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Uncertainties and their treatment in the quantitative risk assessment of domino effects: Classification and review

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A B S T R A C T

Domino accidents are typical low-frequency and high-consequence events in chemical process industries. Applying quantitative risk assessment (QRA) in domino accident assessment is challenging due to the uncertainties in the escalation process. Meanwhile, the outcomes of QRA are subject to a certain degree of unreliability due to the inappropriate representation of uncertainty. This paper reviews the literature in the field of QRA of domino accidents that may happen in the chemical process industries. Firstly, the sources of uncertainty in risk assessment of domino effects are identified and categorized based on a fundamental structure of uncertainty and a QRA framework. Furthermore, the current methodologies and approaches applied for handling various uncertainties (input uncertainty, model parameter uncertainty, and model structure uncertainty) in the QRA related to domino effects are reviewed. Based on the literature review results, current challenges with respect to uncertainty handling in QRA of domino accidents are discussed, and recommendations for future research are given before the conclusions are presented. This study helps researchers to get insights into the interface between uncertainty fundamentals and the QRA framework and the current status of uncertainty handling in the QRA of domino effects. Furthermore, this study promotes the development of new approaches for handling uncertainty in domino accident analysis.

1. Introduction

Domino effects are a category of multi-hazard accidents (He et al., 2022). A domino effect refers to a chain of accidents, such as fire/-explosion/missile generated by an accident in one unit and causes secondary and higher-order accidents in other units (Khan and Abbasi, 1998). It is identified with the features of "propagation" effects and "escalation" effects (Reniers and Cozzani, 2013a). Although the probability of its occurrence is very low, it can cause significant loss of life and property (Khakzad et al., 2013). In European Union, Seveso III directive 2012/18/EU (Seveso III, 2012) requires the safety report to identify the possible places that may result in or increase the risk of a domino effect.

Quantitative risk assessment (QRA) is one of the four main research areas of domino effects in the process industry, in addition to past accident analysis, vulnerability models, and safety management (Necci et al., 2015). QRA of domino effects is used to comply with Seveso III regulations to assess the likelihood of a failure due to a domino effect and helps prevent major hazards (Alileche et al., 2015). Since the early 1990 s, attempts have been made to evaluate domino effects with quantitative methods (Bagster and Pitblado, 1991; Pettitt et al., 1993; Morris et al., 1994). But a complete QRA framework to include domino effects was first proposed by Cozzani et al. (2005), as shown in Fig. 1.

QRA is a systematic method that integrates knowledge and uncertainty to identify and quantify risks of complex engineering systems such as nuclear plants and process industries (Flage et al., 2014; Villa et al., 2016). As opposed to deterministic methods of other chemical engineering operations, QRA typically uses probability information to estimate the risk of chemical plants. Therefore, QRA is also termed as probabilistic risk assessment (PRA) in the nuclear industry (Arendt, 1990). QRA has the merit of studying a large number of possible

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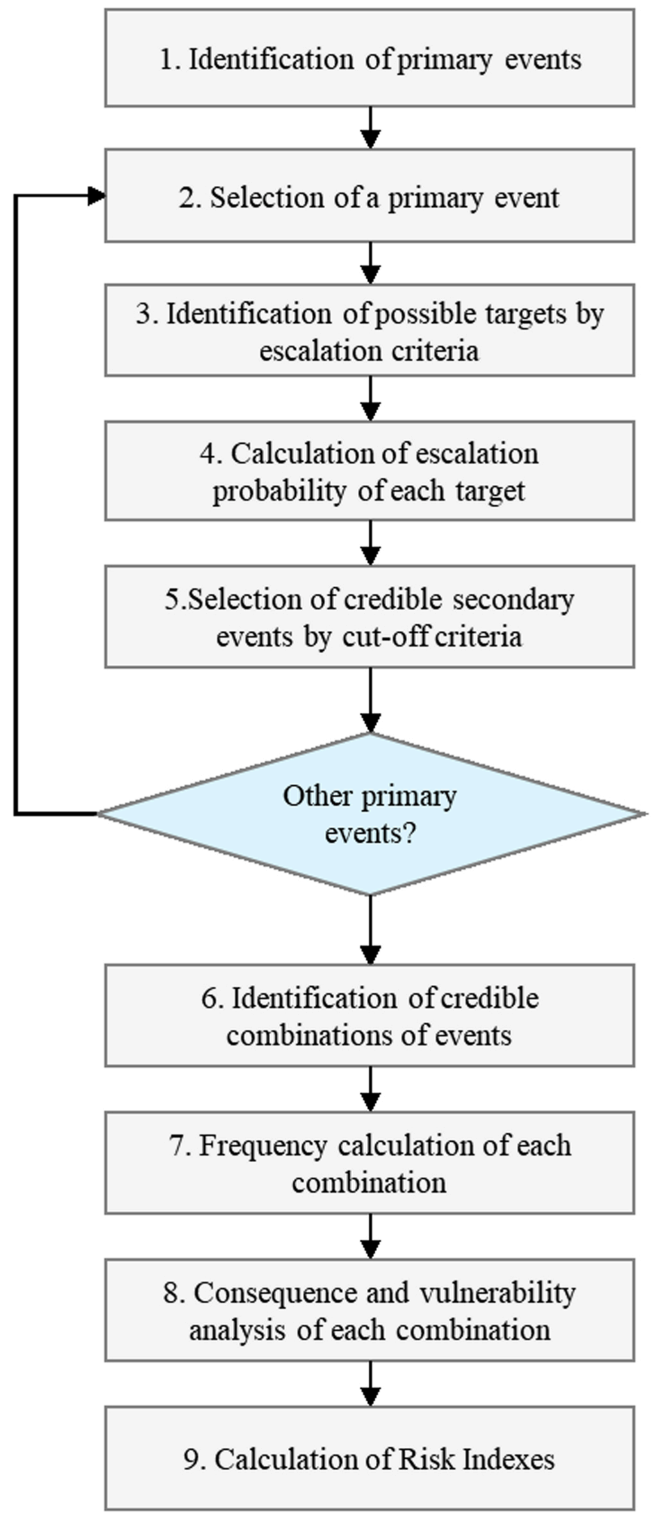

Fig. 1. QRA of domino effects.
Figure adapted from (Cozzani et al., 2005).

accident scenarios to increase the completeness of accident analysis. Additionally, QRA can identify major accident scenarios for subsequent risk management and avoid wasting resources on insignificant risk factors (Apostolakis, 2004). However, due to the complexity of systems in many process industries and the enormous types of components, it isn't easy to obtain quantitative data for all components (Ferdous et al., 2011). QRA methods have received sustained criticism for the reliability and validity of assessment results (Winkler, 1996; Apostolakis, 2004; Villa et al., 2016; Pasman et al., 2017; Goerlandt et al., 2017). How to represent the uncertainty in modeling the system and assessing failure effects with various information sources of complex systems has become a difficult task for QRA (Winkler, 1996).

Generally, uncertainty handling or treatment in a QRA context means applying various methods to characterize/represent/measure uncertainty and then propagating those representations in mathematical models (Quelch and Cameron, 1994; Ferdous et al., 2011). It should be noted that the terms "risk analysis" and "risk assessment" are used interchangeably in some studies. However, if we look into the ISO (31000): 2018 risk management guidelines (ISO 31000, 2018), risk assessment consists of risk identification, risk analysis, and risk evaluation (as reported in Fig. 2). To avoid misinterpretation, risk assessment and risk analysis are used as two separate concepts in this paper. Most of the previous uncertainty research in risk assessment is merely focused on how to characterize uncertainty in quantitative risk analysis (Paté-Cornell, 1996; Flage and Aven, 2009; Aven and Nøkland, 2010). Probability analysis and consequence analysis are two important components of risk analysis. The treatment of uncertainty in risk analysis is only related to the likelihood of consequences of each risk (Purdy, 2010). Probabilistic models that treat uncertainties as random variables are the predominant approach in risk analysis. Other methods of handling uncertainties include probability-bound analysis, imprecise probability, evidence theory, possibility theory, and fuzzy set theory (Flage et al., 2014). By contrast, QRA is a systematic analysis method that includes not only the estimation of risk (specifying likelihoods and consequences) but also the identification of hazards causation and potential escalation pathways, as well as the determination of risk level (Vinnem, 1998). Generally, uncertainties in the QRA process could be classified into three categories: model uncertainty, parameter uncertainty, and completeness uncertainty (Vesely and Rasmuson, 1984; Yazdi et al., 2019). Although previous scholars have investigated the uncertainty treatment approaches of QRA, those studies merely emphasized specific procedures or techniques applied in QRA. For instance, Abdo et al. (2017) studied the uncertainty quantification approaches in risk assessment, with a special focus on inaccuracies related to input data of setting values for certain parameters. Yazdi et al. (2019) reviewed the aleatory and epistemic uncertainty handling methods in QRA on input variables. But the review is limited to a specific risk

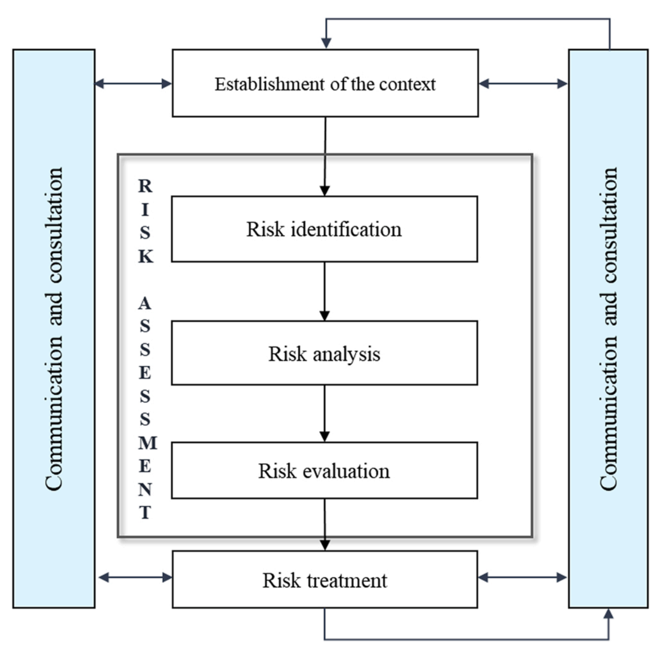

Fig. 2. Risk management for process industry.
Figure adapted from ISO (31000): (2018) (ISO 31000, 2018).

assessment approach, fault tree analysis (FTA).

Compared with single-hazard accidents, data scarcity is more evident due to the complexity and rarity of domino effects (Khakzad et al., 2018; Huang et al., 2022). Moreover, the QRA of domino effects must consider propagation probability, escalation paths, and vulnerability analysis, which is not necessary for the single-hazard QRA process (Swuste et al., 2019). The early attention to uncertainty treatment of domino effects was from vulnerability analysis that applies simple probit models to replace deterministic ways in calculating a number of damage scenarios (Cozzani et al., 2006; Chen et al., 2020a). Although vulnerability analysis is most used in the QRA process, only in recent years has the treatment of uncertainty begun to be highlighted in QRA context (Ji et al., 2018; Khakzad et al., 2018; Ding et al., 2020; Ding et al., 2022a). Previous studies made distinctions between parameter uncertainty and model uncertainty (Khakzad et al., 2018), input data uncertainty and model uncertainty (Kong, 2021), or scenario uncertainty and propagation uncertainty (Chen et al., 2020a) in domino effect analysis. Several scholars have presented literature reviews related to domino effects from different angles, including escalation criteria (Alileche et al., 2015), research topics (Necci et al., 2015), and historical perspectives (Swuste et al., 2019). In addition, Chen et al. (2020a) provided a comprehensive review of approaches to modeling and managing domino effects in process industries. Nevertheless, a systematic review that revealed the uncertainty and uncertainty treatment in QRA of domino effects is still lacking. Xu et al. (2022) conducted an exploratory review of the uncertainties due to the lack of knowledge of experts in QRA of domino effects. A proposed framework for uncertainty factors, including data sources, knowledge, and models, was applied to identify typical uncertainties at each stage of QRA of domino effects.

With respect to our previous research (Xu et al., 2022), this study emphasized how QRA is used to tackle uncertainties in assessing risks of domino effects instead of focusing on "hidden uncertainties" in QRA introduced by experts due to a lack of knowledge. The main research purpose of the present work is to provide insights into the uncertainty in the domino effects modeling and investigate the current approaches for handling various uncertainties in the QRA of domino effects, which may be missing from past reviews. Uncertainty treatment methods under different risk perspectives are elaborated. An uncertainty classification model for QRA is constructed under a modern risk concept perspective. The state-of-the-art QRA approaches in process industries and how they are applied for handling uncertainty in domino effects are reviewed and classified. Current research trends and limitations are analyzed for potential future directions. This review highlights the potential to elevate the reliability of QRA of domino effects.

The rest of the paper is structured as follows. Section 2 elaborates on the fundamentals and relationships of uncertainty and risk. Section 3 explains the research and review methodology used in the paper. The uncertainty with respect to the QRA of domino effects is investigated in Section 4. Section 5 focuses on the current methodologies and approaches applied to handle various uncertainties in the QRA of domino effects. Finally, current research trends, knowledge and technical gaps, and future research directions are discussed in Section 6 before concluding remarks are provided in Section 7.

2. Fundamentals of quantitative risk assessment (QRA) and uncertainty

In risk research, different views exist with regard to the concept of risk and uncertainty. The treatment of uncertainty in QRA under different perspectives of risk and uncertainty varies. To specify the scope of the literature review, this section provides an overview of the fundamentals of risk and uncertainty. Section 2.1 elaborates on the relationship between the definitions of risk and uncertainty. Section 2.2 compares two different views regarding the understanding of uncertainty handling in risk assessment. Section 2.3 gives a theoretical foundation of uncertainty in QRA procedures.

2.1. Relationships between risk and uncertainty

There is abundant literature on definitions of risk and uncertainty. The relationships between risk and uncertainty can be divided into three main categories, as shown in Fig. 3. Risk as objective (quantifiable) uncertainty is proposed by economist Knight (1921) and is mostly adopted in economic and finance literature. In this paper, we put emphasis on the subsequent two perspectives. In contrast to the concept that risk is uncertainty, the other two perspectives regard risk as a different concept. That the definition risk is probability of consequence in engineering fields is mainly following the argument of Kaplan and Garrick (1981), in which risk is defined by three triplets scenarios s_i, probability p_i, and consequencex_i. After Kaplan and Garrick, social scientists began to reconsider the relationships between risk and uncertainty. They introduced the third perspective that uncertainty constitutes a main component of risk (Rosa, 1998). Aven (2010) formalized the uncertainty-based risk definition as $Risk = (A, C, U)$, where

- A denotes the specified or identified events, e.g., the loss of containment (LOC) by lightning;
- C represents the specified or identified consequences that may result from the occurrence of A, e.g., fatalities, damage to equipment, monetary loss, etc;
- and U denotes the uncertainty about A and C.

In recent years, more and more scientists with engineering backgrounds (Milazzo and Aven, 2012; Goerlandt and Reniers, 2016; Paltrinieri et al., 2019) and risk-related standards and guidelines have come to embrace this notion (Cabinet Office, 2002; IRGC, 2017; ISO 31000, 2018;). This perspective sees a clear distinction between risk and how it is measured. Probability is a measurement approach of uncertainty while uncertainties still exist without specifying probabilities. Under this approach, risk assessment is highly related to the treatment of uncertainty of alternative outcomes.

2.2. Risk perspectives and uncertainty treatment

Despite early engineers do not regard uncertainty is a component of risk, however, they still work on dealing with various uncertainties in risk assessments. The above different technical perspectives of risk and uncertainty bring about substantial differences in how they conceptualize and represent relevant uncertainties in risk assessment. Aven and Heide (2009) distinguished these two types of methods in risk analysis as probability-of-frequency approach and Bayesian approach, respectively: 1) Probability-of-frequency approach: Risk analysis is the calculation of the relative frequency of different outcomes. 2): Bayesian approach: Risk analysis is the calculation of uncertainty of different outcomes. This section explores the difference between the two approaches to uncertainty handling with reference to the classification of Aven and Heide (2009).

2.2.1. Probability-of-frequency approach

In probability-of-frequency approach, random variabilities (aleatory

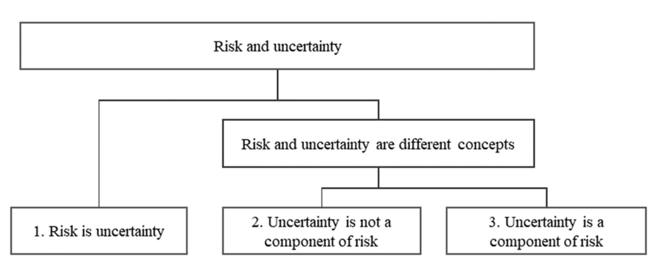

Fig. 3. The relationships between risk and uncertainty.

uncertainty) is considered an integral part of risk (Nilsen and Aven, 2003). Frequentist probability approach and Monte Carlo simulation are the predominant approaches to quantify and propagate uncertainty under this approach (Winkler, 1996; Samson et al., 2009). In addition to this kind of uncertainty that is aroused by natural randomness, frequentists assume there is another kind of uncertainty which is the uncertainty implied in risk assessment results caused by the inadequate knowledge of experts. To facilitate handling these two types of uncertainties, distinctions are made between aleatory uncertainty and epistemic uncertainty. Fig. 4 depicts the types of uncertainty and their relationship.

- Aleatory uncertainty: The uncertainty due to inherent variability.
- Epistemic uncertainty: The uncertainty due to the lack of data, understanding and knowledge about the world.

Epistemic uncertainty is also termed as "secondary uncertainty," and it is interpreted as uncertain about frequentist probability. It is most represented by Bayesian approach (subjective probability) and expert judgment (Paté-Cornell, 1996).

2.2.2. Bayesian approach

By contrast, Bayesian approach agrees that QRA itself is a way to characterize the uncertainty related to the outcome. There is no need to draw a clear border between different types of uncertainty, as there is only one kind of uncertainty, which is uncertainty due to lack of knowledge (Winkler, 1996; Nilsen and Aven, 2003). The "epistemic uncertainty about frequency" in probability-of-frequency approach is, in fact, the deviation between reality and the modeled system. This perspective is in line with ISO (3100)0: (2018) (ISO, 2018), that uncertainty is defined as a state related to knowledge of an event, its consequence, or likelihood.

It is important to note that "epistemic uncertainty" is defined by Flage and Aven (2009) as uncertainty implicit in the background knowledge of QRA. To tackle the hindered uncertainty, qualitative uncertainty assessment based on model assumptions within extended QRA procedure has been developed as an alternative and simpler approach to Monte Carlo simulation (Flage and Aven, 2009; Milazzo and Aven, 2012; Milazzo et al., 2015). However, in subsequent studies, the measurement of the degree of uncertainty of assessment results was changed to the strength of knowledge (Aven, 2013; Flage and Aven, 2017).

2.3. Uncertainty in QRA

Continuing our study on uncertainty in QRA, after a brief review of the concepts of risk and uncertainty. To build an uncertainty classification framework for QRA, we adopted the modern risk definition that risk is a combination of uncertainty and consequences (Aven, 2010). There are three main types of uncertainty in QRA: input uncertainty, model parameter uncertainty, and model structure uncertainty, as shown in Fig. 5.

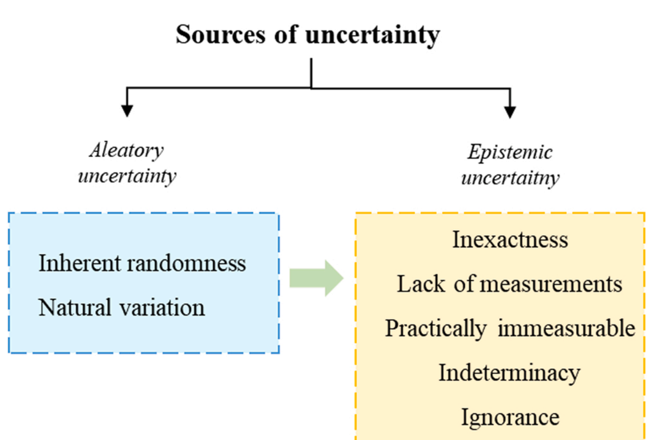

Fig. 4. Sources of uncertainty. Based on Van Asselt and Rotmans (2002) and Hayes (2011).

Risk assessments almost always involve system models representing the uncertainties related to outcomes (Apostolakis, 1990). The real world or the reference system being studied could be regarded as a combination of observable quantities Y, $X(X_1, X_2 \ldots X_n)$, and a set of causal relationships (Draper et al., 1999; Nilsen and Aven, 2003; Cox and Baybutt, 1981). A system whose output depends on a deterministic causal relationship judged by analysts on various parameters could be written as :

$$Y = f(X_1, X_2 \ldots X_n) \tag{1}$$

- Y denotes the system output.
- X represents a set of input parameters.
- f is the assumption of model structure.

QRA starts with defining systems boundaries and describing the technical system (i.e., process, structure, safety, emergency systems, etc.) (IRGC, 2017). Input uncertainty is associated primarily with data that describe the reference system and the system's boundaries. It can be further divided into scenario uncertainty and data uncertainty. Model parameter uncertainty and model structure uncertainty refer to uncertainty about data for parameter analysis and interrelationships between variables. Uncertainties in input, parameters, and model structure propagate through the model, eventually resulting in model output uncertainty.

3. The review methodology

This literature review aimed to identify various uncertainties and uncertainty treatment approaches in QRA of domino effects in chemical process industries. To better understand the link between the uncertainty of domino effects and uncertainty handling methods in QRA, a three-stage literature review methodology was formulated, as shown in Fig. 6.

The first stage of this literature review is to use the database to search the relevant literature according to the research question. This article selects the web of science database to retrieve the risk and safety research related to the domino effect. It is important to note that each phase of QRA of domino effects can be viewed as a way to deal with uncertainty. Yet, most publications on risk assessments of domino effects do not mention uncertainties specifically. For this reason, when setting keywords in the literature screening process, all documents relating to risk assessment are included in the search scope. The keywords used to collect relevant publications include the title ("domino" OR "multi-hazard") AND topic ("process industry" OR "chemical plant" OR "chemical industry" OR "industrial" OR "oil" OR "gas" OR "petroleum" OR "LNG" OR "LPG") AND topic ("risk" OR "risk analysis" OR "risk assessment" OR "risk management" OR "safety"). After obtaining the search results, non-English language articles and non-research articles are filtered. The time span of literature research is before the 28th, September 2022. As a result, 142 articles from 1998 to 2022 were obtained in the first stage.

In the subsequent stage, those articles that are unrelated to the research topic are excluded by reading the titles or abstracts. First, research articles from irrelevant research areas are excluded. After excluding duplicates, 5 articles from spectroscopy, physical geography, polymer science, electrochemistry, materials science, and healthcare science services are removed. Then, 11 articles focused on statistical or past accident analysis and risk management and operation planning are excluded from the results. The screening stage ultimately included 126

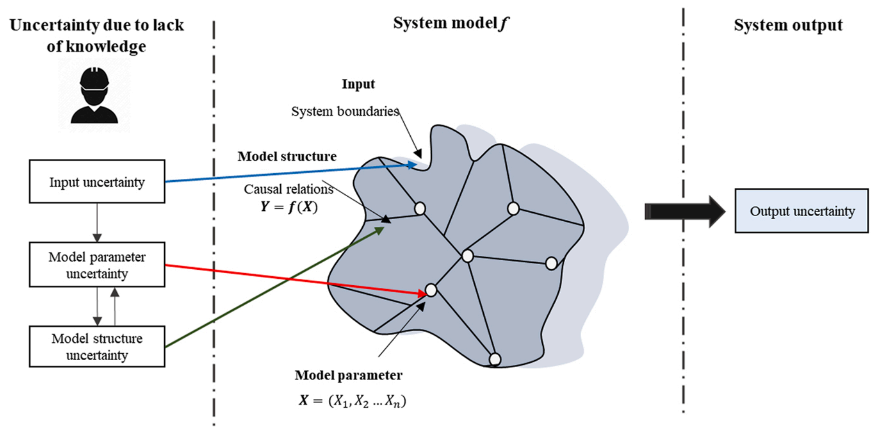

Fig. 5. Illustration of three types of uncertainty in QRA model.

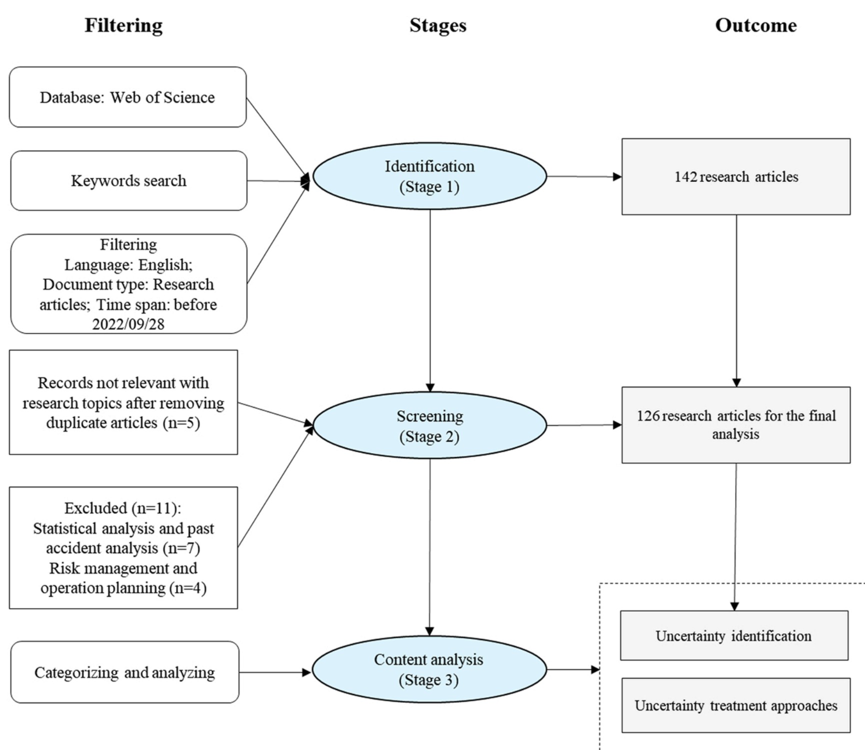

Fig. 6. Research design and stages for literature review of this study.

articles for final content analysis.

Since in many articles on risk assessment, the method of dealing with uncertainty is not emphasized in the title or abstract and keywords. Thus, instead of just analyzing the abstract, this review went further and analyzed the body of the papers in the third stage. The third stage is divided into two steps: uncertainty identification and uncertainty treatment approach analysis.

4. Uncertainty in QRA of domino effects

Based on the categorization, different types of uncertainty are analyzed in QRA of domino effects are investigated by combining the research literature.(Table 1).

Table 1
Types of uncertainty in QRA of domino effects.

Types	Descriptions	Examples
Input uncertainty uncertainty	Defining system boundaries and description of system	Environmental factors Cooperative management Type of domino accidents Prevention and mitigation management measures
Model parameter uncertainty	Variables used to calculate likelihood and consequence of domino effects	Probability of primary events Threshold of damage Probability of escalation LOC intensity
Model structure uncertainty	The interrelationships among variables	Propagating sequence Spatial-temporal effects Synergistic effects

4.1. Input uncertainty

4.1.1. Scenario uncertainty

In the QRA of domino effects, four driving factors of scenario uncertainty are identified: (i) environmental conditions, (ii) organization factors, (iii) type of domino accidents, and (iv) prevention and mitigation management measures. The uncertainty of various scenarios is depicted in Fig. 7.

According to the cause of primary events, domino effects can be classified as accidental domino effects caused by accident events, Natech domino effects triggered by natural disasters, and intentional domino effects induced by intentional attacks (Chen et al., 2020a). Although the frequencies of domino events induced by intentional attacks or natural disasters are lower than non-deliberate events, the overall consequences may be more severe due to the simultaneous release of hazardous materials in several installations or multiple sources in one installation. Thus, the Natech and intentional events are more likely to result in multiple primary events than accidental events in the impact area (Krausmann et al., 2011; Khakzad and Reniers, 2019). Different from the other two types of domino effects, quantitative approaches to assessing the risk of intentional domino effects are challenging as it is difficult or even impossible to estimate the probability of attacks (Reniers and Audenaert, 2014). The frequencies or probabilities of the initiating events are hardly included in the assessment of intentional events while with a focus on vulnerability analysis of installations (Landucci et al., 2015b; Chen et al., 2019, 2020a; Khakzad and Reniers, 2019).

Safety management measures such as inherent safety design, safety barriers, and security barriers are other factors that contribute to scenario uncertainty. Safety barriers or protection layers, including the basic process control system, safety instrumented systems, passive and active devices, safety shutdown systems, protective systems (post-release actions) and emergency response plans reduce escalation probability and impacts of related consequences (Landucci et al., 2015). For instance, in fire escalation domino scenarios, installations do not fall out immediately, and time is needed before the structure of target installations is damaged. The "time to failure (*ttf*) is a key parameter representing the resistance of equipment to external fires. It depends on both the characteristics of the primary fire scenarios and the features of the secondary equipment involved in the fire. Available fire protection systems and safety barriers can prevent or mitigate the escalation by delaying the time to failure. Furthermore, the potential security attacks in chemical and process facilities evoke the integration of safety and security barriers in quantitative risk assessment studies aiming at intentional domino effects.

An industrial region consists of a number of separate chemical plants

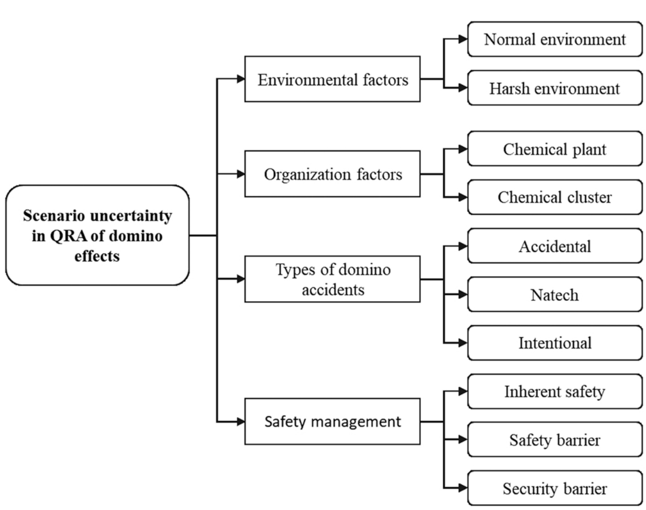

Fig. 7. Scenario uncertainty of domino effects.

called chemical cluster or chemical industrial park. The safety and security resources allocated in domino effects occurring within the boundaries of a plant are defined as internal domino effects, while domino effects that are struck by neighboring plants are called external domino effects (Reniers, 2009). Although a chemical plant may benefit from the safety systems of neighboring chemical plants, it may decrease the security level due to the change of attractiveness of counterparts (Reniers and Audenaert, 2014).

Meanwhile, the potential degradation of the safety barrier is also considered in scenario uncertainty. The relevant decrement in protection availability due to the harsh environment may have a strong impact on the frequency of domino accidents. The probability and frequency of second scenarios with safety barriers in harsh environment are higher than in normal environments (Landucci et al., 2017).

4.1.2. Data uncertainty

Lack of adequate information of modeled system and inaccurate data are the two common types of data uncertainty (Hayes, 2011). In the QRA of domino effects, the input phase mainly relates to the data collection of chemical industry park(s) and atmosphere. Normally, the input for the chemical industry includes the layout (i.e., number of equipment, the position of equipment), operational data of equipment (i.e., stored/processed substance, operative pressure, shape, capacity, etc.), performance data of safety or security barrier associated with each equipment, conditions of human and assets (i.e., number of people, location of the building) and the information about the surrounding environment (humidity, wind direction, wind speed, etc.).

4.2. Model parameter uncertainty

The model parameter used to calculate the likelihood and consequence of domino effects varies according to the specific accidents scenario. It generally includes the frequency of primary events, LOC intensity, escalation vectors, escalation probability, probability of damage states, etc. When conducting QRA of domino effects, lack of data for certain parameters to perform probability or consequence analysis is common (Abdolhamidzadeh et al., 2010; Ji et al., 2018).

For instance, the availability of reliable damage analysis models is the key point QRA of domino effects. The damage to the second equipment is influenced by a list of variables such as the physical effect intensity, mechanical properties of the target equipment, operative conditions, safety resources, etc. These variables together constitute the uncertainties that rule the vulnerability of equipment (Necci et al., 2015). The LOC intensity is mainly affected by the intensity of the structural damage, the damaged installations' operating conditions, and the released substance's physical state (Antonioni et al. (2009)). Although detailed structural analysis is available, the framework of QRA requires introducing simplified methodologies to describe damage intensity.

4.3. Model structure uncertainty

Model structure uncertainty arises from a need for a sufficient understanding of the behavior of the system and the interrelationships among its elements (Walker et al., 2003). It reflects in the QRA of domino effects as the omission of dependencies between the variables. The two most critical dependencies are synergistic effects and temporal-spatial evolution.

4.3.1. Temporal-spatial dependency

The temporal-spatial dependency is one of the main uncertainties associated with modeling the sequence of events during a domino scenario. A domino effect is a dynamic process involving space and time. The spatial dimension is reflected in the diverse propagation patterns. According to the spatial propagation characteristics, the propagation patterns can be divided into simple propagation, multilevel domino chain, and multilevel propagation (Reniers and Cozzani, 2013b; Chen et al., 2018). The temporal dimension is reflected in the evolution process. Depending on the specific accident scenario, the dynamic evolution of a pool fire-induced domino accident can be divided into safety, under radiation, pool fire, and burnout (Huang et al., 2021); The evolution process of Natech domino effects can be classified as the Natech stage, the derivation stage, the domino stage, the deterioration stage, the extinguish stage (Men et al., 2022).

4.3.2. Synergistic effects

A synergistic effect is “the collaboration of concurrent primary and secondary accidents to trigger another accident in a tertiary unit and so forth, making an already started domino effect continues” (Khakzad, 2015). The synergistic effects will aggravate the escalation of induced secondary accidents, thereby increasing the risk of domino effects. The research on domino effects is focused on two types of synergistic effects: the synergistic effect of multi-hazards of the same type and the synergistic effect of multi-hazards of different types (Ding et al., 2022a). But more broadly, the synergic effects include not only the triggering relationship between different incidents, but also the severity and the intervention of the fire brigade (He and Weng, 2020b).

5. Uncertainty treatment approaches in QRA of domino effects

In this section, how the various categories of uncertainties are treated in QRA of domino effects are reviewed. Fig. 8 summarizes the uncertainty treatment approaches used in the cited literature. Based on the locations of uncertainty mentioned in the previous section, each category of uncertainties and their treatment are analyzed in the following content.

5.1. Methodologies to handle input uncertainty

5.1.1. Event tree analysis

Event tree analysis (ETA) is a technique used to describe the consequences of an event (initiating event) and estimate the likelihood (frequency) of possible outcomes of the event (Ferdous et al., 2011). To extend the framework with the integration of different types of domino accidents, ETA is frequently used to deduce the scenarios that occurred after initial accidents and quantify primary accidents.

Yang et al. (2018) proposed a predicting method to evaluate the probability of a domino effect triggered by lightning in a chemical tank farm. The accident sequences following the lightning strike are obtained using ETA. However, it did not consider the analysis of the consequences of the overall scenarios and the calculation of the additional risk deriving from escalation due to domino effect. Misuri et al. (2020) further proposed a comprehensive procedure tailoring lightning risk

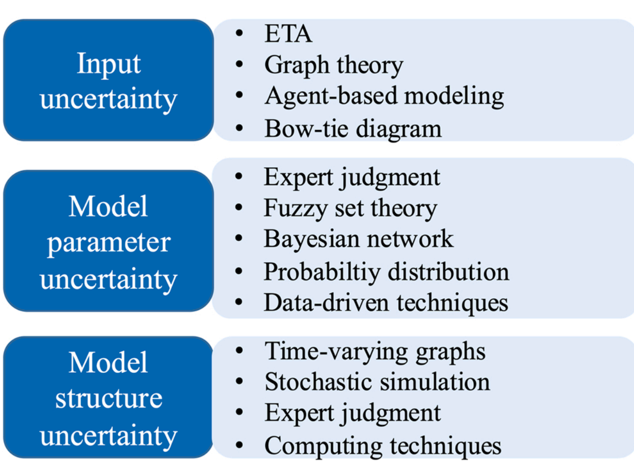

Fig. 8. Uncertainty treatment approaches in QRA of domino effects.

assessment to include probabilistic models for domino escalation based on probit approach and combinatorial analysis. The impacts on different types of storage tanks by lightning strike are investigated using ETA. Huang et al. (2020) conducted a quantitative analysis of Natech events in chemical tank farms triggered by earthquakes based on Monte Carlo simulation considering the domino effect. The possible fire and explosion scenarios of flammable and volatile liquid materials after the LOC of the earthquake are obtained by ETA. Zeng et al. (2021) developed a comprehensive procedure assessing the probability of flood-induced domino escalation and applied ETA to analyze the possible primary accidental scenarios and their probabilities after a LOC event.

ETA allows considering the detailed barrier performance through specific operators. The event tree acts to include all the possible events in the case of success and/or failure of the installed active and passive protection. Landucci et al. (2015a) quantified the effects of safety barriers on fire escalation probabilities based on LOPA (layer of protection analysis). The various domino scenarios are analyzed with the consideration of water deluge systems (WDS), pressure relief valves, fireproofing, and emergency teams. Based on the methodology, the role of each safety barrier in preventing a domino effect at a given location was determined by a specific set of key performance indicators (KPI) utilizing advanced event trees (Landucci et al., 2016). Landucci et al. (2017) investigated the dynamic evolution of fire protection systems during domino effects and used ETA to implement the degradation events into the quantitative assessment framework. Moreno et al. (2022) developed a probabilistic study accounting for the combined contributions of safety barriers and physical protection systems (PPSs) in preventing cascading events triggered by security scenarios. Each identified attack scenario and the performance of safety barriers and PPSs are represented by ETA.

Safety barriers or protective layers to prevent the propagation of cascading events can be affected by external factors such as harsh environments. Landucci et al. (2017) developed a structured approach to the quantitative assessment of cascading events, accounting for the availability and effectiveness of emergency response in the presence of harsh environment. The effects of harsh environmental conditions on safety barrier performance were quantified by applying a modified ETA. The approach was adopted by Bucelli et al. (2018) to extend the application conditions from onshore to offshore installations.

5.1.2. Graph theory

Despite the event tree being simple and effective tool to tackle the scenario uncertainty of domino effects, they are not applicable to the higher-level domino scenarios. In the mathematical graph theory, each installation can be denoted as a node, and the (causal) relationships between the components of a system are represented by vertices(nodes) and a set of edges (arcs) (Khakzad and Reniers, 2015). The graphical methods include Bayesian network (BN), dynamic Bayesian network (DBN), dynamic graph, and Petri-nets have the advantage of modeling and capturing the uncertainties of higher-order domino effects through their simple structure.

To quantify the possible performance degradation of the barrier among the events of fire escalation domino scenarios, a dynamic Bayesian network (DBN) methodology based on event tree analysis is developed to model the evolution of fire scenarios with the consideration of time-dependent fire protection systems’ performance (Khakzad et al., 2017). The implementation of a safety barrier into the system of DBN can be modeled by adding chance nodes and auxiliary nodes. Naderpour and Khakzad (2018) developed a methodology to assess the risk of domino effects of LPG fire triggered by natural hazards. The possible natural hazards, potential consequences, and safety barriers are presented as nodes of the Bayesian network (BN) model. Zhou et al. (2016) assessed the risk of fire-induced domino effects under emergency response in chemical storage plants. The uncertainties of sequence, duration, correctness, and mutual interaction of the emergency response actions are considered by applying event sequence diagram (ESD). Zhou and Reniers (2017) proposed a fuzzy Petri-net (FPN) based reversed reasoning approach to analyze the effectiveness of emergency response actions impacting domino effects. Factors influencing a possible domino effect, including the delay of emergency personnel and the correctness of firefighting measures are elaborated and discussed. Zhou and Reniers (2022) studied the success of emergency response based on time analysis. The cooperation modes of emergency response actions and their time characteristics are analyzed based on a timed colored Petri-net (TCPN) based approach. Chen et al. (2019) developed Dynamic Vulnerability Assessment Graph (DVAG) model based on dynamic graphs to integrate safety and security resources to reduce the risk of intentional attacks. Arief et al. (2020) developed a risk-based decision-making methodology based on Bayesian network and graph theory to investigate and evaluate the robustness of the segmentation of industrial control systems. George and Renjith (2021) applied Bayesian networks to model the intentionally induced domino propagation sequence in the chemical storage area of the industry and to estimate the domino probabilities at different levels. Zeng et al. (2020) proposed a dynamic probability prediction methodology based on DBN, which considers the performance of add-on safety barriers in case of fire-related escalating accidents. In Natech events, the primary events caused by different hazard scenarios vary greatly. Lan et al. (2022) developed a hazard scenario-based primary events generator (HSPE) based on a network-based approach to initialize a large number of primary event sets for the construction of a local domino effect net. HSPE considers hazard intensity and structure response simultaneously and rapidly synthesizes a large number of potential primary events for statistical analyses.

5.1.3. Agent-based modeling and simulation

Agent-based modeling is an alternative approach to model domino scenarios. Zhang et al. (2018) first applied agent-based modeling and simulation (ABMS) techniques to the domino risk assessment of chemical plants. ABMS is a bottom-up approach to studying complex systems that focuses on the basic units of the system, including their attributes and interactions. It can evaluate the without introducing complexity and uncertainty to the scenario evolution. Ovidi et al. (2021) developed a structured approach for the assessment of complex cascading events accounting for the influence of safety barriers adopting an agent-based model and simulation approach describing a complex system by simple rules and actions.

5.1.4. Bow-Tie diagram

Bow tie diagram is another tool used for the creation of scenarios. The bow-tie model is a graphical tool with the combination of a fault tree and an event tree to illustrate an accident scenario. Due to the capability of representing the cause and consequences together, it was widely used in the quantitative risk assessment (Khakzad et al., 2012) and the safety barriers performance assessment (Yuan et al., 2022; Yuan et al., 2023). However, utilizing bow tie to model higher-order domino effects would make the diagram highly complex. Thus, the bow tie diagrams are seldom used in the QRA of domino effects. Recently, Zeng et al. (2022) integrated barrier management framework with Natech domino accidents. The multi-level propagations of domino effects between units with safety barriers are modeled through several connected bow tie diagrams. Aliabadi et al. (2022) assessed the risk of gas condensate storage considering domino effects by an adapted bow-tie analysis technique. The initial failures to the final consequences are graphically visible and safety barriers that prevent the occurrence of dominoes are also considered. This approach is based on the "simple" propagation assumption that a single primary event starts a single secondary event.

5.2. Methodologies to handle model parameter uncertainty

5.2.1. Expert judgment

Expert judgment and historical data are widely used in risk assessment to address parameter uncertainty. Expert judgment has different forms. Experts can use experience and knowledge to identify and select parameters from databases and literature. They also can give an estimation on the severity of consequences and probability of primary events as direct input parameters (Pasman and Rogers, 2020). To quantify the influence of the protection system on fire-related domino effects, Khakzad et a. (2017) used expert judgment to estimate the parameters time to alert and the maximum time required for onsite mitigation. Chen et al. (2020b) applied expert judgment to determine the likelihood of primary events related to successful intentional attacks based on device complexity and data from attack possibility from American Petroleum Institution (API). Additionally, expert judgment is utilized in scale transformation. A common example is transforming the qualitative description of a damage state, such as "catastrophic failure" or "partial failure," to discrete failure probability in vulnerability analysis (as shown in Table 2**)**.

5.2.2. Fuzzy set theory

Experts' opinions are important information sources in some data-scarce situations. But the qualitative terms they used bring vagueness and ambiguity, such as "moderate" or "severe," to distinguish the severity of consequences in quantitative risk assessment. The same description could mean different things to another. Some scholars termed this type of uncertainty of linguistic uncertainty that is independent of the uncertainty caused by variability and lack of knowledge (Hayes, 2011). Generally, linguistic uncertainty is introduced in the process of handling a lack of information in QRA and thus is closely tied to subjective uncertainty. Fuzzy set theory (FST) can be applied to convert expert subjective linguistic terms into fuzzy probabilities for risk quantification. Ji et al. (2018) applied fuzzy inference system (FIS) to handle data uncertainties in DBN to tackle the uncertainties involved in the interaction of fire and explosion in domino effects. FIS is implemented to semi-quantitatively analyze the risk index of a unit to identify the most critical units exposed to fire or explosion. FIS is implemented for the variables related to the calculation of domino risk, including the frequency of leakage, the probability of the presence of ignition source, flash point, inventory of each unit, the closeness of each unit, and exposure duration.

Table 2
Probability and damage state of atmospheric vessels caused by peak overpressure.

Author (s)	Damage state	Damage probability
Cozzani and Salzano (2004)	Partial failure, deformation, minor damage of the auxiliary equipment or to minor structural damage of atmospheric equipment	10%
	complete rupture of connections or for minor structural damage of pressurized equipment	30%
Mingguang and Juncheng (2008)	DS1LI1: light damage to the structure of equipment, followed by the partial loss of inventory or total loss of inventory in a time interval of more than 10 min from the impact of the blast wave.	0–30%
	DS2LI2: intense, or catastrophic damage, or even total collapse of structure, followed by the total loss of inventory in a time interval between 1 and 10 min from the impact of the blast wave.	30–70%
	DS2LI3: intense, or catastrophic damage, or even total collapse of structure, followed by complete loss in a time interval of less than 1 min from the impact of the blast wave.	70–100%
Mukhim et al. (2017)	L: Minimal loss or damage	0–10%
	M: Moderate loss or damage	10–50%
	S: Severe loss or damage	50–90%
	C: Catastrophic loss or damage	90–100%

5.2.3. Bayesian network

Graphical structure and relationships among variables in the form of probability are two essential components of Bayesian network (BN) (Borsuk et al., 2004). In data-scarce situations, experts can hardly make a reliable estimation of the parameter values. The advantage of using BN in risk assessment is that BN can use expert knowledge and data information to model the causal relations between variables and update probabilities with new likelihood data (Sahlin et al., 2021). By merging the information gained from experience, experts' judgment, and observations, BN is used to estimate the domino effect probability at different levels (Khakzad et al., 2013). It is one of the few methods that can perform uncertainty propagation with little or no data (Hayes, 2011). Thus, the advantages of BN can be realized in poor-data situations. For example, it is hard or even impossible to obtain the attack likelihood of deliberately induced incidents. A more common approach is to link the likelihood of attack to target attractiveness. The one with higher attractiveness tends to have a higher probability of being attacked. In theory, the conditional probabilities associated with different levels of target attractiveness can refer to relevant standards (George and Renjith, 2021). Landucci et al. (2017) proposed a probabilistic approach based on BN to analyze the attack likelihood. It enables the site-specific factors to be considered.

5.2.4. Probability distributions

To cope with the uncertainties in the escalation process, probit functions are developed to express the damage potential with a set of those related variables. A characterization of representative studies on parameter uncertainty using probability distributions is shown in Table 3.

Eisenberg et al. (1975) used a simplified model to assess the damage probability of process equipment caused by the blast wave, as shown in Eqs. (2)–(3).

$$Y = k_1 + k_2 \ln(\Delta P) \tag{2}$$

Where Y is the probit for equipment damage, k_1 and k_2 are the probit coefficients, ΔP is the peak static pressure.

$$P = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{Y-5} e^{-u^2/2} \mathrm{d}u \tag{3}$$

Where P is the cumulative density function of standard normal distribution. For the sake of generality and simplicity, the damage to the equipment is simply related to the static peak overpressure. The equation is valid only when the "far-field" hypothesis, solid "point" explosions assumptions are satisfied (Cozzani and Salzano, 2004). Although probability models are very convenient for estimating the escalation probability because of their simplicity and generality, domino effect evaluation using static models can lead to both conservative and dangerous conclusions considering the wide domain of loading and geometry (Noret et al., 2012). Typically, the probit models are derived based on past accidents and experimental data. Because available data is often scarce, and expert opinions can vary widely, different researchers might derive different probit models (as shown in Table 4).

Monte Carlo simulation is usually coupled with probability models to

Table 3
Characterization of representative studies on parameter uncertainty using probability distributions.

Author (s)	Parameters	Escalation vectors	Keywords
Hauptmanns (2001)	Monte Carlo	Fragment	Flight of missiles; Explosions; Cylindrical vessels
Cozzani and Salzano (2004)	Probit model	Overpressure	Domino effect; Blast wave; Probit analysis; Quantitative risk analysis; Explosion
Mingguang and Juncheng (2008)	Probit model	Overpressure	Overpressure; Process vessels; Damage probability; Damage degrees; Domino effect; Probit model
Zhang and Chen (2009)	Probit model	Fragment	Fragment; Domino effect; Flight rule; Projection uncertainty
Landucci et al. (2009)	Probit model	Heat radiation	Major accident hazard; Escalation; Domino effect; Fire; Damage probability models
Sun et al. (2012)	Monte Carlo	Fragments	Domino effect; Industrial explosion; Monte-Carlo simulations; Number of fragments; Parametric approach
Sun et al. (2015)	Monte Carlo	Fragments	Domino effect risk; Fragments; Monte-Carlo simulations; Source size
Lisi et al. (2015)	Monte Carlo	Fragments	Domino effect; Probabilistic analysis; Fragments projection; Tank explosion; Monte Carlo simulation; Quantitative Risk Analysis
Sun et al. (2016)	Monte Carlo	Fragment	Risk assessment; Multiple domino scenarios; Industrial explosion; Fragments
Mukhim et al. (2017)	Probit model	Overpressure	Explosion; Overpressure; Blast wave; Escalation probability; Probits

Table 4
Summary of probit models of overpressure developed in the present works.

Author (s)	Category of equipment	Probit function
Khan and Abbasi (1998)	No categorization	$Y = -23.8 + 2.92\ln(\Delta P)$
Cozzani and Salzano (2004)	Atmospheric vessels	$Y = -18.96 + 2.44\ln(\Delta P)$
	Pressurized vessels	$Y = -42.44 + 4.33\ln(\Delta P)$
	Elongated equipment	$Y = -28.07 + 3.16\ln(\Delta P)$
	Small equipment	$Y = -17.79 + 2.18\ln(\Delta P)$
Mingguang and Juncheng (2008)	Atmospheric vessels	$Y = -9.36 + 1.43\ln(\Delta P)$
	Pressurized vessels	$Y = -14.44 + 1.82\ln(\Delta P)$
	Elongated equipment	$Y = -12.22 + 1.65\ln(\Delta P)$
	Small equipment	$Y = -12.42 + 1.64\ln(\Delta P)$
Mukhim et al. (2017)	Horizontal pressurized vessels	$Y = -88.88 + 8.79\ln(\Delta P)$
	Spherical pressurized vessels	$Y = -49.16 + 4.93\ln(\Delta P)$
	Vertical pressurized vessels	$Y = -248.00 + 22.33\ln(\Delta P)$
	Conical roof atmospheric pressure vessels	$Y = -13.31 + 2.02\ln(\Delta P)$
	Other atmospheric pressure vessels	$Y = -22.74 + 3.00\ln(\Delta P)$
	Floating roof atmospheric pressure vessels	$Y = -15.79 + 2.02\ln(\Delta P)$
	Cooling towers	$Y = -6.56 + 1.24\ln(\Delta P)$
	Fractionation columns	$Y = -35.10 + 3.95\ln(\Delta P)$
	Extraction columns	$Y = -55.89 + 5.63\ln(\Delta P)$
	Reactors used for cracking	$Y = -22.67 + 2.67\ln(\Delta P)$
	Other chemical reactors	$Y = -26.76 + 3.08\ln(\Delta P)$
	Heat exchangers	$Y = -201.20 + 18.98\ln(\Delta P)$
	Filtration units	$Y = -17.42 + 2.19\ln(\Delta P)$

estimate the probabilities of escalation or fatalities. Unlike the overpressure, the damage caused by fragments cannot be simply reduced to one factor. The damage probability is influenced by the projection angle, the number of fragments, the source size, and other variables (Zhang and Chen, 2009; Sun et al., 2012, 2015). To incorporate the effects of fragment projection into the QRA framework, Monte Carlo simulation and probability density functions are applied to obtain probabilistic models for the impact of fragments (Sun et al., 2012; Lisi et al., 2015). The objective volume, the degree of filling of the source vessel, the kind of explosion, the fragment rotation, and wind direction are treated as stochastic variables using Monte Carlo-based probabilistic approaches.

5.2.5. Data-driven techniques

With the advent of the era of big data, a vast amount of data is available for exploitation and analysis through automatic vehicles and sensors (Swuste, 2016). Unlike BN which needs predictive elicitation, the failure frequency and degree of variability can be estimated with enough sample data (Choi and Lambert, 2017). Thus, big data risk analysis can reduce the assumptions of probability-based models. The application of data-driven techniques in the QRA of domino effects is very limited. Zeng et al. (2021) analyzed the domino effects caused by flood, the fragility function to predict the failure probability of a tank was obtained using a machine learning technique. Ding et al. (2022b) first applied data mining (DM) technique in domino effect risk management. DM is proposed to collect risk evidence from inspection records of chemical installations to determine scores of occurrence of LOC-related failure modes of storage tank components.

5.3. Methodologies to handle model structure uncertainty

5.3.1. Temporal-spatial evolution

The earlier research on domino accident propagation modeling is based on simple deterministic approaches or oversimplified assumptions (Khakzad et al., 2013). The potential propagation sequence is tackled by: 1) Taking all potential domino scenarios into account; or 2) Comparing damage probabilities through threshold values and distance (Khakzad et al., 2014). To cope with the time and space dependency in propagations, existing studies were mainly developed on the time-varying graph and stochastic simulation, of which the Monte Carlo method has been widely used. The characterization of representative studies on modeling the evolution of domino chains is shown in Table 5.

5.3.2. Time-varying graphs

Time-varying graph tools are widely used to model the evolution of domino effects and to accurately assess the vulnerability of installations. A classic graph consists of a set of nodes and arcs to represent the causal relationships between the components of a system, supposing the graph structure is static. The characteristic of dynamic graphs is the vertices/edges of each graph change over time.

The conventional BN approach does not consider the interaction in the temporal dimension. The identification of secondary units is based on a comparison among the escalation probabilities of the target units. The one with a higher escalation probability is selected as the secondary unit, whereas the other is the tertiary unit (Khakzad et al., 2013). Based on the conventional BN approach, Khakzad et al. (2018) developed a method based on DBN to model the time and space dependence for the identification of the most likely sequence of events. DBN allows modeling of the temporal evolution of domino scenarios rather than just considering all possible sequences of events. Chen et al. (2018) applied dynamic graphs to model the spatial-temporal evolution of domino effects, considering the impact of safety and security resources. Kamil et al. (2019) developed a generalized stochastic Petri-net model to model the time-dependent domino effect accident.

5.3.3. Stochastic simulation

The stochastic simulation is another approach that was used to deal with the uncertainty of the evolution path and capture the characteristics of the time evolution, of which the Monte Carlo method has been widely used to cope with the complexity of high-level domino propagations. Huang et al. (2020) modeled the accident propagation sequence of earthquake-induced Natech events using a Monte Carlo-based algorithm. The multiple escalation vectors of the same unit and the synergistic effects of different units are taken into account. Huang et al. (2021) used matrix calculations coupled with Monte Carlo simulations to analyze the dynamic propagation of pool fire domino accidents. Huang et al. (2022) proposed a method based on Monte Carlo simulation for the dynamic evolution of the domino effect, considering the dependency of time and space. Men et al. (2022) proposed an event-driven quantitative methodology to assess the domino risk induced by natural hazards. The evolution of domino effects is modeled by a Markov decision process and a temporal-difference learning algorithm.

Table 5
Characterization of representative studies on modeling the evolution of domino chains.

Author (s)	Chacteristics	Methodologies	Other keywords
Khakzad et al. (2018)	Spatial-temporal	DBN	Domino effect; Oil terminal; Dynamic Bayesian network; Model uncertainty; Graph theory
Chen et al. (2018)	Spatial-temporal	Dynamic graph	Domino effects; Heat radiation; Spatial-temporal evolution; Domino evolution graph; Minimum evolution time
Kamil et al. (2019)	Spatial-temporal	Petri-net model	Domino effect; Stochastic Petri nets; Risk analysis; Hazardous materials; Process safety
Huang et al. (2020)	Spatial	Monte-Carlo simulation	Natech events; Earthquake; Domino effect; Probability; Quantitative analysis
Huang et al. (2021)	Spatial	Monte-Carlo simulation	Domino effect; Dynamic probability; Chemical process industry; Monte Carlo
Ovidi et al. (2021)	Spatial	Monte Carlo simulation	Agent-based modelling; Computational experiments; Process safety; Safety barriers; Domino effect; Chemical tank farm
Huang et al. (2022)	Spatial-temporal	Monte-Carlo simulation	Domino effect; Dynamic risk assessment; Monte Carlo method; Spatial-temporal evolution
Men et al. (2022)	Spatial-temporal	Stochastic simulation	Natural hazard-induced domino chain; Chemical industrial park; Dynamic risk analysis; Disaster chain evolution system; Event-driven probabilistic methodology

5.3.4. Synergistic effects

In current studies, the synergistic effects are handled either by superposition or numerical simulation methods. The characterization of representative studies on modeling the synergistic effects of domino chains is shown in Table 6.

5.3.5. Superposition

- Superposition of escalation factors with consideration of spatial dependency
- Superposition of escalation factors with consideration of spatial-temporal dependency

Normally, for simplification, the synergistic effects of multi-hazards are calculated by superimposing escalation vectors. For example, if the equipment received thermal radiation from multiple fires, then the total

Table 6
Characterization of representative studies on modeling the synergistic effects of domino chains.

Author (s)	Characteristics	Escalation vectors	Other keywords
Khakzad et al. (2015)	Spatial superposition	Multiple fires	Chemical infrastructure; Domino effect; Dynamic Bayesian network; Influence diagram; Risk analysis
Yang et al. (2018)	Spatial superposition	Multiple fires	Domino effect; Probability prediction method; Bayesian network; Lightning; Chemical tank farm
Zhang et al. (2018)	Spatial superposition	Multiple fires	Agent-based modeling; Computational experiments; Domino effect; Major accident hazard
Chen et al. (2018)	Spatial superposition	Multiple fires	Domino effects; Heat radiation; Spatial-temporal evolution; Domino evolution graph; Minimum evolution time
Zhou and Reniers (2018)	Spatial superposition	Multiple fires	Domino effect; Probability analysis; Matrix modeling; Process industry
Ji et al. (2018)	Spatial superposition	Multiple fires	/
Ding et al. (2019)	Spatial-temporal superposition	Multiple fires	Domino effect; Synergistic effect; Contribution; Failure criterion; Numerical solution
Zeng et al. (2020)	Spatial-temporal superposition	Multiple fires	Domino effect; Dynamic Bayesian Network; Synergistic effect; Temporal evolution; Safety barrier
Ding et al. (2020b)	Spatial-temporal superposition	Multiple fires	Domino effects; Spatial-temporal evolution; Synergistic effect; Accident evidence; Risk analysis
Ding et al. (2020a)	Spatial-temporal superposition	Multiple fires	Domino effects; Risk analysis; Uncertainty reasoning; Deterministic modeling; Dynamic Bayesian network; Fire synergistic effect model
Li et al. (2021)	Numerical simulation	Pool fires	Synergistic effect; Pool fires; CFD; Consequence modeling; Domino effect; Radiation heat flux
Huang et al. (2021)	Spatial superposition	Multiple fires	Domino effect; Dynamic probability; Chemical process industry; Monte Carlo
Huang et al. (2022)	Spatial superposition	Multiple fires	Domino effect; Dynamic risk assessment; Monte Carlo method; Spatial-temporal evolution
Ding et al. (2022a)	Spatial-temporal superposition	Multiple fires and explosions	Multi-hazard coupling; Synergistic effect; Domino effect; Yield strength; Equivalent stress

amount of heat radiation is the sum of thermal radiation from all sources. Due to the space and time dependency, the synergistic effects of escalation vectors can be divided into spatial synergistic effects and temporal synergistic effects (As shown in Fig. 9). In traditional and simplified risk assessments, only spatial concurrent events are considered to examine the possibility of higher-order accidents (i.e., Khakzad et al., 2015; Yang et al., 2018; Zhang et al., 2018; Chen et al., 2018; Zhou and Reniers, 2018; Ji et al., 2018).

The uncertainties of spatial-temporal synergistic effects are handled by introducing new model and algorithms. With the assumption that domino propagation is likely to occur when the parameter time to burnout (*ttb*) of the external fire is larger than the time to failure (*ttf*) of the target unit, Zeng et al. (2020) considered the time-evolving synergistic effects in fire-related domino accidents by introducing the "Temporal judgment" model. Based on superimposition approach, a fire synergistic effect model (FSEM) was developed that able to model temporal-spatial evolution of thermal flux received by units (Ding et al., 2019; Ding et al., 2020b). Since FSEM can only model the evolution process of domino effects after a primary accident occurs, Ding et al. (2020a) further combined uncertainty reasoning by adopting DBN with FSEM to assess the escalation sequence before a primary accident happens. The above studies only include the synergistic effects among multiple fires, the synergistic effects of different escalation vectors are not considered. Based on FSEM, Ding et al. (2022a) developed a novel vulnerability model called "fire and explosion synergistic effect model" (FESEM). It combined the lowered yield strength and equivalent stress, and the logistic function is used to estimate the time to failure and escalation probability under the synergistic effect of fire and overpressure.

5.3.6. *Numerical simulation*

In the actual domino scenarios, the synergistic effects are combined logically to be a coupling system rather than a superposition (Zeng et al., 2020). Advanced simulation tools such as computational fluid dynamic (CFD) and the finite element method (FEM) can obtain more realistic and reliable assessment results of the failure modes of equipment (Chen et al., 2020). Meanwhile, the complex geometries, conditions of units, and environmental conditions can be modeled by numerical simulations. Several studies conduct domino effects analysis using simulation approaches. Landucci et al. (2009) modeled the failure of vessels triggered by fire scenarios using a commercial FEM code. The detailed temperatures on the vessel shell and the transient stress field as a function of the local temperatures are calculated. Escalation thresholds and escalation probabilities are obtained by comparison of vessel time to failure with the time required for effective mitigation actions. Jujuly et al. (2015) integrated a CFD-based pool fire model with domino effects. The temperature and radiation distributions of the units and encompassed area are obtained. It demonstrates that wind direction has a significant impact on pool fire. Li et al. (2021) developed a CFD-based method to estimate the consequences and domino effects under pool fires with consideration of synergistic effects. It took into account the complex geometry and mutual influence. The results demonstrated that the traditional superposition method underestimates the heat radiation intensity received by the target tanks under the synergistic effect for double pool fires, due to ignoring the mutual influence between fire zones.

6. Discussion

Following up the analysis of uncertainty treatment approaches in the QRA of domino effects in the process industry, this section focused on summarizing the current research trends and identifying the knowledge or technical gaps for potential future directions.

6.1. *Current research trends*

Uncertainty treatment development pathway in QRA of domino effects can be divided into three stages, as shown in Fig. 10. Early QRA of domino effects concerned with methods to treat model parameter uncertainty starting from the probability approach of defining the likelihood of domino effects (Bagster and Pitblado, 1991). Probability distribution models and expert judgment are the predominant approaches to representing parameter uncertainties in QRA of domino incidents. A few years later, the introduction of dynamic risk assessment techniques allowed the study of higher-level domino likelihood with higher uncertainties (Khakzad et al., 2013).

The second stage started with the establishment of the systematic procedure for QRA of domino effects (Cozzani et al., 2005). Since then, QRA of domino incidents began to draw attention to scenario uncertainties related to Natech events, safety barrier management, and

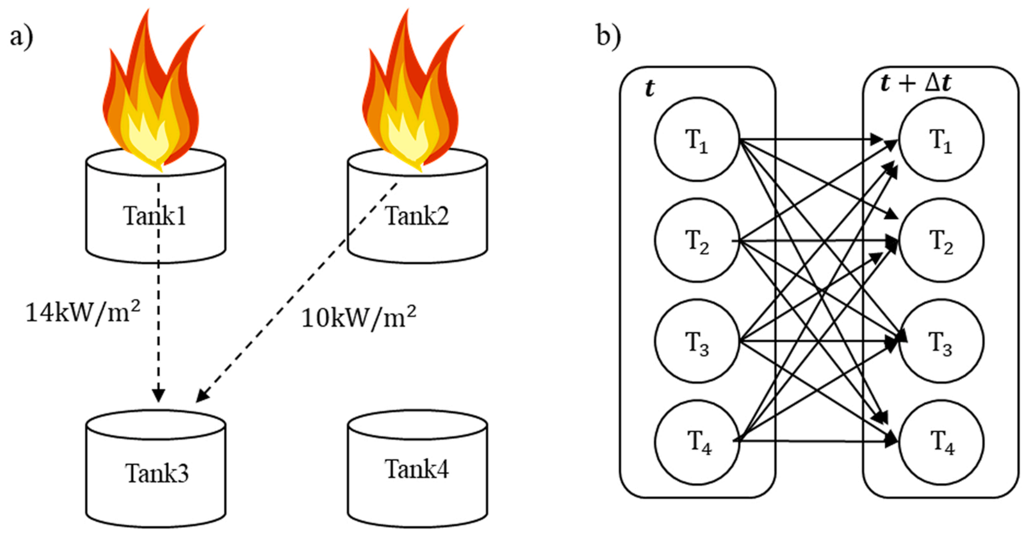

Fig. 9. An illustrative chemical plant with four storage tanks a) spatial synergistic effects, and b) temporal synergistic effects (Ding et al., 2020).

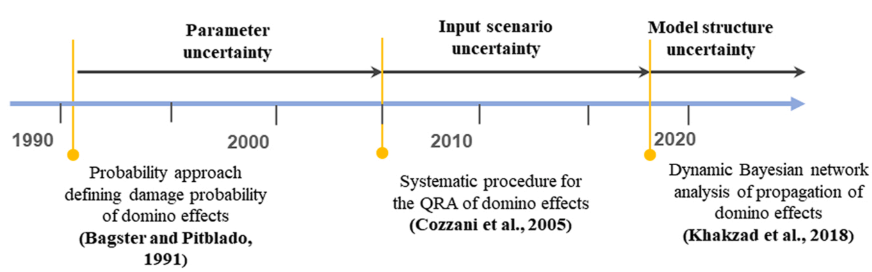

Fig. 10. development pathway of uncertainty treatment in QRA of domino effects.

intentional attacks. Generally, scenario uncertainty is addressed as modifying the current framework by introducing new scenarios within QRA. FTA is the most common method for addressing scenario uncertainty, especially when introducing safety and security barrier systems. With the demand for simulating multi-level domino accidents, graph theory methods are introduced due to their flexible graphical structure (Khakzad and Reniers, 2015; Zhou and Reniers, 2017; Chen et al., 2019). Agent-based modeling to QRA of domino effects as a bottom-up approach that focused on elements of the system was developed to avoid introducing additional uncertainty (Zhang et al., 2018). Additionally, to facilitate barrier management in domino effects, bow-tie diagrams are applied to tackle scenario uncertainty in the latest study (Zeng et al., 2022).

The introduction of DBN techniques brought QRA of domino effects to the stage of model structure uncertainty research (Khakzad et al., 2018). Afterward, various new time-varying graph methods began to be applied to address the time-dependent propagation process. However, with the advancement of uncertainty research, QRA techniques must address highly combined and non-linear behavior within the complex system. Currently, computing techniques introducing new algorithms can provide an adequate framework to tackle such uncertainties.

6.2. Knowledge and technical gaps

6.2.1. Natech domino scenarios

Compared with ordinary domino accidents, the Natech domino effect requires consideration of uncertainty in the linkage of natural disasters and technical accidents. Currently, most studies do not consider the uncertainty related to the primary events induced by natural disasters due to the complex feature of accident chains. Rather, the randomness of nature is simplified by using general data retrieved from related standards. To increase the accuracy of the model's outputs, additional research is required to investigate these uncertainties.

6.2.2. Intentional attacks and security barriers

The main challenge in handling scenario uncertainty is the integration of various domino scenarios and QRA. With the increasing trend of cyberattacks targeting critical infrastructures, there is a concern that such cyberattacks may trigger domino effects (Arief et al., 2020). However, the QRA of cyberattack-induced domino effects is still limited. Furthermore, although existing methods such as event tree and graphical methods are reliable for modeling the effects of new-added scenarios on the probability of domino accidents, the uncertainty of domino consequences with the intervention of new-added scenarios is insufficiently addressed.

6.2.3. Synergistic effects

Despite dynamic graph tools can model the dynamic evolution and synergistic effects between the same escalation vectors by applying superposition methods. However, the synergistic effects between different escalation vectors cannot be handled through simplified assumptions. Ding et al. (2022a) developed the FESEM process to model synergistic effects between fire and explosion; however, the model involves a recursive numerical procedure. The mechanisms of synergistic effects still need further investigation.

6.2.4. Variability of human behavior

Previous studies mainly focused on the synergistic effects between physical effects. However, the broader synergistic effects also encompass the interrelationships between people affected, fire brigade, and fire and explosion incidents. Another challenge of QRA of domino effects is dealing with the uncertainty of human behavior related to affected people, and emergency response (He and Weng, 2020a). Current research uses simple and idealized assumptions to set the arrival time of firefighters and the time to extinguish fire; however, their intervention with major hazards is seldom considered. The impact of fire, explosion, and toxic gas on fire brigades and people affected still needs in-depth research.

6.3. Future directions

Based on the analysis of mainstream research on QRA of domino effects and discussion of research gaps, a few directions in the future study of uncertainty treatment in QRA of domino effects can be foreseen.

6.3.1. Need treatment of input data uncertainty

Currently, data uncertainty at the input stage induced by the inaccuracy of data is usually ignored in the QRA of domino effects. With the development of big-data risk analysis, a vast number of data are available for observation and analysis. Data-driven techniques such as machine learning and data mining have the advantage of reducing expert elicitation and subjective assumptions in the risk assessment process. However, to obtain reliable risk assessment results, the accuracy and background knowledge of input data needs to be assessed (Nateghi and Aven, 2021).

6.3.2. Need resilience-based approach to risk assessment

The deep uncertainty is one of the major factors that hinder the development of QRA in the domino effects domain. Resilience engineering is a relatively new approach to process risk assessment and safety management. It is good at dealing with threats of high uncertainty (specifically low probability events) in complex socio-technical systems (Steen and Aven, 2011; Pasman et al., 2013). In contrast to contemporary risk assessment that concerns scenario identification, resilience analysis focuses on the capability of planning, preparing for, absorbing, and recovering targeted systems (Florin and Linkov, 2016). Currently, domino effect studies have introduced the concept of resilience to help decision-making (Cincotta et al., 2019) and barrier management (Zeng et al., 2023). However, a resilience-based approach to QRA of domino effects still needs development.

6.3.3. Need experiment and numerical simulation

Relying on the "experimental data" that derives from historical and accident analysis can no longer provide reliable guidance for the complex model uncertainties in QRA of domino effects, especially synergistic effects. On the one hand, current probit models still refer to old experimental data that do not consider synergistic effects (Ding et al., 2022b). On the other hand, modeling complex synergistic effects require experimental and simulated data to handle the uncertainties in the model structure. Experiments and numerical simulations are complex, expensive, and time-consuming, but a safer technical system can prevent greater economic loss.

6.3.4. Need validation analysis of QRA

QRA uses mathematical and conceptual models to represent technical systems, and no matter how to optimize it, discrepancies inevitably exist between reality and the modeled system. This does not mean that uncertainty treatment is not important in QRA; however, some argue that traditional risk assessment cannot guarantee the reliability of its results because it is not complete (Sjöberg, 1980) and the level of knowledge behind the assessment results is not assessed (Milazzo et al., 2015). Hence, the additional validation analysis to measure the evidence or background knowledge related to the assumption and model used is suggested to be part of the QRA (Goerlandt et al., 2017; Pasman and Rogers, 2018).

7. Conclusions

This paper presented an overview of uncertainty and widely used uncertainty treatment methods in QRA of domino effects following a modern risk perspective. In the context of risk assessment, QRA techniques act as tools for dealing with uncertainties related to outcomes of specific events. This study proposed an uncertainty classification model in the QRA context. The output uncertainty is impacted by input uncertainty, parameter uncertainty, and model uncertainty by cascading effects. Current methods for dealing with uncertainty in the domino effect QRA are reviewed based on the type of uncertainty. Wide varieties exist between uncertainty handling measures in each type of uncertainty. However, due to the capability of accident analysis and probability updating, DBN is the only method that can handle the uncertainty in the whole process of QRA relating to domino effects. The change of research hotpots and the development of various uncertainty treatment approaches are given. Additionally, the current challenges and possible future directions are summarized in the discussion section.

To conclude, although QRA has been shown to be an effective tool for predicting risks, QRA techniques still need to be improved to narrow the gap between reality and modeled systems. The results and proposed directions for future work may benefit researchers in understanding the importance of uncertainty treatment in QRA of domino effects and provide the basis for conducting validation analysis.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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