

Toward Monitoring Organizational Safety Indicators by Integrating Probabilistic Risk Assessment, Socio-Technical Systems Theory, and Big Data Analytics

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Abstract: Many catastrophic accidents have organizational factors as key contributors; however, current generations of Probabilistic Risk Assessment (PRA) do not include a comprehensive representation of the underlying organizational failure mechanisms. This paper reports on the current status of new research with the idealistic goal of monitoring organizational safety indicators. Because of the evolving nature of computational power and information-sharing technologies, ‘Internet of Things’ has been adopted as a metaphor to describe the authors’ vision for combining multiple levels of organizational analysis into a real-time application for monitoring the changing landscape of risk. The short-term objectives are: (1) identifying the organizational root causes of failure and their paths of influence on technical system performance, utilizing theoretical models of social phenomena, (2) quantifying the models using advanced measurement and predictive methodologies, big data analytics, and uncertainty analysis, and (3) proposing preventive approaches. Socio-Technical risk analysis deals with wide-ranging, incomplete, and unstructured data. Therefore, this research focuses on developing hybrid predictive technologies for PRA that are not only grounded on Socio-Technical Systems theory, but also serve to expand the classical approach of data extraction and execution for risk analysis by incorporating techniques such as text mining, network data analytics, and data curation.

Keywords: Organizational Safety Indicators, Socio-Technical Risk Analysis, Big Data, Probabilistic Risk Assessment, Real-Time Safety Monitoring

1. INTRODUCTION

Organizational failure mechanisms are widely recognized as key contributors to some of the world’s worst accidents (e.g., Piper Alpha, Columbia, Three Mile Island, Chernobyl, Bhopal, Challenger, Deepwater Horizon, and Fukushima). Recently, the International Atomic Energy Agency (IAEA) reported that in Nuclear Power Plants (NPPs), 80% of significant events are caused by human error, and of those human error events, 70% are due to organizational weaknesses (e.g., lack of line-management ownership, weak self assessments, insufficient training), and 30% are due to individual mistakes [1]. This means that only 20% of all significant events are caused by equipment failure [2, 3], and 56% of all significant events at NPPs are caused by organizational weaknesses [1]. Therefore, the ability to detect organizational weaknesses is critical for preventing catastrophic technological accidents, and maintaining public health and safety.

1.1. Organizational Failure Mechanisms in Probabilistic Risk Assessment

Safety methods continue to be developed based on the understanding that “the performance of a complex socio-technical system is dependent on the interaction of technical, human, social, organizational, managerial and environmental factors” [4]. There is considerable evidence from

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organizational psychology and management science that organizational factors (e.g., safety culture and climate, leadership style, leader priorities, reward practices) are strongly related to safety, injuries, and accidents [5-8], however these organizational factors have not been fully incorporated into complex technological risk models. One potential reason for this is that, through training and socialization in engineering and technical disciplines, researchers may have developed cognitive-frameworks that constrain them from viewing organizations as an external or implicit source of influence [9], thereby reducing the likelihood that organizational factors will be incorporated in the analysis of system failure scenarios. The primary purpose of this paper is to begin to develop a process for better incorporating the *socio* aspect in social-technical system models of risk through the development of a multi-level model. Moving beyond current Probabilistic Risk Assessment (PRA) and dynamic frameworks in human reliability analysis, a networked monitoring system of organizational safety indicators is proposed to theoretically link together a range of technical, human, and organizational factors.

Human Reliability Analysis [10, 11], which is the study of the nature, causes, and probability of human actions in the design and operation of systems and processes, concentrates on individual error and typically ignores the effects of organizational factors in a formal and comprehensive way. As Reason [12] states, “while cognitive psychology can tell us something about an individual’s potential for error, it has very little to say about how these individual tendencies interact within complex groupings of people working in high-risk systems”. Although PRA [13] is an effective tool for calculating risk due to the interactions of equipment failure and human error, (1) it is not possible to explicitly assess the risk due to the specific organizational weaknesses, (2) it is not feasible to locate the organizational root causes of failures in order to take effective corrective action, and (3) there is the possibility of underestimating the risk associated with human error [14]. There are two major challenges that hinder the full integration of organizational factors into PRA. First is the requirement of a common multidisciplinary language among social scientists and engineers for understanding deep organizational factors. Second, is that the regulatory agency and industrial organization are deeply embedded in the socio-technical system, making it difficult to internally assess organizational factors in an unbiased or comprehensive way.

Over the past 20 years, a number of models have begun to integrate organizational factors. Mohaghegh [15], conducted a thorough review of literature related to the incorporation of organizational factors into risk models and categorized them in two generations with respect to both *theories* and *quantitative techniques*. The first generation included Reason’s Swiss Cheese Model [12, 16], a well-known example of organizational accident theories describing the process of organizational effects on human error, and, consequently, on the rate of accidents. There are also a number of first-generation models that attempt to quantify the impact of organizational factors on system risk, including; MACHINE [17], WPAM [18, 19], SAM [20], Omega Factor Model [21], ASRM [22], and Causal Modeling of Air Safety [23]. The nature of first-generation theories and techniques can be characterized in terms of “deviations from normative performance” [24].

The second generation of models began to incorporate the *actual behavior* of individuals and the social system structures of organizations. Second-generation “organizational models” of risk frameworks are still evolving. These models are beginning to represent the underlying organizational mechanisms of accidents, with a focus on the systemic and collective nature of organizational behavior, as opposed to focusing on individual actors alone. On the theoretical side, Rasmussen [24] cites the self-organizing nature of High Reliability Organizations [25] and Learning Organizations [26, 27] as concepts useful in analyzing the managerial and organizational influences on risk. The Normal Accident Theory [28], which views accidents caused by interactive complexity and close coupling, can be considered to be a second-generation perspective on organizational safety. More recently, Wahlström and Rollenhagen [29] utilized the control metaphor for assessing safety management systems in a combined Man, Technology, Organization, and Information (MTOI) framework. From a quantitative stance, second-generation techniques primarily tackle the dynamic aspects of organizational influence. For example, Biondi [30] uses the qualitative model developed by Bella [31] to describe the changes in the reliability of a system due to organizational dynamics. Other researchers, e.g., Cooke [32] and Leveson [33], used the System Dynamics (SD) approach [34] to

describe the dynamics of organizations, but these models do not include detailed, PRA-style models of the technical system. Yu et al. [35] and Gajdosz et al. [36] also used the SD approach to assess the effects of organizational factors on risk models; however, the interconnections between PRA and SD have not been clarified. Some of the newer aviation safety models such as the Traffic Organization and Perturbation AnalyZer (TOPAZ) use Monte Carlo simulation [37], while Bosse, T., et al. [38] have included Agent Based Modeling (ABM) for modeling organizational performance. In the most recent iteration of the National Aerospace Laboratory of the Netherlands' 'Safety Methods Database,' there are approximately 137 safety methods associated with the nuclear domain, and 124 documented theoretical models that include Organizational Factors [39].

Based on the analysis of the existing research in this field, Mohaghegh [15] concluded that in the absence of a comprehensive theory, or at least a set of principles and modeling guidelines backed by theory, it would be difficult to assess the validity and quality of the existing modeling techniques. Integrating concepts from multiple disciplines, she introduced a set of thirteen principles [40] for the field of Socio-Technical Risk Analysis. A new framework, called Socio-Technical Risk Analysis (SoTeRiA) [15, 41], was then developed based on these thirteen principals, to more comprehensively incorporate the organizational factors into risk models. Section 1.2 in this paper explains the SoTeRiA theory and its areas of advancement.

1.2. Combining Socio-Technical Systems Theory with Big Data Analytics

SoTeRiA has foundations in Social-Technical Systems (STS) theory and PRA, and further can be used with big data analytics. STS theory emerges from an 'eclectic empiricism' [42] that addresses the interactions of people and technology in the workplace [43] as well as the differences between complex living systems and complex mechanical systems with respect to their failure mechanisms [44]. STS theory has been operationalized in the SoTeRiA framework [15] (See Figure 1), which explicitly recognizes causal relationships among organizational constructs at multiple levels of analysis [45], and also in an integrated modeling technique [46, 47], which combines probabilistic tools (Bayesian Belief Network (BBN)), deterministic and dynamic simulation techniques (SD) with classical PRA methods (Event Tree (ET) and Fault Tree (FT)).

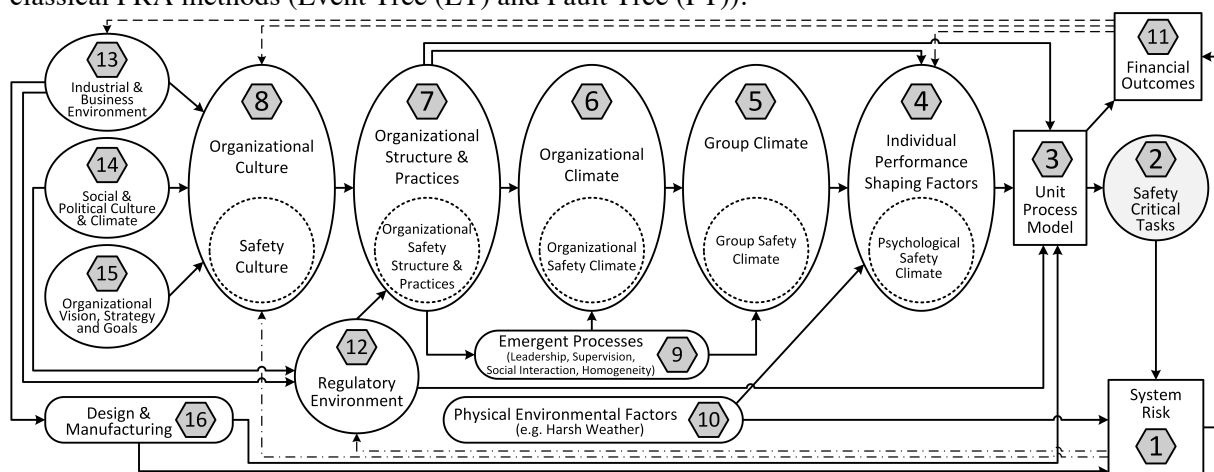


Figure 1. The Socio-Technical Risk Analysis (SoTeRiA) Theoretical Framework

While SoTeRiA represents a significant improvement in integrating organizational factors in technical system risk models, additional work is needed to enhance its theoretical details, quantified methodological features, and practicality in order to develop a more accurate decision-making tool for high-risk organizations. Thus, the focus of this paper is on the advancement of the theory, quantification and measurement of the SoTeRiA framework.

Recently, Bar-Yam [48] asserted that (a) big data is critical for addressing complex systems, (b) theory is essential for understanding complex systems, and (c) that theory makes data more useful. Organizations produce, process and store a large volume of 'information assets' used for regular

business activities and compliance purposes. After these incomplete, unstructured, information assets are used, they are stored (often without indexing), and become part of the underutilized [49] ‘long tail’ of organizational *dark data*[†]. The big data movement is quickly uncovering areas of analytics (i.e., predictive analytics, forensic data analytics, human resource analytics, team analytics, people analytics [50]) and methodologies (e.g., data mining, text mining) capable of interpreting dark data with a focus on organization-level constructs (e.g., reporting, performance indicators, business intelligence, and budgeting). Also, the growing application of ‘network thinking’ (e.g., Knowledge Management Networks [51], Policy Network Analysis [52]) is advancing research on complexity modeling.

Compared to the equipment and human errors modeled in PRA, the sub-level interactions of organizational failure mechanisms are not well understood and, currently, safety oriented organizational-level (meso-level) datasets beyond safety climate surveys do not exist. The SoTeRiA framework has many constructs, and aside from safety climate surveys, there are not many reliable measurements that can be included into organizational models. Furthermore, such models need to explicitly consider the dynamic interactions and interdependencies that create the collective social systems. This paper proposes a hybrid combination of (1) big data (analytics) and (2) theory (Socio-Technical Risk Analysis, i.e., an integration of STS theory and PRA) to efficiently extract organizational metrics and executes them in a network of organizational safety indicators. This hybrid integration would help (a) avoid the potential misleading results of solely data-informed approaches (big data methods, “top-down” approaches) and, at the same time, (b) overcome the challenges of “bottom-up” methods in quantifying socio-technical risk theories. Section 2.2 of this paper explains this hybrid measurement approach in more detail.

1.3. Toward Monitoring Organizational Safety Indicators

This paper reports on the current status of new research with goal of developing a networked monitoring system for organizational safety indicators. Due to the evolving nature of computational power and information-sharing technologies, the concept of Internet of Things (IoT) [53] has been adopted as a metaphor to describe the authors’ vision for combining multiple levels of organizational analysis into a real-time application for monitoring the changing landscape of risk. The IoT commonly refers to networked physical objects (e.g., embedded sensors), and the IoT metaphor provides a way to describe interconnected ‘objects’ communicating (e.g., machine-to-machine) in real-time. Therefore, in the context of this paper, the IoT is utilized as a metaphor for the purpose of monitoring organizational safety indicators to; (1) explicitly define the varying safety/risk contributing factors among multiple levels of analysis, (2) bridge and quantify their dynamic interactions in a causal model capable of considering the underlying social and physical phenomena, and (3) conduct real-time analysis of multivariate data streams.

The continuously evolving IoT architecture has been described in many different ways; for example, Unit IoT (man-like nervous system model), Ubiquitous IoT (Social Organization Framework model) [54], and Social IoT (i.e., integration of social networking concepts into IoT) [55]. The ‘objects’ being linked in the IoT primarily include ‘smart objects’ (e.g., embedded sensors, GPS, and cellular communications to provide equipment operations data), and ‘social objects’ [55] (i.e., social behavior of smart objects). These models are limited for assessing safety of social phenomena, because they are not based in theory and do not explicitly include broader organizational constructs.

This research proposes to bring objects of ‘organization-level constructs’ into the IoT metaphor. A networked monitoring system of organizational safety indicators would integrate a wide range of organization-level safety metrics into a ‘theory-data dialectical network’. Such a system would be capable of monitoring and detecting leading and lagging organizational safety indicators by bringing together real-time results of multiple levels of analysis for monitoring the changing landscape of safety and risk. Taking the concept one step further, and drawing a specific example for NPPs, a full scope

[†] Gartner Inc. Gartner IT Glossary - Dark Data Available from: <http://www.gartner.com/it-glossary/dark-data>.

‘internet of safety indicators’ would span the entire socio-technical system, from the micro-level (components; embedded sensors; existing control room indicators), to the meso-level (the proposed organization-level constructs), and to the macro-level (PRA of complex socio-technical systems). Although the research is still at the level of conceptualization of this long-term goal, the authors assert that the path toward monitoring organizational safety indicators begins with the enhancement of a *big theory* [56] capable of handling big data (dark data) and the complexity of socio-technical systems risk theory.

2. RESEARCH STRATEGY

Section 2, Research Strategy, has been broken down into 8 Tasks as listed below. The first Task relates to the development of a strong theory-based understructure (See Section 2.1). The research will require several levels of methodological discovery (Tasks 2-7; See Sections 2.1-2.7) before being applied to NPPs (Task 8; Section 2.8) and, being used as an input for the further implementation of the concept of monitoring organizational safety indicators.

Task 1. Develop Factors, Sub-Factors, and Causal Relationships in SoTeRiA

Task 2. Develop Measurement Techniques for Factors, Sub-Factors and their Causal Relationships in SoTeRiA

Task 3. Develop a Predictive Socio-Technical Causal Modeling Technique

Task 4. Uncertainty and Sensitivity Analysis

Task 5. Verification and Validation of the Causal Model

Task 6. Integrate SoTeRiA with PRA

Task 7. Estimate Risk Importance Measures

Task 8. Implement with the Nuclear Power Plant Specific Data

2.1. Develop Factors, Sub-Factors, and Causal Relationships in SoTeRiA (Task 1)

SoTeRiA provides theory-based, multi-level causal paths for influence of organizational factors on the elements of the PRA models. While it provides a roadmap for organizational risk analysis; it requires an increased level of granularity before it can be operationalized and is capable of giving industries a way to effectively manage their organizational risk. Each of the elements of SoTeRiA (i.e., Nodes 1-16 in Figure 1) need to be populated by relevant constructs, their associated factors and sub-factors, taking into consideration certain levels of validity and adequacy. In this research, the goal is to expand the level of detail of the causal elements of the SoTeRiA framework by mapping (1) theoretical (e.g., academic literature), (2) regulatory (e.g., regulations, standards and recommendations) and (3) industrial (e.g., knowledge management, management systems, training materials, logs, and expert opinion) perspectives. In other words, using these three perspectives, related constructs will be identified and placed within the sixteen elements of SoTeRiA. In addition, each construct will be broken down into factors and sub-factors. Sub-factors will be further decomposed according to their attributes, features, and dimensions. After developing the factors and sub-factors, each construct will undergo another detailed level of theoretical and practical validation to determine the adequacy of its placement within the key elements of SoTeRiA.

Another aspect of the theoretical advancement of SoTeRiA relates to developing details in the causal relationships of the model. For instance, the evaluation of the relationship between safety/risk performance (Node 1 in Figure 1) and the financial outcome (Node 1 in Figure 1) of an organization is the topic of an ongoing research [57]. As another example, organizational structure and practices (Node 7 in Figure 1) are strongly interrelated, but in the initial development of SoTeRiA, the relation between safety structure (e.g., centralization, formalization) and safety practices (e.g., human resource practices, procedure-related activities) was left unanalyzed. Research needs to uncover the detailed relations between organizational safety structure and safety practices.

An ongoing literature review is being conducted for the three perspectives (i.e., theoretical, regulatory, and industry) to develop a taxonomy of organizational factors supporting the SoTeRiA theoretical

framework. High-level classification of elements includes; external environment (i.e., regulatory, governmental, international agency, industry and business), internal environment (i.e., processes, procedures, training manuals, performance records), financial outcomes, and risk models (i.e., PRA). The result of *Task 1* will theoretically map the key elements of SoTeRiA (i.e., Nodes 1-16 in Figure 1) to sub-nodes (factors, sub-factors, attributes), and their causal relationships. For example, organizational culture (as a high-level element of SoTeRiA) has factors of artifacts, espoused values and basic assumptions. Sub-factors of organizational culture include different culture orientations (i.e., hierarchy, clan, adhocracy, market, safety [58]), and the associated attributes are consensus on cultural values across employees; strength of the culture; degree of socialization of new employees to culture; and the highest priority among values and culture.

2.2. Develop Measurement Techniques for Factors, Sub-Factors and their Causal Relationships in SoTeRiA (Task 2)

Organizational factors have been widely recognized as major contributors to risk, yet their sub-level interactions are not well understood, and have been excluded from accepted risk quantification methodologies. *Task 1* (Section 2.1) of this research addresses this need by theoretically developing the factors and sub-factors and their relationships. *Task 2* of this research focuses on developing a new ‘theory-data dialectical network’ of complex organizational systems.

There are two distinct epistemological approaches for developing models, (1) the *bottom-up* (Baconian) approach and (2) the *top-down* (data-informed) approach. The bottom-up approach is based on developing theoretical models and quantifying them using observations and experiments. The bottom-up approach is the most common practice in engineering and science because there are available quantified equations and theories that have been developed and validated (empirically and/or analytically) over the years. The top down approach is through data-informed discovery, where large data sets are used to observe patterns of causality without having an underlying theory.

In social science, the key challenge of the bottom-up approach is that, the quantification and validation of the theoretical models require reduction of factors at the beginning of analysis in order to handle the scope of factors relating to complex systems. Since there are not enough quantified underlying theories for organizations (unlike engineering and science), in order to quantify the models (e.g., using correlations), the contextual factors need to be reduced at the beginning of the analysis. This reduction of factors would decrease the completeness of the depiction of contexts. The main criticism of top-down approaches is the potential for being misled by data due to lack of the underlying theories [59], and the misuse of “associations” instead of “causations” [60].

This paper proposes a *hybrid* measurement approach that integrates the bottom-up and top-down approaches. This hybrid approach will remove the need for the initial reduction of factors (common in the bottom-up approach) by providing a method to scientifically reduce the number of factors, while providing a theory-based network to direct the analysis. In the hybrid approach, big data can be used in a structured way using the underlying theory. The hybrid approach will create initial networks of factors extracted directly from documents (e.g., root cause analysis reports, near-miss reports, corrective action program reports), and place them into a causal model (SoTeRiA). Once the critical factors and paths in the model are determined, the analysis can be re-focused, using scientific reduction to change the scope and to measure and quantify the most important factors and causal paths. The hybrid approach takes advantage of both data-informed approaches and an underlying theory by introducing a SoTeRiA network-generating algorithm. The algorithm provides a methodology for the extraction and analysis of socio-technical data, placing and ‘folding’ data into the SoTeRiA network structure, and operationalizing the network to provide input for the predictive causal model. The algorithm has the following steps:

1. Extract data and develop an initial network:
 - a. Using a combination of text mining with network data, extract factors from documents (e.g., NPP incident reports) and develop a data network. A candidate

software code is ConText [61]. Popova and Sharpanskykh [62, 63] also demonstrate a framework for semantic organizational modeling, which uses Temporal Trace Language (TTL) (first order predicate logic) to formalize *Nodes* (attributes; n) and their relationships (*Edges*; q). This candidate technique could be used to represent the relationships “between the descriptions of different elements” [64].

- b. By comparing the underlying theory (SoTeRiA) and the data network, calibrate and adjust the network.
- c. For unavailable or missing data relationships in the network, generic causal relationships will be applied from theory.
- d. If data are unavailable (e.g., for new organizational design), use theory to generate experimental (simulated) scenarios and create observational documents for experiments (i.e., documented interpretations of the experiments). Then, extract network data from the new documented observations utilizing the tool from step 1.a.

Comparatively, the difference between the SoTeRiA network (developed from Step 1) and traditional network analysis or, the more recent Knowledge Network Analysis [51, 65], is that the SoTeRiA network enables a theory-data dialectical network for risk analysis, meaning that the network developed from data analytics will be adjusted and directed by the SoTeRiA theory.

2. Scientific reduction of contextual network factors:

- a. Determine the value of causal Edges (e.g., frequency of occurrence) in the network data (i.e., $q_1, q_2 \dots q_k$), where “ q_k ” represents frequency of Edge k in the network.
- b. Determine the Node values (e.g., frequency of occurrence) in the network data (i.e., $f_1, f_2 \dots f_n$), where “ f_n ” represents the frequency of Node n in the network.
- c. Use ($q_1, q_2 \dots q_k$) to quantify the causal links in a predictive modeling tool (e.g., BBN; Jensen, et al. [66]) and also, utilize ($f_1, f_2 \dots f_n$), to quantify the aggregate probability of causal factors (e.g., Node 1, Node 2... Node n) in the BBN.
- d. Sensitivity analysis (See Section 2.4) and Importance Measure analysis (See Section 2.7) will be used to rank the importance of nodes and causal paths in the predictive model. This will provide an opportunity to reduce the scope (number of factors and causal paths) and re-focus on the important factors.
- e. Once the important high-level factors have been identified, the associated sub-factors (identified in Section 2.1) will be used to create a network that leads to the higher-level important factors. In other words, for each important high-level factor identified, a network should be developed, repeating Steps 1 & 2 to develop a network of sub-factors, and to identify the most important sub-factors associated to high-level important factors of the SoTeRiA network.
- f. The network of important sub-factors will be integrated with the network of high-level important factors to create one main three-dimensional network. The Importance Ranking analysis will be implemented in the main network to run another round of scientific reduction and to pass the important sub-factors to Step 3 for measurement.

3. Measurement of Important Factors:

Once the important sub-factors have been identified (from Step 2), all classical measurement approaches (subjective, objective), i.e., common measurement approaches in bottom-up approaches, should be utilized. It is a common practice in social science to develop surveys to measure the limited list of contextual factors. Kongsvik [67] addresses that the variation of scales, questionnaires and dimension in safety climate surveys (due to differences in developmental histories between industries), is “seen as a sign of the immaturity of this field of research”. Also, there is much ambiguity and inconsistency in the literature on assessing safety culture and climate among the safety community. To avoid the automatic use of surveys, Steps 1 and 2 will be used to find the most important factors and sub-factors before moving on to Step 3, where measurement techniques will be applied only to the most

important sub-factors remaining after scientific reduction. In other words, the purpose of this SoTeRiA hybrid algorithm is to rely less on surveys by directly embedding sub-factors into the main network and, dedicating the focus of measurement (e.g., if necessary, to develop surveys) on the identified important sub-factors.

Technical bases for the development of measurement approaches of important sub-factors will be built based on the advancement of a multidimensional measurement perspective [68]. According to this perspective, measurement methods should be selected based on the type and level of model constructs (i.e., individual, global, configural, and shared), the required level of accuracy, and the availability of data. The sub-factors can be measured using subjective (perception-based), objective (compliance-based) and hybrid (i.e., combination of *subjective* and *objective*) methods. Mohaghegh and Mosleh [46], also demonstrated that the Bayesian approach is an effective technique to operationalize multidimensional measurements. In this research, data analytics will introduce a new suite of textual and numerical data into the *hybrid* measurement methods.

4. Developing a large-scale SoTeRiA network:

Once the important factors and sub-factors have been quantified, the entire SoTeRiA network should be populated with a combination of detailed information for important nodes (from Step 3), and generic information (i.e., solely based on the theoretical model) for the rest of the nodes. The algorithm will proceed, with the large-scale SoTeRiA network, to Tasks 3 to 7.

Figure 2 visualizes a three-dimensional sub-network and surface-level network based on the SoTeRiA network-building algorithm. For technical systems, PRA has been used as a structured and formal method for developing high-level risk scenarios (using ETs). PRA implements reductionism, or a *breaking down* of the high-level events of ETs into basic events (component-level) using FTs to the point where; (1) reliability data can be more available, and (2) more understanding of common root causes of failures can be possible. Much like the classical PRA philosophy, the high-level causal network in SoTeRiA (i.e., the surface causal relationships among the grey nodes in Figure 2) can be visualized as the ETs and the associated network of each factor (i.e., the cones in Figure 2) can be considered as the FTs (under the elements of ETs) connecting the sub-factors to the high-level factors.

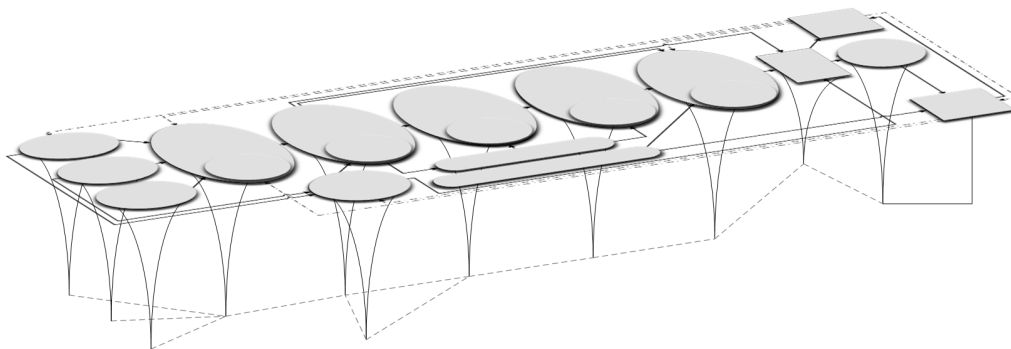


Figure 2. Visual Example of the Expanded Three-Dimensional SoTeRiA Network

2.3. Develop A Predictive Socio-Technical Causal Modeling Technique (Task 3)

The resulting network developed from *Task 2* will represent data of different varieties, therefore, the final choice of predictive modeling technique must relate to the type of analytics used, and the nature and the scope of the organization-level phenomena. Because of the multidisciplinary nature of the SoTeRiA theoretical framework, a single modeling technique is not adequate for its quantification, and so the integration of probabilistic and deterministic approaches is required. The SoTeRiA

modeling approach applies a combination of BBN (a probabilistic method), and SD (a deterministic method), to quantify the SoTeRiA theoretical framework [15, 47]. BBN can establish explicit probabilistic relations among elements of the model, where objective data are lacking and use of expert opinion is necessary. This, of course, is very important for the quantification of socio-technical models, when dealing with the soft nature of human and causal organizational failure mechanisms. BBN can be mathematically linked to classical PRA techniques, and is also capable of incorporating the positive features of regression-based techniques and process-modeling methods. However, BBN alone is inadequate for representing dynamic aspects such as feedback loops and delays. Combining SD with BBN enables BBN with dynamic features.

2.4. Uncertainty and Sensitivity Analysis (Task 4)

This task relates to the development of efficient uncertainty and sensitivity analysis methodologies for propagation of uncertainty in the organizational causal model. Uncertainty and sensitivity analysis will be conducted for all assumptions, input variables and models, including the integrated predictive causal modeling techniques, as well as data analytics techniques. Uncertainty propagation can be accomplished by assuming that the input parameters are random variables with distributions derived from historical data, experimental data, expert elicitation, or a combination of these sources. These values would be propagated through the organizational causal model to yield an output, an estimator of a key performance measure, such as the probability of a subsystem failure, which is then passed to the PRA model. A rich simulation environment will be developed that will allow uncertainty and sensitivity investigations of arbitrary model inputs and measurements.

2.5. Verification and Validation of the Causal Model (Task 5)

This research has multiple layers of validation:

(A) Theoretical validation: the development of constructs, factors, and sub-factors (*Task 1*) will be based on the theoretical grounds of the SoTeRiA framework, and in accordance with the analysis of the related theories and literature.

(B) Calibration of theories with up-to-date regulatory results: regulatory perspectives will be incorporated using samples from agencies that consider safety management and safety culture in their operations and oversight (e.g., NRC Safety Culture Common Language [69]). Perspectives will be derived from domestic and international rules, regulations, policies, guidelines, and associated documents. Potential sources for construct mapping include guidelines for safety management systems, safety culture policy statements, human factor engineering and human reliability guidance documents, etc.

(C) Qualitative & quantitative validation with industry observations: industrial perspectives will be incorporated using indicators from safety management systems, training programs and procedures, incident reporting systems, administrative documents, and expert elicitation. Industrial observations will be used to provide a practical and realistic context to the entire SoTeRiA ontology and theory-data dialectical network, while regulatory perspectives will be used to identify gaps in theoretical and industrial perspectives.

2.6. Integrate SoTeRiA with PRA (Task 6)

This task is dedicated to developing a methodology for the quantitative interface of the organizational causal model (SoTeRiA) and the PRA to create an *Integrated PRA*. At this stage, we need to find the associated basic events in PRA that are going to receive updated probabilities from the organizational causal model, and determine if any basic events need to be added to the PRA. In this integrative modeling approach, the classical PRA of the plant would be used, but the organizational performance phenomena would be modeled in a separate module (developed and quantified using the SoTeRiA framework and algorithm) and the module would then be linked to the classical PRA. The linkage will

convert the outputs of the organizational causal modeling module into distributions, and connect them to the basic events of the FT (See Figure 3). This linkage will help analyze the changes in the key elements of PRA due to the changes in the quality of key factors in the organization. The SoTeRiA hybrid modeling technique uses a proven methodology [70] to ‘fold’ phenomenological uncertainties associated with organizational failure mechanisms into plant performance metrics in order to support risk-informed decision-making.

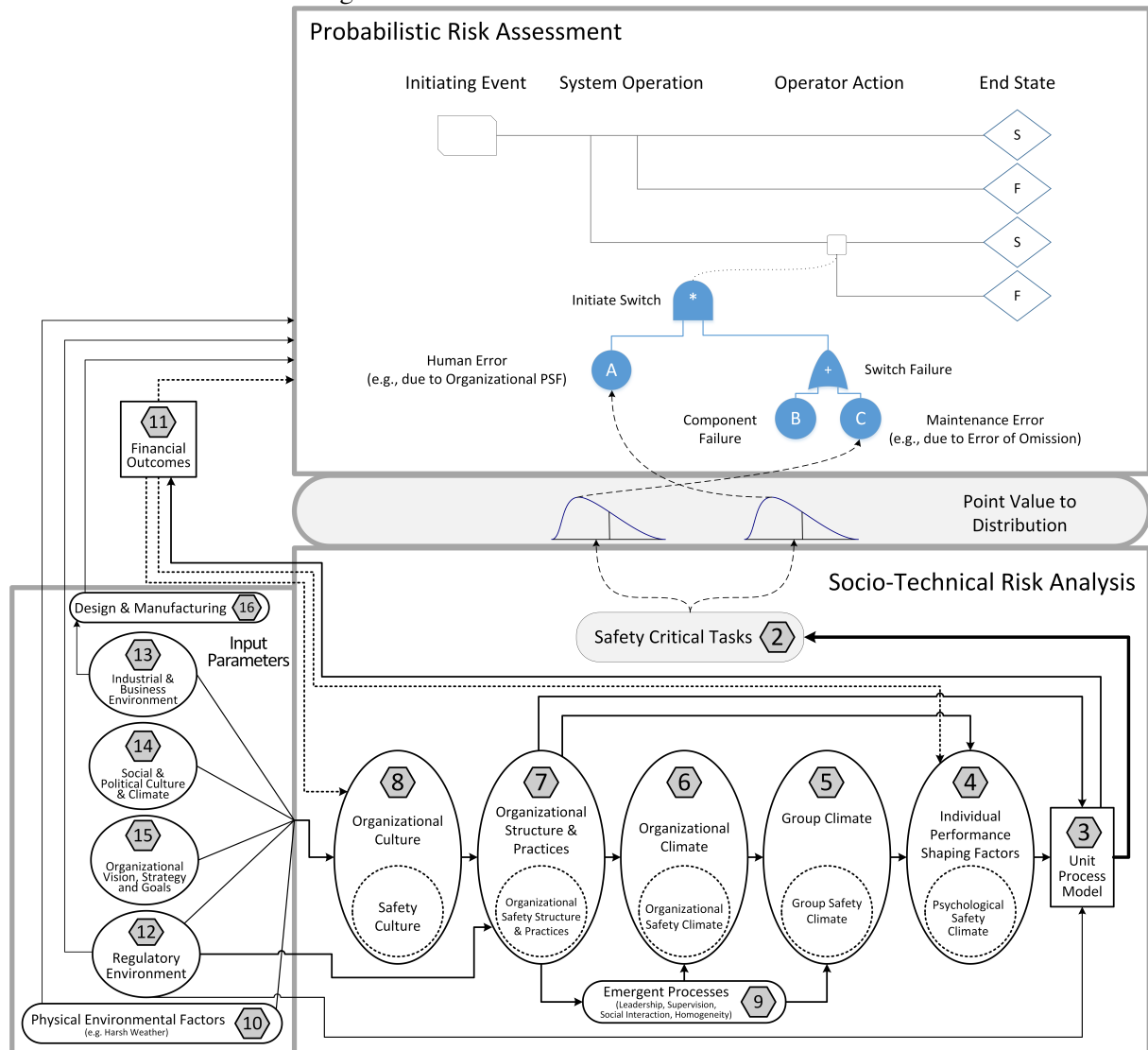


Figure 3. Illustration of the Integrated PRA Framework

2.7. Estimate Risk Importance Measures (Task 7)

This task focuses on the comparative studies of Risk Importance Measure (RIM) methodologies and the selection of an RIM approach for the SoTeRiA frameworks. The ultimate goal when using a RIM method is to find the most critical organizational failure mechanisms with respect to NPP risk (i.e., Core Damage Frequency) and to rank them based on the degree of their contribution to the risk. Doing so would allow an organization to dedicate more resources and time to the accuracy and validity of the values (and their associated uncertainties) for the most critical factors. Several types of RIMs have been developed and used for classical PRA. Sakurahara et al. [71] conducted a literature review on the methods of importance measures including both local measures (e.g., Fussel-Vesely (FV) and derivative-based importance measures) and global analysis (e.g., variance-based and moment-independent approaches). Based on the characteristics of the *integrated* PRA framework (e.g., uncertainty quantification and propagation, dynamic interactions, and dependencies among parameters and variables in the simulation module), the authors selected a Global Importance Measure (GIM) as

the most suitable RIM method for *integrated* PRA frameworks. In this research, we will analyze the application of GIM for the SoTeRiA-PRA model in order to rank the critical organizational failure mechanisms. This ranking will also help us find the most critical factors and sub-factors of SoTeRiA (with respect to risk) and, then run a more detailed measurement for them (i.e., Step 3 in section 2.2). The difference between the initial ranking in Step 2.d and the ranking of this section is that, in the initial ranking, the output performance is the output node of the network, but in this section the output is the total risk of the system and the factors are ranked based on their contributions to system risk. This possible feedback of the analysis will certainly increase the reliability of the quantifications and measurements.

2.8. Implement with the Nuclear Power Plant Specific Data (Task 8)

This section relates to the implementation of the developed theoretical model (*Task 1*) and the methodological approaches in *Tasks 2 to 7* for NPP risk analysis. It will lead to the building of a causal model for plant-specific organizational failure mechanisms of a NPP, and the linkage of the model as a separate module to the existing PRA. The causal model will be able to highlight the root organizational weaknesses of a ‘Significant Event’ and their paths of influence on the technical system risk scenario. We will quantify the organizational failure mechanism module and will quantitatively link it to PRA. This linkage will provide an estimate of the total risk associated with organizational failure mechanisms. It will also help to develop a precursor analysis and a risk importance measure analysis (*Task 7*) to find the most critical organizational failure mechanisms requiring high priority for correction at a given NPP and, will provide indicators of important factors for other high-risk industries. The integrated model (integration of the organizational module and PRA) will facilitate the analysis and quantification of the effects of change in total risk, due to the change in the root organizational weaknesses, and will help managers make decisions regarding optimum corrective actions. It is important to identify the controllable characteristics of an organization in order to prevent incidents or accidents.

3. CONCLUSION

Illusive organizational factors remain a significant hazard of complex socio-technical systems and the current generations of PRA do not include a comprehensive representation of the underlying organizational failure mechanisms. The SoTeRiA theoretical framework [15, 41] provides a roadmap for the analysis of organizational risk-contributing factors by integration of STS theory and PRA. The focus of the research, summarized in this paper, is to enhance SoTeRiA’s theoretical details, quantified methodological features, and practicality in order to develop a more accurate decision-making tool for high-risk organizations.

The *Theoretical* contributions of this research include the advancement of the detailed factors, sub-factors, and their casual relationships in the SoTeRiA framework, based on theoretical, industrial and regulatory perspectives. This improvement would help identify in-depth organizational root causes of failure and their paths of influence on technical system performance, utilizing theoretical models of social phenomena.

The *Methodological* contributions of this research relate to quantifying the SoTeRiA framework using advanced measurement and predictive methodologies, big data analytics, and uncertainty analysis. Socio-technical risk analysis deals with wide-ranging, incomplete, and unstructured data. Therefore, this research is dedicated to developing new predictive technologies for PRA that are not only grounded on socio-technical system theories, but also serve to expand the classical approach of data management for risk analysis by incorporating techniques such as text mining, data mining, data analytics, network analysis, as well as data curation and storage. In other words, this study proposes a hybrid combination of (1) big data (analytics) and (2) theory (SoTeRiA; an integration of STS theory and PRA) in order to efficiently extract organizational metrics and execute them in a network of organizational safety indicators. This hybrid integration would help (a) avoid the potential misleading results of solely data-informed approaches (big data methods, top-down approaches) and, at the same

time, (b) overcome the challenges of bottom-up approaches in quantifying socio-technical risk theories.

The *Practical* contributions of this research include the identification of organizational factors influencing technical system risk of NPPs, the aggregation and analytics of organizational data from NPPs in a causal modeling framework, and the development of a dynamic model for risk-informed organizational decision-making. By applying SoTeRiA to the PRA of a NPP, this research will quantify the effects of organizational factors on system risk and, analyze the criticality of organizational decision parameters. The research will provide a technology for industry that can quantitatively rank the importance of organizational risk contributing factors, and report on areas of organizational strengths and weaknesses based on their influence on risk, and propose effective preventive approaches.

The *Future* contributions of this research include the long-term goal of monitoring organizational safety indicators, capable of harmonizing the automated SoTeRiA network-generating algorithm and hybrid modeling technique to provide a real-time analysis that monitors the changing landscape of risk. By operationalizing a system capable of monitoring organizational safety indicators, real-time information can help set management decision-making thresholds to limit harmful organizational factors, detect root causes of organizational weaknesses, advance knowledge management for high-risk industries, and contribute to the development of organizational requirements for the safe operation of NPPs.

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