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Data-theoretic methodology and computational platform to quantify organizational factors in socio-technical risk analysis

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ABSTRACT

Organizational factors, as literature indicates, are significant contributors to risk in high-consequence industries. Therefore, building a theoretical framework equipped with reliable modeling techniques and data analytics to quantify the influence of organizational performance on risk scenarios is important for improving realism in Probabilistic Risk Assessment (PRA). The Socio-Technical Risk Analysis (SoTeRiA) framework theoretically connects the structural (e.g., safety practices) and behavioral (e.g., safety culture) aspects of an organization with PRA. An Integrated PRA (I-PRA) methodological framework is introduced to operationalize SoTeRiA in order to quantify the incorporation of underlying organizational failure mechanisms into risk scenarios. This research focuses on the Data-Theoretic module of I-PRA, which has two sub-modules: (i) DT-BASE: developing detailed causal relationships in SoTeRiA, grounded on theories and equipped with a semi-automated baseline quantification utilizing information extracted from academic articles, industry procedures, and regulatory standards, and (ii) DT-SITE: conducting automated data extraction and inference methods to quantify SoTeRiA causal elements based on site-specific event databases and by Bayesian updating of the DT-BASE baseline quantification. A case study demonstrates the quantification of a nuclear power plant's organizational “training” causal model, which is associated with the training/experience in Human Reliability Analysis, along with a sensitivity analysis to identify critical factors.

1. Introduction and statement of objectives

Organizational factors can either help or hinder safety performance [1], and they have been identified as significant contributors to incidents [2] and major accidents [3–5]. Probabilistic Risk Assessment (PRA)/Probabilistic Safety Assessment (PSA) [6], a formal methodology for estimating risk emerging from the interactions of equipment failure and human error, utilizes Human Reliability Analysis (HRA) [7,8] for modeling and quantifying human error in risk scenarios. Despite the overwhelming evidence from the fields of organizational psychology and management science that strongly relates organizational factors such as safety culture, leadership style and priorities, and reward practices to safety, injuries, and accidents [9–14], organizational performance models are not explicitly incorporated into HRA or PRA [15,16]. HRA provides an estimation of individual human error based on the states of internal Performance Shaping Factors (PSFs) (e.g., fatigue, cognitive mode) and external PSFs (e.g., physical work environment, teamwork, managerial and organizational factors) [7]. The

Abbreviations: BBN, Bayesian Belief Network; CAP, Corrective Action Program; CCF, Common Cause Failure; CCO, Communicative Constitution of Organization; CPT, Conditional Probability Table; DT, Data-Theoretic; GSI-191, Generic Safety Issue 191; HRA, Human Reliability Analysis; I-PRA, Integrated Probabilistic Risk Assessment; LV, Leak Variable; NPP, Nuclear Power Plant; NRC, Nuclear Regulatory Commission; PRA, Probabilistic Risk Assessment; PSF, Performance Shaping Factor; SoTeRiA, Socio-Technical Risk Analysis; SPAR-H, Standardized Plant Analysis of Risk-Human Reliability Analysis (SPAR-H)

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external organizational PSFs in HRA techniques are represented at an abstract level of analysis that does not "explicitly" consider underlying mechanisms. "Explicit" incorporation/consideration of underlying mechanisms refers to the model-based integration of organizational performance and processes with HRA to analyze the effects on human error due to changes in underlying organizational contributing factors. It has been argued that "*all PSFs should be looked at as organizational factors since it is an organization that could maintain or modify conditions that affect all of these factors*" [17]. However, due to the complexity of organizational performance modeling, the integration of organizational mechanisms with PSFs of HRA has been a challenging topic. This paper is a product of a line of research to incorporate organizational factors into HRA and PRA to (1) explicitly assess the risk due to specific organizational weaknesses, (2) find and rank the critical organizational root causes of failure, which help efforts to take effective corrective action, and (3) avoid the possibility of underestimating the risk associated with human error. This section provides a literature review of studies in the field of risk analysis, specifically associated with PRA, that evaluated the influence of organizational factors on technological system risk and safety.

In the last two decades, many researchers have studied organizational factors in the context of risk analysis by evaluating; their role in historical incidents and accidents [15,18], their classification [9] and use in regulatory applications [19], their implicit consideration in existing HRA guidance [17,20,21], their application in frameworks for equipment reliability [22] considering multi-level phenomenology [23,24], and their potential use as performance indicators [25,26]. In Mohaghegh's review of existing *theoretical frameworks* and *quantitative techniques* related to the incorporation of organizational factors into risk models, she categorizes them in two generations [27–34]. The nature of first-generation theories and quantitative techniques is characterized in terms of "deviations from normative performance" [35]. For example, Reason's Swiss Cheese Model [1,36] is a well-known metaphor for describing the organizational effects on the occurrence of accidents. According to Reason, the accident sequence starts with failed or missing defenses in the organization (e.g., managerial decisions), and these defects create latent conditions that are transmitted along organizational pathways. Similarly, there have been several static quantitative frameworks, based on this theoretical concept, that aim at modeling and quantifying the impact of organizational factors on system risk. Examples are WPAM [37,38], SAM [39] and similar models [22], Omega Factor Model [40,41], ASRM [42], ORIM [22], I-Risk [43], and Causal Modeling of Air Safety [44]. The second-generation approaches to develop organizational models for risk analysis frameworks focus on modeling the 'actual behavior' of organizations. These approaches have been evolving and attempt to represent the underlying organizational mechanisms of accidents. On the theoretical side, Rasmussen [35] cites the self-organizing nature of High Reliability Organizations [45] and Learning Organizations [46,47] as concepts useful in analyzing the managerial and organizational influences on risk. The Normal Accident Theory [48], which views accidents caused by interactive complexity and close coupling, can also be considered in the second generation of theories for organizational safety. Second-generation quantitative techniques primarily address the dynamic aspects of organizational influences. For example, Cooke [51], Leveson [52], and Marais [53] use the System Dynamics approach [49,50] to describe the dynamics of organizational safety, but these models do not include detailed PRA-style models of the technical system [50–53]. Yu et al. (2004) also use a System Dynamics approach to incorporate the effects of organizational factors into nuclear power plant PRA models [54]. The interconnection between PRA and System Dynamics, however, is not established.

More recently, concepts from resilience engineering have been added to the second-generation socio-technical models. While the concept of resilience is beneficial for describing the adaptive nature of organizations [55], the benefits of resilience compared to a reliability approach in risk analysis have not yet been adequately analyzed [56].

Table 1
Socio-technical risk analysis principles [27,29].

Categories	Principles
I. Designation & Definition of Objectives	(A) Unknown-of-Interest (B) Multidimensional Performance Objectives
II. Modeling Perspective	(C) Safety Performance and Deviation (D) Multilevel Framing (E) Depth of Causality and Level of Detail (F) Model Generality
III. Building Blocks	(G) Basic Unit of Analysis (H) Factor Level and Nature (I) Factor Selection (J) Link Level, Nature, and Structure (K) Dynamic Characteristics
IV. Techniques	(L) Measurement Techniques (M) Modeling Techniques

The theoretical relationships between resilience and organizational safety in high-consequence industries remain underdeveloped and require further research; however, it should be acknowledged that various factors (e.g., capabilities of organizations [57]) from resilience engineering can be useful to enhance organizational safety methods [58,59]. Recent studies in safety and risk analysis continue to emphasize the need for organizational modeling techniques, with a systematic perspective, that can include a broader set of influencing factors [4] and is capable of capturing an organization's adaptive performance, emergent phenomena, and success paths [60].

Integrating concepts from multiple disciplines, Mohaghegh introduced a set of thirteen principles (Table 1) for the field of organizational risk analysis or Socio-Technical Risk Analysis [27,29]. These principles are distributed in the following four categories; Categories I, II, and III relate to *theory* building, and Category IV relates to developing *methodological techniques*. In summary, these principles address two requirements for incorporating emergent organizational safety behavior into PRA: (i) the integration of a theoretical model of how organizations perform, considering causal factors with their corresponding level of analysis and relational links; (ii) the adaptation of appropriate techniques (i.e., "modeling" and "measurement"), capable of capturing complex interactions of causal factors within their possible ranges of variability and across different levels of analysis, to quantify the theoretical framework.

With respect to the first requirement, a theoretical framework, called Socio-Technical Risk Analysis (SoTeRiA) (Fig. 1) [27,29], was developed based on the theory-building principles (Categories I, II, and III in Table 1) and based on a multi-level organizational performance model developed by Ostroff et al., [61,62]. SoTeRiA is a theoretical causal framework for explicitly integrating both the social aspects (e.g., safety culture; Node 8 in Fig. 1) and the structural features (e.g., safety practices; Node 7 in Fig. 1) of one organization with technical system PRA (i.e., Node 1 in Fig. 1). The SoTeRiA framework is further explained in Section 2.1, but for more details on the development of SoTeRiA, readers are directed to Refs. [27,29].

Operationalization and quantification of SoTeRiA required the development of appropriate techniques (Principles IV in Table 1) including "modeling" and "measurement" techniques. With respect to modeling techniques (Principle IV-M), Mohaghegh and Mosleh developed a hybrid approach [30,33] by combining a probabilistic method, i.e., Bayesian Belief Network (BBN), and a deterministic/dynamic simulation technique, i.e., System Dynamics, with classical PRA methods, i.e., Event Tree (ET) and Fault Tree (FT), to quantify SoTeRiA. This paper introduces the Integrated PRA (I-PRA) methodological framework (explained in Section 2.1 and instantiated in Fig. 2) that is an advancement of the original work by Mohaghegh et al. [30] and is based on an adaptation of the I-PRA approach which has been already applied for incorporating physical failure mechanisms into PRA for GSI-

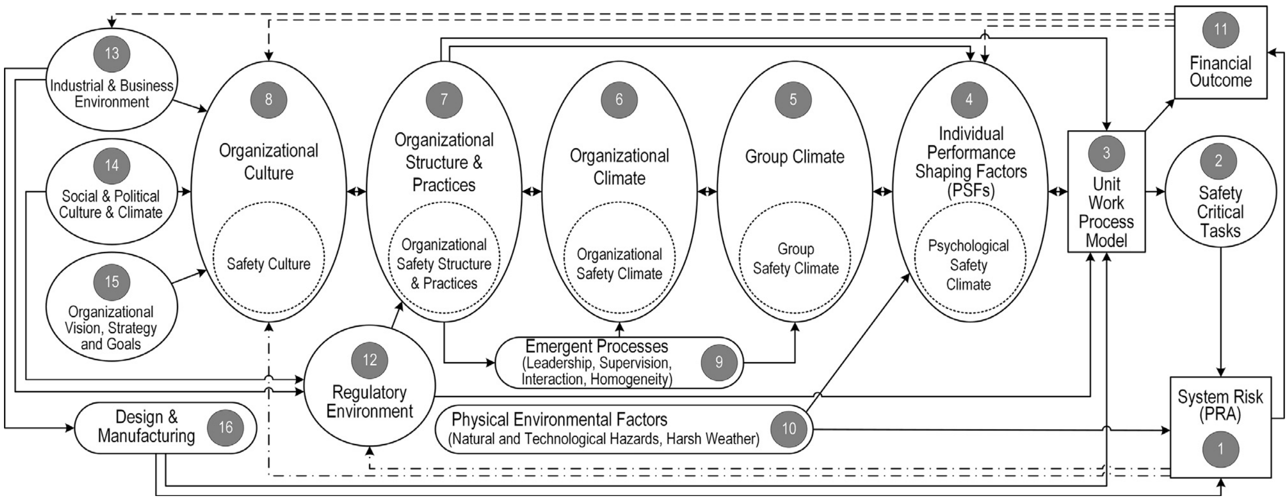

Fig. 1. Socio-technical risk analysis (SoTeRiA) theoretical framework [27].

191 [63] and fire PRA [64,65].

Measurement techniques (Principle IV-L in Table 1) relate to data analytics (i.e., data extraction and interpretation) for the factors and the links in the SoTeRiA framework. Mohaghegh and Mosleh [28,31] highlighted the importance of integrating subjective and objective measurement techniques for SoTeRiA. In the application of SoTeRiA, one of the challenges was the unstructured nature of data for organizational risk analysis. This research develops a Data-Theoretic approach, which is the focus of this paper and builds the data input module of the I-PRA framework. The Data-Theoretic is an approach where "data analytics" are guided by "theory." Theory enhances the accuracy and completeness of "causality" being analyzed from data and helps avoid potentially misleading results from solely data-oriented approaches.

Section 2.2 covers the foundation, methodology, and computational platform for the Data-Theoretic approach. The Data-Theoretic approach not only contributes to the development of new measurement techniques for the SoTeRiA framework but also makes theoretical contributions to SoTeRiA. The SoTeRiA framework (Fig. 1) covers high-level paths of causality while still requiring further theory building to generate more detailed causal factors, sub-factors, and their interactions. The computational platform of the Data-Theoretic approach eases the execution of theory-building principles to expand theoretical details in SoTeRiA. As an example, the Data-Theoretic approach is applied for the organizational training processes of a Nuclear Power Plant (NPP) (Section 3), and a theoretical causal model is built and quantified for "training," which is one of the factors related to Node 7 in SoTeRiA (Fig. 1). The training quality would influence the state of Experience/Training PSF in HRA, and consequently, would affect the risk estimated from the I-PRA framework. The scope of this paper is on one organization, and future work by the authors will address multiple organizations and inter-organizational factors.

2. Integrated probabilistic risk assessment methodology for socio-technical risk analysis

The central risk assessment technique used in this research is Probabilistic Risk Assessment (PRA). This systematic risk methodology was originally developed for the nuclear power industry [6] and has grown into a technical discipline with a wide range of applications. In classical PRA, a static PRA logic, consisting of ET and FT (see the site-specific PRA module in Fig. 2), represents the causal relationships among the Initiating Events (IEs), system failures (e.g., SYS_A, SYS_B), component failures (e.g., basic event "b"), and human failure events (e.g., basic event "a") that can result in undesirable system end states (e.g., core damage in NPPs) [66]. These static PRA techniques have limitations in their capabilities to account for the dynamic evolution of risk scenarios [67].

To overcome the limitations of classical PRA, dynamic PRA (also referred to as simulation-based PRA) methodologies have been developed [67–69]. Although a fully-dynamic PRA may generate more realism in risk modeling, it would not be economically efficient or practical for NPPs in the short term because (i) classical PRA is widely utilized by both the nuclear industry and the regulatory agency and would require a significant amount of time and resources to transition to fully-dynamic PRA, and (ii) the need for reaching the degree of realism that a fully-dynamic PRA could generate has not yet been scientifically justified for either the industry or the regulatory agency. Therefore, as a more feasible short-term alternative, the authors developed the Integrated PRA (I-PRA) methodological framework (Fig. 2). I-PRA generates a "unified" computational framework to integrate simulation modules of underlying failure mechanisms associated with areas of concern (e.g., fire, seismic) with classical PRA (i.e., logic-based ET, FT). I-PRA is equipped with an interfacing methodology, including uncertainty analysis, Bayesian updating and dependency treatment, to more comprehensively capture information on the relationships between PRA scenarios and the underlying failure mechanisms. For instance, the influences of underlying contributing factors (e.g., material properties, room configuration) on the plant risk metrics (e.g., core damage frequency) are explicitly captured through I-PRA unified platform; hence, the importance measure analysis for the input parameters at the failure mechanism level, more directly related to the design parameters than the PRA basic events, can be performed. Development of a unified computational framework, which seamlessly integrates the plant PRA model with the underlying failure mechanisms, can also improve the treatment of dependent failures in PRA (as discussed in another publication by the authors [70]). Another advancement of I-PRA is the "explicit" incorporation of interactions between physical failure mechanisms and human performance [71,72]. For example, a fire-induced scenario at NPPs is a socio-technical process involving two-directional interactions between fire progression and human actions for manual fire detection and suppression: (i) influences of fire progression (e.g., dense smoke, high temperature) on the human performance, and (ii) influences of manual action (e.g., spray of suppressant, activation of smoke purge) on fire progression. In the existing Fire PRAs, those physics-human interactions are "implicitly" treated by a simplified and conservative approach based on the competition between two timings, time-to-cable-damage and time-to-suppression [73]. In contrast, I-PRA creates an "explicit" interface between a Computational Fluid Dynamics (CFD)-based fire model (Fire Dynamics Simulator; FDS) and the human

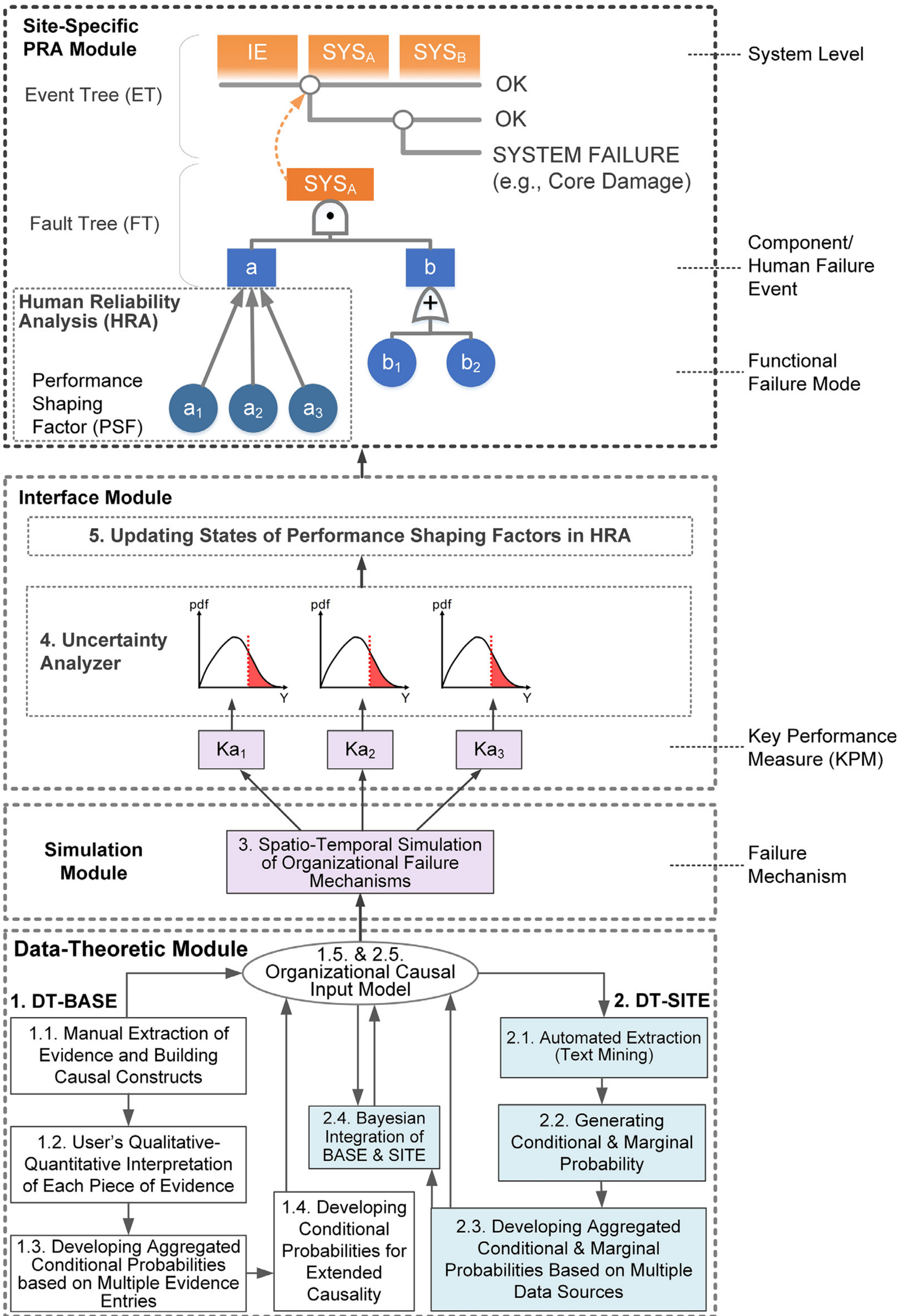

Fig. 2. Integrated probabilistic risk assessment (I-PRA) methodological framework for socio-technical risk analysis. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

performance model through modifications to the Heat Release Rate (HRR) curve. The methodological development of I-PRA, mainly for the incorporation of physical failure mechanisms and their interface with human performance, is covered in the authors' previous publications for several applications, such as (1) risk-informed resolution of Generic Safety Issue 191 (GSI-191) [74–76], (2) Fire PRA [64,71,77], and (3) Seismic PRA [78].

This paper adapts I-PRA for the quantification and operationalization of SoTeRiA (Fig. 1) to quantify the incorporation of organizational failure mechanisms into classical PRA. The I-PRA framework (Fig. 2) quantifies the incorporation of underlying organizational failure mechanisms (i.e., simulation module in Fig. 2) into risk scenarios in classical PRA (i.e., the site-specific PRA module in Fig. 2). Section 2.1 explains key modules of I-PRA, in relationship with different nodes in the SoTeRiA framework, to clarify how I-PRA is designed to operationalize SoTeRiA. The focus of this paper is on the Data-

Theoretic module of I-PRA that is explained in detail in Section 2.2. The implementation of the Data-Theoretic approach for NPPs is included in Section 3.

2.1. Integrated PRA modules to quantify the SoTeRiA framework

The SoTeRiA framework (Fig. 1) theorizes multiple levels of 'internal' mechanisms, including individual, unit, group, and organization (Nodes 2 to 9 of Fig. 1), and their interactions with the 'external' environment, including physical, regulatory, business, and sociopolitical climates (Nodes 10 to 16 in Fig. 1), along with their causal influences on technical system risk (PRA; Node 1). Because different organizations can have unique organizational designs at multiple levels of performance (e.g., management, supervisor, team), it is the analyst's choice to determine the boundary among levels (e.g., between unit and group).

Based on SoTeRiA, the first step in developing a socio-technical risk model is to build the scenarios for the technical "system risk" (Node 1 in Fig. 1). The system risk is modeled in the site-specific PRA module in I-PRA (Fig. 2). The second step is to identify the safety critical tasks (Node 2 in Fig. 1) that affect the elements of risk scenarios. For example, maintenance performance is a safety critical task since it affects hardware failure. The next step is to model the work processes (e.g., maintenance work processes) that lead to safety critical performance. This helps create the "unit process model" (Node 3 in Fig. 1). Next, human performance models for individuals involved in the work processes of the unit process model need to be developed. This research is not implying the development of a separate model for each human; instead it considers modeling each team (who conducts similar tasks in its work processes) in the aggregate. For example, regarding a group of maintenance technicians performing similar categories of tasks in the maintenance unit, team performance would be modeled in the aggregate level. Lastly, the organizational aspects such as safety culture (Node 8 in Fig. 1) and safety climate (Nodes 5 and 6 in Fig. 1), and structural features such as safety practices (Node 7 in Fig. 1) of the supporting organization are linked to human performance models.

Another safety critical task includes operator performance that can be associated with a unit (e.g., an operator action in a main control room) or that can refer to an individual action in risk scenarios. In the I-PRA framework (Fig. 2), an operator action, basic event "a," stands for an example of a safety critical task, although I-PRA can cover other safety critical tasks (e.g., maintenance performance) related to the site-specific PRA. Node 4 in Fig. 1, "individual Performance Shaping Factors" (PSFs) refers to the PSFs in the HRA of I-PRA (Fig. 2), and the remaining organizational nodes in the SoTeRiA framework (Fig. 1) help model organizational failure mechanisms (#1.5, #2.5 and #3) in I-PRA.

As Fig. 2 shows, I-PRA is a multi-level risk assessment framework that begins with the Data-Theoretic module extracting and formalizing the organizational data required for the simulation of underlying organizational mechanisms (#3) that affect the states of PSFs (e.g., a_1, a_2, and a_3) and that, therefore, influence the probability of human errors (e.g., event "a" in the FT) in the site-specific PRA module. Through the interface module, the "spatio-temporal simulation of organizational failure mechanisms" (#3) is connected to the associated PSFs in the site-specific PRA module. In the interface module, the uncertainties associated with input data are characterized and propagated by the uncertainty analyzer (#4 in Fig. 2) to make the simulation module probabilistic and ready to be connected to the site-specific PRA model.

The *Data-Theoretic* module uses the high-level causal relationship of SoTeRiA (Fig. 1) as a preliminary causal structural shell in Element 1.5 to guide the analyst when adding more detailed causal constructs. Elements 1.1 to 1.4 of DT-BASE are the steps for adding more detailed causal constructs and quantifying the targeted causal model in Element 1.5. The scope of the targeted causal model in Element 1.5 can include adding details to one node of Fig. 1, or adding details to multiple nodes of Fig. 1 while preserving the high-level interconnections among those nodes (based on the causal connection of SoTeRiA in Fig. 1). In this paper, the scope of the targeted causal model is Training, which is related to Node 7 in Fig. 1. The targeted causal model that is gradually built and quantified through Elements 1.1 to 1.4 of DT-BASE forms the organizational causal input model in Element 1.5 as the input to DT-SITE. The quantification of the organizational causal input model is updated through DT-SITE Elements 2.1 to 2.4 to generate an updated version of the same causal model in Element 2.5, ready to provide input for the simulation module. In other words, the organizational causal input model in Element 2.5, a targeted-scope model of SoTeRiA (Fig. 1) with more detailed levels of causality, gives the input information (i.e., the causal structures and their associated measures) for the spatio-temporal simulation module (#3), where the analyst can add temporal and/or spatial dimensions. For example, the hybrid modeling approach by Mohaghegh and Mosleh [30] added the temporal dimension to the quantification of SoTeRiA by combining the System Dynamics technique with BBN. Ongoing research by the authors is focusing on the incorporation of spatial aspects, in addition to temporal, to socio-technical risk analysis [72,79–81].

The modeler has the choice of connecting the quantified organizational causal input model (#2.5 in Fig. 2) directly to the PSFs through the interface module or of making it temporal or spatio-temporal in the simulation module and then letting the simulation outputs pass to the interface module. This choice depends on criteria such as the level of available resources (e.g., computational resource, data availability) and the desired level of accuracy and resolution in the system risk estimation. The authors recommend that the first-phase of risk estimation be done without adding spatio-temporal dimensions, followed by advanced risk Importance Measure analysis [82] to determine the risk significance of each failure mechanism. In the next phase, the spatio-temporal dimensions can be added to the risk-significant failure mechanisms identified by the risk Importance Measure analysis.

The key performance measures (e.g., Ka_1, $Ka_{2,}$ Ka_3 in Fig. 2) refer to the measured performance outputs of the organizational model that help define the states of PSFs. For example, the quality of organizational training affects the state of training/experience PSF in HRA. Thus, the estimated quality of training from the organizational model is a key performance measure associated with the training/experience PSF in I-PRA. In the interface module, by having the probability distributions of the key performance measures resulting from the uncertainty analysis, the probability of each state of PSFs (e.g., low, nominal, high) is generated (#5 in Fig. 2) by estimating the probability that the associated key performance measure exceeds threshold values (See discussion in Section 3.3). This paper focuses on the development of the *Data-Theoretic* module, explained in Section 2.2, and its application (Section 3) for modeling the quality of NPP training. A more detailed explanation and advancement of other modules of the I-PRA framework are the focus of ongoing publications by the authors.

2.2. Methodological and computational developments for the Data-Theoretic module of Integrated PRA

The role of the Data-Theoretic module in the I-PRA framework is the execution of measurement techniques (Principle IV-L in Table 1) to extract and interpret organizational data associated with the structure and state (or value) of factors, sub-factors, and links in the SoTeRiA framework. Based on the evaluation of measurement techniques for organizational safety/risk frameworks [31], two common categories of methods including "subjective" and "objective" are listed. In the subjective measurement, the state of a factor is based on employees' perception. The subjective measurement is often taken by surveys or interviews conducted with the entire organization, a random sample, or specific members (e.g., supervisors and managers). In contrast, the objective measurement refers to the case where a person (or a group) measures the factor using checklists and/or by inspections and auditing (compliance-based). Auditors only get a snapshot of the organization, and often a limited number of subjects are audited. Perception surveys (subjective measurements) can capture some aspects of the reality that are overlooked by objective auditing. However, subjective measures also have their own limitations and biases. For example, employees' perceptions can be influenced by supervisors' interpretations [31]. Individual-level subjective measurements through surveys are usually limited to a set of factors; otherwise, they can be time consuming and expensive. Correlation between individual-level and organizational-level aggregation [83] relies on in-group agreement [84]; however, when factors are 'elusive' and unknown to individuals at the time of subjective measurement, it is not possible to gather meaningful data for highly granular organizational factors. Previous studies have introduced empirical data analysis for associating organizational factors with performance indicators [25] and cause codes [85] from industry data, however, these methods do not use theory to guide their analysis, and are not designed to be integrated with HRA or PRA methods. Readers are referred to Ref. [31] for a more detailed review of methods for measuring organizational factors at different levels of analysis. Neither a subjective or objective measurement approach alone has been proven to be a reliable approach for measuring the systematic multi-level relationships of organizational factors, and therefore, hybrid integration of these methods is required [31]. In order to address this challenge, this research proposes a new measurement method called the Data-Theoretic approach, having its preliminary development published in Ref. [86].

The Data-Theoretic module of I-PRA executes the Data-Theoretic approach, covering two main parts: (1) DT-BASE (#1 in Fig. 2; the white boxes on the left in the Data-Theoretic module) that focuses on the development of detailed causal relationships in SoTeRiA, based on a theory-building process (explained in Section 2.2.1.1) and equipped with a semi-automated baseline quantification utilizing analyst interpretation of generic information extracted from articles and standards; (2) DT-SITE (#2 in Fig. 2; the light blue boxes on the right in the Data-Theoretic module) that relates to conducting automated data extraction and inference methods (text mining) to quantify SoTeRiA causal elements based on site-specific event databases and by Bayesian updating of the baseline quantification established by DT-BASE. The Data-Theoretic approach is advancing measurement techniques for organizational factors in the following ways:

1 It guides "data analytics" with "theory." The problem with solely data-oriented approaches is that, due to the lack of guidance from an underlying theory, analysts can be misled by data, creating what Lazer (2014) calls "big data hubris," mistaking correlation for causation and "algorithm dynamics issues," when an algorithm is not capable of capturing the theoretical construct of interest [87]. In the Data-Theoretic approach, the theoretical causal structure of the SoTeRiA framework (Fig. 1) and the contextual keywords of each node in SoTeRiA guide data analytics; therefore, the underlying theory supports the completeness of causal factors, the accuracy of their causal relationships, and helps avoid the potentially misleading results of a solely data-oriented approach. Bar-Yam (2013) emphasized that (a) big data is critical for addressing complex systems, (b) theoretical modeling is essential to the scientific process for understanding complex systems, and (c) theory makes data more useful [88].
2 It combines different sources and types of information, for example (i) information pieces from academic literature, practical industry procedures, and regulatory standards are integrated through DT-BASE elements, (ii) analysts' "subjective" interpretation of information in DT-BASE is combined with "objective" event data extracted in DT-SITE, and (iii) "generic" information obtained in DT-BASE is integrated with "site-specific" information extracted in DT-SITE.
3 It uses text mining (in DT-SITE), in addition to expert opinion (in DT-BASE), as a measurement technique. Although lack of data has been mentioned as one of the key reasons for making slow progress in the incorporation of organizational factors into PRA [15,20], this research provides a new perspective by highlighting that data is available for organizational factors; however, the data has a nature that is different from tabular equipment reliability data. Archival data, documents, and texts serve as primary organization-level data. The Communicative Constitution of Organization (CCO) is a widely-accepted multidisciplinary perspective of organizational communication theory, which asserts that "*organizations are constituted (and maintained) through human communication*" [89]. For example, organizational documents in circulation at NPPs are tangible data structures that move forward through space and time, and these documents are what constitute the organization [90–92]. The extraction, interpretation, and analysis of communicative symbols present a new opportunity for analyzing organizational safety performance and risk contribution. Through the communication process, organizations produce, synthesize, and store a large volume of textual information used for regular business activities and compliance purposes. This large and complex volume of information (big data) needs a new measurement technique to analyze its contents. Data of organizational communications are a compilation of operational experience documents such as Corrective Action Program (CAP) entries, Licensee Event Reports (LERs), Root Cause Analysis (RCA) documents, and maintenance logs. Because these documents are unstructured and heterogeneous, it is necessary to incorporate data analytics techniques such as text mining for socio-technical risk analysis [81,93]. Text mining is widely used for big data due to its ability to extract information from unstructured textual information [94–96].

Sections 2.2.1 and 2.2.2 explain the status of methodological and computational developments for DT-BASE and DT-SITE, respectively.

2.2.1. DT-BASE elements of the data-theoretic module

The following sub-sections explain the five methodological elements of DT-BASE, including:

- Manual Extraction of Evidence and Building Causal Constructs (# 1.1 in Fig. 2).
- Analyst's Qualitative-Quantitative Interpretation of Each Piece of Evidence (#1.2 in Fig. 2).
- Developing Aggregated Conditional Probabilities based on Multiple Evidence Entries (#1.3 in Fig. 2).
- Developing Conditional Probabilities for Extended Causality (#1.4 in Fig. 2).
- Integration in a Bayesian Belief Network Computational Platform (#1.5 in Fig. 2).

The above methodological elements are computationally implemented following the flowchart in Fig. 3, which has three phases: (i) Data Entry, (ii) Aggregation, and (iii) Bayesian Belief Network Platform. Fig. 3 maps DT-BASE elements (the box at the top of Fig. 3) to the computational flowchart sequence (below the box in Fig. 3) and uses color-coding to show the relationships between DT-BASE elements and flowchart phases. Elements #1.1. and #1.2 of DT-BASE are executed in phase (i) of the flowchart (Fig. 3). Elements #1.3 and #1.4 of DT-BASE are conducted in phase (ii) of the computational flowchart. Phase (iii) of the flowchart (Fig. 3) executes element #1.5 of DT-BASE.

2.2.1.1. Manual extraction of evidence and building causal constructs (Element #1.1 in Fig. 2). For element #1.1 of DT-BASE (Fig. 2), the SoTeRiA framework (Fig. 1) provides the initial causal structure, and the analyst utilizes a theory-building process, along with their interpretation of "evidence" extracted from references, to expand causal constructs associated with the nodes in SoTeRiA. In this paper, "evidence" means a textual statement in a reference that supports the causal construct between two factors (e.g., cause "B_i" ($i = 1, 2, \ldots n$) or

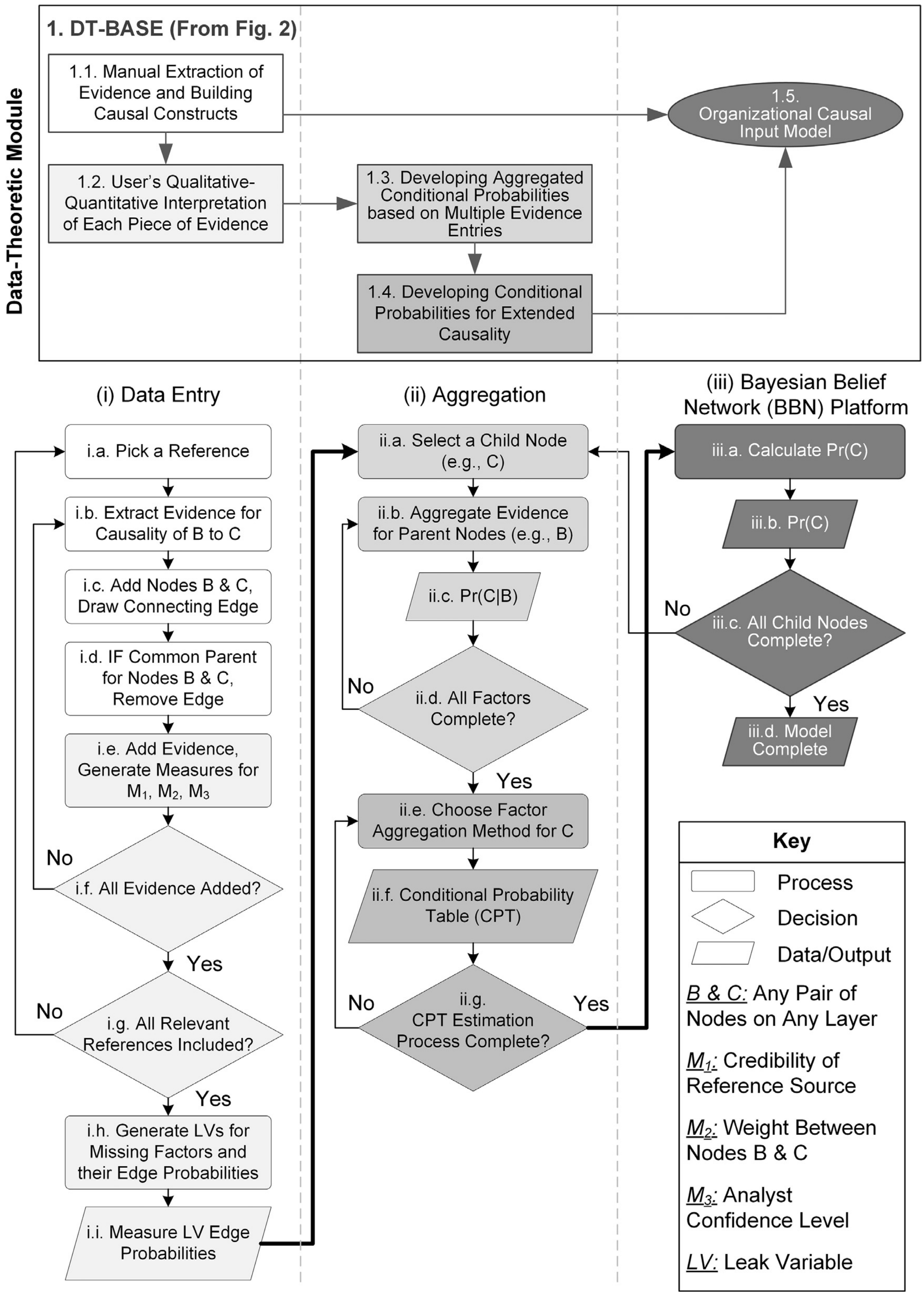

Fig. 3. DT-BASE module on the top of the figure surrounded by a solid black line and the associated computational flowchart below each phase: (i) data entry (Associated with 1.1 and 1.2 in Fig. 2); (ii) Aggregation (Associated with 1.3 and 1.4 in Fig. 2), and (iii) BBN (Associated with 1.5 in Fig. 2).

the parent node, effect “C” or the child node, and the edge (causal link) between B_i and C in Fig. 4).

Theory building (e.g., [97–99]) does not have a purely rule-based prescriptive process, and therefore, this element of DT-BASE (#1.1) cannot be fully automated. The theory-building process in this research not only utilizes the socio-technical risk analysis principles (Principles I, II, II, and IV-M in Table 1) [27], but also is consistent with Sterman's [50] conceptualization of an iterative learning process [50] and reflects Weick's (1989) perspective on the intuitive nature of theory-building [100]. Element #1.1 of DT-BASE has the following five-step manual

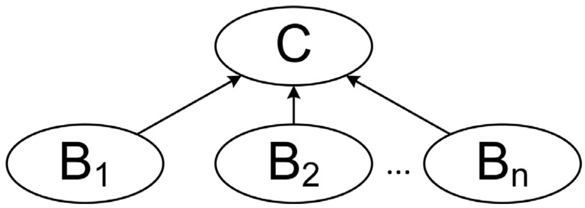

Fig. 4. Causes (Parent Nodes) and Effect (Child Node) in a simple theoretical causal construct.

theory-building process as well as computational features that help in structuring the causal model:

- Step 1: Identifying the unknown of interest, i.e., the selected target node/organizational factor (e.g., training). This step refers to Principle I.A. in Table 1.
- Step 2: Identifying the literature (i.e., regulatory and industry standards as well as academic articles) associated with the selected organizational factor.
- Step 3: Locating the selected organizational factor within the SoTeRiA framework (Fig. 1). For example, "training" is an organizational factor associated with Node 7 in SoTeRiA.
- Step 4: Identifying logical abstract-level phases (e.g., plan, do, check, act) evolving and leading to the performance quality of the selected organizational factor. This helps develop causal levels at the abstract level of analysis.
- Step 5: Developing theoretical causal constructs for the organizational mechanisms leading to the performance quality of the selected organizational factor by satisfying theory-building principles (Principles II and III in Table 1) and by utilizing semi-formal process modeling techniques (e.g., business process modeling [101], flowcharts [102], etc.). Although semi-formal modeling techniques are related to Principle IV-M (Table 1) that is focused on modeling techniques (rather than theory building), they can be considered as the bridging techniques that help turn a theory into a causal model equipped with a formal modeling technique (e.g., BBN). Semi-formal process modeling techniques help expand the causalities from the abstract level of analysis (developed in Step 4) to more detailed functional and task levels. We refer the readers to Mohaghegh et al. [30] for the details on the application of semi-formal process modeling techniques for the development of multi-level causalities. In this research, the Structured Analysis and Design Technique (SADT) [103, 104] (Fig. 5) is used as the selected process modeling technique due to its (1) ease of conversion from a 'semi-formal' to 'formal' (e.g., BBN) technique, (2) ease of communicating the model and results, and (3) the generality of the technique for different organizational factors [27]. In SADT, the activity transmits the inputs (I) to the outputs (O), given the resources (R) and the control/criteria (C) [30]. The inputs can include, but are not limited to, information, hardware, raw materials, and people. Outputs are the products of the process. Resources are the things needed to perform the activity, such as tools, equipment, and people. Controls/criteria include requirements such as job control mechanisms, constraints, procedures, applicable rules and regulations, and standards that are used to direct, control, and judge the conduct of an activity. The SADT input-output structure can be converted to a BBN causal structure, as demonstrated by Mohaghegh et al. [30], and is implemented in Section 3 of this paper to build and quantify the training causal model.

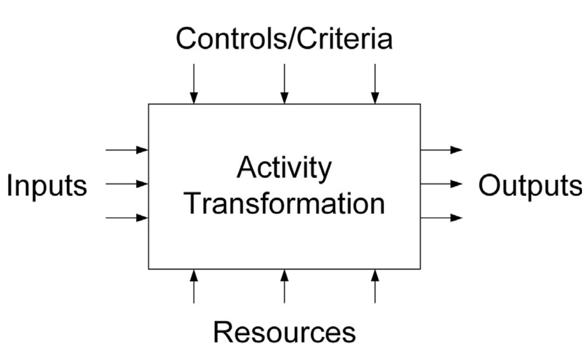

Fig. 5. Structured analysis and design technique [104].

The computational feature of element #1.1 of DT-BASE is a part of the data entry phase (i.a., i.b., i.c., and i.d.) in Fig. 3 and helps the analyst add the causal constructs, in the right location and at the right level of analysis, to gradually build the final structure of the organizational causal input model (delivered to element #1.5 in Fig. 2). As Fig. 3 shows, the analyst picks a reference (e.g., from academic literature, practical industry procedures, or regulatory standards), and based on their interpretation of each piece of evidence and following the theory-building steps (Step 3 to Step 5 listed above), they add the causal construct to the model.

Section 3.1. further explains element # 1.1 by applying it in the case study to build the causal model for training in NPPs.

2.2.1.2. Analyst's qualitative-quantitative interpretation of each piece of evidence (Element #1.2 in Fig. 2). Once element #1.1 of DT-BASE (Fig. 2) has been executed for a causal construct (i.e., a minimum of two nodes and an edge in Fig. 4), the analyst is prompted through element #1.2 to enter a set of information based on their interpretation of the evidence supporting the causal construct. The computational execution of element #1.2 is included in the data entry phase (i.e., i.h., i.i.) of Fig. 3. Because SoTeRiA is explicitly modeling "performance quality" for each node, the analyst first defines the "states" of each node based on their potential quality states (or the existence of a specific quality); for example, "good/high" (or true or existent) (State 1) and "bad/poor/low" (or false or absent) (State 2). For each causal construct, the analyst is then prompted to enter the following information:

- *Reference information:* The analyst imports reference information (.ris file) or enters the title, year, authors' names, type of publication, publisher, etc. into data fields. In DT-BASE, evidence dependencies are managed through a bibliometric analysis which cross-compares reference information to find potential overlaps and avoids double counting of evidence. Current dependencies considered are: same author or authors, same institution, and concurrent publications (i.e., which may indicate similar subject populations or case studies). This information is presented to the analyst to guide them to remove potential information dependencies based on the entered references. In other words, the current scope of dependency treatment is "binary", meaning that, if a potential overlap is identified between two references, they are counted only once; otherwise, both of them are included in the DT-BASE.
- *Keywords associated with the parent node and child node (see Fig. 4)*: The relevant keywords for each node are created as tags in the entry. Multiple keywords can be added to represent the context of a factor. Synonyms and alternative industry-specific phrasing should be included to account for the textual context in other data sources.
- *A verbatim copy of the textual statement explaining the causal relationship:* The exact statement, which supports the relationship between the two nodes, is copied as supporting evidence.

Next, the analyst is prompted to provide the following subjective quantitative values associated with the piece of evidence:

- **[$M_{1,\ EV}$]** *Credibility of the reference source (e.g., Journal Impact Factor):* The weight or impact factor of the publication, based on a "low estimate point" and a "high estimate point" from zero to one, where the current value used is the median.

- **[$M_{2, EV}$]** *Weight between node Bi and node C indicated in the evidence:* The analyst's interpretation of the author's statement about the strength of causal influence of B_i on C. $M_{2, EV}$ is represented by a numerical scale from zero to one. For the example of B_i (State 1) affecting C (State 1) (see Fig. 4), $M_{2, EV}$ refers to the conditional probability of C, given B_i, as in, $Pr(C \mid B_i)$. Language may include that "it is very likely B_i causes C." It is also possible that the reference has a numerical analysis and that the results show the strong or weak influence of B_i on C.
- **[$M_{3, EV}$]** *Analyst confidence level in the subject matter material:* The analyst's familiarity with the two nodes and their causal relationship. $M_{3, EV}$ ranges from zero to one.

In order to support consistency among different analysts with respect to their judgments for M_1, M_2, and M_3, this research utilizes a set of natural language expressions that are associated with probabilities, initially developed by Wallsten [105] and adapted by the International Panel on Climate Change (IPCC) [106,107]. The IPCC probability language has seven categories of probability values to describe a degree of belief in a proposition; "virtually certain, very likely, likely, medium likelihood, unlikely, very unlikely, extremely unlikely" [106,108]. The categories and ranges are shown in Table 2. Because these categories were developed for the context of climate change and have not been calibrated or measured to specifically address NPP contexts, future research is needed to conduct sensitivity analysis to determine whether changing categorical bin thresholds make a significant difference to PRA results, and if so, additional effort is needed to calibrate these bins for nuclear power industry applications. For example, future work will consider specific questions to assist individuals in assessing their confidence likelihood for M_3.

As step (i.i.) of the data entry phase of Fig. 3 shows, to introduce a measure of incompleteness uncertainty into the causal model, a Leak Variable (LV) is introduced at each 'layer' of causality. The LV stands for nodes that are not included in the model. The analyst can enter a value for LV edge probability. The meaning of LV edge probability is explained in Section 2.2.1.4, where it is used in the extended causality equation. The analyst can create as many evidence entries as literature supports. The next step of the DT-BASE approach performs aggregation as each piece of evidence is added.

2.2.1.3. Developing aggregated conditional probabilities based on multiple evidence entries (Element #1.3 in Fig. 2). Element #1.3 of DT-BASE, which relates to the second phase (ii.b.) of the computational flowchart (Fig. 3), focuses on the estimation of aggregated conditional probabilities when the analyst's interpretations of multiple evidence entries are elicited for the same conditional probability. In Element #1.2, based on each piece of information $EV_{i,\ j}$, the analyst provides $M_{2,\ EV_{i,j}}$ that indicates the strength of the causal relationship between the factors B_i and C and can be treated as an estimate of the conditional probability $Pr(C|B_i)$, if there is only one piece of information available. In Element #1.3, the aggregated estimate of $Pr(C|B_i)$ is estimated by combining $M_{2,\ EV_{i,j}}$ derived from multiple pieces of information $EV_{i,j}; j \in \{1,\ ...,\ K\}$.

To compute the aggregated conditional probabilities, this research uses two axiomatic approaches for aggregating multiple experts' probability estimates that have been commonly used in PRA: arithmetic mean (Eq. (1)) and geometric mean (Eq. (2)) [109,110], formulated as follows:

$$Pr(C|B_i) = \sum_{j=1}^{K} w_{EV_{i,j}} M_{2,EV_{i,j}}\ \forall\ i \in I, \tag{1}$$

$$Pr(C|B_i) = \prod_{j=1}^{K} M_{2,EV_{i,j}}^{w_{EV_{i,j}}}\ \forall\ i \in I, \tag{2}$$

where $w_{EV_{i,j}}$ is the normalized weight, representing the relative quality of different pieces of information [109]. Considering that quality of $M_{2,\ EV_{i,j}}$ estimate is influenced by both (i) quality of the original evidence (e.g., literature), measured by $M_{1,\ EV_{i,j}}$, and (ii) quality of the analyst who interpreted the original evidence, measured by $M_{3,\ EV_{i,j}}$; $w_{EV_{i,j}}$ is formulated as a function of $M_{1,\ EV_{i,j}}$ and $M_{3,\ EV_{i,j}}$:

$$w_{EV_{i,j}} = \frac{M_{1,\ EV_{i,j}} \times M_{3,\ EV_{i,j}}}{\sum_{j=1}^{K} M_{1,\ EV_{i,j}} \times M_{3,\ EV_{i,j}}}\ \ \forall\ i \in I,\ j = 1,\ \ ...,\ K \tag{3}$$

The selection between the arithmetic mean (Eq. (1)) and geometric mean (Eq. (2)) could depend on the applications. For instance, as suggested by Morton et al. [111], the arithmetic mean may generate a misleading output when there is a large dispersion between the experts' assessment as the extreme estimates dominate the result; under such a situation, the geometric mean can generate a more stable and reasonable output that captures the 'center' of the group's opinion. More detailed guidelines for when to use which aggregation method need to be developed in future research.

In these aggregation equations, index 'i' (i = 1, 2,..., I) is used to denote one instance (parent node) that has a shared effect on C, pertaining to one causal relationship (i.e., $Pr(C|B_i)$ in Fig. 4). Index 'j' (j = 1, 2,..., K) denotes one evidence entry that is related to the causal relationship between B_i and C. K stands for a total number of evidence entries. The analyst decides between the two aggregation methods. In Eq. (3), the normalization factor Z is developed to normalize the weight for each piece of evidence based on the combination of $M_{1,EV}$ and $M_{3,EV}$ so that the resultant value obeys probability axioms.

2.2.1.4. Developing conditional probabilities for extended causality (Element #1.4 in Fig. 2). Element #1.4 of DT-BASE focuses on the estimation of the conditional probability of the child node given multiple parent nodes (i.e., $Pr(C|B_1, B_2, \cdots, B_n)$in Fig. 4) based on the aggregation of estimated values from element #1.3 (i.e., $Pr(C|B_1)$, $Pr(C|B_2)$, ..., $Pr(C|B_n)$). The estimated conditional probabilities build the Conditional Probability Table (CPT), which is an input to the next step of the methodology, i.e., the Bayesian Belief Network (BBN) platform (element #1.5 explained in Section 2.2.1.5). Element #1.4 of DT-BASE is made computational in the second phase (ii.d.) of the flowchart shown in Fig. 3.

In element #1.2 (Section 2.2.1.2), the analyst is asked to elicit information for each piece of evidence of the causal relationship between one parent (B_i) and the child node (C), implicitly assuming that a single

Table 2
Mapping between probability words and probability values (Adapted from [106]).

Lower Bound	Upper Bound	M_1	M_2	M_3
0.99	1	Virtually Certainly Credible	Virtually Certain	Virtual Certainty in Confidence
0.9	0.99	Very Likely Credible	Very Likely	Very Likely Confident
0.66	0.9	Likely Credible	Likely	Likely Confident
0.33	0.66	Medium Likelihood of Credibility	Medium Likelihood	Medium Likelihood of Confidence
0.1	0.33	Unlikely Credible	Unlikely	Unlikely Confident
0.01	0.1	Very Unlikely Credible	Very Unlikely	Very Unlikely Confident
0	0.01	Extremely Unlikely to be Credible	Extremely Unlikely	Extremely Unlikely to be Confident

parent can lead to the child (C). This assumption is related to the concept of Independence of Causal Influence (ICI) [112,113]. Therefore, a common aggregation model that is used in element #1.4 of DT-BASE is the Noisy-OR [41, 112-115] that governs the following relationship:

$$\Pr(C|B_1, B_2, \cdots, B_n) = 1 - \prod_{i \in I} (1 - z_i), \tag{4}$$

where, "i" shows all configurations of parent nodes that are present, and z_i is the probability of C given that *only* cause B_i is present (i.e., $\Pr(C|B_i)$), utilizing the probabilities being aggregated in Section 2.2.1.3.

For multi-state variables, the Noisy-OR representation of causal influence can be extended to the Noisy-MAX representation with the same ICI assumption. Diez's definition of Noisy-MAX [116] is as follows:

$$\Pr(C \le c|b) = \prod_{i} \Pr(C \le c|B_i = b_i, B_{-i} = 0), \tag{5}$$

where; b is a configuration of parent nodes and B_{-i} represents all factors other than B_i. It should be noted that $\Pr(C \le c|B_i = b_i, B_{-i} = 0)$ also considers conditional influence towards C given that *only* cause B_i is present. The CPT can then be computed by applying the following equation to each configuration of the parent nodes:

$$\Pr(C|B_1, B_2, \cdots, B_n) = \begin{cases} \Pr(C = 0|b), & c = 0 \\ \Pr(C \le c|b) - \Pr(C \le c - 1|b), & c > 0 \end{cases}. \tag{6}$$

Using Eqs. (4) and 6, the CPT can be calculated for binary-state nodes using Noisy-OR and for multi-state nodes using Noisy-MAX, respectively.

The effects of LV and the associated incompleteness uncertainty can be considered by defining an edge probability that refers to the conditional probability of C, given that not any of B_i exists and only LV exists [113], as it is shown in Eq. 7. In that case, the aggregated conditional probability is estimated from Eq. (8).

$$z_L = \Pr(C|\mathrm{not\,any\,}B_i\mathrm{\,exists\,except\,}LV), \tag{7}$$

$$\Pr(C|B_1, B_2, \cdots, B_n, LV) = 1 - (1 - z_L) \prod_{i \in I} (1 - z_i), \tag{8}$$

It should be noted that the Noisy-OR method and the concept of ICI generate limitations for capturing factor interactions [115]. Future research will evaluate the possibility of using more advanced methods to address these limitations.

2.2.1.5. Integration in a Bayesian belief network computational platform (Element #1.5 in Fig. 2). In element #1.5 of DT-BASE (Fig. 2), the results of quantitative interpretations and measurements that are generated in elements # 1.2, #1.3, and #1.4 of DT-BASE, are combined with the causal model structure constructed in element #1.1 to develop organizational causal input model (built in the BBN environment) that provides input for the spatio-temporal simulation module of the I-PRA framework. As mentioned in Section 2.2.1.1., a semi-formal modeling technique (i.e., SADT) is used in element #1.1 of DT-BASE to transition theoretical constructs to a formal modeling technique structure (i.e., BBN's probabilistic modeling environment). Other aspects of modeling techniques (associated with Principle IV-M) such as space and time will be executed in the simulation module (#3) of I-PRA.

Element #1.5 is executed in the third phase of the computational flowchart (Fig. 3), where information is integrated into a BBN platform to calculate the probability of the final target node (i.e., the child node in the last layer of the causal model) based on the CPT developed in phase (ii) of Fig. 3. BBN, widely used in HRA research, provides graphical formalism and structure, a probabilistic representation of uncertainty, structuration of interrelationships, accommodation of diverse data sources, and representation of belief for factor influences [115, 117] in the organizational causal input model (#1.5 in Fig. 2). Readers are referred to Ref. [118] for more background on BBN.

The computational platform of DT-BASE is an open-source web application powered by the MEAN full-stack framework (MongoDB, ExpressJS, AngularJS, NodeJS) [119]. DT-BASE is developed as a web application to enable a scientific network for collaborative model building where analysts can build and share modular theoretical models. Using a client-server architecture, multiple analysts can collaborate on a single causal model.

2.2.2. DT-SITE elements of the data-theoretic module

As the I-PRA framework (Fig. 2) shows, the output of element #1.5 of DT-BASE, the organizational causal input model, provides the causal factors, their related keywords, and causal relationships as inputs for the elements of DT-SITE. At this stage of the research, the causal model structure that is developed at the end of DT-BASE (element #1.5) does not change based on the data analysis in DT-SITE, but its quantification is updated using the DT-SITE analysis. Depending on the scope and availability of site-specific data, it is possible that some nodes in the updated organizational causal input model (element #2.5) are only quantified by DT-BASE, while others are quantified by Bayesian integration of DT-BASE and DT-SITE analyses. Future research will evaluate the value of adding an element in DT-SITE to consider updating the causal model (i.e., adding/deleting nodes or causal paths) based on the data analysis in DT-SITE.

Currently, DT-SITE has the following five methodological elements:

- Automated Extraction of Information; Text Mining (#2.1 in Fig. 2).
- Generating Conditional and Marginal Probabilities for BBN (#2.2 in Fig. 2).
- Developing Aggregated Conditional and Marginal Probabilities based on Multiple Data Sources (#2.3 in Fig. 2).
- Bayesian Integration of SITE and BASE Probabilities (# 2.4 in Fig. 2).
- Integration in a Bayesian Belief Networks Computational Platform (#2.5 in Fig. 2).

DT-SITE is still in an early stage of development, and its computational platform has not yet been integrated with DT-BASE in the Data-Theoretic Module. The following sub-sections explain the purpose of each of the current five elements of DT-SITE, and Section 3.2 demonstrates its limited-scope implementation for the NPP case study.

2.2.2.1. Automated extraction of Information; text mining (Element #2.1 in Fig. 2). The DT-SITE element for the automated extraction of information includes the following two steps:

i *Information searching:* Factors, causal relationships, keywords, and contextual statements from element #1.5 of DT-BASE are used to guide the text mining [120], to extract semantic 'safety-oriented' terminology from organizational communications. This step implements computational approaches for pre-processing unstructured textual information to ensure that extracted information maintains conformity to the original texts. At this stage of research, text mining is designed for one specific type of database, i.e., the NPP incident reporting system called the Corrective Action Program (CAP), which is also used in Section 3 for the case study. Ongoing research by the authors is focused on the development of more advanced text mining that can be applied to other safety-related databases.

ii *Frequency development*: To convert the outputs of the information searching step to frequencies, depending on the type and format of the database, specific subjective and objective interpretations should be included in the computational process. Also, each database needs to be normalized into performance period timeframes. For instance, the CAP database of NPPs can receive thousands of entries in a year. Each CAP entry refers to one incident (or one safety-related issue) that is represented by a row in a table. For each entry, multiple contributing causes are possible and are written in a text narrative. Using the DT-BASE causal factors (from element #1.5 of Fig. 2) as the keywords included in the 'input file' of the text mining code, the process is guided to find the number of occurrences of a construct (or multiple constructs) in each CAP entry. For simplification, at this stage of research, the following assumption is made; a factor is counted only once as a contributor despite the number of times it appears in the narrative of one entry. For example, f_{B_1}, which stands for the frequency of factor "B_1," refers to the number of CAP entries including factor B_1 in the data collection period (e.g., one year); $f_{B_1,C}$ represents the number of CAP entries which include both B_1 and C in the data collection period; and $f_{B_1,B_2,C}$ represents the number of CAP entries which simultaneously include B_1, B_2, and C in the data collection period.

2.2.2.2. Generating conditional and marginal probabilities for BBN (Element #2.2 in Fig. 2). In this element of DT-SITE, frequencies developed in element #2.1 are used to estimate marginal and conditional probabilities associated with the CPT values of the BBN model developed in element #1.5 of DT-BASE. For instance, consider one parent node B_1 and a child node C. The marginal probability of node B_1, $\Pr(B_1)$, can be estimated from the frequency outputs of text mining using Eq. (9):

$$\Pr(B_1) = \frac{f_{B_1}}{N_{CAP}}, \tag{9}$$

where N_{CAP} represents the total number of CAP entries in the same data collection period as f_{B_1}.

Meanwhile, the conditional probability of the child node C, given a specific state of the parent node B_1, $\Pr(C|B_1)$, are defined in Eq. (10);

$$\Pr(C|B_1) = \frac{\Pr(B_1 \cap C)}{\Pr(B_1)}. \tag{10}$$

On the right-hand side of this equation, the estimate of the denominator, $\Pr(B_1)$, is obtained from Eq. (9). The numerator, $\Pr(C \cap B_1)$, refers to the probability of joint occurrence of B_1 and C, and can be estimated based on Eq. (11):

$$\Pr(B_1 \cap C) = \frac{f_{B_1,C}}{N_{CAP}}. \tag{11}$$

When there is more than one parent node in the BBN, for example, three parent nodes in Fig. 4, Eq. (12) represents the conditional probability, of which the numerator can be estimated based on the frequency data obtained by the text mining using Eq. (13);

$$\Pr(C|B_1, B_2) = \frac{\Pr(C \cap B_1 \cap B_2)}{\Pr(B_1 \cap B_2)}, \tag{12}$$

$$\Pr(B_1 \cap B_2 \cap C) = \frac{f_{B_1,B_2,C}}{N_{CAP}}. \tag{13}$$

It should be noted that the probabilities estimated by the approach shown in this section are biased by (or conditioned on) the number (and quality) of CAP entries, and this bias is further explained in Section 3.3.

2.2.2.3. Developing aggregated conditional and marginal probabilities based on multiple data sources (Element #2.3. in Fig. 2). The mathematical structure of aggregating conditional and marginal probabilities, estimated from multiple databases, would be similar to the Arithmetic (Eq. (1)) or Geometric (Eq. (2)) aggregation methods used in Section 2.2.1.3. Similarly, the analyst will have the option to give credibility and importance weights to each database. Since at this stage of the research only one data source (the CAP database of an NPP) has been used, this element of DT-SITE has not yet been implemented. Possible challenges of element #2.3 would be dealing with dependencies among diverse data sources or conflicting information among the data sources. Future research will address these challenges.

2.2.2.4. Bayesian integration of DT-BASE and DT-SITE probabilities (Element #2.4 in Fig. 2). In this element of DT-SITE, each conditional probability, estimated from element #2.3, is combined with the associated conditional probability estimated from the DT-BASE that is stored in the BBN of the organizational causal input model (#1.5). This helps develop the updated conditional probabilities and leads to the generation of the updated organizational causal input model (#2.5 in Fig. 2). In other words, the updated organizational causal input model (#2.5) has the same causal structure developed from element #1.5, but it has the updated (i.e., integration of SITE and BASE) conditional probabilities. Note that it also has the marginal probabilities estimated from element #2.3 of DT-SITE. The mathematical mechanism for integrating conditional probabilities from DT-SITE and DT-BASE is Bayesian updating, as described in Eq. (14):

$$\pi(p|\underline{D}) = \frac{L(\underline{D}|p)\ \pi_0(p)}{\int L(\underline{D}|p)\pi_0(p)dp}, \tag{14}$$

where $\pi_0(p)$ refers to the prior distribution of an unknown quantity, p, referring to the conditional probability of interest that is needed to be updated. $L(\underline{D}|p)$ stands for the likelihood function for a set of new evidence, given that the true value of the unknown quantity is p, and $\pi(p|\underline{D})$ is the posterior (updated) distribution of p, given the set of new evidence $\underline{D}$. In this research, the DT-SITE and DT-BASE estimations of p is treated as two pieces of evidence to help find the updated value for the conditional probability; hence, $\underline{D} = \{\hat{p}_{\mathrm{BASE}}, \ \hat{p}_{\mathrm{SITE}}\}$ where $\hat{p}_{\mathrm{BASE}}$ and $\hat{p}_{\mathrm{SITE}}$ are the estimate of p generated by DT-BASE and DT-SITE, respectively. With the assumption of independence between the estimations from DT-SITE and DT-BASE, the likelihood function, $L(\underline{D}|p)$, can be formulated as the product of two likelihood functions:

$$L(\underline{D}|p) = \ L(\hat{p}_{\mathrm{BASE}}|p)^{*}\ L(\hat{p}_{\mathrm{SITE}}|p). \tag{15}$$

In this formulation, $L(\hat{p}_{\mathrm{BASE}}|p)$ represents a measure of accuracy of the DT-BASE estimation, and $L(\hat{p}_{\mathrm{SITE}}|p)$ is a measure of accuracy of the DT-SITE estimation with respect to the conditional probability of the specific construct. Depending on the type of knowledge available regarding the accuracy of measurements in DT-BASE and DT-SITE, a mathematical model needs to be chosen for the likelihood functions. One example of such a likelihood function is demonstrated in Section 3.2, where the DT approach is applied to a case study for the training causal model.

3. Application of the data-theoretic approach to develop and quantify the training causal model in nuclear power plants

The focus of this section is on the implementation of the Data-Theoretic approach (Data-Theoretic Module in Fig. 2) for a single factor – "training" – as an exemplar among the myriad of factors at the 'organizational-level' of analysis (i.e., the overall training program that supports different groups at an NPP). Based on an independent third-party review at an NPP, 'training quality' was identified as risk-significant. Because it has not been explicitly modeled and integrated with PRA, understanding the contribution of training quality to risk needed additional modeling. The results of this research help model the underlying organizational mechanisms associated with the training/experience PSF in HRA. Ref. [121] states that, if training is considered to be a performance driver, *"this PSF might also include the quality of the training provided."* The goal of this research is to go beyond the qualitative judgment derived from HRA workbook estimations and to develop a plant-specific distribution of training quality utilizing plant CAP data.

In this research, the training causal model (Fig. 6) is developed and quantified based on theoretical literature and using industry and regulatory guidelines and plant database, receiving validation on the structure and contents from training experts at an NPP. By Bayesian integration of generic and site-specific information, the plant-specific distribution of the training quality (Fig. 7) estimation is generated. More thorough validation regarding the estimated probabilities relates to the Probabilistic Validation methodology [71] under development by the authors for the I-PRA framework. Probabilistic Validation is a methodology to characterize and propagate sources of epistemic uncertainty (e.g., parameter uncertainty, model uncertainty, statistical convergence, analyst's epistemic uncertainty about M_1, M_2, M_3, etc.) in an integrated manner to construct the total epistemic uncertainty, associated with the model output, as a measure for the degree of validity of the probability estimated from the model. The following subsections cover the implementation of DT-BASE and DT-SITE elements.

3.1. Applying DT-BASE elements to model and quantify training quality in nuclear power plants

This section explains the implementation of DT-BASE elements (#1.1 to #1.5 in Fig. 2) for the development of the "training" theoretical causal model and its generic quantification. As it is stated in Section 2.2.1.1, the theory-building process in element #1.1 starts with five key steps that are applied in the following:

- *Step 1*: Identifying the unknown of interest: The unknown of interest is the target node "Training," which stands for the organization's ability to provide adequate training to its workforce, based on the programmatic, process-based approaches implemented at the NPP. "Training Program" is placed at the target node (Level 0) of the causal model (Fig. 6) and is divided into in-house and outsourced training. In this research, we focus on causal modeling of in-house training. For simplification, the causal model developed in the scope of this paper does not cover some of the contributing factors such as student performance, availability of student time, availability of simulator time, cultural factors, or management attitudes towards training. Therefore, in the quantification phase, a LV (introduced in Section 2.2.1.2) is considered at each layer of the causal model to represent model uncertainty, which implicitly considers the potential of excluding some factors in the causal model.
- *Step 2*: Identifying the literature related to training: Starting with the language of industry and based on NPP documentation, diverse training categories were identified, such as electrical maintenance, mechanical maintenance, chemistry technician, etc. The NPP implements a Systematic Approach to Training (SAT), and therefore, each theoretical construct associated with SAT was used as an initial search term to identify relevant literature from industry, regulatory and academic sources, expanding the scope of search terms. The criteria for adding sub-factors was if they were supported by either industry, regulatory or academic sources (i.e., written evidence could be found to support the inclusion and placement of each sub-factor). For example, if some aspects of training were implicitly included in the industry SAT but were explicitly included and supported in the academic literature, they could be added. The literature is added dynamically as we progress through the remaining steps of the methodology. Therefore, the literature review in Step 2 is not final, it is the starting point of an iterative process, and the identification of relevant literature continues to process through the remaining steps. It should be noted that the Nuclear Energy Institute issued Efficiency Bulletin: 17–15 'Standardization of the Systematic Approach to Training' [122], provides suggestions to the industry that are not fully incorporated into the training causal model shown in this paper.
- *Step 3*: Locating the selected organizational factor within the SoTeRiA framework (Fig. 1): Training is a sub-factor of "human resource practices," which is a factor of "organizational structure and practices," i.e., Node 7 of SoTeRiA; Fig 1.
- *Step 4*: Identifying logical abstract-level phases evolving and leading to the quality of training: Based on evidence supporting independent causality and cross-level causality, high-level patterns depicting programs and processes associated with training follow the high-level phases of Analysis, Design, Development, Implementation and Evaluation (ADDIE) [123]. The phases of SAT are consistent with those of ADDIE, with the differentiation of 'design and development' being considered as one phase in SAT. Therefore, for the SAT, the phases are; needs assessment, design and development, implementation, and evaluation [124]. In the causal model developed in this research, "implementation" and "evaluation" are considered as two types of activity factors in Level 1 of Fig 6, influencing the quality of "In-House Training." The other two phases including "design and development" and "need assessment" are covered through the causal factors affecting "Implementation." For example, "Program Design" and "Training Needs Analysis" are the causal factors in Levels 2 and 2.1 of Fig. 6, respectively. This section only demonstrates the causal model associated with implementation quality, and the causal models supporting evaluation factors (e.g., internal evaluation and regulatory evaluation in Level 1 of Fig. 6) are not covered.
- *Step 5*: Developing theoretical causal constructs for the organizational mechanisms leading to the quality of training: Using the semi-formal process modeling approach of SADT (Fig. 5), any activity in Level 1 of Fig. 6 is affected by its direct causes including the direct resource/tool, procedure, and personnel. These causal factors are placed in Level 1.1 of Fig. 6. For example, the quality of implementation depends on the quality of "Training Procedures (procedure)/Facility (resource/tool)" and the "Instructor Performance" (personnel). In the SADT approach for the "implementation" activity node, procedure and resource/tool are lumped into one factor, i.e., "Training Procedures/Facility," because enough evidence to separately quantify them have not been found. The next level of causality, Level 1.1.1 in Fig. 6, includes the sub-factors influencing the quality of resources, procedures, and instructors in Level 1.1. For example, "Instructor Performance" is influenced by "Instructor Training," "Instructor Time & Preparation," and "Instructor Knowledge." Level 2 of the causal model includes "Program Design," that is, the activity supporting the factors in Level 1.1.1 of the model. Again, based on SADT approach, Level 2.1 covers the direct resource/tool ("Training Records Documentation System" in Fig. 6), procedure ("Training Needs Analysis" in Fig. 6), and personnel ("Instructional Technologists" in Fig. 6) that are needed for the activity in Level 2 (i.e., Program and Design). Level 2.1.1 of the causal model includes the sub-factors influencing the quality of the resource and procedures in Level 2.1. Every node and relationship between layers are supported by evidence from literature (academic articles, regulatory and industry documents) and standards to create a theoretical justification and validation of its placement and interrelationships within the model. For example, Table 3 shows a partial list for the industry, regulatory and academic references that are used for the factor "Job/Task Analysis" in Level 2.1.2 of the causal model. The full implementation information for the 'Training' organizational causal input model in DT-BASE can be found in the supplementary dataset [125].

It should be noted that the numbers associated with the Levels in Fig. 6 are used to organize and communicate the causal model. However, there is theoretical support for the ordering and arrangement of these Levels in the model. The logical order of Levels 0, 1, and 2, is explained in Step 4 (above), and is supported by ADDIE [123] and the SAT [122, 126, 127]. The logical order of levels 1.1, 1.1.1, 2.1, 2.1.1, and 2.1.2 is explained in Step 5 (above) and is structured by SADT [103, 104].

In element #1.2 of DT-BASE (Fig. 2), the analyst enters the values for M_1, M_2, and M_3 based on his/her interpretation of each piece of

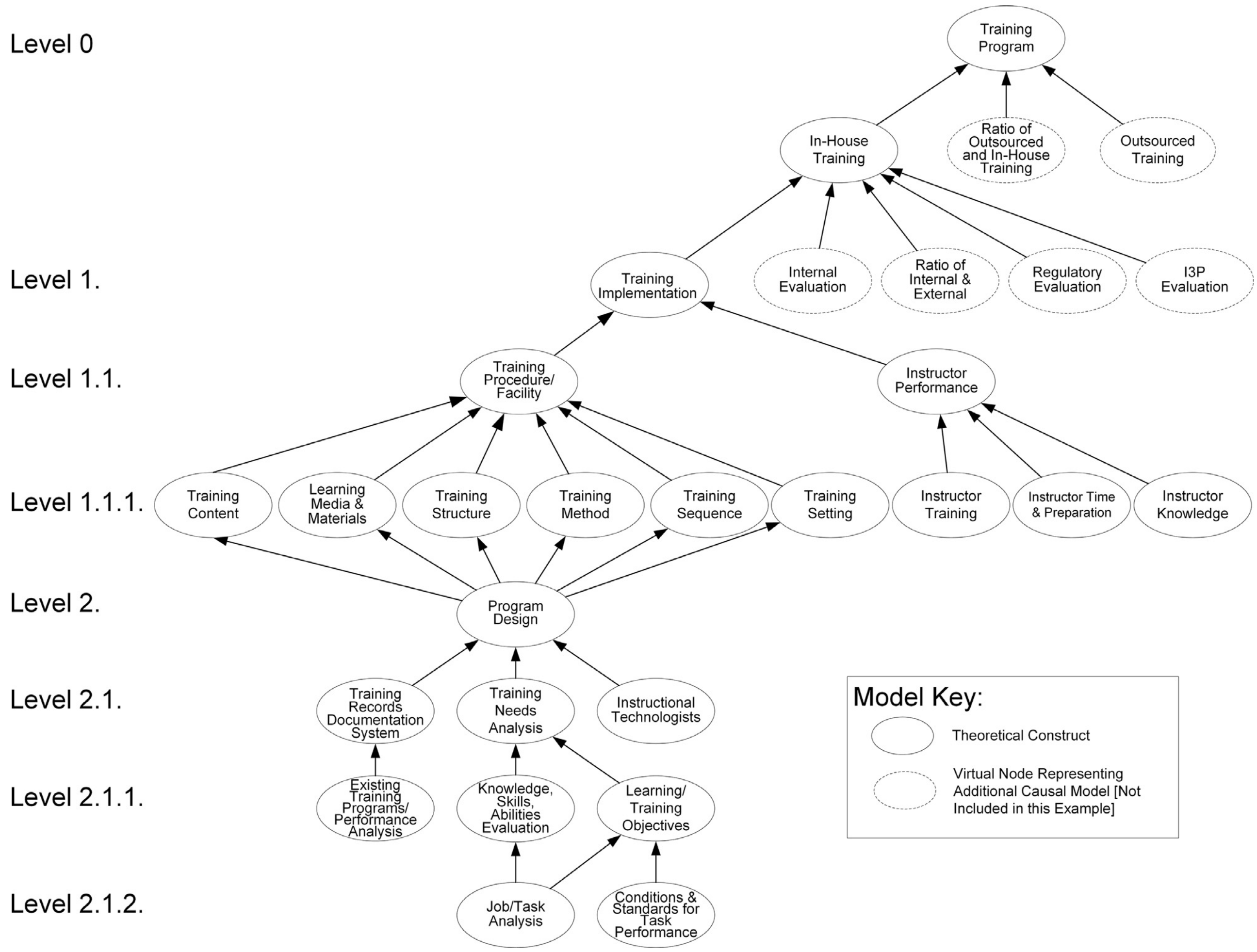

Fig. 6. NPP training causal model developed based on element #1.1 of DT-BASE.

evidence and using the probability categories listed in Table 2. The full M values used for the 'Training' organizational causal input model in DT-BASE can be found in the publicly available supplementary dataset [125]. As an example of one entry in the database, evidence to support the connection between 'Job/Task Analysis' (JTA) and 'Knowledge, Skills and Abilities (KSA) Evaluation' (i.e., pre-training evaluation of KSAs) is extracted from a reference with the following contextual statement; "entry-level requirements should be based on a familiarity with the general level of KSAs of the trainees and by a careful review of documents such as job descriptions, position descriptions or personnel qualification requirements" [130]. Considering this piece of evidence, the analyst's interpretation based on probability language is shown in Table 4. Another piece of evidence for the same causal edge is shown in Table 5 to demonstrate the aggregation of conditional probabilities based on multiple evidence in element #1.3.

The analyst interpretation process is repeated with multiple evidence entries, generating unique M_1, M_2, and M_3 values for each entry. For the training causal model, a minimum of three references were entered for each causal connection. Each piece of evidence can be seen in the Training model database [125]. Once all evidence is added to support causality, element# 1.3. of DT-BASE (Fig. 2) is performed using either Arithmetic (Eq. 1) or Geometric (Eq. 2) aggregation methods. For example, considering two evidence entries in Tables 4 and 5, and adding a third evidence, where $M_1 = 0.945$, $M_2 = 0.995$, and $M_3 = 0.78$, the results of arithmetic and geometric aggregations for the conditional probability of good quality KSA, given a good quality JTA has been performed, are $\Pr(KSA|JTA) = 0.86$ and $\Pr(KSA|JTA) = 0.85$, respectively.

The resulting conditional probabilities for each causal relationship in the network are then extended in element #1.4 of DT-BASE to generate the CPT for the BBN (Element #1.5) using ICI modeling (explained in Section 2.2.1.4). In this example, the Noisy-OR method (Eq. 4) is used. Using the evidence entries in the Training causal model [125], the CPT for the target node Training Implementation is shown in

Table 3
Example for the construct of job/task analysis from [125].

Perspective*	Node: Job/Task Analysis
Industry Perspective	"The systematic process of examining a task by collecting data from subject-matter experts and/or source documents to identify conditions standards references knowledge and skills associated with each task element." [125]
Regulatory Perspective	"The result of the job analysis will be a set of typical tasks which represents the training content of the job. Skills and knowledge needed for the job can be derived from the typical tasks." (Ref. [128])
Academic Perspective	"Abilities-oriented job analysis is concerned with identifying human attributes necessary to perform the job" (Ref. [129])

* This example is reduced to one reference for each perspective.

Table 4
Evidence entry for the first reference supporting the causality between 'Job/Task Analysis' (JTA) and 'Knowledge, Skills and Abilities' (KSA) (Source: [127]).

Parameter	Lower Bound	Upper Bound	Median	Memo
M_1	0.9	0.99	0.95	Official Government Document, Revised in 2014 (Very Likely Credible)
M_2	0.66	0.9	0.78	Knowledge, Skills and Abilities are developed after careful review of job descriptions [127] (Likely)
M_3	0.66	0.9	0.78	Analyst is likely confident about the topic of Job Analysis and Knowledge, Skills and Abilities (Likely Confident)

Table 5
Evidence entry for the second reference supporting the causality between 'Job/Task Analysis' (JTA) and 'Knowledge, Skills and Abilities' (KSA) (Source: [128]).

Parameter	Lower Bound	Upper Bound	Median	Memo
M_1	0.66	0.9	0.78	International Government Document, Over 30 Years Old (Likely Credible)
M_2	0.66	0.9	0.78	"The result of the job analysis will be a set of typical tasks which represents the training content of the job. Skills and knowledge needed for the job can be derived from typical tasks" [128] (Likely)
M_3	0.66	0.9	0.78	Analyst is likely confident about the topic of Job Analysis and KSA (Likely Confident)

Table 6. It should be noted that the conditional probabilities in Table 6 are not direct representations of the outcome (success or failure) of a training program, instead they are indicators of the quality of the elements comprising a training program; for example, the 50% probability shown in Table 6 is a conditional probability of having "poor training implementation" given "poor quality training procedure" and "poor quality instructor performance." In this example, an LV is assigned to each layer based on probability language, considering it is 'unlikely' that the model is complete, with a lower bound of 0.1 and an upper bound of 0.33 to represent model uncertainty. Integration in a BBN computational platform (Element #1.5) is performed using the DT-BASE web application [131].

3.2. Applying DT-SITE elements to model and quantify training quality in nuclear power plants

This section explains the results of implementing DT-SITE elements (Fig. 2) to quantify the training causal model utilizing plant-specific data. Since DT-SITE has not yet been integrated into the DT-BASE application, a preliminary text mining approach, in the form of a keyword search, was run in MATLAB Simulink software [81]. Using string search functions in MATLAB, each CAP entry was analyzed for the occurrence of keywords from the training causal model, and the results were mapped to a matrix resembling the conditional probability table of the training causal model. The approach was applied to one full year (2013–2014) of CAP data from one NPP, which initially included fifty thousand initial entries and follow-up entries. The algorithm, applied only to 'initial' CAP entries (i.e., not corrective actions or resolutions) totaling around fifteen thousand, searched for keywords associated with nodes in the causal model (Fig. 6), finding the occurrence and co-occurrence of theoretical constructs within each entry of CAP. Using truth tables, the results are stored in a CPT, serving as the new frequency dataset. Frequencies were converted to probabilities by dividing the total number of entries during the data collection period of one year (see Section 2.2.2.2) [81]. The resulting conditional probabilities were used to calculate the probability of the target node probability of the Training BBN (Fig. 6).

This simplified word search approach is applicable for CAP entries because of the format of the CAP entries, where 'cause identification' is explicitly separated from other text data. Therefore, using MATLAB Simulink string search functions, it was possible to analyze each entry for the occurrence of keywords and assign matches in a matrix which resembled the conditional probability tables of our causal models. In future work, a more rigorous text mining will be developed to expand DT-SITE applicability to more unstructured datasets (e.g., Licensee Event Reports (LERs), root cause analysis documents, and maintenance logs) which require preprocessing for cleaning text.

Because of the difficulty in obtaining CAP data, and the use of CAP data for only one year from one NPP in this example, the accuracy of estimated probabilities is dependent on the quantity of CAP entries, as well as the quality of CAP entries. To partially overcome the limitation of data quantity, as explained in Section 2.2, a two-step methodology is used in this research, where DT-BASE is used to generate the preliminary causal model and quantification based on generic information from literature and analyst interpretation, and DT-SITE then analyzes the plant-specific data (i.e., CAP data in this case study) to update the causal model using a Bayesian approach. With this approach, the lack of plant-specific data is partially addressed by combining it with generic information from the literature. The authors also plan to improve these estimates in future work by increasing the CAP dataset size and considering the quality of CAP data entries (as also mentioned in Section 3.3). Also, ongoing research by the authors focuses on developing a methodology to quantify the degree of confidence in the probability estimates by characterizing the epistemic uncertainty associated with limited data size, the relevancy of the data, and subjective interpretation of information.

Since DT-SITE has not yet been integrated into the DT-BASE application, it is not feasible at this stage of the research to integrate each conditional probability of SITE and BASE in element #2.4 of DT-SITE in order to develop an updated organizational causal input model (Element #2.5 in Fig. 2). Therefore, for this example, only the "target node" probability from DT-BASE and DT-SITE are integrated using the Bayesian method explained in Section 2.2.2.4. Bayesian updating is performed using the open source program OpenBUGS [132] to integrate the target node probability resulted from DT-BASE (Section 3.1) [125] and the target node probability resulting from a simplified demonstration of DT-SITE using a sample dataset [81].

In this Bayesian updating, the unknown of interest is Pr (Training Quality = Poor), denoted as P_{TQ}. A non-homogeneous population is assumed over P_{TQ}, as the evidence extracted from literature in the DT-

Table 6
Conditional probability table for training implementation target node.

Training Procedure		Good Quality		Poor Quality	
Instructor Performance		Good Quality	Poor Quality	Good Quality	Poor Quality
Training Implementation	Good Quality	0.98	0.93	0.87	0.51
Training Implementation	Poor Quality	0.02	0.07	0.13	0.50

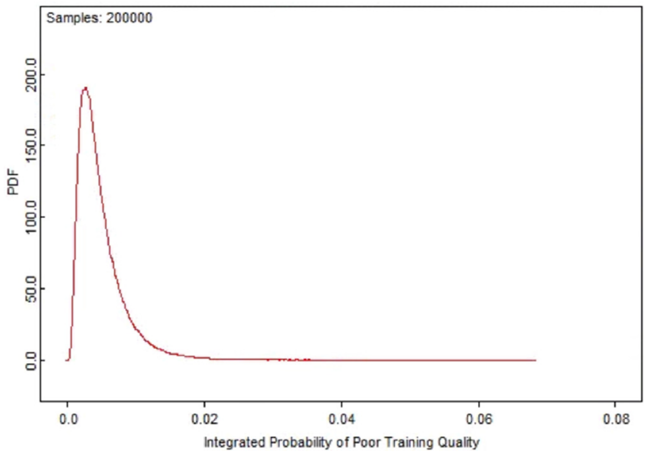

Fig. 7. DT-BASE and DT-SITE Bayesian integration for poor training quality distribution: OpenBUGS output.

BASE (Section 3.1) can include information from multiple sources and contexts. The population variability over P_{TQ} is represented by the beta distribution with two hyperparameters, α, and β. The beta distribution is a convenient choice because; (i) its range is [0, 1], which is consistent with the theoretical range of the P_{TQ}, and (ii) it does not impose strong assumptions on the shape of the probability distribution. For two hyperparameters, α and β, independent flat hyper-prior distributions spread over all positive values are developed [133, 134]. Under this setting, the Bayes' theorem is formulated as follows:

$$\pi(\alpha, \beta|\underline{D}) \propto \int_{P_{\mathrm{TQ}}} L(\underline{D}|P_{\mathrm{TQ}})\varphi(P_{\mathrm{TQ}}|\alpha, \beta)dP_{\mathrm{TQ}}\cdot\pi_0(\alpha, \beta), \tag{16}$$

where

$\pi(\alpha, \beta|\underline{D})$: Posterior distribution of the hyper parameters α and β
$L(\underline{D}|P_{\mathrm{TQ}})$: Likelihood function for the evidence $\underline{D}$, given the true value P_{TQ}
$\varphi(P_{\mathrm{TQ}}|\alpha, \beta)$: Probability distribution for the hyper parameters α and β (beta distribution)
$\pi_0(\alpha, \beta)$: Prior distribution of the hyper parameters α and β

After computing the posterior distribution for α and β based on Eq. 16, the updated probability distribution for P_{TQ} is obtained using the law of total probability.

As mentioned in Section 2.2.2.4, the likelihood function should be chosen based on the types of evidence available for informing the estimation of the unknown of interest. In this case study, the available evidence consists of the P_{TQ} estimates generated by DT-BASE and DT-SITE, $\underline{D} = \{\hat{P}_{\mathrm{TQ,BASE}}, \hat{P}_{\mathrm{TQ,SITE}}\}$. As shown in Eq. 16, if we assume that the P_{TQ} estimates from DT-BASE and DT-SITE are independent, the likelihood function is written as follows:

$$L(\underline{D}|P_{\mathrm{TQ}}) = L(\hat{P}_{\mathrm{TQ,BASE}}|P_{\mathrm{TQ}})^{*}L(\hat{P}_{\mathrm{TQ,SITE}}|P_{\mathrm{TQ}}) \tag{17}$$

In Eq. 17, both pieces of evidence, $\hat{P}_{\mathrm{TQ,BASE}}$ and $\hat{P}_{\mathrm{TQ,SITE}}$, are outputs from the BBN model; thus, an additive or multiplicative model would be a reasonable choice for the likelihood function that represents the degree of model error [135, 136]. The selection between additive and multiplicative models depend on the nature of the problem and available evidence. At this stage of research, for demonstration of the methodology, the multiplicative error model is selected as the likelihood function. Based on this model, $\hat{P}_{\mathrm{TQ},i}$; $i \in \{\mathrm{BASE},\ \mathrm{SITE}\}$, is represented by the product of the true value of the unknown quantity and the error term: $\hat{P}_{\mathrm{TQ},i} = P_{\mathrm{TQ}}\cdot E_i$. The likelihood function for each piece of evidence is given as the lognormal distribution shown in Eq. 18:

$$L(\hat{P}_{\mathrm{TQ},i}|P_{\mathrm{TQ}}) = \frac{1}{\sqrt{2\pi}\,\sigma_i \hat{P}_{\mathrm{TQ},i}}\exp\left[-\frac{1}{2}\left(\frac{\ln\hat{P}_{\mathrm{TQ},i} - (\ln P_{\mathrm{TQ}} + \ln b_i)}{\sigma_i}\right)^2\right];\ i \in \{\mathrm{BASE},\ \mathrm{SITE}\}, \tag{18}$$

where b_i and σ_i stand for the bias factor and the logarithmic standard deviation of the error term E_i, respectively. For example, the analyst can assume that the causal models developed for DT-BASE and DT-SITE have no systematic bias concerning the true value ($b_{\mathrm{BASE}} = b_{\mathrm{SITE}} = 1$). Meanwhile, σ_i for each model can be estimated by considering upper and lower bounds for $\hat{P}_{\mathrm{TQ},i}$, which need to be entered by the analyst or estimated by performing uncertainty propagation in the DT-BASE and DT-SITE models. When the upper and lower bounds of $\hat{P}_{\mathrm{TQ},i}$ are entered as $P_{\mathrm{TQ},i;\mathrm{upp}}$ and $P_{\mathrm{TQ},i;\mathrm{low}}$, then σ_i can be estimated from Eq. 19 by considering the 95th and 5th percentiles of the lognormal likelihood equal to the upper and lower bounds:

$$\sigma_i = \frac{1}{\Phi^{-1}(0.95)}\ln\sqrt{\frac{P_{\mathrm{TQ},i;\mathrm{upp}}}{P_{\mathrm{TQ},i;\mathrm{low}}}}, \tag{19}$$

where Φ^{-1} is the inverse cumulative distribution function of the standard normal distribution. As the conversation-text cycle progresses in an organization, a new piece of evidence can be generated. Using BBN inference techniques, the new piece of evidence can be conditioned in the BBN engine to provide real-time updating for the target node probability of the BBN model.

The results from BASE and SITE are treated as two independent pieces of evidence: $\hat{P}_{\mathrm{TQ,BASE}} = 0.0296$ and $\hat{P}_{\mathrm{TQ,SITE}} = 0.00023$. σ_i is estimated using Eq. 17, assuming: (i) the upper bound and lower bounds of the target node probability estimates are 0.1 and 0.005, respectively, and (ii) DA-BASE and DT-SITE models have the common σ_i, because the structure of the causal model developed for DT-BASE is unchanged for DT-SITE. Using OpenBUGS, the posterior distributions for hyper parameters α and β are computed, and the expected beta distribution for the integrated probability of the poor quality of training target node is obtained by calculating the mean of the family of beta distributions over the posterior distributions of hyper parameters. The Bayesian integration of DT-BASE and DT-SITE results in the expected beta distribution shown in Fig. 7, with a median of 0.0039.

3.3. Sensitivity analysis & extended discussion

One of the advantages of the I-PRA framework is that sensitivity and importance measure analyses can be used to obtain the ranking of organizational risk-contributing factors based on their contribution to human errors and system risk. To illustrate this advantage, sensitivity analysis is conducted to rank factors based on their influence on the target node probability, i.e., Pr (Training Quality = Poor). This study uses the Fussell-Vesely Importance Measure (FV-IM) method, developed in classical PRA [137, 138] and extended to BBN by Groth et al. [139]. The FV-IM method measures the sensitivity of the model output (i.e., target node probability, P_{TQ}) to individual factors by:

$$I_{\mathrm{B}_i}^{\mathrm{FV}} = \frac{P_{\mathrm{TQ}} - P_{\mathrm{TQ}|\mathrm{B}_i=\mathrm{GoodQuality}}}{P_{\mathrm{TQ}}}, \tag{19}$$

where $I_{\mathrm{B}_i}^{\mathrm{FV}}$ is the FV-IM computed for the factor B_i, P_{TQ} is the nominal output of the target node probability, where each causal node has its nominal/realistic state, and $P_{\mathrm{TQ}|\mathrm{B}_i=\mathrm{GoodQuality}}$ is the target node probability computed by conditioning that the node B_i has a 'Good Quality' with certainty. Conceptually, Eq. 19 assesses how much the target node probability decreases (i.e., the probability of Poor Quality of Training decreases) when each child node has a perfectly 'Good Quality' ; hence, $I_{\mathrm{B}_i}^{\mathrm{FV}}$ indicates the importance of each factor in terms of improving the training quality. In the commercial BBN software GeNIe Modeler, the *set evidence* function is used to compute Eq. 19 for each factor by setting

Table 7
DT-BASE Fussell-Vesely importance measure results ('Node' *Set Evidence_Poor* = 0).

Level of Causality in Fig. 6	Node (Poor Quality = 0)	FV-IM	Ranking
2.	Training Program Design	26.8%	1
1.1.	Training Procedure	25.7%	2
1.1.	Instructor Performance	21.5%	3
1.1.1.	Training Sequence	12.0%	4
1.1.1.	Training Method	12.0%	5
1.1.1.	Training Setting	12.0%	6
1.1.1.	Training Content	12.0%	7
1.1.1.	Training Structure	11.8%	8
1.1.1.	Training Media	11.8%	9
1.1.1.	Instructor Training	11.8%	10
1.1.1.	Instructor Knowledge	11.7%	11
1.1.1.	Instructor Time Preparation	11.7%	12
2.1.	Training Records Documentation System	10.3%	13
2.1.	Training Needs Analysis	9.9%	14
2.1.	Instructional Technologist	6.2%	15
2.1.1.	Performance Analysis	4.3%	16
2.1.1.	Training Objectives	2.9%	17
2.1.1.	Knowledge, Skills, and Abilities Evaluation	2.2%	18
2.1.2.	Job/Task Analysis	1.9%	19
2.1.2.	Conditions & Standards	1.8%	20

the occurrence of 'Poor Quality' to 0 for each node in the model to see the changed probability of the training implementation target node, Pr (Training Quality = Poor), which is logged in Table 7.

It should be noted that due to the limited data set used in this analysis, the FV-IM differences identified below 1% are not interpreted as significant. As additional data is included in future work for this type of analysis, these small differences can be evaluated in a more meaningful way for risk management. The FV-IM results (Table 7) for the DT-BASE model reveal the following:

- Among all the causal factors, "Program Design," "Training Procedures/Facility," and "Instructor Performance" are identified as the first, second, and third most important factors, respectively.
- From Level 1.1. of the causal model (Fig. 6), "Training Procedures/Facility" is ranked more important than "Instructor Performance," with a 4% difference.
- In Level 1.1.1 of the causal model (Fig. 6), there are small differences among the estimated FV-IMs, and so the factors are considered at the same level of significance.
- In Level 2.1 of the causal model (Fig. 6), among the sub-factors influencing the quality of "Program Design," "Training Records Documentation System" and "Training Needs Analysis" are identified as more important than "Instructional Technologists." These two factors may require more attention for the improvement of the training program. For example, Training Records and Documentation Systems manage information to help maintain employee licenses, qualifications, and certifications by scheduling training and continuing training. Training Records and Documentation Systems may also keep track of attendance/completion for crediting, and of performance evaluation results to inform the next cycle of training scheduling.

The importance ranking results provide insights for decision-makers responsible for resource allocation in order to develop effective strategies for improving operator training and decreasing human errors. It also gives the analyst the important factors that require more accurate data extraction and interpretation in order to generate more accurate practical recommendations for improvement policy. Future work will address methodological advancements in sensitivity analysis for the Data-Theoretic Module in the I-PRA (Fig. 2): (i) conducting multi-way [140] and global sensitivity methods [77, 82, 141, 142] to account for the influences of non-linearity and interactions among multiple input parameters; and (ii) integration of DT-BASE and DT-SITE into one computational platform to run the sensitivity analysis on a single causal model. The ongoing research by the authors is focusing on the integration of the DT-BASE and DT-SITE into one computational platform so that the Bayesian updating of DT-BASE and DT-SITE (explained in Section 2.2.2.4) can be conducted at the level of conditional probabilities (rather than at the level of target node that is the case in Section 3.2) to develop one updated training causal model to be used for the SA.

As mentioned in Section 2.2.2.2, the estimated marginal probabilities are biased by the number (and quality) of CAP entries; therefore, Pr (Training Quality = Poor) = P_{TQ} is also biased by CAP entries. Future research should focus on resolving this bias; for example, by the following conceptualization. The ideal goal is to find the unbiased probability of "Poor Training Quality" (P), which can be defined as of A'/N_{Demand} where (A') stands for the real number of incidents involving operator training as a contributor, during the data collection period and, (N_{Demand}) represents the total number of operator demands during the data collection period. With this definition, (P) takes on values between 1.0 (every demanded action involves training issues) and 0.0 (training is never a contributor). Eq. 20 shows the relationship between P, which is the unbiased probability of poor training quality, and the output of the Data-Theoretic (P_{TQ}) (i.e., the biased probability of poor training) which is associated to 'A/N_{CAP}' (i.e., the ratio of all training issues (A) to all reported incidents during the data collection period (N_{CAP})). In Eq. 20, A'/A stands for the quality of the CAP program in terms of accurately identifying training contributions. If all incidents involving training are correctly identified (A'/A) = 1; if there is any underreporting, A'/A > 1 and P is correspondingly increased. To calculate P, future research will focus on the application of a qualitative/qualitative strategy to assign a value to the quality of NPP CAP programs. Another required term to estimate P is the value of (N_{Demand}) in Eq. 20, and its estimation also needs further empirical research.

$$P = \frac{A'}{N_{\mathrm{Demand}}} = \frac{A}{N_{CAP}} \times \frac{N_{CAP}}{N_{\mathrm{Demand}}} \times \frac{A'}{A} \tag{20}$$

As stated in Section 2.1, to operationalize the entire I-PRA framework (Fig. 2), the key performance measures (e.g., Ka_1, Ka_2, Ka_3 in Fig. 2), indicating the measured performance outputs of the organizational model, need to be generated to help define the states of PSFs in HRA. For instance, in the training case study, a key performance measure associated with the training/experience PSF in I-PRA needs to be generated. Ongoing research by the authors is on developing a methodology for using the estimated training quality distribution (Fig. 7) from the Data-Theoretic Module, along with the analysis in Eq. 20, to develop a plant-specific training indicator that can be used as a key performance measure in I-PRA. By developing threshold values that can be associated with the low, nominal, and high training/experience PSFs in the Standardized Plant Analysis of Risk-Human Reliability Analysis (SPAR-H) HRA method [143], the authors plan to develop a technique for calibrating the model outputs and mapping them to the states of PSFs for the same plant's risk scenarios. It should be noted, however, that the scope of the training causal model in this paper is not specific to one procedural action, and therefore, additional research is needed to develop causal factors associated with task-specific training quality that creates an interface to the PSFs of HRA. The authors envision that updating the states of PSFs (#5 in Fig. 2) in the interface module of I-PRA would not only help develop site-specific human error probabilities but would also help address issues of HRA dependencies [143, 144] as well as dependency among human actions.

Because it is not practical to connect all organizational factors to all PSFs in HRA, future research will focus on developing a structured approach to analyze the following items: **(a)** which HEPs need to be connected to the underlying organizational mechanisms, **(b)** which PSFs need to be connected to the underlying organizational mechanisms, **(c)** what organizational factors should be explicitly and causally modeled, and **(d)** the depth of causality and level of details that selected organizational factors should be expanded to. With respect to items (a) and (b), because the Data-Theoretic approach is developed for integration with PRA, importance measure analysis (e.g., Fussell-Vesely importance measure, Risk Achievement Worth, and Birnbaum importance measure [145]) can be used to identify human failure events that significantly contribute to risk. Within each of these events, the dominant PSFs could be identified based on (i) existing guidance, task type, operating context, and/or (ii) a quantitative sensitivity analysis which aims to assess the sensitivity of the system risk estimate to each PSF. At this point, the Data-Theoretic approach can be applied for developing detailed causal models for those important HEPs and their dominant PSFs. Item (c) relates to the first step of the theory building process in Element #1.1 of DT-BASE and, as it is mentioned in Section 2.2.1.1, this step is associated with Principle I.A (i.e., identifying unknown of interest) in Table 1. The selection of dominant organizational factors associated with a specific PSF can be conducted using data (if available) and/or organizational science literature. Item (d) relates to Step 5 of theory building in Element #1.1 of DT-BASE as well as Principle II.E in Table 1. The depth of causality and level of detail in this context need to be determined by the analyst, considering several aspects, such as (i) risk importance of each causal factor, (ii) availability of data at each level of causality, and (iii) usefulness in accident prevention (e.g., the level of causal factors that are more effective for risk management). It should be noted that the process of model development and data analytics for Data-Theoretic approach is iterative. In other words, the analyst needs to start with a certain level of causality, by conducting risk importance measure and sensitivity analyses, to identify the causal factors where extension and quantification is needed

To produce a more accurate distribution of training quality (Fig. 7), the authors are executing uncertainty analysis with respect to the analysts' manual extraction and interpretation of generic information in DT-BASE (Section 2.2.1). In the current training case study, the point values of the evidence weighting variables M_1, M_2, and M_3 are used. However, there are potential issues associated with different meanings by different analysts, and with different contextual interpretations [108, 146]. In this paper, the authors make the assumption that subjectivity and between-analyst variability is allowable for theory-building if the associated uncertainty is explicitly identified and characterized. The authors have ongoing research to incorporate uncertainty analysis techniques in the DT-BASE code to consider the entire range of probability values for M_1, M_2, and M_3.

The boundary between 'good' and 'poor' in the performance outcome nodes (e.g., safety critical tasks) in the SoTeRiA framework is reasonably clear; however, as the analyst gets further from the performance outcome nodes, the boundary between good and poor in the causal factors involves expert or analyst subjective judgment and uncertainty. The current stage of this research does not focus on analyzing the uncertainty involved in the measurement of good versus poor in each single factor; instead, the goal of this paper is to the develop a unified platform to quantitatively connect underlying organizational causal factors (as well as their associated variability and uncertainty) to the safety performance outcome (e.g., estimated risk). The next stage of the research will focus on running sensitivity analysis with respect to these variabilities and uncertainties to prioritize the critical areas that need more in-depth studies. Future research will also consider running sensitivity analysis with respect to underlying assumptions (e.g., unbiased estimates, lognormally distributed uncertainties, etc.) in the methodology and application to provide additional justification for the identified critical assumptions.

4. Concluding remarks

Organizational factors have an ever-present underlying influence on socio-technical systems and have been identified as important contributors to incidents and accidents in diverse industries. Due to the complexity of organizational performance modeling, the integration of organizational mechanisms into Probabilistic Risk Assessment (PRA) has been a challenge. This paper is a product of a line of research to incorporate organizational factors into Human Reliability Analysis (HRA) and PRA to (a) explicitly assess the risk due to specific organizational weaknesses, (b) find and rank the critical organizational root causes of failure, which enhances risk management, and (c) avoid the possibility of under-or-over estimating the risk associated with human error.

Two requirements for incorporating emergent organizational safety behavior into PRA include: (i) the integration of a theoretical model of how organizations perform, considering causal factors with their corresponding level of analysis and relational links; (ii) the adaptation of appropriate techniques (i.e., "modeling" and "measurement"), capable of capturing complex interactions of causal factors within their possible ranges of variability and across different levels of analysis, to quantify the theoretical framework.

To meet the first requirement in this research, the Socio-Technical Risk Analysis (SoTeRiA) (Fig. 1), a multi-level theoretical framework that connects the structural and behavioral aspects of an organization with PRA, is used [27]. Regarding the "modeling" techniques, this research introduces the Integrated PRA (I-PRA) methodological framework (Fig. 2) to operationalize SoTeRiA and to improve the realism of risk estimations by quantifying the incorporation of human and organizational performance into PRA. I-PRA preserves plant-specific PRA models while generating a probabilistic interface to connect the model of underlying failure mechanisms to PRA. This makes I-PRA economically efficient and practical for adoption by the nuclear industry. Regarding "measurement" techniques, this research develops the Data-Theoretic approach, the focus of this paper, which is executed in the data input module of I-PRA (Fig. 2). The Data-Theoretic is an approach where "data analytics" are guided by "theory" to enhance the accuracy and completeness of "causality" being analyzed from data. The Data-Theoretic approach not only contributes to the development of a new "measurement" technique for organizational factors, but also makes theoretical contributions by expanding the theoretical causal details of SoTeRiA.

The Data-Theoretic module of I-PRA Fig. 2) has two sub-modules including DT-BASE and DT-SITE, and their elements are explained in detail in Sections 2.2.1 and 2.2.2. The Data-Theoretic approach is advancing the measurement of organizational factors in the following ways: (1) it combines different sources and types of information: (a) articles from academic literature, practical industry procedures and regulatory standards from industry are integrated through DT-BASE elements, (b) analysts' "subjective" interpretation of information in DT-BASE is combined with "objective" event data extracted in DT-SITE, and (c) "generic" information obtained in DT-BASE is integrated with "plant-specific" information extracted in DT-SITE; (2) it guides "data analytics" with "theory." The theoretical causal structure of the SoTeRiA framework and the contextual keywords of each node in SoTeRiA guide data analytics; therefore, the underlying theory supports the completeness of causal factors, the accuracy of their causal relationships, and helps avoid the potentially misleading results of a solely data-oriented approach; (3) it uses text mining (in DT-SITE), in addition to expert opinion (in DT-BASE), as a measurement technique. Although lack of data has been suggested as one of the key reasons for making slow progress in the incorporation of organizational factors into PRA, this research provides a new perspective by highlighting that data is available for organizational factors; however, this data is different from tabular equipment reliability data. Organizational data are a compilation of textual operational experience documents such as

Corrective Action Program (CAP) entries, Licensee Event Reports (LERs), root cause analysis documents, and maintenance logs that are unstructured and heterogeneous; therefore, it is necessary to use text mining as a data analytics technique for socio-technical risk analysis.

A case study in this paper demonstrates the implementation of DT-BASE elements for the development of the theoretical causal model for organizational "training" (Fig. 6) and for its generic quantification. The case study also explains the application of DT-SITE elements to quantify the causal model for training, utilizing plant-specific CAP data. The Bayesian integration of DT-BASE and DT-SITE results has generated the distribution of poor training quality (Fig. 7) with a median of 0.0039. An importance measure analysis is performed on the causal model for training, and as a result, "Program Design," which is highly influenced by the quality of "Training Records Documentation System," is identified as the most important factor. More detailed results of the ranking of the factors are included in Table 7. This type of ranking contributes to more scientific and in-depth root cause analysis and more effective prevention of system failures caused by human errors or organizational factors. The causal model for training is not only theoretically validated but is also verified on its structure and contents by training experts at a Nuclear Power Plant (NPP). However, it should be noted that there are several assumptions and simplifications that were made in this analysis, and these are highlighted throughout the paper; hence, the numerical outputs of the case study, presented in this paper, are only for demonstration and should not be used directly in the context of specific practical applications. In ongoing research, the authors are conducting a Probabilistic Validation [71] methodology to evaluate and measure the epistemic uncertainty (or the degree of confidence) associated with the estimated probability from the model as a measure of validation.

The computational platform of DT-BASE is an open-source web application [131] to enable a scientific network for collaborative model building. Using a client-server architecture, multiple analysts can work in parallel on a single causal model. Ongoing research by the authors focuses on advancing several modules of I-PRA (Fig. 2), as follows: (a) developing advanced safety-oriented text mining that can be applicable for a wide range of unstructured organizational communications such as root cause analysis documents, work packages, training records, management systems, maintenance reports, and policy documents for DT-SITE; (b) integrating DT-SITE and DT-BASE into one computational platform to improve the Bayesian updating (See discussion in Section 3.3); (c) adding uncertainty analysis into the DT-BASE code (See discussion in Section 3.3); (d) advancing spatio-temporal methodologies [72, 79, 147, 148] for the simulation module (#3 in Fig 2) of I-PRA and facilitating the interface of the Data-Theoretic module and the simulation module; (e) developing methodologies for updating PSFs (# 5 in Fig. 2) of existing HRA techniques based on the results of organizational causal modeling (See discussion in Section 3.3); (f) applying Data-Theoretic approach to other factors of SoTeRiA, such as the quality of organizational safety procedures and safety culture; and (g) developing global sensitivity analysis and importance measure analyses [82, 140] for the Data-Theoretic approach to increase the validity of the ranking of factors in the training causal model (See discussion in Section 3.3).

The topic of analyzing organizational influence on the risk of technological systems is a complex multidisciplinary research area. Although this paper provides a scientific contribution from the perspectives of modeling and measuring of organizational factors in PRA, many critical challenges remain, requiring future research. Some of these challenges may include: (i) the need for comprehensive calibration and integration of organizational mechanisms into HRA and PRA across the lifecycle (i.e., design, construction, operation, decommissioning), (ii) the need to include inter-organizational and broader factors in organizational performance models, (iii) dealing with a wider variety and larger volume of unstructured data sources (e.g., Licensee Event Reports, Root Cause Analysis reports, etc.), and calibrating those data sources to explicitly consider data quality and bias, (iv) dealing with dependencies among diverse data sources and amongst underlying performance shaping factor models, (v) implementing quantitative techniques for handling complex interactions in a causal model growing exponentially, (vi) considering the role of automated data analytics and data mining techniques in the building of theoretical causal models, (vii) methodological advancement of sensitivity analysis and importance measure analysis in the I-PRA framework, and (ix) Probabilistic Validation to characterize and propagate sources of epistemic uncertainty. Forthcoming publications by the authors will provide more thorough reviews of studies associated with theorizing, modeling, and measuring organizational factors, considering their impact on technological system risk to comprehensively adopt knowledge from diverse disciplines for the advancement of PRA.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at https://databank.illinois.edu/datasets/IDB-6772942.

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