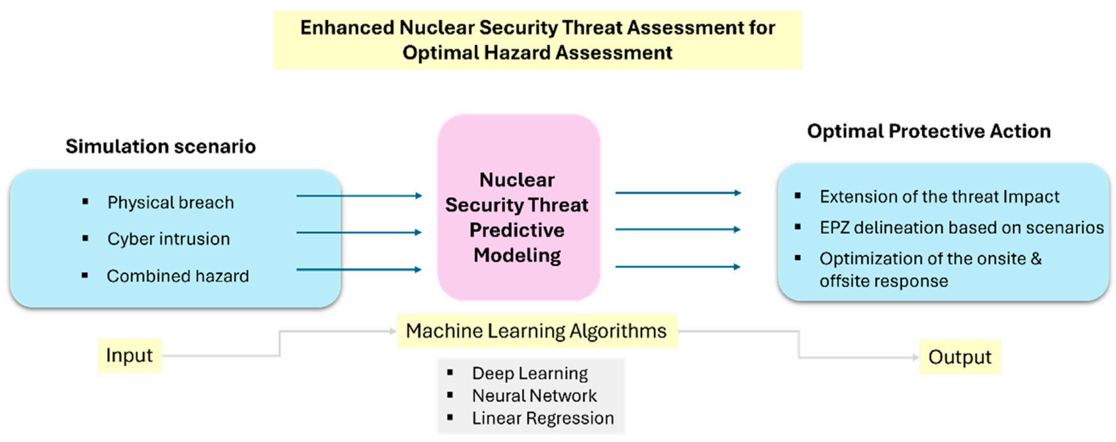

FIGURE 2
Enhanced nuclear security threat assessment for optimal hazard assessment.

characteristics scenarios (Filho, 2024). In his paper, Filho (2024) employed LSTM model to predict the movement of the point of the maximum whole-body dose rate coordinates at an optimized timing during the passage of the radioactive plume in the scenario of a severe accident from pressurized water reactor (PWR) in Brazil (Filho, 2024). The LSTM model used the maximum point of the simulated plume coordinates, wind speed and wind direction as input variable to the AI model to predict the whole-body dose rate (Filho, 2024). Furthermore, regression models, such as Linear Regression (LR) can be employed in this context to predict the intensity of the ground deposition based on variable input data such as the wind speed, the stability class and the height of the release (Al-Aizari et al., 2024). Other ML algorithms such as Gradient Boosting (GB) and Random Forest (RF) algorithms can enhance the emergency preparedness by handing complex interactions between the atmospheric dispersion variables such as the topography, precipitation patterns and the interplay of the wind (Al-Aizari et al., 2024). Artificial Neural Network (ANN) algorithms are also very useful tools that can be employed in the context of EPR for plume modelling as they have proved to deliver accurate

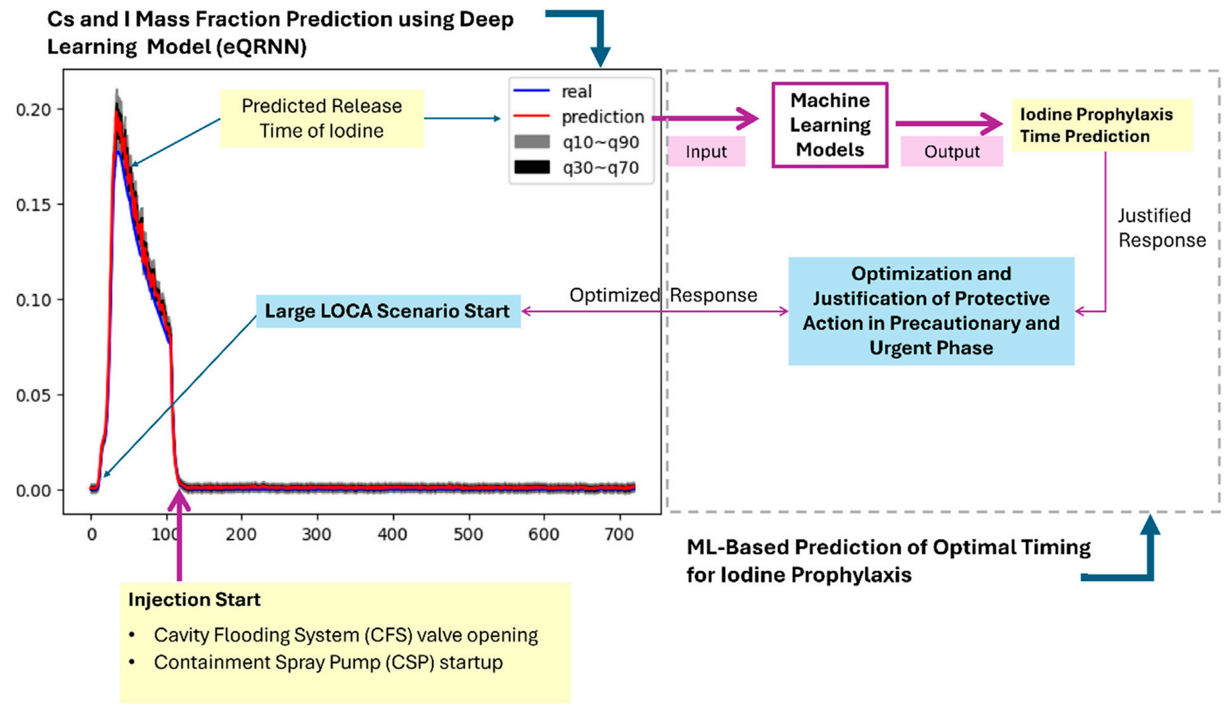

FIGURE 3
AI-based prediction of radioactive iodine release and optimal iodine prophylaxis timing.

prediction for temporal data-based model (Ayoub, 2024), such as the plume model. In his paper, Desterro et al. (2020) used Deep Rectifier Neural Network (DRNN) to predict the spatial dose rate distribution for accident scenarios with radioactive material release, where the AI based model shows a better dispersion pattern than the simulated model.

For instance, Recurrent Neural Network (RNN) are neural network algorithms and can be used to model the evolution of the plume dispersion over time (Ma, 2023). Convolution Neural Network (CNN) is another ANN algorithm that is very useful in the context of spatial data modelling, in the case of EPR, the CNN can be utilized to train the AI model and predict deposition areas with high resolution (Asahi et al., 2023). In his paper, Asahi et al. (2023) was able to predict the ground plume concentration for the future 30 min in less than a second using CNN, by predicting the speed of the plume dispersion. Furthermore, as the plume dispersion model is vulnerable to many variations, and during the emergency preparedness phase, the goal is to predict as close as possible the emergency scenario so that the protective action is optimized. Combining RNN and CNN algorithms can be a useful hybrid model to predict the dispersion model with less uncertainty because these two algorithms account for both spatial and temporal variations in the dispersion (Mas-Pujol, 2022).

Traditional atmospheric dispersion models such as HOTSPOT use Gaussian models to predict the plume dispersion model based on static assumptions (Ren, 2024). Artificial Intelligence can be used in the context of these traditional model to replace the static assumptions with dynamic and real time predictions inputs, that will eventually enhance plume behavior, thus the response plans (Snoun, 2023).

3.3 Prediction of optimal timing for iodine prophylaxis

Following nuclear accident, the World Health Organization (WHO) recommends iodine prophylaxis for children, adolescent and pregnant women, and restrict it for persons over 45 years (Portius, 2013). The dosage of the stable iodine and the distribution radius of the tablets depends on the released quantity of the radioactive iodine from the NPP (Portius, 2013), thus optimizing the planning radius for the distribution of the iodine tablets is crucial in the preparedness phase to ensure that the iodine tablet are distributed to the affected member of public. The Chernobyl accident has proven that radioactive iodine I-131 released in a nuclear accident can trigger cancerous thyroid nodules to develop in young population that is located within a 300 mile radius of the nuclear accident (Braverman et al., 2014). Additionally, timely potassium iodide (KI) management can avoid the progress of thyroid cancer (Braverman et al., 2014), and as the iodine prophylaxis has effect only less than 24 h prior to the release and up to 2 h after the exposure to radioactive iodine (Paladino, 2022), it is important to predict accurately the release time and quantity so that the stable iodine can be taken by the public at the right time. Artificial intelligence can be employed for this purpose to monitor the critical nuclear power plant data and detect any anomalies in these data to predict the failure of the system thus the release quantity and timing. In his paper, Jendoubi and Asad (2024) explained how machine learning algorithms such as ANN are able to predict the nuclear releases based on comparison between the measured NPP data and the forecasted data from the neural network. Another Yang et al. (2024) used DL models such as

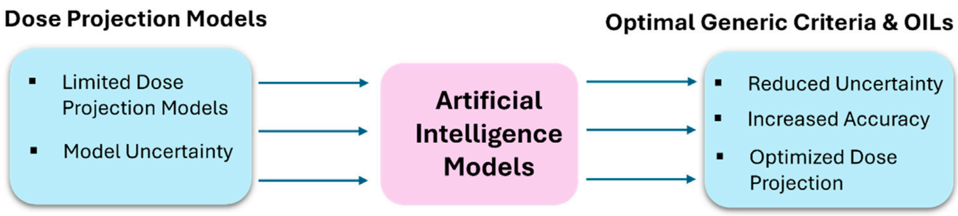

FIGURE 4
Concept of optimization of generic criteria and OILs using AI models.

Conventional Transformer (ConvTran) for rapid diagnosis and prediction of the radioactive Cs and I release during large Loss of Coolant Accident (LOCA).

By predicting the radioactive releases, artificial intelligence algorithms can use these releases as inputs, along with the population distribution around the plant, to predict and determine the radius of the zones in which the stable iodine tablets may be distributed and taken to mitigate the stochastic effect caused by the radioactive iodine releases. Therefore, the utilization of artificial intelligence in EPR can enhance protective action also during the Precautionary and Urgent phase to reduce the risk of thyroid cancer due to radioactive iodine releases. This idea is modelled in Figure 3.

3.4 Artificial intelligence for smart evacuation during nuclear emergencies

During a nuclear emergency, radioactive contamination in the air and on the ground presents significant challenges for implementing protective actions such as public evacuation. Evacuation becomes particularly complex because contaminated zones can restrict safe routes, delay transportation, and increase exposure risks for both the public and emergency responders. These challenges can be further amplified in combined emergencies, such as when a nuclear incident coincides with a natural disaster, as occurred during the 2011 Fukushima Daiichi NPP accident in Japan (Tsujiguchi et al., 2018). The integration of smart computational approaches such as artificial intelligence can improve the effectiveness of the evacuation process by recommending the safest route to evacuate the residents within the Precautionary Action Zone (PAZ), Urgent Protective Action Planning zone (UPZ) or out of UPZ based on the declared emergency class. The implementation of artificial intelligence capabilities and the Internet Of Things (IoT) technology, the evacuation process during a nuclear emergencies can be automated via a smart system based on machine learning algorithm and IoT sensors (Alqahtani, 2024). These sensors have the ability to collect remotely different radioactivity measurements due to the passage of the plume (Alqahtani, 2024), and the ML algorithms have the ability to process these data and create dynamic risk map (Jendoubi and Asad, 2024), with the recommended routes for evacuation. In his paper, Alqahtani (2024) used Support Vector Machine (SVM) as ML algorithm to process the sensor data during emergencies and used Markov Decision Process (MDP) to compute the processed data and propose safe evacuation routes. The proposed idea here is to use the different ML algorithm as used by the previous author to recommend evacuation routes during nuclear emergencies and incorporates the Markov decision process (MDP) to determine the optimal route for emergency management, particularly in the Early phase, where the actual emergency situation deviate from the planned scenario, and the planned response action are no longer valid to mitigate the consequence of the nuclear emergency. In this situation, the application of artificial intelligence to generate fast and optimal evacuation routes map based on real-time data transmission is paramount to take the most effective protective action that are not executed ad planned.

3.5 Optimization of generic criteria and operational intervention level (OILs)

Generic criteria and OILs are tools to assist EPR authorities when planning protection strategies for nuclear emergency (Health Canada, 2018). The generic criteria are conveyed as dose levels over a specified time interval which, when surpassed, indicate that protective actions and accompanying response actions are warranted (Health Canada, 2018). The OIL intervention levels are instead employed after the release to adjust the execution of protective actions based on monitoring data measurements (Health Canada, 2018). The generic criteria and the OILs are used to develop protective action that are optimized and justified on the basis of the identified hazards as required by the IAEA (Requirement 5) (IAEA, 2015). The generic criteria are based upon the projected dose and the received dose, which are based on code and simulation modelling. Artificial intelligence can play a pivotal role in strengthening the accuracy and the stability of these models which will result in optimized generic criteria, thus effective emergency protective strategies, as modelled in Figure 4. The existing simulation models used for dose projections to develop the generic criteria contain uncertainties (Warner, 2023), however, is these models are enhanced using machine learning algorithm, the uncertainties levels decrease considerably. In his paper, Tyralis (2024) explores the benefit of Random Forest and DL algorithms in quantifying and filtering the uncertainties associated with the modeling and the simulation spatial and temporal models, which are very similar to the release of radioactivity models during nuclear emergency that evolve over the time and over the space.

```
Proposed algorithmic framework
Initialize
Monitoring Current Protective Actions
    IF Current Action = "Sheltering" THEN
            Check Radiation Inside Shelters
            Check Population Health Data
    IF Current Action = "Evacuation" THEN
            Check Evacuation Route Radiation
            Check Traffic Status
            Check Evacuation Center Capacity
Diagnosing Protective Action Effectiveness
    IF Current Action = "Sheltering" THEN
          IF Radiation Inside Shelters > Safe Threshold THEN
                Mark Sheltering = "Ineffective"
          ELSE
                Mark Sheltering = "Effective"
    IF Current Action = "Evacuation" THEN
          IF (Traffic Status = "Congested") OR (Evacuation Route Radiation > Safe
          Threshold) THEN
                Mark Evacuation = "Problematic"
          ELSE
                Mark Evacuation = "Effective"
          IF Evacuation Center Capacity = "Full" THEN
                Mark Evacuation = "Ineffective"
Prediction of Dose
     IF Mark Sheltering = "Ineffective" THEN
       Predict Dose If Evacuation Initiated
     IF Mark Evacuation = "Problematic" OR (Evacuation Center Capacity = "Full") THEN
       Predict Dose If Population Remains
     IF Radiation Outside Shelters < OIL THEN
       Predict Dose If Sheltering Continues
Suggestion of Recommended Next Protective Actions
     IF (Mark Sheltering = "Ineffective") AND (Mark Evacuation = "Effective") THEN
  Recommend Action = "Evacuate Affected Zone"
     IF (Mark Evacuation = "Problematic") OR (Evacuation Center Capacity = "Full") THEN
       IF Radiation Outside Shelters < OIL THEN
              Recommend Action = "Return to Sheltering"
       ELSE
              Recommend Action = "Find Alternative Evacuation Routes or Centers"
     IF (Radiation Levels Stabilizing) THEN
              Recommend Action = "Monitor and Maintain Current Actions"
Reassessment Report Generation
     PRINT Current Radiation Levels
     PRINT Evacuation Center Status
     PRINT Effectiveness of Current Actions
     PRINT Proposed Next Steps
Reassessment Repetation
     Wait 5 Minutes
     Collect New Data
     Go Back to Step Monitoring Current Protective Actions

END
```

FIGURE 5
Proposed algorithm framework for intelligent reassessment.

3.6 AI-based decision support system during nuclear emergency

Deterministic and stochastic effects are two concerns associated with nuclear power plant accidents, and managing a nuclear emergency adds supplementary pressure on decision-makers to address the direct and long-term consequences of these type of emergencies. The decision-making process is more challenging during the early phases of the nuclear emergency due to the increased levels of uncertainties in the unpredictable aspect of the

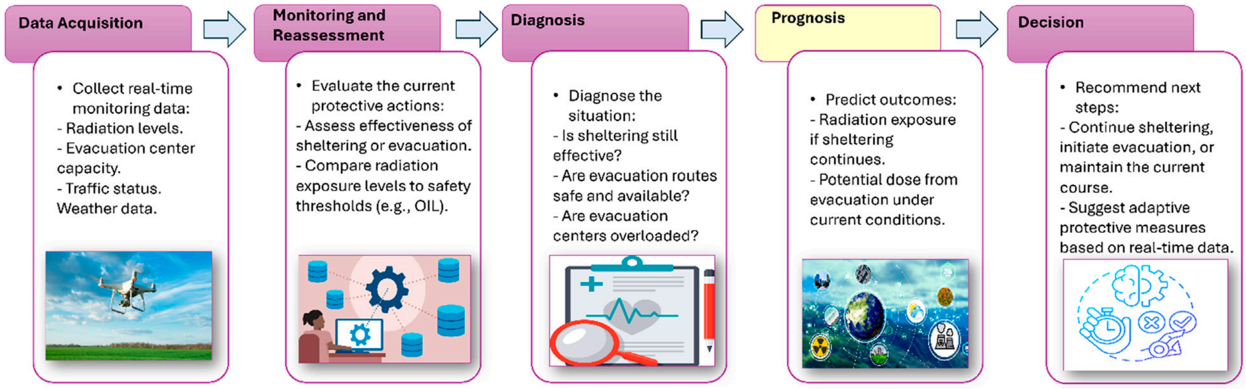

FIGURE 6
Intelligent reassessment of protective action effectiveness during emergency.

emergency circumstances and due to the unavailability of the information. For thee reasons, we are proposing a novel idea to implement artificial intelligence for this purpose to create a smart decision support system that serve as an important decision-making tool to support and help the emergency authorities to make the best decision during the early phases of the nuclear emergency. This AI-based Decision Support System would be composed of a real-time decision emergency attribute processing unit and an ML-based decision-making unit. The real time decision emergency attribute processing unit would collect and process the emergency attributes such as data from sensors, data regarding the containment integrity, data regarding the core meltdown risk, data regarding the available resources, data regarding the available trained and professional staff, data regarding radiation measurement, data regarding the weather, data regarding the number of beds available in hospitals, data regarding the capacity of the evacuation center and the energy shelters, etc. The ML-based decision-making unit analyze the processed emergency attributes, compare it to the historical emergency data, forecast the future trend, then decide about the optimized decision using advanced artificial intelligence techniques. In his paper, Soori et al. (2024) employed Natural Language Processing (NLP) and DL to train the AI model to learn from previous data, analyze real-time data and propose the optimal decision with never before-seen accuracy and efficiency. In his paper, Hussain et al. (2023) introduced a systematic approach called ROSYNA to serve as real-time decision support system during nuclear emergency when the uncertainties level are high. The different emergency attributes used in his proposed approach included six attributes, Risk of core melt, Maintaining of containment integrity, Information on release of radioactivity, Reliable weather forecast data, Reliable modelling products, Radiation measurement data, and Impeding factors in the implementation of protective measures (Hussain et al., 2023). Although, Hussain et al. (2023) and Soori et al. (2024) used, respectively, real-time decision making system and ML-based decision-making techniques, they did not combine the power of real-time data transmission and AI in decision making which makes the proposed idea in this section unique and novel in the field of EPR for nuclear emergencies. Furthermore, the proposed AI-Based Decision Support System would serve as valuable means during nuclear emergencies and can be used to obtain decision support regarding classifying the severity of the emergency, prioritizing the response tasks, and allocating the human and emergency resources to ensure critical tasks are addressed promptly.

3.7 Intelligent chatbots communication system during nuclear emergency

Nuclear emergencies pose significant concerns to people if the emergency is not managed and communicated adequately with the public. Generally, the management of natural emergencies has always integrated a major communication component in the form of notification, alerts, warnings of civilians about fluctuations in risks, evacuation instructions, etc., (Ogie, 2018). The communication component is vital to ensure effective management of nuclear emergencies, because inadequate communication weakens the decisions and responses from both emergency workers and residents, possibly worsening the effect of nuclear accident on the people (Ogie, 2018). In the case of lack of an effective communication system, first responders might not be able to retrieve the right information at the exact time. Furthermore, inadequate decisions may possibly develop due to lacking or misleading information, or even due to overlapping explanation of the same facts (Ogie, 2018), which will result in ineffective communication. In order to address this issue of communication, we are proposing a novel idea for artificial intelligence application to improve the communication system during nuclear emergencies. This intelligent communication system would operate as an AI Chatbot which would enhance communications during the different phases of the emergency (CISA, 2024). The foundation for AI in emergency communication is that machines can be trained to accelerate rapid extraction of appropriate information and the classification of same to enhance the overall awareness and warnings communication process (Ogie, 2018). In his paper, Aslam (2023) used Natural Language Processing (NLP), Natural Language Understanding (NLU) and Elaboration Likelihood Model (ELM) to train the data set and develop Chatbots technology.

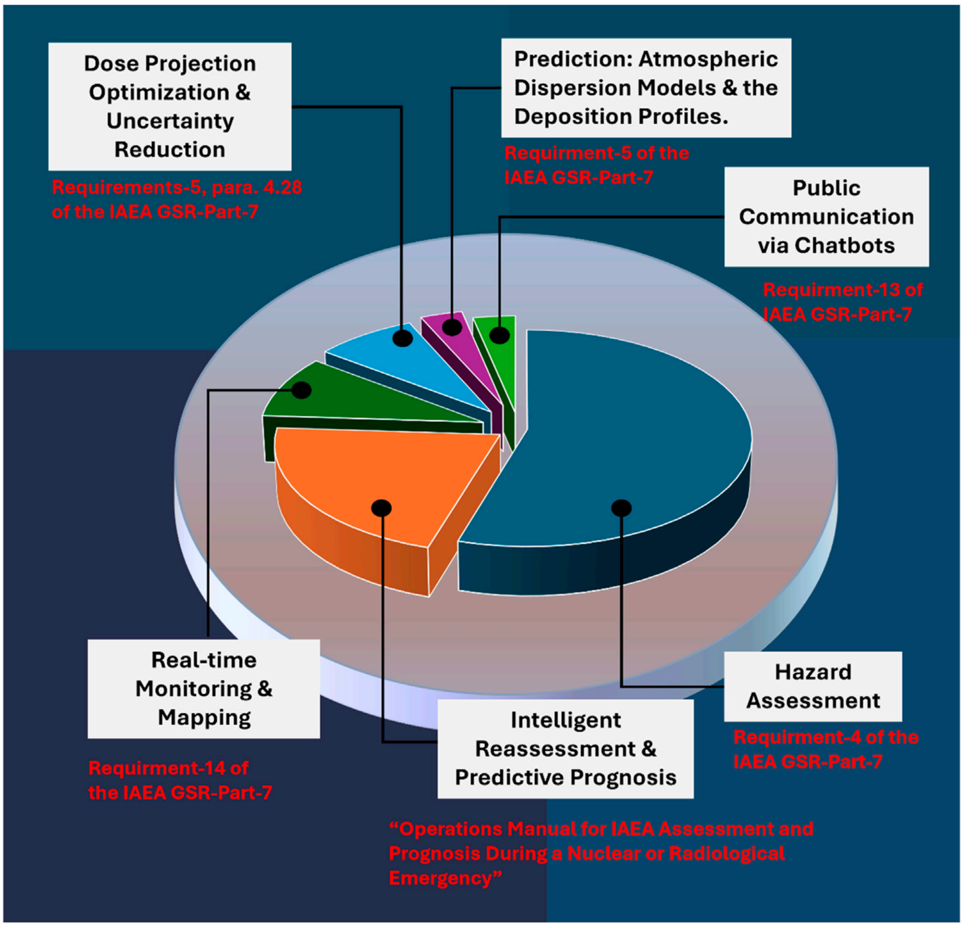

FIGURE 7
Significance of AI application in addressing GSR-part-7 requirements.

Similarly, Alazzam (2023) explored the Chatbots development using Artificial Intelligence Markup Language (AIML), Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN).

3.8 Intelligent reassessment of protective action effectiveness during emergency

Actual emergency situations do not necessarily follow the planned scenario patterns. The existing emergency circumstances sometimes deviate from the assumption made during the preparedness phase. For these reasons, the preplanning strategies should include different emergency scenarios and implement different contingencies to ensure the efficacy of the protective actions. Furthermore, as the emergency evolve, there is a need to reassess the effectiveness of certain protective action. For instance, the reassessment of "sheltering" as protective action taken according to the planned response may reveal the inefficacity of sheltering people in place while the radioactivity levels are increasing and consequently the dose rate is increasing. Therefore, the revaluation of the "Sheltering" as protective action would result in more effective action in the existing emergency circumstances such as "Evacuation". In this paper we are proposing a novel idea to automate the reassessment process of the nuclear emergency using Artificial Intelligence. This intelligent reassessment would use ML and DL algorithms to assess how the situation is evolving and suggest different protective actions as the emergency situation progress. This novel idea is modelled in a simplified algorithmic framework as shown in Figure 5. The proposed algorithm includes seven input data, "Radiation Outside Shelters", "Radiation Inside Shelter", Evacuation Route Radiation", "Evacuation Center Capacity", "Traffic Status", "OIL Value" and "Population Health Data". This algorithm aims to monitor the current protective action, diagnose it and compare it with the OIL values (IAEA, 2017), the evacuation center capacity, dose values in evacuation route, and the public health data coming from hospitals and medical points. After that, the proposed algorithms predict the safety and the effectiveness of the current protective action based on the previous comparison and suggest the recommended next protective action or it can suggest continuing to use the current protective action. The algorithm will also collect the data every 5 min, as a conservative assumption, and repeat the assessment. In essence, the proposed novel idea of intelligent reassessment of protective action effectiveness during nuclear emergencies would dynamically adjust the next protective action recommendation based radiation levels and the available resource to

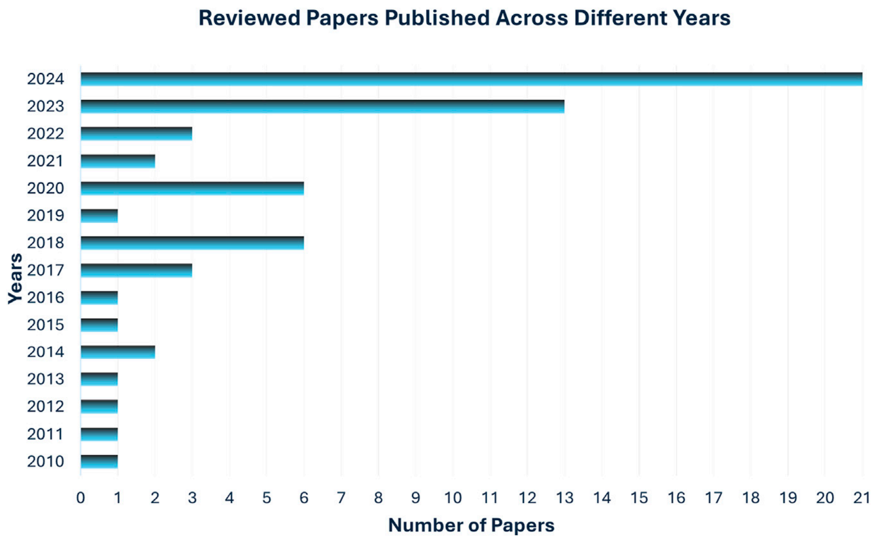

FIGURE 8
Number of the reviewed paper in this article.

ensure that the taken protective actions are working well, as modelled in Figure 6.

3.9 Predictive prognosis based real-time monitoring

During a nuclear emergency triggered by nuclear reactor severe accident, the level of release of radioactivity might continue to increase even after the declaration of the emergency class. This can happen during a reactor core meltdown accident where the reactor core melts gradually. The core meltdown can happen at the level of one channel as seen in CANDU reactor Unit 2 at Pickering NPP in 1983 (Government of Canada, 2021), partial meltdown as in Three Mile Island Accident in 1979 (Wikipedia, 2024) or total core meltdown as seen in Chernobyl accident in 1986 (IAEA, 2024a). In every case, the quantity of the radioactive material release is different and depend on the meltdown scheme. The radioactive releases can continue to increase while the reactor is shuttled down, e.g., in case of breach of containment integrity. At that point the protective action that has been already implemented may not be effective anymore as the radiation levels are increasing. In case the change in the radioactive material release from the affected reactor is fast, the emergency responders authorities may not notified promptly, thus the intervention of the protective actions can be delayed and the consequence of the release might not be mitigated on time. For these reasons predicting the quantity of the radioactive releases to diagnostic the prognosis of the nuclear emergency is paramount in the early phase of the emergency. Artificial intelligence can be employed to serve as the prediction tool in this purpose. In his paper, Joo et al. (2023) used Long Short-Term Memory (LSTM) to predict the radioactive material releases from Kori NPP in the event of severe accident scenario with high accuracy. Similarly, Fu et al. (2023) employed Gated Recurrent Unit (GRU) algorithm and SHapley Additive exPlanations (SHAP) method to forecast and train the trends of large severe accidents in NPP. The prediction of evolution of the nuclear power plant data during nuclear emergencies imply early prediction of the emergency prognosis which result in informative decision making and robust protective action implementation or reconsideration.

3.10 Enhancing human reliability in nuclear emergencies through artificial intelligence

In Nuclear Power Plants (NPPs), emergency situations such as Loss-of-Coolant Accidents (LOCA), Steam Generator Tube Ruptures (SGTR), or external events like earthquakes and cyberattacks require rapid and accurate decisions by human operators and emergency planners (Liu et al., 2021). The success of these decisions is critical to mitigating radiological consequences and ensuring public safety. However, human reliability during such high-stakes scenarios is challenged by multiple factors, including time pressure, fatigue, cognitive overload, and stress. Under these conditions, the likelihood of human error increases, as demonstrated in several Human Reliability Analyses (HRA) such as the Technique for Human Error Rate Prediction (THERP) (Kirwan, 1995) and the Standardized Plant Analysis Risk-Human Reliability Analysis (SPAR-H) (USNRC, 2004). Artificial Intelligence (AI) presents a transformative opportunity to enhance human reliability during emergencies (Liu et al., 2021). AI systems can continuously collect and process data from multiple plant sensors, identify early signs of component degradation or abnormal behavior, and support predictive diagnostics (Liu et al., 2021). During a severe accident such as a LOCA, AI can rapidly simulate accident progression, predict reactor core damage, and recommend optimal mitigation strategies. These AI-driven insights help operators and emergency planners make faster, evidence-based decisions, ultimately reducing the risk of human error. Recent studies published have explored the integration of AI-based decision support systems into nuclear safety infrastructures. For instance, models trained on historical incident data and real-time sensor input have demonstrated high accuracy in forecasting radiological releases and equipment failures (Liu et al., 2021). In a simulated SGTR scenario, AI systems equipped with natural language processing and real-time reasoning were shown to reduce decision latency by over 30%, while improving procedural compliance among operators (Liu et al., 2021). These findings underscore AI's growing role in strengthening Emergency Preparedness and Response (EPR) by complementing human judgment with timely and data-driven insights.

4 Challenges

Although artificial intelligence is advanced enough to assist in managing nuclear emergencies, its application is associated with different types of challenges.

4.1 Data related issues

The deployment of AI in EPR relies on a large amount of data to train and test the AI algorithms. The data related issues include data availability and accessibility (Soori et al., 2024). In numerous cases, the data available might be incomplete or inconsistent which may cause inadequate output (Ang et al., 2020). Additionally, the data related issue could be due to the data privacy and security because in the case of EPR the data used is related to safety and security of the public. Hence, some ethical and legal issue could arise from this application. In order to overcome this issue, the emergency authorities must ensure the most sensitive information is secured while used by AI models.

4.2 Computational resources issues

Implementation of Artificial intelligence in nuclear emergency management requires application of considerable computational resource, especially to train and process the deep learning algorithms (Guo, 2020). The limitation in computational resources in some areas, such as in remote location or in isolated location, may cause a challenge for these resources to support the artificial intelligent model (Velev, 2023) in some scenarios of nuclear emergencies. This limitation in computational resources might affect the application of AI to support the emergency response during real nuclear emergencies.

4.3 Integration with existing emergency system

The proposed novel idea in this paper implies introduction of artificial intelligence in the emergency preparedness and reason se systems. This introduction is not going to ignore the current systems that are working, instead, the idea is to implement AI within the existing systems and infrastructure of the emergency management program onsite and offsite. Integrating AI based system with the existing technological system, equipment, sensors, and other devices would require continuous interoperability (Soori et al., 2024). Machine learning based solutions for emergency management should have the ability to integrate with existing systems, e.g., command and control centers, sensors networks and emergency response networks (Wang, 2018). Furthermore, unrelated technologies often delay smooth integration, thus developing standardized interfaces and protocols to exchange the AI data with the existing emergency system is need (Werbrouck et al., 2024) to overcome the challenge of integrating intelligent algorithms with the existing emergency infrastructure.

4.4 Real-time performance capabilities

The application of AI in EPR is based on two main concepts, real-time data transmission and future trend prediction. One of the challenges associated with these concepts is the performance of real-time data transmission and processing. Real-time performance capabilities are essential in all the emergency scenarios (Velev, 2023). In order for the AI algorithms to be able to support the emergency responders and to provide real-time situation awareness and mapping, they must have the capability to process and analyze big amounts of data in real-time (Velev, 2023).

4.5 Scalability

The scalability in this context is to develop scalable solutions that are capable of handling vast amounts of data generated (Soori et al., 2024). In the case of the proposed topic in this paper, the scalability challenge refers to the ability of the ML algorithms to handle huge volumes of data and sustain real-time decision-making during nuclear emergencies. Furthermore, the scalability of the AI models and ML algorithms to reach expanding needs while sustaining performance levels might be challenging. Therefore, in order to ensure the performance and scalability of AI in EPR applications, there is a need to balance computational resources, processing power and memory, with the complexity of ML algorithms (Simaiya et al., 2024).

4.6 Black-box dilemma

Several modern AI systems act as black boxes, which means very little information is accessible to the user regarding how the system produces an output from its inputs (CNSC, 2024). Machine learning and deep learning algorithms are commonly viewed as "black boxes" in because of their complex topologies (Soori et al., 2024), hidden layers and complex feature for encoding the process (Jendoubi and Asad, 2024) and sometimes it can be challenging to recognize and understand the predicted information by these algorithms (Wang et al., 2024).

In a regulated industry like the nuclear industry, applying AI in EPR can be challenging due to the "Black Box" aspects of the ML and DL algorithms that are used to train the AI-based emergency preparedness models.

4.7 AI and human collaboration

The implementation of AI in emergency preparedness and response implies a shift in emergency responders and planners duties, moving from direct physical operation to supervisory and decision-support functions. Therefore, an active collaboration between emergency planners, emergency responders and decision-makers and AI systems is crucial to ensure safe and ideal application of artificial intelligence in EPR.

4.8 Transparency and interpretability

The deployment of artificial intelligence in emergency preparedness and response might raise concerns about the transparency and interpretability of ML and DL algorithms. Thus, it is indispensable to confirm that these algorithms are transparent, and their predictability and decision-making processes can be understood and analyzed (Velev, 2023).

Furthermore, AI models that could potentially be applied to support the EPR program are complex and can be hard for emergency planners to comprehend these models. Therefore, it is important to ensure interpretability and transparency in the AI model output (Ejigu, 2024).

4.9 Bias and fairness issues

Artificial intelligence models and ML algorithms can preserve biases and unfairness, in the case the data used to train these algorithms is biased or in the case the ML algorithms are intended to preserve selected biases (Velev, 2023). The preserved bias and fairness are considered as a challenge during emergencies, because the decisions made by ML algorithms can be affected by the bias which might cause indefinite outcomes (Velev, 2023).

In order to mitigate bias and the fairness, emergency organizations must apply fairness-aware algorithms and consistently examine the ML algorithms and the AI models for bias (Soori et al., 2024). Furthermore, the transparency in AI decision-making methods and the insertion of distinct perspectives during model development might further reduce the bias (Soori et al., 2024).

4.10 Cybersecurity challenges

The deployment of artificial intelligence in emergency response and preparedness poses a challenge for data security, privacy and cybersecurity. For instance, the implementation of AI to support the decision system during nuclear emergency requires to process very sensitive data which could raise many concerns regarding the privacy and the security of the data (Soori et al., 2024). Therefore, the emergency response authorities must follow a careful data protection regulation and employ robust cybersecurity measures to safeguard data (Allahrakha, 2023).

Furthermore, cyberattacks are another challenge associated with the automation of the emergency management system, for instance, the cybersecurity attacks could be in form of interference with the critical computer-controlled infrastructures that support the AI models, hi-jack, cut off sensors, cut off actuators, or even the cyberattacks may compromise the emergency-computing infrastructure (Nunavath, 2020). Therefore, qualifying the AI models against the cybersecurity threats is paramount in order to ensure safe and reliable application of artificial intelligence in managing nuclear emergencies.

4.11 Regulatory compliance

The upgrading of nuclear emergency preparedness and response by artificial intelligence requires amendments to existing regulations as well as development of new regulations, because the actual regulatory document does not include any requirement or guidance regarding the safe use of AI in the nuclear industry. This guidance is essential to guarantee compliance while maintaining the highest values of safety and reliability (Ejigu, 2024).

4.12 Technical expertise and training challenge

Deploying and implementing artificial intelligence-based systems to manage and support the nuclear emergency response might be challenging in case of lack of technical expertise.

Furthermore, the deployment of AI in EPR needs a high level of technical expertise, which might not be immediately available in many areas of application (Forsyth, 2019).

4.13 Cost burdens challenge

The proposed concept of applying AI in EPR is associated with a considerable cost burden. This burden is related to infrastructure expenses, new expert workforce expenses and continuous training expenses (Jendoubi and Asad, 2024). Matching the benefits of the AI technologies with the accompanying expenses could be a challenge for EPR authorities to take the initiative to deploy it in their systems. Additionally, implementing I to manage nuclear emergencies can be expensive for the countries that might lack the infrastructure or the resource to support such technology (Velev, 2023).

5 Significance of AI application in EPR

The application of artificial intelligence in the area of emergency preparedness and response holds significant potential to improve the readiness and the performance of the response during nuclear emergencies. The different artificial intelligence algorithms and real-time data transmission enable robust management of emergency situations and mitigation of the associated consequences.

The integration of artificial intelligence within the emergency preparedness systems can revolutionize the hazard assessment process by optimizing the identification of all the possible hazards that can trigger a nuclear emergency, based on the large computational capabilities of the AI algorithms to generate different hazard scenarios. This feature helps in meeting Requirement 4 of the IAEA GSR-Part-7 document.

Artificial intelligence algorithms are able to predict the release of radioactive material from nuclear power plant during an accident, and they are also able to predict the atmospheric dispersion models and the deposition profiles, which support the decision makers and help them decide about the safest protective actions to mitigate the stochastic effects from the radiation exposure. This feature helps in meeting Requirements 4 and Requirement 5 of the IAEA GSR-Part-7 document.

The integration of artificial intelligence and real-time data transmission offers the feature of fast and accurate mapping of the contaminated area and routes which could potentially enhance the monitoring and evacuation process during large nuclear accidents. This feature helps in meeting Requirement 14 of the IAEA GSR-Part-7 document.

Furthermore, the artificial intelligence algorithms are able to filter the uncertainties in the EPR simulation models, leading to more accurate modeling of the emergency scenarios, hence optimizing the dose projections during the preparedness phase. This feature helps in meeting Requirements 5, paragraph 4.28 of the IAEA GSR-Part-7 document.

By leveraging the predictability features of AI algorithms, the EPR system can benefit from it by forecasting the prognosis of the emergency situation, hence optimizing the protective actions in the early phase. This feature help in meeting the recommendation of the IAEA in their document "Operations Manual for IAEA Assessment and Prognosis During a Nuclear or Radiological Emergency".

Artificial intelligence can also be employed to enhance communication to the public during emergencies by potential implementation of intelligent Chatbots. This feature helps in meeting Requirement 13 of the IAEA GSR-Part-7 document.

In essence, the application of AI in EPR includes several features that hold promises to enhance the emergency response from the preparedness phase to the termination phase. Additionally, this application would eventually help the EPR authorities to meet the general and the functional requirements in GSR-Part-7 document, as shown in Figure 7, hence meeting the international standards and guidelines for dealing with nuclear emergencies.

6 Future work directions

The deployment of artificial intelligence in emergency preparedness and response is an evolving field with high potential to have robust application in the next years. Based on the comprehensive literature review, that is based on the most recent research papers as shown if Figure 8, and the proposed novel ideas in the present paper, the future work should focus on enhancing the reliability of AI algorithms to be able to be applied safely in nuclear emergency preparedness and response. More research to improve predictability and the real-time performance of AI is recommended as future work. This will lead to more accurate output of the AI algorithms and models during nuclear emergencies. Furthermore, enhancing the EPR hazard assessment by deployment of AI in hazard scenario prediction and threat identification is another area of research that is recommended based on the comprehensive established in this paper. Additionally, application of AI in contamination monitoring and mapping holds many promises and requires further research and development to be able to be employed safely by emergency responders authorities. We are also recommending more research on the proposed idea of autonomous assessment and prognosis of the emergency situation using artificial intelligence. This is because currently, the assessment of the emergency, which is critical to determine the efficacy of the protective actions, is only performed by humans. Added to that, as the AI algorithms rely heavily on the data, in our case the data that are coming from the sensors, we are recommending more research to develop advanced measurement devices and IoT sensors that can be integrated easily within the EPR systems and can be exploited smoothly by the AI algorithms and models. It is also highly recommended to develop and upgrade the current AI algorithms to be able to deliver more accurate outputs in the area of decision-making. This is because the decision-making process in EPR is very important and requires optimized output to be considered in the final decision.

Another important area of future development is cybersecurity. This is not only related to applying AI in EPR, but it is related to any application that integrates AI with its systems, especially in the nuclear engineering field. This is because the different inputs to the AI algorithms are the data that is coming from NPP or from radiation levels sensors, etc. which are critical to the safety and the security of the plant and the public. Therefore, more work is recommended to be done in the area of cybersecurity to make sure that the data is transmitted securely from the EPR systems to the AI algorithms. Lastly, the last area of future research recommendation is the regulatory compliance area. More work should be done to address the different concerns that the regulatory authorities might have regarding the application of AI in emergency preparedness and response. Additionally, the regulatory authorities should also conduct more work in the future to develop new regulatory documents regarding the safe use of AI in EPR, with a clear set of requirements and guidance.

7 Conclusion

The application of artificial intelligence in emergency preparedness and response systems is a transformative approach to optimize the readiness and response during nuclear emergencies. The combination of the predictability capabilities and the computational features of artificial intelligence models and machine learning techniques holds many promises the enhance the readiness and the protective action strategies during emergencies. Through the continuous evolution of technology, future development will further enhance these capabilities leading to more enhanced and optimized protections strategies. The significance of integration artificial intelligence in EPR includes enhanced hazard assessment, optimized dose projections models, advanced evacuation strategy, improved communication and enhanced decision-making throughout the different stages of the emergency. However, the adoption of these technologies also necessitates addressing challenges related to cybersecurity, regulatory compliance, and algorithm reliability. In this paper, we have reviewed the most recent papers published in the areas of emergency management, we have emphasized the significance of applying artificial intelligence in EPR and we have highlighted the need for further research on this application with a particular focus on addressing the associated challenges to ensure safe and reliable implementation of the AI models in the nuclear emergency management systems.

Author contributions

CJ: Methodology, Visualization, Resources, Writing – original draft, Data curation, Conceptualization, Validation, Writing – review and editing.

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Glossary

AI	Artificial Intelligence
AIML	Artificial Intelligence Markup Language
ANN	Artificial Neural Network
ASC	Advanced Simulation and Computing
CANDU	Canada Deuterium Uranium
ConvTran	Conventional Transformer
CNN	Convolutional Neural Network
DHS	Department of Homeland Security
DL	Deep learning
DRNN	Deep Rectifier Neural Network
DiD	Defence in Depth
ELM	Elaboration Likelihood Model
EPR	Emergency Preparedness and Response
EPZ	Emergency Planning Zone
GB	Gradient Boosting
GRU	Gated Recurrent Unit
IAEA	International Atomic Energy Agency
IoT	Internet of Things
LOCA	Loss Of Coolant Accident
LR	Linear Regression
LSTM	Long-Short Term Memory
MDP	Markov Decision Process
ML	Machine Learning
NLP	Natural Language Processing
NLU	Natural Language Understanding
NNSA	National Nuclear Security Administration
NPP	Nuclear Power plant
OIL	Operational Intervention Level
PAZ	Precautionary Action Zone
PWR	Pressurized Heavy water reactor
RF	Random Forest
RNN	Recurrent Neural Network
SHAP	SHapley Additive exPlanations
SVM	Support Vector Machine
UPZ	Urgent Protective Action Planning zone
WHO	World Health Association